Sustainability Analysis and Resource Management for Wireless Mesh Networks with Renewable Energy Supplies

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***Abstract*—There is a growing interest in the use of renewable energy sources to power wireless networks in order to mitigate the detrimental effects of conventional energy production or to enable deployment in off-grid locations. However, renewable energy sources, such as solar and wind, are by nature unstable in their availability and capacity. The dynamics of energy supply hence impose new challenges for network planning and resource management. In this paper, the sustainable performance of a wireless mesh network powered by renewable energy sources is studied. To address the intermittently available capacity of the energy supply, adaptive resource management and admission control schemes are proposed. Specifically, the goal is to maximize the energy sustainability of the network, or equivalently, to minimize the failure probability that the mesh access points (APs) deplete their energy and go out of service due to the unreliable energy supply. To this end, the energy buffer of a mesh AP is modeled as a $G/G/1(/N)$ queue with arbitrary patterns of energy charging and discharging. Diffusion approximation is applied to analyze the transient evolution of the queue length and the energy depletion duration. Based on the analysis, an adaptive resource management scheme is proposed to balance traffic loads across the mesh network according to the energy adequacy at different mesh APs. A distributed admission control strategy to guarantee high resource utilization and to improve energy sustainability is presented. By considering the first and second order statistics of the energy charging and discharging processes at each mesh AP, it is demonstrated that the proposed schemes outperform some existing state-of-the-art solutions.**

***Index Terms*—Energy sustainability, resource management, wireless mesh networks, renewable energy supply.**

I. INTRODUCTION

THE EXPLOSIVELY growing demand for ubiquitous broadband wireless access has led to a significant increase in energy consumption by wireless communication networks. To counter this increase, future generations of wireless networks are expected to make use of renewable energy sources, e.g., wind, solar, tides, etc., to fulfill the ever-increasing user demand, while reducing the detrimental effects of conventional energy production. However, unlike traditional energy supplied from the electricity grid, renewable energy sources are intrinsically dynamic with unstable availability and time varying capacity. For example, a wind turbine usually provides intermittent power which depends on how windy the weather is. Although solar panels can provide relatively continuous power supply, the energy supply varies across the time of a day and the season of the year, and is influenced by atmospheric conditions and geography. As a result, when renewable energy is deployed to power wireless communication networks, its dynamic and unreliable nature will affect the availability and efficiency of communications, and therefore will make energy-sustainable network design a necessity.

Improving energy efficiency has long been a fundamental research issue in wireless communications, mainly because of the limited battery power of mobile terminals and/or the increasing cost of the energy from the electricity grid. In traditional systems powered by batteries, the energy is a limited resource but it is stable during the battery lifetime. The electricity grid generally provides continuous power on demand with no stringent usage limit; however, this power is primary generated from limited and non-sustainable resources, such as coal, natural gas, and petroleum. In contrast, renewable energy sources are sustainable in the long term but are unstable and intermittently available in the short term. As a result, *the fundamental design criterion and the main performance metric have shifted from energy efficiency to energy sustainability* in a network powered by renewable energy [1]. While many existing works focus on energy efficiency, energy sustainability has not been well explored and deserves further investigation. Thus motivated, we first develop a mathematical model to study the "energy sustainability" performance of wireless devices theoretically and, based on this analysis, we further dimension the resource management and admission control strategies to improve the sustainable network performance under an energy sustainability constraint.

The possibility and advantages of deploying a sustainable energy powered wireless system are reported in [2]. In particular, it is shown that solar or wind powered access points (APs) provide a cost-effective solution in wireless local area networks (WLANs), especially for APs installed in off-grid locations. Since the publication of that study, resource management for sustainable wireless networks has been studied in multiple contexts. In [1] and [3], the AP placement problem

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has been re-visited in the context of sustainable WLAN mesh networks, in which a minimal number of APs with renewable energy sources are deployed in an area such that the quality of service (QoS) requirements of users can be fulfilled. In [4], by comparing sustainability performance of various routing algorithms, it is shown that traditional routing strategies without considering energy charging capability achieve poor performance; it is crucial to adapt routing decisions to the time varying energy supplies. However, without an accurate analytical model for energy supply dynamics, how to effectively make routing decisions in an energy sustainable wireless network remains an open issue. Moreover, most existing works use residual energy or the mean energy charging rate for resource allocation, by either assuming the energy charging rate is known a *priori* or using an oversimplified model, e.g., that the charging rate is uniformly distributed. In reality energy charging is known to be a complicated and dynamic process due to the restricted energy charging capabilities of hardware and diverse charging environments which are usually location dependent. Coupled with the dynamic end host demands on multimedia services, e.g., bursty media streaming and data applications, it is thus crucial to fully understand the impact of dynamic energy availability on resource management and traffic routing at distributed nodes to provision satisfactory, robust, and sustainable performance of a renewable energy powered mesh network.

In this paper, we develop an analytical model to evaluate the instantaneous volume of buffered energy at mesh APs with dynamic energy charging and discharging. By exploring the transient behavior of the energy buffer, adaptive and optimal energy resource management schemes are proposed to maximize the network-wide energy sustainability such that the probability of mesh APs depleting their energy and going out of service is minimized. Our main contributions are three-fold:

- *Analytical Model*: A generic analytical framework to study the transient evolution of the energy buffer is presented. Specifically, we model the energy buffer as a $G/G/1/\infty$ and $G/G/1/N$ queue with the general energy charging and discharging processes in infinite and finite energy buffer cases, respectively. Based on the first two statistical moments, i.e., the mean and variance, of the energy charging and discharging intervals, we apply the diffusion approximation to obtain closed-form distributions of the transient (energy) queue length and the energy depletion duration.
- *Adaptive Resource Management*: Based on the developed analytical framework, we propose an adaptive resource management scheme to assure the energy sustainability of the network. In the proposal, traffic flows are distributively scheduled on multi-hop paths towards the minimal energy depletion probability of mesh APs. The proposed scheme is adaptive to the residual energy level at mesh APs and the dynamic traffic demands of flows.
- *Distributed Admission Control*: A distributed admission control strategy is deployed at mesh APs to strike a balance between high resource utilization and energy sustainability.

The remainder of the paper is organized as follows. Related works are discussed in Section II. The system model is presented in Section III and an analytical framework is developed to study the transient buffer evolution in Section IV. Based on the buffer analysis, an adaptive resource management scheme is proposed in Section V. Simulation results are given in Section VI, followed by concluding remarks in Section VII.

II. Related Work

Energy efficiency is a fundamental research issue in wireless communication networks [5], [6], [7], [8]. An extensive body of research has been devoted to resource management for energy efficient communication and networking, ranging from network capacity planning and topology control [9], [10], traffic scheduling and routing [11], [12], and adaptive sleep control of mobile devices [13], [14], to energy efficient communication and cooperation [15], [16], and optimal power management [17], [18], etc. In these works, the energy supply is typically considered to be a fixed yet limited resource.

With recent advances in energy technologies, sustainable wireless networks with renewable energy sources have been emerging. The development of prototypes of sustainable sensors with solar energy harvesting capability was the first issue to be studied in this context. In [19] and [20], experimental results show that such prototypes can enable near-perpetual operation of a sensor node. The solar/wind powered AP has been recognized as a cost-effective alternative to the traditional AP in WLAN mesh networks, especially when a fixed power supply is not available. Resource allocation and energy management in sustainable mesh networks have also been studied in multiple contexts. Sayegh *et al.* in [2] consider a hybrid solar/wind powered WLAN mesh network and argue that a hybrid solution provides the optimal cost configuration. Farbod and Todd in [21] describe a solar battery configuration methodology based on the mean offered capacity profile, and propose an outage control algorithm to improve the node outage performance. Cai *et al.* in [1] study the dynamic characteristics of sustainable energy sources and elaborate on the fundamental design criterion for a sustainable mesh network. Under the green network paradigm incorporating renewable energy, network deployment and resource management issues have been re-visited. Different routing schemes have been examined and compared in the context of sustainable networks, aiming to distribute the traffic loads evenly over the network to improve the network sustainability. For example, it is shown in [4] that traditional routing strategies that do not consider the variable nature of renewable energy supplies achieve poor performance, and it is crucial to adapt the routing decisions to the time varying power supply conditions in a sustainable network environment. However, how to accurately capture and model the power conditions remains an open research issue. Most existing works on sustainable communications use the residual energy, a fixed energy charging rate, or an oversimplified energy charging model, e.g., that the charging rate is uniformly distributed, for resource allocation. As the available energy is inherently dynamic due to variations in both energy charging and discharging processes, it is essential to characterize the variations in the analytical model of energy conditions. In addition, previous routing algorithms mainly focus on routing metric design and/or route discovery issues. To provide satisfactory sustainable network performance, both load balancing over various paths and effective admission control should be incorporated into one resource management framework.

To tackle this challenging issue, we model the energy buffer as a G/G/1/∞ and G/G/1/N queue in infinite and finite battery capacity cases, respectively. Based on the first and second order statistics of the charging and discharging processes, we apply diffusion approximation to analyze the distributions of the queue length and the first passage time at which a node's energy depletes. As an efficient and accurate approach for studying transient behavior of queueing systems [22], [23], [24], diffusion approximations have been widely applied in adaptive buffer management [25]. To the best of our knowledge, this is the first work to apply a diffusion approximation to analyze the energy sustainability performance of network devices, and to use the derived closed-form distributions for adaptive resource management in a sustainable wireless mesh network.

III. System Model

A. Energy Model

We consider a sustainable wireless mesh network as shown in Fig. 1. Each mesh AP is equipped with a battery that can be charged repeatedly via a renewable energy supply. Let $R_i(0)$ denote the initial battery energy of node i and $\mathcal{A}_i(t)$ denote the amount of energy charged over the time interval $[t-1, t]$ at node i. Note that due to differing environments, e.g., different solar radiation intensities or wind speeds at different geographical locations, the energy charging capacity of each mesh AP varies uniquely over time. Hence, we model the energy charging process at a node as a continuous-time stochastic process with an arbitrary but stable distribution, and count the charged energy units as the arrival events of the queue. The mean and variance of the inter-charging intervals are denoted by μ_a and v_a, respectively. μ_a and v_a can be estimated to be an exponentially weighted moving average or other estimation approaches. The charged energy can be stored in the batteries. Denote by $R_i(t)$ the residual energy of node i at time t, by R_i^{max} the maximum energy storage or the battery capacity of node i, and by $R_i^{min} \geq 0$ the minimal residual energy level based on battery life and safety considerations. In other words, the energy level of node i is within the range $[R_i^{min}, R_i^{max}]$. Without loss of generality, we simplify the model by considering $0 \leq R_i(t) \leq N_i$, where $N_i = R_i^{max} - R_i^{min}$ which reflects the maximum number of energy units that a node can use. In the following, we study the two scenarios of an infinite energy buffer capacity, i.e., $N_i \to \infty$ and a limited energy buffer capacity, i.e., N_i is finite.

The energy consumption includes the energy used for receiving a packet, processing it, and forwarding it en route to the destination. Receiving and processing energy can be considered to be a constant, e_r, while the transmission energy should be adjusted to ensure a desired bit error rate at the receiver. As the signal energy attenuates over a wireless channel [26], [27], the energy path loss is usually characterized by $d_{i,j}^n$, where $d_{i,j}$ is the distance between nodes i and j, and n is the path loss exponent. For a given signal to noise ratio (SNR) requirement, the minimal energy required for transmitting one bit over link $i \rightharpoonup j$ should be proportional to path loss, i.e.,

$$e_{t_{i,j}} \propto d_{i,j}^n. \tag{1}$$

The total energy consumption of node i during the time interval $[t-1, t]$ is given by

$$\mathcal{S}_i(t) = \sum_j \sum_k p_{i,j,k}(t)(e_r + e_{t_{i,j}}), \tag{2}$$

where $p_{i,j,k}(t)$ is the traffic demand of flow k over link $i \rightharpoonup j$ during $[t-1, t]$. The residual energy of node i at time t can thus be given as

$$R_i(t) = \min\Big\{ \max\{R_i(t-1) + A_i(t) - S_i(t), 0\}, N_i \Big\}. \tag{3}$$

We model the traffic arrivals at each AP as a Poisson process. The mean and variance of the energy inter-discharge interval are denoted as μ_s and v_s, respectively. The values of μ_s and v_s can be estimated via standard estimation approaches.

B. Network Model

We consider a distributed wireless mesh network consisting of multiple stationary mesh APs with sustainable energy supplies, as shown in Fig. 1. Each mesh AP manages a local WLAN with multiple wireless users, while serving as a mesh router that forwards traffic from other mesh APs or WLANs. One typical application scenario is a home or office WLAN in which an AP with sustainable energy supply can be installed on the roof to harvest energy from the environment, e.g., sun, wind, etc. Users of the WLAN may communicate with local or remote users. Therefore, each mesh AP not only bridges traffic inside its coverage, e.g., within the house or an office, but also routes traffic from other APs toward the destination over the mesh backbone. Both intra- and inter-WLAN traffic demands are considered in the system model. Using orthogonal frequency division multiplexing, mesh APs can select orthogonal channels for data transmissions and receptions, and therefore there is no interference among intra- and inter-WLAN communications. As the first step, we assume that the bandwidth is sufficient and that the sustainable energy supply is the performance bottleneck. This is acceptable because bandwidth is typically an ample resource with advanced wireless technologies while energy is more limited in the current setting. Future research on joint bandwidth and energy management is required to study the impact of limited bandwidth on the network performance.

We construct a directed graph $G = (V, E)$ for the mesh backbone network such that mesh APs are represented by vertices ($v \in V$) and wireless links between APs are represented by edges ($e \in E$). Each vertex is associated with a weight w_v which represents the energy sustainability level of the node, i.e., how likely the node is to drop out by depleting all its energy to serve the traffic flows traversing it. Each edge, e.g., edge $i \rightharpoonup j$ from node i to node j, is associated with a transmission energy, $e_{t_{i \rightharpoonup j}}$, which is a function of the

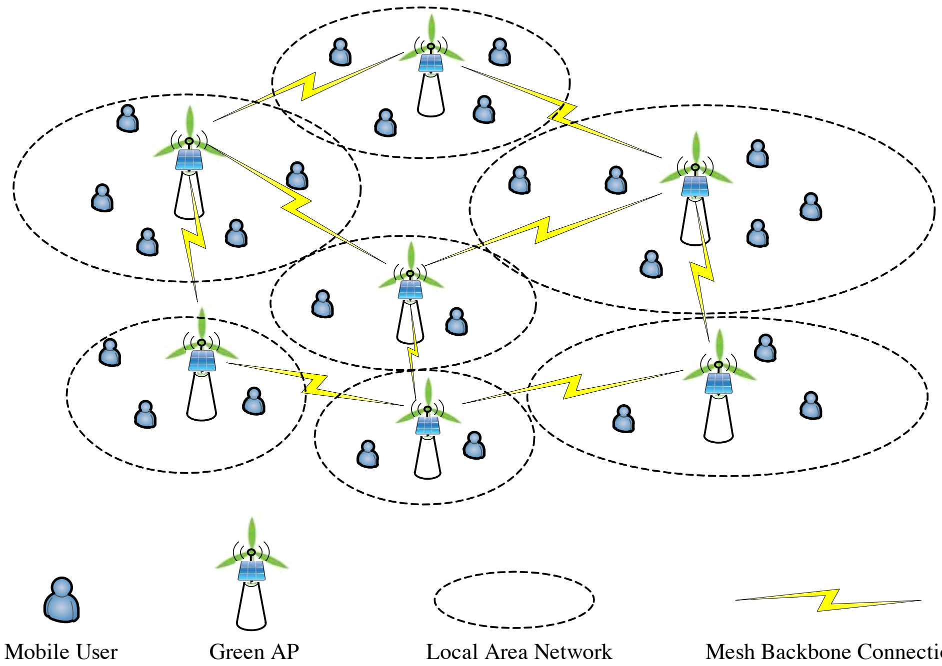

Fig. 1. WLAN Mesh Network

link distance. Notice that the energy consumed for relaying traffic is not only determined by the transmission energy of the forwarding links, but also the traffic demands for the relay.

IV. Transient Queueing Analysis of Energy Buffer

In this section, we develop a general framework for energy buffer analysis. Specifically, we apply a diffusion approximation to study the transient evolution of an energy buffer in both infinite and finite battery storage cases of a mesh AP. Initially, a mesh AP has energy $R(0) = x_0$.[1] Energy harvested from the environment is stored in the energy buffer until the battery capacity N is reached, and energy is discharged from the buffer while serving traffic demands. The evolution of the energy buffer is shown in Fig. 2. Due to the dynamics in the charging and discharging process, a mesh AP may deplete its energy buffer when $R(t)$ reaches 0. In this case, the AP is considered temporarily unreachable and all associated links are broken. Therefore, a fundamental problem arising is how to properly distribute the traffic demands across the network according to the energy levels of APs such that the probability that a link is broken or an AP becomes unavailable is minimized.

A. Queue Model of Infinite Energy Buffer

We first consider the situation in which the battery capacity is sufficiently large such that all charged energy can be stored in the battery. Therefore, the energy buffer can be modeled as a $G/G/1/\infty$ queue, with means and variances of inter-arrivals (inter-departures) denoted as μ_a (μ_s) and v_a (v_s), respectively.

We use the diffusion approximation or Brownian motion approximation approach to analyze the $G/G/1/\infty$ queue [22].

[1]For notational simplicity, we neglect the node index in the notation in Section III, e.g., the subscript i in $R_i(t)$.

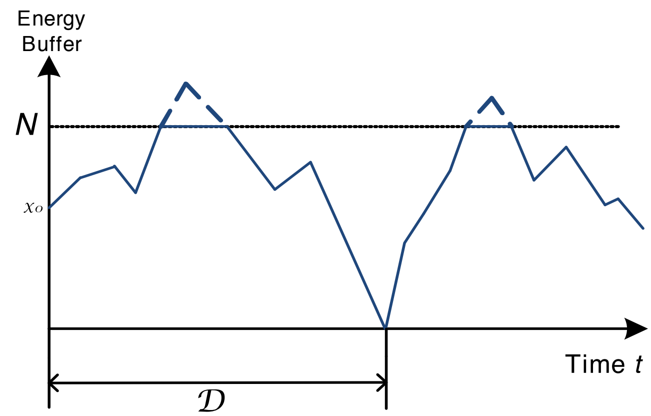

Fig. 2. Evolution of an energy buffer

The discrete buffer size $R(t)$ can be approximated by a continuous process $X(t)$ such that its incremental change over a small interval dt is normally distributed with mean βdt and variance αdt,

$$dX(t) = X(t + dt) - X(t) = \beta dt + G(t)\sqrt{\alpha dt}, \quad (4)$$

where $G(t)$ is a white Gaussian process with zero mean and unit variance. β and α are the mean and variance of the change in $X(t)$, respectively, which are also referred to as drift and diffusion coefficients defined by

$$\beta = 1/\mu_a - 1/\mu_s \quad (5)$$

and

$$\alpha = v_a/\mu_a^3 + v_s/\mu_s^3. \quad (6)$$

Given the initial energy level at $X(t = 0) = x_0$, the conditional probability density function (p.d.f.) of $X(t)$, i.e., the energy buffer size at time t $(t > 0)$,

$$f(x,t;x_0)dx = Pr(x \le X(t) < x + dx | X(0) = x_0), \quad (7)$$

satisfies the forward diffusion equation

$$\frac{\partial f(x,t;x_0)}{\partial t} = \frac{\alpha}{2}\frac{\partial^2 f(x,t;x_0)}{\partial x^2} - \beta \frac{\partial f(x,t;x_0)}{\partial x}, \quad (8)$$

under the boundary condition

$$X(t) \ge 0, \quad t > 0. \quad (9)$$

By applying the method of images [24], we can use (8) and (9) to obtain

$$f(x,t;x_0) = \frac{\partial}{\partial x}\left\{\Phi\left(\frac{x - x_0 - \beta t}{\sqrt{\alpha t}}\right) - \exp\left\{\frac{2\beta x}{\alpha}\right\}\Phi\left(-\frac{x + x_0 + \beta t}{\sqrt{\alpha t}}\right)\right\}, \quad (10)$$

where $\Phi(x)$ is the standard normal integral defined as

$$\Phi(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}z^2)dz. \quad (11)$$

Denote by $\mathcal{D}(x_0)$ the energy depletion duration given the initial condition x_0, i.e., the duration from $X(0) = x_0$ until the moment when the AP depletes its energy,

$$\mathcal{D}(x_0) = \inf(t \ge 0 | X(t) = 0, X(0) = x_0). \quad (12)$$

$\mathcal{D}(x_0)$ is also referred to as the first passage time of $X(t)$ from $x_0 > 0$ to 0.

The density function of $\mathcal{D}$ can be obtained from the diffusion equation with the absorbing barrier at the origin, which is equal to

$$f_{\mathcal{D}}(t;x_0) = \lim_{x\to 0}\left\{\frac{\alpha}{2}\frac{\partial f(x,t;x_0)}{\partial x} - \beta f(x,t;x_0)\right\}. \quad (13)$$

Solving the partial differential equation (13), we obtain the conditional p.d.f. of $\mathcal{D}$ as

$$f_{\mathcal{D}}(t;x_0) = \frac{x_0}{\sqrt{2\pi\alpha t^3}}\exp\left\{-\frac{(x_0 + \beta t)^2}{2\alpha t}\right\}. \quad (14)$$

The moment generation function of $\mathcal{D}$ is given by

$$\begin{aligned} f^*_{\mathcal{D}}(s;x_0) &= \int_0^{\infty} e^{-st} f_{\mathcal{D}}(t;x_0)dt \quad (15)\\ &= \exp\left\{-\frac{x_0}{\alpha}(\beta + \sqrt{\beta^2 + 2\alpha s})\right\}. \end{aligned}$$

Note that when $s \to 0$, (15) gives the probability $\mathcal{P}(0;x_0)$ of reaching the absorbing barrier starting from x_0 [22],

$$\begin{aligned} \mathcal{P}(0;x_0) &= \lim_{s\to 0} f^*_{\mathcal{D}}(s;x0)\\ &= \begin{cases} 1, & \text{for } \beta < 0\\ \exp\left(-\frac{2x_0\beta}{\alpha}\right), & \text{otherwise.} \end{cases} \quad (16) \end{aligned}$$

Eq. (16) indicates that the energy buffer depletes with probability 1 when the energy replenish rate is lower than or equal to the energy discharging rate, i.e., $1/\mu_a \le 1/\mu_s$. On the other hand, even if the mean energy charging rate is larger than the mean energy discharging rate, it is still possible that the AP depletes it energy due to the variance of energy charging and discharging processes. In the case $1/\mu_a > 1/\mu_s$, the energy depletion probability is dependent on the initial energy level x_0, and the mean and variance of energy charging and discharging processes.

Differentiation of (15) w.r.t. s gives the mean and variance of $\mathcal{D}$ for $\beta \ne 0$,

$$\begin{aligned} E[\mathcal{D};x_0] &= x_0/|\beta|, \quad (17)\\ V[\mathcal{D};x_0] &= x_0\alpha/|\beta|^3. \quad (18) \end{aligned}$$

B. Queue Model of Finite Energy Buffer

In practice, a mesh AP will have a limited battery capacity. In this case, the energy buffer can be modeled as a $G/G/1/N$ queue.

Similar to the infinite buffer case, given the initial condition and the buffer size N, the conditional p.d.f. of the buffer size satisfies the forward diffusion equation,

$$\begin{aligned} &\frac{\partial f(x,t;x_0,N)}{\partial t} \quad (19)\\ =\ & \frac{\alpha}{2}\frac{\partial^2 f(x,t;x_0,N)}{\partial x^2} - \beta\frac{\partial f(x,t;x_0,N)}{\partial x}\\ &+\mu_a P_0(t;x_0,N)\delta(x-1)\\ &+\mu_s P_N(t;x_0,N)\delta(x-N+1), \end{aligned}$$

where $P_0(t)$ and $P_N(t)$ are the probability mass functions at the boundaries $x = 0$ and $x = N$ at time t, given the initial value x_0, respectively:

$$\begin{aligned} P_0(t;x_0,N) &= Pr[X(t) = 0 | X(0) = x_0] \quad (20)\\ P_N(t;x_0,N) &= Pr[X(t) = N | X(0) = x_0]. \quad (21) \end{aligned}$$

When $X(t)$ reaches one of the boundaries $x = 0$ or $x = N$, it stays there for a random interval, referred to as a holding time, with mean $1/\mu_a$ and $1/\mu_s$, respectively. The probability mass functions $P_0(t;x_0,N)$ and $P_N(t;x_0,N)$ should also satisfy the following equations:

$$\begin{aligned} \frac{dP_0(t;x_0,N)}{dt} &= -\mu_a P_0(t;x_0,N) \quad (22)\\ &+ \lim_{x\to 0}\left[\frac{\alpha}{2}\frac{\partial f(x,t;x_0,N)}{\partial x} - \beta f(x,t;x_0,N)\right] \end{aligned}$$

and

$$\begin{aligned} \frac{dP_N(t;x_0,N)}{dt} &= -\mu_N P_N(t;x_0,N) \quad (23)\\ &+ \lim_{x\to N}\left[-\frac{\alpha}{2}\frac{\partial f(x,t;x_0,N)}{\partial x} + \beta f(x,t;x_0,N)\right], \end{aligned}$$

subject to the initial condition

$$f(x,t;x_0,N) = \delta(x - x_0) \quad 0 < x < \infty, \quad (24)$$

and boundary conditions

$$\begin{aligned} \lim_{x\to 0} f(x,t;x_0,N) &= 0 \quad t > 0 \quad (25)\\ \lim_{x\to N} f(x,t;x_0,N) &= 0 \quad t > 0. \quad (26) \end{aligned}$$

By applying a doubly infinite system of images [22], we can obtain the transient solution of the probability function

$$f(x,t;x_0,N) = \frac{1}{\sqrt{2\pi\alpha t}}\sum_{n=-\infty}^{\infty}(A - B), \quad t > 0, \quad (27)$$

where

$$\begin{cases} A = \exp\left(\frac{\beta 2nN}{\alpha} - \frac{(x-x_0-2nN-\beta t)^2}{2\alpha t}\right), \\ B = \exp\left(\frac{\beta(-2x_0-2nN)}{\alpha} - \frac{(x+x_0+2nN-\beta t)^2}{2\alpha t}\right). \end{cases}$$

Since $\sum_i P_i = 1$, we have

$$\int_0^N f(x,t;x_0,N)dx + P_0(t;x_0,N) + P_N(t;x_0,N) = 1. \quad (28)$$

Similar to (13), the density function of the first passage time in the finite buffer case satisfies

$$f_{\mathcal{D}}(t;x_0,N) = \lim_{x\to 0}\left[\frac{\alpha}{2}\frac{\partial f(x,t;x_0,N)}{\partial x} - \beta f(x,t;x_0,N)\right]. \quad (29)$$

We derive the Laplace transform of the density function $f_{\mathcal{D}}(t;x0,N)$ with a finite energy capacity N as

$$f^*_{\mathcal{D}}(s;x_0,N) = \exp\left\{-\frac{\beta}{\alpha}x_0\right\}\frac{\sinh[C(N-x_0)] - D}{\sinh(CN) - D} \quad (30)$$

where

$$\begin{cases} C = \frac{\sqrt{2\alpha s+\beta^2}}{\alpha}, \\ D = \frac{\mu_a}{\mu_a+s}\exp\{\beta/\alpha\}\sinh[C(N-1)]. \end{cases}$$

The inversion of $f^*_{\mathcal{D}}(s;x_0,N)$ can be approximated by

$$\begin{aligned} & f_{\mathcal{D}}(t;x0,N) \quad (31) \\ = \; & \frac{1}{2t}\exp\left\{\frac{E}{2}\right\}\Re\left(f^*_{\mathcal{D}}\left(\frac{E}{2t};x_0,N\right)\right) \\ & +\frac{1}{t}\exp\left\{\frac{E}{2}\right\}\sum_{k=1}^{\infty}(-1)^k\Re\left(f^*_{\mathcal{D}}\left(\frac{E+2k\pi i}{2t};x_0,N\right)\right), \end{aligned}$$

where E is the approximation error function such that the error is bounded by $\frac{\exp\{-E\}}{1-\exp\{-E\}}$[28]. For instance, by setting $E = 5\ln(10)$, the approximation error is smaller than $0.99 \cdot 10^{-5}$.

Differentiation of (30) w.r.t. s gives the first moment of $\mathcal{D}$ as

$$\begin{aligned} & E[\mathcal{D};x_0,N] \quad (32) \\ = & \begin{cases} -\frac{x_0}{\beta} + (\mu_a + \frac{1}{\beta})\frac{\exp\{-\frac{2\beta}{\alpha}(N-x_0)\}-\exp\{-\frac{2\beta}{\alpha}N\}}{1-\exp\{-\frac{2\beta}{\alpha}\}}, & \beta \neq 0, \\ x_0(\mu_a + \frac{2N-x_0-1}{\alpha}), & \beta = 0. \end{cases} \end{aligned}$$

Solving Eqs. (19)-(23) at the stationary state when $\lim_{t\to\infty} P_0(t;x_0,N) = P_0$, $\lim_{t\to\infty} P_N(t;x_0,N) = P_N$, and $\lim_{t\to\infty} f(x,t;x_0,N) = f(x;x_0,N)$,

$$\begin{aligned} & \frac{\alpha}{2}\frac{\partial^2 f(x,t;x_0,N)}{\partial x^2} - \beta\frac{\partial f(x,t;x_0,N)}{\partial x} \quad (33) \\ = \; & -\mu_0 P_0\delta(x-1) - \mu_N P_N\delta(x-N+1), \end{aligned}$$

$$\lim_{x\to 0}\left[\frac{\alpha}{2}\frac{\partial p(x,t;x_0,N)}{\partial x} - \beta p(x,t;x_0,N)\right] = \mu_0 P_0, \quad (34)$$

$$\lim_{x\to N}\left[\frac{\alpha}{2}\frac{\partial p(x,t;x_0,N)}{\partial x} - \beta p(x,t;x_0,N)\right] = -\mu_N P_N, \quad (35)$$

we can obtain the steady state probability function of the energy buffer length [29]

$$\begin{aligned} & f(x;x_0,N) \quad (36) \\ = & \begin{cases} -\frac{\mu_a P_0}{\beta}[1-e^{rx}], & 0 \le x \le 1 \\ -\frac{\mu_a P_0}{\beta}[e^{-r}-1]e^{rx}, & 1 \le x \le N-1 \\ -\frac{\mu_a P_0}{\beta}[e^{r(x-N)}-1]e^{r(N-1)}, & N-1 \le x \le N, \end{cases} \end{aligned}$$

where $r = (2\beta)/\alpha$.

The probability that an AP depletes its energy in the finite buffer case is given by

$$\begin{aligned} & \mathcal{P}(0;x_0,N) \quad (37) \\ = & \begin{cases} (1 + \frac{\mu_s}{\mu_a}e^{r(N-1)} + \frac{\mu_s}{\mu_a-\mu_s}[1-e^{r(N-1)}])^{-1}, & \beta \neq 0, \\ \frac{1}{2}(1 + \frac{N-1}{v_a^2/\mu_a^2+v_s^2/\mu_s^2})^{-1}, & \beta = 0. \end{cases} \end{aligned}$$

Eq. (37) indicates that in the finite energy buffer case, due to the variance of the charging and discharging processes, the energy buffer is depleted with a certain probability, which is jointly determined by the first and second moments of the sojourn times at the boundary conditions, regardless of whether $\beta \geq 0$ or $\beta < 0$. The depletion probability decreases with increased battery capacity N or energy charging rate. A larger variance in either charging or discharging results in a higher energy depletion probability $\mathcal{P}(0;x_0,N)$.

V. Adaptive Resource Management

In this section, we present an energy-aware adaptive resource management framework based on the transient energy buffers of mesh APs. To improve network sustainability, we aim to minimize the probability that mesh APs deplete their energy in serving traffic demands. Based on the transient energy level, energy charging capability, and existing traffic demands at each AP, a path selection metric is designed to distribute traffic flows over diverse relay paths across the network. A distributed admission control strategy is also presented to further guarantee the energy sustainability of the network.

A. Relay Path Selection

In a WLAN mesh network depicted in Fig. 1, users' traffic may be relayed over multiple hops until reaching the destination. To ensure the energy sustainability and network connectivity, traffic flows should be scheduled over relay paths such that the APs along the paths have the minimal probability of being out of service, i.e., depleting their energy and becoming temporarily unavailable. To track the dynamics of the traffic demands and charging capability, the scheduling should be updated periodically and when new events occur (e.g., a new flow joins in the network or traffic demands of existing flows change).

Based on the analysis in Section IV, the relay path selection performs as follows: a source user first broadcasts a request that includes the destination and the estimated first and second order statistics of the energy consumption of the traffic flow. When the destination AP receives the request, it first calculates the probability of energy depletion, $\mathcal{P}(0;x_0)$ in (16) or $\mathcal{P}(0;x_0,N)$ in (37), based on its current energy level and the accumulated traffic demands. The destination AP updates its weight as

$$w_v = \mathcal{P}(0; x_0) \quad \text{or} \quad \mathcal{P}(0; x_0, N). \tag{38}$$

The destination then attaches its weight in the reply message back to the source user. Upon receiving the reply message, each mesh AP also updates its weight accordingly. By computing its own $\mathcal{P}(0; x_0)$ with the accumulated load energy consumption over each link, the source AP can make a decision about the data forwarding path. For example, the source AP may select the path with the minimal sum of the energy depletion probability (MEDP) along the path, i.e., the path with Min $\sum w_v$, to ensure the overall sustainable performance of the network; or the AP may prefer to select the path along which the maximum value of w_v is minimized, i.e., the path with Min Max w_v, to ensure that the least sustainable AP can sustain the traffic demands longer. The process of weight updates in these cases is the same as the shortest path algorithm, with the metric of the number of hops replaced by the path selection metric, i.e., $\sum w_v$ or Max w_v.

Notice that in the infinite energy capacity case, $\mathcal{P}(0; x_0)$ may increase to 1 when $\beta \leq 0$, which implies that the AP will eventually deplete its energy by relaying this flow. Therefore, to differentiate their weights for path selection, the AP needs to further evaluate whether its current energy level can sustain the flow demand within a finite duration. Denote the survival time of a traffic flow as T, i.e., the flow is expected to survive in the network in the following T time slots. The AP then computes the probability that it depletes its energy before T expires, which is given by

$$F_{\mathcal{D}}(T; x_0) = Pr(\mathcal{D} \leq T) = \int_0^T f_{\mathcal{D}}(t; x_0) dt. \tag{39}$$

In the infinite buffer case, the destination AP updates its weight according to the flow request as

$$w_v = \mathcal{P}(0; x_0) + I(\beta \leq 0) F_{\mathcal{D}}(T; x_0), \tag{40}$$

where the indicator $I(\cdot)$ equals to 1 if condition $(\cdot)$ is true and 0 otherwise. In a network of queues, the buffer of the relaying AP may absorb the traffic variance in some degree and the output traffic characteristics may vary. If the estimated traffic demand changes during time duration T, APs should update the traffic parameters in the remaining time of duration T, and repeat the aforementioned path selection process. A mesh AP may also need to retransmit a packet after a random period if its next hop mesh AP is currently out of service, which may change the energy consumption statistics of the ongoing flow. In the case that $\mathcal{P}(0; x_0)$ is large, energy consumption statistics may vary hop by hop, and mesh APs need to update the energy consumption statistics and recalculate $\mathcal{P}(0; x_0)$. However, by minimizing the energy depletion probability and ensuring a sufficiently large depletion duration, the probability that an AP is out of service is reduced and becomes negligible.

B. Admission Control

Due to the limited network resources in a wireless network, admission control plays a critical role in providing satisfactory quality of service to the existing users. Generally, admission control tackles the trade-off between resource utilization and quality of service provisioning. For instance, more users admitted to the network can exploit more network resources to achieve a higher network throughput, but they may also use up the network resources faster, e.g., the residual energy of mesh APs depletes quickly, and some APs may be out of service which causes long service delays and jitter. Therefore, an effective admission control strategy is necessary to assure high resource utilization under the energy sustainability constraint and guaranteed user performance.

We provision guaranteed service to admitted users by ensuring a sufficiently large energy depletion duration, e.g., that $\mathcal{D}$ is larger than the longest survival time of traffic flows $\hat{\mathcal{D}}$, in a stochastic manner as

$$Pr(\mathcal{D} \leq \hat{\mathcal{D}}) = \int_0^{\hat{\mathcal{D}}} f_{\mathcal{D}}(t; x_0) dt < \varepsilon, \tag{41}$$

where the parameter $0 < \varepsilon \ll 1$ is an adjustable parameter which reflects the energy sustainability level. A smaller ε implies a stricter energy sustainability constraint for admitting a new flow. As such, according to the estimated flow statistics in the request, each mesh AP verifies its availability to relay, i.e., a mesh AP responds only when its energy sustainability condition satisfies (41). If the source AP cannot establish a valid relay path to the destination from the received response messages, indicating that one or more APs' energy supply cannot sustain the traffic demands of the flow, the source AP will reject the flow request from the end user. By upper bounding the energy depletion probability, satisfactory sustainable network performance can be achieved.

VI. Simulation Results

In this section, we validate the energy buffer analysis and evaluate the performance of the proposed resource management schemes via extensive simulations, based on a discrete time event-driven simulator coded in C++.

A. Simulation Setup

In this section, we simulate a WLAN mesh network with ten APs and multiple mobile users, as depicted in Fig. 1. The distances between adjacent APs are randomly selected in $[R_0, 3R_0]$ where R_0 is the communication radius of an AP. Ten groups of users are randomly distributed in the coverage of APs. The energy charging intervals of an AP are randomly selected from $\vec{t_a} = \{1, 2, 3, 4\}$ (in unit of time slots) with a given probability distribution $\vec{p_{t_a}}$. For example, if $\vec{p_{t_a}} = \{0.3, 0.3, 0.2, 0.2\}$, the mean and variance of the duration of the charging intervals are $\mu_a = 2.3$ and $v_a = 1.21$, respectively. The energy discharging of an AP depends on the traffic load demands of users. In each simulation run, a number of flows are sequentially generated between any two users in the mesh network. Unless otherwise specified, the inter-packet arrivals of a flow are exponentially distributed with mean $\mu_s = 14$. The energy consumption per packet at an AP includes both reception and transmission. For intra-WLAN traffic, i.e., the transmission between the AP and any user within its coverage radius R_0, the energy consumption of a packet is set as a constant $e_0 = 1$ energy unit. For

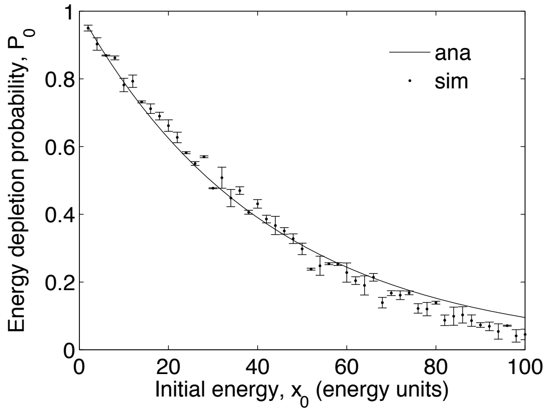

Fig. 3. $\mathcal{P}(0; x_0)$ (Infinite buffer, $\mu_a = 2.3$, $v_a = 1.21$, $\mu_s = 2.33$, $v_s = 5.44$)

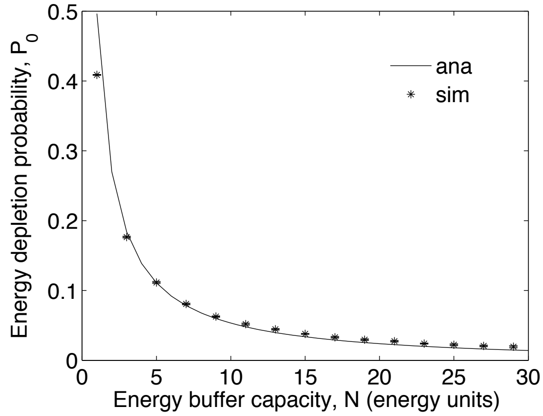

Fig. 4. $\mathcal{P}(0; x_0, N)$ (Finite buffer, $\mu_a = 2.3$, $v_a = 1.21$, $\mu_s = 2.33$, $v_s = 5.44$)

inter-WLAN traffic, i.e., the transmissions between mesh APs, the energy consumption of one packet is dependent on the link distance R between the APs, which is given by $max\{1, (R/R_0)^n\}e_0$ where n is selected from $\{1, 2, 3, 4\}$. We ignore the energy consumption due to the signaling exchange, which is relatively negligible compared to the traffic demands in the mesh backbone. We repeat each experiment 10 times, and each experiment contains 1000 runs with different random seeds. The average results are calculated with 95% confidence.

B. Energy Buffer

We first examine the energy depletion probability in both infinite and finite buffer cases. To study the relationship between the charging capability and traffic load consumption, we gradually add six flows to transmit over a link of distance R_0, and collect the buffer depletion statistics. For six flows, the energy arrival rate is larger than the departure rate, and we have $\beta > 0$. To illustrate the buffer evolution, these flows are not associated with a survival time. To compute $P(0; x_0)$ in the simulation, we collect the number of runs on which the energy buffer of node A reaches 0 when the simulation runs 6000 time slots, and divide it by the total number runs of 1000 and plot the results in Fig. 3. It can be seen from Fig. 3 that $\mathcal{P}(0; x_0)$ decreases with the initial energy x_0. As we only conduct the simulation with limited duration (6000 time slots), the simulation results are conservative and thus slightly lower than the analytical results (which converge as time goes to infinity). In the finite buffer case, it can be seen in Fig. 4 that the energy depletion probability decreases when the energy buffer capacity N increases.

Fig. 5 plots the cumulative distribution function (CDF) of the energy depletion duration for the infinite energy buffer cases. To effectively obtain the CDF of $\mathcal{D}$, we add six more flows to transmit over a link distance R_0 and calculate the first passage time. Notice that for 12 flows, the energy arrival rate is lower than the departure rate indicating that we have a stable energy buffer with $\beta < 0$ and the energy buffer will eventually deplete. As shown in Fig. 5, for a smaller x_0, an AP is more likely to deplete its energy in the near future, and thus the CDF curve shifts to the left. Fig. 6 shows the CDF of the energy depletion duration for the finite energy buffer cases. The initial energy buffer is full, i.e., $x_0 = N$. It can be seen that with a large energy buffer capacity and initial buffer size, an AP is less likely to deplete its energy soon, and therefore the CDF shifts to the right.

C. Sustainable Network Performance

In this section, we evaluate the sustainable network performance in terms of the network lifetime, which is defined as the maximal duration that all APs are available until one of the APs depletes its energy. We consider a heterogeneous network where green APs deployed at different locations have diverse charging capabilities by selecting different probability vectors $\vec{p_{t_a}}$ for different APs.

We compare the proposed MEDP using the path selection metric of $\sum w_v$ and Max w_v with two other schemes, namely, the minimum energy (ME) scheme [30], and the minimum path recovery time (MPRT) scheme [4]. In ME, a relay path is selected such that the total energy consumed along the path is minimized. Unlike ME, the MPRT algorithm selects the path with the minimum cumulative recovery time such that the total consumed energy can be recovered in the shortest duration. Thus, MPRT is more likely to select a path with a higher charging rate.

The three path selection schemes are compared in Fig. 7 and Fig. 8. Without considering the energy charging capability in the path selection, the sustainable performance of ME is much lower than those of MPRT and MEDP. The proposed MEDP outperforms MPRT since MPRT considers only the charging capability of mesh APs, neglecting the traffic demands and variations in both charging and discharging processes. For the proposed MEDP, the use of the metric $\sum w_v$ favors the overall network sustainability while that of Max w_v ensures the worst case sustainability performance. There is no obvious difference for the use of the two metrics in the MEDP. It can also be observed that the network lifetime increases with the initial energy buffer x_0 in Fig. 7 and the energy buffer capacity N in Fig. 8. By studying the transient queue length distribution for a given initial buffer x_0 or the buffer capacity N, our proposed MEDP scheme can significantly extend the network lifetime in both finite buffer and infinite buffer cases.

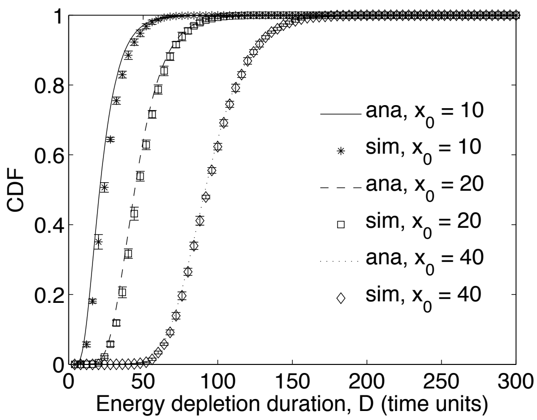

Fig. 5. CDF of $\mathcal{D}$ (Infinite buffer, $\mu_a = 2.3$, $v_a = 1.21$,$\mu_s = 1.16$, $v_s = 1.36$,)

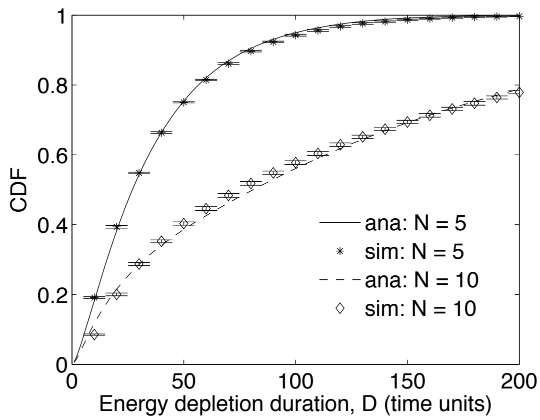

Fig. 6. CDF of $\mathcal{D}$ (Finite buffer, $\mu_a = 2.3$, $v_a = 1.21$, $\mu_s = 2.33$, $v_s = 5.44$)

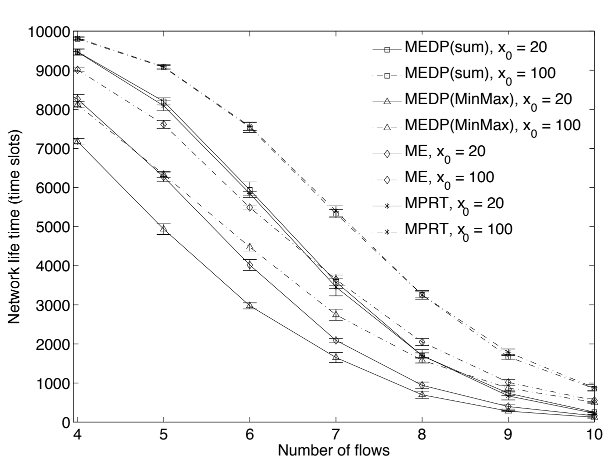

Fig. 7. Path selection comparison (Infinite buffer)

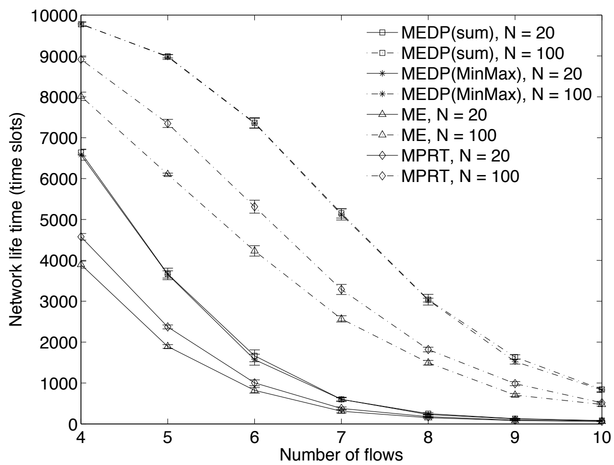

Fig. 8. Path selection comparison (Finite buffer)

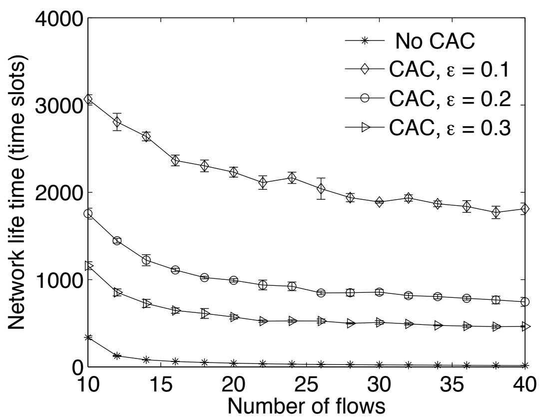

Fig. 9. Network life time w/wo CAC (Infinite buffer)

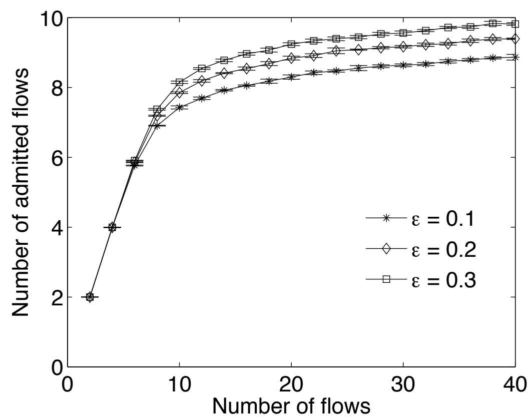

Fig. 10. Number of admitted flows (Infinite buffer)

Fig. 9 shows the comparison of the network lifetime with and without CAC schemes applied. We use the metric of $\sum w_v$ for MEDP path selection. With more flows joining the network, the increased traffic loads degrade the network lifetime significantly when no CAC is applied. In this simulation, the first fix flows are always admitted to the network, but some following requests are rejected due to the fact that the energy conditions of some APs cannot sustain their traffic demands. The number of admitted flows under different values of ϵ is shown in Fig. 10. A smaller ϵ represents a stricter admission condition and thus limits the number of admitted flows and the network throughput. It is seen that by increasing ϵ from

0.1 to 0.2, one more flow can be admitted. However, adding one more flow is likely to drain the energy of some APs and reduce the network lifetime significantly, as shown in Fig. 9. Therefore, with a smaller ϵ, each AP is less likely to deplete its energy and be out of service, which improves the overall network connectivity and service provisioning to the existing flows.

VII. Conclusion

In this paper, we have developed a generic analytical model to study the energy sustainability of mesh APs powered by renewable energy sources, by characterizing the transient evolution of an energy buffer of a mesh AP. Based on the closed-form solutions of energy buffer analysis, i.e., the energy depletion probability and energy depletion duration, we have further proposed an adaptive resource management framework for relay path selection and admission control. By mitigating the energy depletion probability and ensuring a large energy depletion duration of mesh APs, the sustainable network performance can be significantly improved.

For our future work, we plan to consider bandwidth constraints in this framework and jointly design the bandwidth allocation and energy management in a sustainable energy powered mesh network. We also plan to investigate how one can deploy a minimal number of mesh APs to ensure that the charged energy can sustain the traffic demands of users will also be under investigation.

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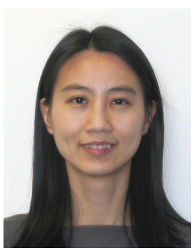

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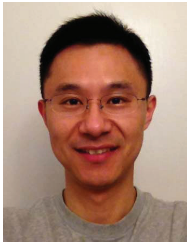

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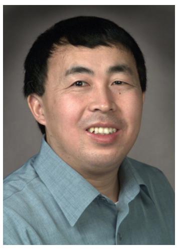

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