On Reducing Power Consumption of Transmitting Stations in 802.11 MIMO Networks

Mehmet Özgün Demir, *Student Member, IEEE*, Mehmet Karaca, *Member, IEEE*, and Güneş Karabulut Kurt, *Senior Member, IEEE*

***Abstract*—We propose an online algorithm for energy minimization of transmitting stations in IEEE 802.11 wireless local area networks (WLANs). Our algorithm configures radio frequency (RF) parameters such as the number of transmitting antennas based on the real-time traffic demand and channel condition so that the power consumption of the device is reduced, and the minimum data rate requirements of the stations at a target error rate are satisfied. The process of the transition between different RF configurations is investigated by employing a two-dimensional Markov chain model. Using an IEEE 802.11ac hardware testbed, we experimentally demonstrate that with our algorithm the power consumption of a transmitting station can be reduced upto 33%. We also validate that the experimental result and the simulation result obtained with our Markov model closely match.**

***Index Terms*—IEEE 802.11, power saving algorithm, dynamic RF configuration, Markov model, QoS preserving transmission.**

I. Introduction

THE TOTAL network traffic on the Internet is expected to reach to 1.6 zettabytes per year by 2018, and more than 60% of this traffic will be transmitted over IEEE WLANs. [1]. This huge traffic demand results in the development of the new IEEE WLAN standards with the improved multiple input multiple output (MIMO) capability to support very high data rates. For instance, it is possible to use 8x8 MIMO system with IEEE 802.11ac devices [2]. However, as more transmit and receive antennas are utilized, the power consumption of wireless devices dramatically increase due to the use of multiple RF chains. The measurements studied in [3] and [4] show that the most power hungry part of a Wi-Fi device is its RF front end, and the transmit chain consumes significantly more power than that of the receive chain.

There are several works in the literature to reduce the power consumption of the receiving 802.11 devices. In [4], the authors are interested to minimize power consumption of a receiving device by activating and deactivating receive antenna chains. Additionally, IEEE 802.11n [5] standard provides an energy efficient method, namely Spatial Multiplexing Power Save feature, to reduce the power consumption on the receiver side. However, there appears to be a gap in the literature on the energy consumption of transmitting stations in IEEE WLANs. Recently, in [6], the authors attempt to reduce the power consumption of the transmit chain of 802.11 device, but their algorithm requires a modification in the standard, and it does not provide any quality of service (QoS) guarantee. Also, the authors in [7] and [8] aim at minimizing transmit power by developing antenna selection algorithms for OFDM-MIMO systems. However, these works require Channel State Information (CSI) at the transmitter, which is costly and not practical. In this letter, we address the joint power minimization and transmit antenna selection problem with considering both the practical limitations and the QoS requirements of users. Without loss of generality we consider that only Access Points (APs) can transmit in the rest of the paper but our algorithm is applicable for any transmitting station.

Our contributions are summarized as follows. First, we formulate the problem of minimizing the power consumption of the RF chain of an AP, while providing the minimum required data rate of each station with a tolerable packet error rate, i.e., QoS. Second, we develop a practical online algorithm to solve this problem, which activates/deactivates the number of RF chains depending on the traffic load and the channel condition. Our algorithm can be easily implemented for the commodity 802.11 hardware without any modification in the standard. Third, we experimentally demonstrate the performance of our algorithm by using 802.11ac APs, and show that the power consumption of the transmitting AP can be reduced by 33% without sacrificing QoS requirements. Lastly, we propose a two-dimensional Markov model for the tractable performance analysis of our algorithm, and validate that the experimental results closely match the prediction of our Markov model.

II. System Model and Problem Statement

We denote $\mathcal{U}$ as the set of users to which an AP are transmitting data in a WLAN. For user u, let r_t^u and λ^u be the received signal strength indicator (RSSI) level at transmission time t, and the average arrival rate [packet/sec], respectively. In general, the AP provides a data rate $R(\boldsymbol{C}_t^u)$ to user u at time t depending on r_t^u and a *configuration vector* $\boldsymbol{C}_t^u$ which contains the decisions about all the transmission parameters of the AP such as the number of transmit antennas, the transmit power level, or the beamforming decision. In the rest of the paper we drop the user index u for notational simplicity. The decision for $\boldsymbol{C}_t$ is given based on r_t and λ, and $\boldsymbol{C}_t$ is a function of both r_t and λ, i.e., $\boldsymbol{C}_t = F(r_t, \lambda)$. We assume that when the AP transmits to user u with the configuration $\boldsymbol{C}_t$ at time t the AP consumes $P(\boldsymbol{C}_t)$ amount of power [Watt], which has Gaussian type distribution [9]. Here, we jointly target: *i)* to satisfy the associated QoS

Manuscript received July 13, 2015; accepted October 31, 2015. Date of publication November 12, 2015; date of current version February 12, 2016. This work was supported by TUBITAK under Grant 3130876. The associate editor coordinating the review of this paper and approving it for publication was W. Xu.

M. Ö. Demir and G. K. Kurt are with the Department of Electronics and Communication Engineering, Istanbul Technical University, Istanbul 34469, Turkey (e-mail: demirmehmet1235@itu.edu.tr; gkurt@itu.edu.tr).

M. Karaca was with Airties Wireless Networks, Istanbul 34469, Turkey. He is with the Department of Electrical and Information Technologies, Lund University, Lund 221 88, Sweden (e-mail: mehmet.karaca@eit.lth.se).

Digital Object Identifier 10.1109/LCOMM.2015.2500223

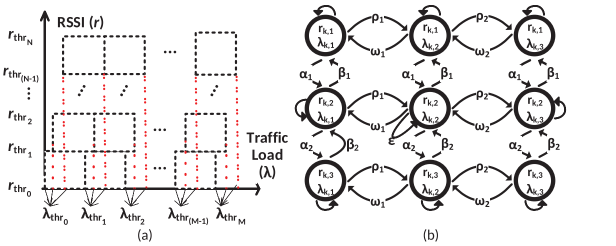

Fig. 1. (a) The general partition scheme of λ_k and r_k values in system design. Each partition indicates a state in two-dimensional Markov model. (b) The $N \times M$ Markov model. The state selection process is done for the transition probability 5-tuple $(\rho, \omega, \alpha, \beta, \epsilon)$.

requirements by supporting the traffic load, λ at a target packet error rate, *ii)* to minimize the average power consumption $\bar{P}$ of the AP by deciding the proper configuration $\boldsymbol{C}_t$. For each user $u \in \mathcal{U}$ we have the following optimization problem:

$$\min \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} P(\boldsymbol{C}_t) \qquad \text{s.t. } \lambda L \leq \bar{R}, \tag{1}$$

where L is the packet length in bits and $\bar{R}$ is the expected data rate provided by the AP, where the expectation is taken over all possible $R(\boldsymbol{C}_t)$ values in each transmission time. The optimization problem in (1) is known as network control problem [10], which has well-known solution for centralized network. However, to the best of our knowledge, there is no optimal solution for 802.11 Distributed Coordination Function (DCF) based network with fading channel (e.g., we refer the readers to [11]). Below, we propose an online algorithm to tackle (1), which can be easily implemented in actual hardware.

III. Online Algorithm

In our experimental measurements, we observed that the total system power consumption is dominated by the power consumed by the RF chains, and particularly adjusting the transmit power does not significantly affect $P(\boldsymbol{C}_t)$ due to the designed operating conditions at the linear region of the power amplifier, and it may create a risk of reducing coverage area. Hence, at any transmission time only the number of transmit antennas denoted as $a_t \in \mathcal{A} = \{1, 2, \ldots, M\}$ is determined as the configurable parameter, where M denotes the maximum number of transmit antennas on the AP.

Our online algorithm periodically measures the channel condition and traffic rate of each user for a duration of T_p seconds. Let r_k and λ_k be the averaged RSSI level and traffic rate at period k. In order to determine $\boldsymbol{C}_k$, we employ a threshold policy based on r_k and λ_k. Specifically, in Fig. 1(a), the (λ, r) plane is divided into sub-regions by using decision thresholds. Each region represents an AP configuration, which corresponds to a state in our two-dimensional Markov model (as will be introduced in Section III-A) with a unique power consumption. To determine the RSSI thresholds, the r axis is divided into N pieces by using $N+1$ distinct RSSI thresholds $(r_{thr_0}, r_{thr_1}, \ldots, r_{thr_N})$. Here, N is the total number of quantization levels for r_k. We define $\mathcal{RS} = \{r_{k,1}, r_{k,2}, \ldots, r_{k,N}\}$ as the set of the quantized RSSI values, and $r_k \in \mathcal{RS}$ for all k. The elements of $\mathcal{RS}$ are experimentally determined by taking into account the fact that the signal quality differs between two adjacent Modulation and Coding Scheme (MCS) levels typically by 3 dB (e.g., Receiver Sensitivity threshold for 802.11ac [2]). Hence, the difference between any two consecutive thresholds is chosen to be higher than 3 dB. We note that although RSSI may not be proper metric to quantify the link quality, other metrics such as Signal-to-Noise Ration (SNR) or Packet Error Rate (PER) are difficult to compute in practice, and are not provided by many commodity devices [12]. In any case, our algorithm can work with any other link metrics as long as they are computed in practice.

To determine the traffic load thresholds, in Fig. 1(a) we divide the λ axis into M regions and we have $M+1$ different thresholds for each $r_k \in \mathcal{RS}$, and let $\mathcal{TH}^j = (\lambda^j_{thr_0}, \lambda^j_{thr_1}, \ldots, \lambda^j_{thr_M})$ be the set of the quantized traffic, and $j \in [1, N]$. In other words, we quantize λ_k into M levels and the set of λ_k is $\mathcal{L} = \{\lambda_{k,1}, \lambda_{k,2}, \ldots, \lambda_{k,M}\}$. Then, we determine how many antenna should be used for a given traffic load $\lambda_k \in \mathcal{L}$ at the RSSI level $r_k \in \mathcal{RS}$.

The algorithm consists of two steps: in the first step, the AP measures r_k, and quantizes the measured r_k. Then, it determines the corresponding threshold set $\mathcal{TH}^j$. In the second step, the AP measures and quantizes λ_k, and then determines proper configuration $\boldsymbol{C}_k$ by using the quantized traffic λ_k and the selected $\mathcal{TH}^j$ set. Here, the AP decides the minimum number of antennas, which must support the traffic load λ_k. As an example, if the traffic load is between λ_{thr0} and λ_{thr1}, the AP activates only one antenna (i.e., $a_k = 1$). Similarly, the AP activates two antennas (i.e., $a_k = 2$), if $\lambda_{thr1} < \lambda_k \leq \lambda_{thr2}$. The pseudo code of the online algorithm is given in Algorithm 1. Here, we present $\lambda_{thr_i}, \lambda_{thr_d} \in \mathcal{TH}^j\ \forall j$, which are the thresholds for activating and deactivating more antennas, respectively for notational simplicity.

Algorithm 1. Online Energy Efficient Algorithm

$a_k \leftarrow$ active transmit antenna in k^{th} period
$\mathcal{A}(i) \leftarrow$ current i^{th} element of the set $\mathcal{A}$
$L \leftarrow$ Constant packet length in bits
for $k = 1 : K$ **do**
  Measure and quantize r_k into one of the N level
  Determine corresponding $\mathcal{TH}^j\ \forall j \in [1, N]$
  if $\lambda_k L > \lambda_{thr_i}$ **then**
    $a_k \leftarrow \mathcal{A}(i+1)$
  else if $\lambda_k L < \lambda_{thr_d}$ **then**
    $a_k \leftarrow \mathcal{A}(i-1)$
  else
    $a_k \leftarrow \mathcal{A}(i)$
  end if
end for

A. Analysis of the Online Algorithm

We present a two-dimensional Markov model to characterize the performance of the online algorithm. For the target user, the stochastic process (r_k, λ_k) is modeled as two-dimensional Markov chain, where r_k is the quantized RSSI level and λ_k is the quantized traffic load. Fig. 1(b) shows our exemplary Markov model, where the maximum number of transmit antennas is three (i.e., $M = 3$) and the RSSI is measured at three different locations (i.e., $N = 3$). In general, it is possible to move from one state to any other state with a non-zero probability. However, in our simplified form, we allow at most one additional antenna can be activated (or deactivated) at a time, due to hardware limitations. Specifically, if more than one antennas are activated at a time, we observe intolerable packet losses. Hence, at state (r_k, λ_k), if the channel condition changes, the system may move to state $(r_k + 1, \lambda_k)$ or $(r_k - 1, \lambda_k)$. For the simplicity of both analytical and experimental validation in Sec. IV-C we assume that r_k and λ_k do not change at the same time and all one-step transition probabilities are equal, (i.e., $\rho_1 = \rho_2 = \rho$, $\alpha_1 = \alpha_2 = \alpha$). We note that our algorithm can still work well without these assumptions since any of these assumptions are not a design parameter in our algorithm. In general, transition probabilities 5-tuple $(\rho, \omega, \alpha, \beta, \epsilon)$ can be found by analyzing the traffic load. In this letter, we generate these values artificially to make controlled experiments, and to show the validation of the Markov model.

In order to determine the average power consumption with our Markov model, the steady state probabilities denoted as $\pi_{n,m}$ must be calculated. We know that the sum of all steady state probabilities must be equal to 1. Also, we know that $\rho + \omega + \alpha + \beta + \epsilon = 1$. Then, the steady state probabilities can be found as a direct solution of a linear system with $N \times M$ independent balance equations. (e.g., nine independent equations in our exemplary Markov model.) After solving those equations, we have:

$$\pi_{1,1} = \frac{\omega^{M-1}(\rho - \omega)\beta^{N-1}(\beta - \alpha)}{(\rho^M - \omega^M)(\beta^N - \alpha^N)}. \tag{2}$$

Then, by using (2), we have,

$$\frac{\pi_{j,i}}{\pi_{(j+1),i}} = \frac{\beta}{\alpha}, \quad \frac{\pi_{j,i}}{\pi_{j,(i+1)}} = \frac{\omega}{\rho}, \quad \forall j, i, \tag{3}$$

where $j \in [1, N]$ and $i \in [1, M]$. All the steady state probabilities can be calculated by using (3), when the transition probabilities $(\rho, \omega, \alpha, \beta, \epsilon)$ are given. Then, the average RF power consumption under our Markov model is given as follows:

$$\bar{P}^{RF} = \sum_{n=1}^{N} \sum_{m=1}^{M} P^{RF}(r_{k,n}, \lambda_{k,m})\pi_{n,m}, \tag{4}$$

where $P^{RF}(r_{k,n}, \lambda_{k,m})$ is the instantaneous power consumption of the RF part of the AP at state (n, m).

IV. Experimental Results

In this section, we first introduce our experimental and simulation setups. Then, we present our experimental results of the performance of our online algorithm and the validation of our Markov model.

A. The Experimental and Simulation Setup

In our experimental setup, we use two APs with Broadcom 4360 chip-set, which support IEEE 802.11ac standard with 3 transmit antennas, i.e., $M = 3$. One AP acts as the transmitting station, while the other AP is configured as a receiving station (i.e., user u). The location of the transmitting AP is fixed, and the location of the user u is dynamically changed between three measurement points (i.e., $N = 3$), which are 2.4, 4.8 and 7.2 meters away from the AP, and the corresponding RSSI set is measured as $\mathcal{RS} = \{-40, -46, -52\}$ dBm. A power meter is connected to the AP to measure the power consumption of the device during the data transmission. The average throughput and packet loss are measured and recorded at the user side. UDP traffic with random rates is generated by *Iperf*. To measure λ_k at the transmitter, we periodically examine */proc* file system in Linux on the AP. We also measure $\bar{R}$ from *wireless driver*. The exponential moving average each second is employed to smooth out the RSSI and traffic variations and also to avoid too much processing overhead of reading */proc* and *driver* interfaces. Also in our setup packet length is chosen $L = 1470$ bytes.

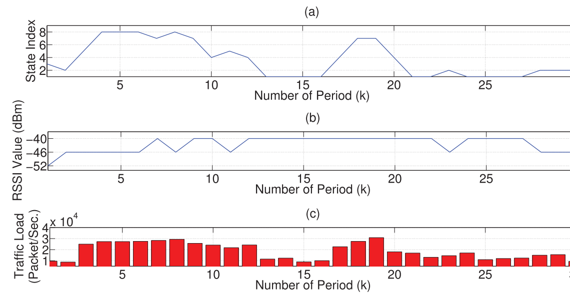

Fig. 2. (a) Generated state sequence using determined 5-tuple $(\rho, \omega, \alpha, \beta, \epsilon)$ for $\max\{k\} = 30$. (b) Generated RSSI distribution r_k for each k. (c) Generated traffic load λ_k distribution for each k.

In our simulation setup to validate our Markov model, we artificially generate input traffic and RSSI sequences, which are used both experiment and simulation. To do that, we first determine a state sequence. Each state (r_k, λ_k) indicates a quantized traffic load and RSSI value. In our Markov model, we arbitrarily select an initial state uniformly. The transitions to the rest of the states ($\max\{k\} - 1$ states in total) are determined according to the Markov chain transition probabilities $(\rho, \omega, \alpha, \beta, \epsilon)$, which are set to $(0.1509, 0.2505, 0.1517, 0.2325, 0.2144)$, respectively. In Fig. 2(a), an exemplary state selection result is shown for $0 < k \leq 30$ and $T = 20$ seconds for given transition probability 5-tuple $(\rho, \omega, \alpha, \beta, \epsilon)$. In our simulation, we measure $P(\boldsymbol{C}_t)$ for a predetermined sets of $\mathcal{A}$ and $\mathcal{RS}$ according to the known thresholds. Then, for the given transition probabilities, we calculate the steady state probabilities by using (2) and (3), and we use (4) to determine the average power consumption.

In the experiments, the location of the user is changed dynamically between three points and the measured RSSI values at these points are almost constant according to our measurements. The related RSSI distribution is given in Fig. 2(b) for the selected state distribution in Fig. 2(a). In order to determine a traffic load for a selected state, we should select proper $\mathcal{TH}^j$ sets according to the RSSI sequence given in Fig. 2(b). The possible traffic threshold sets are determined by using the results of previous data rate measurement at these locations, then we have $\mathcal{TH}^1 = \{100, 200, 300, 400\}$, $\mathcal{TH}^2 = \{90, 190, 290, 390\}$ and $\mathcal{TH}^3 = \{80, 180, 280, 380\}$ [Mbps]. We assume that at each interval (s.t. between $\lambda^j_{thr_0}$ and $\lambda^j_{thr_1}$), the values are distributed uniformly, and a traffic load for a selected state (r_k, λ_k) is determined randomly. This process is repeated for all states. An exemplary input traffic load sequence for the state distributions in Fig. 2(a) is shown in Fig. 2(c).

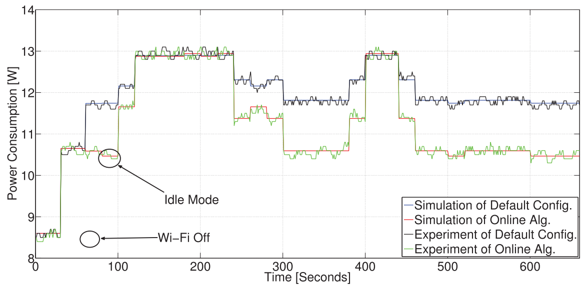

Fig. 3. Simulation and experiment results, including both default configuration and online algorithm processes, for $T = 20$ seconds and $k \leq 32$, where $k = 1$ is the Wi-Fi turned off and $k = 2$ is the idle mode.

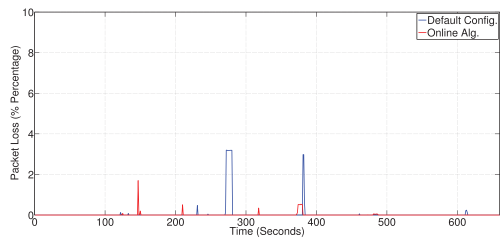

Fig. 4. Packet losses for both default configuration and online algorithm operation modes, where first 20 seconds is the Wi-Fi turned off and second 20 seconds is the idle mode.

B. Power Consumption Gain

Fig. 3 shows the power consumption of the online algorithm for both simulations and experiments over the test duration. We compare the online algorithm with the default configuration, which activates all transmit antennas without considering traffic. We note that the APs with the default configuration are deployed in many practical usages. Since an AP included several factors that lead to power consumption, we first measure the power consumption of the device when Wi-Fi module is turn off, and it consumes $P(r_k, \lambda_k) = 8.5$ W. Then, $P(r_k, \lambda_k) =$ 10.5W when we turn on the Wifi module, and the user is associated to the AP without receiving any data, which we call the idle mode of Wi-Fi. We measure that in the idle mode, RF power consumption is $P^{RF}(r_k, \lambda_k) = 2$W. Next, the AP starts transmitting data according to the generated traffic. Clearly, $P^{RF}(r_k, \lambda_k)$ varies between 2.1W to 4.4W for the online algorithm whereas it varies between 3.3W to 4.4W for the default configuration. When λ_k is high, the online algorithm activates all the antennas and consumes similar amount of power as that of the default configuration. However, with moderate and low traffic conditions, the online algorithm can make more intelligent decisions and deactivates one or two antennas to save power. For the given set of traffic distribution $\mathcal{L}$, we observe that $\bar{P}^{RF}$ can be reduced up to 33%.

The performance of the online algorithm and default configuration in terms of packet losses is depicted in Fig. 4. The packet errors are due to poor channel conditions, and the online algorithm and default operation have similar packet losses, which is less than 1% on the average over the test duration. This result tells us that the online algorithm does not violate the QoS requirements, and supports all the incoming traffic.

C. Validation of the Markov Model

In Fig. 3, we also depict the validation of our Markov model with the experimental results. We use the following metric as our performance metric, which measures the relative error between the measurement and the simulation based results:

$$RE_P = (|\bar{P}_e^{RF} - \bar{P}_s^{RF}|)/\bar{P}_e^{RF}, \tag{5}$$

where $\bar{P}_e^{RF}$ and $\bar{P}_s^{RF}$ are the average power consumption of the RF part in the experiment and in the simulation result that is obtained through our Markov model, respectively. We observe that the Markov model shows very good agreement with the measured results, and for all λ_k values RE_P varies between 0.72% and 8%. We also observe that our Markov model reaches the state steady after $k = 1000$ iterations. Then, we determine $\bar{P}^{RF}$ by using the steady state probabilities (2) and (3) for the given λ_k and r_k, and observe that the numerical average power gain is approximately 31%, which is very consistent with the experimental gain that is equal to 33%.

V. CONCLUSION

In this letter, we propose a practical algorithm for Wi-Fi devices to minimize the power consumption during data transmission. The basic idea behind our algorithm is to adjust the number of active antennas depending on the current amount of the traffic arriving into the transmitting station, and the channel quality. We experimentally show that a Wi-Fi device with our algorithm can save up to 33% energy, and support all the traffic. We also employ a Markov model to analyze our algorithm, and our results suggest that Markov model can be a useful tool to predict the power consumption of the RF part of a Wi-Fi device.

REFERENCES

[1] Cisco, "The zettabyte era-trends and analysis," White Paper, 2014.
[2] *IEEE Standard for Information Technology—Telecommunications and Information Exchange Between Systems Local and Metropolitan Area Networks—Specific Requirements—Part 11*, IEEE Std 802.11ac, 2013.
[3] D. Halperin, B. Greenstein, A. Sheth, and D. Wetherall, "Demystifying 802.11n power consumption," in *Proc. Int. Conf. Power Aware Comput. Syst.*, 2010, pp. 1–5.
[4] I. Pefkianakis, C.-Y. Li, and S. Lu, "What is wrong/right with IEEE 802.11n spatial multiplexing power save feature?," in *Proc. IEEE Int. Conf. Netw. Protocols (ICNP)*, 2011, pp. 186–195.
[5] *IEEE Standard for Information Technology—Telecommunications and Information Exchange Between Systems Local and Metropolitan Area Networks—Specific Requirements—Part 11*, IEEE Std. 802.11n, 2009.
[6] I. Pefkianakis, C.-Y. Li, C. Peng, S.-B. Lee, and S. Lu, "CMES: Collaborative energy save for MIMO 802.11 wireless networks," in *Proc. IEEE Int. Conf. Netw. Protocols (ICNP)*, 2013, pp. 1–10.
[7] N. P. Le, L. C. Tran, and F. Safaei, "Adaptive antenna selection for energy-efficient MIMO-OFDM wireless systems," in *Proc. Int. Symp. Wireless Pers. Multimedia Commun. (WPMC)*, 2014, pp. 60–64.
[8] A. He *et al.*, "Power consumption minimization for MIMO systems—A cognitive radio approach," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 2, pp. 469–479, Feb. 2011.
[9] M. Demir, G. Kurt, and M. Karaca, "An energy consumption model for 802.11ac access points," in *Proc. SoftCOM*, Sept. 2014, pp. 67–71.
[10] L. Georgiadis, M. J. Neely, and L. Tassiulas, "Resource allocation and cross-layer control in wireless networks," *Found. Trends Netw.*, vol. 1, no. 1, pp. 1–144, Apr. 2006.
[11] C. Joo, X. Lin, J. Ryu, and N. B. Shroff, "Distributed Greedy approximation to maximum weighted independent set for scheduling with fading channels," *IEEE/ACM Trans. Netw.*, to be published.
[12] A. Vlavianos, L. K. Law, I. Broustis, S. V. Krishnamurthy, and M. Faloutsos, "Assessing link quality in IEEE 802.11 wireless networks: Which is the right metric?" in *Proc. IEEE Pers. Indoor Mobile Radio Commun.*, 2008, pp. 1–6.