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RESEARCH ARTICLE

Novel Mathematical Framework for Performance Analysis of Energy Harvesting-Based Point-to-Point Communications

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ABSTRACT This paper presents a novel performance evaluation framework for energy harvesting communications. As the harvested energy may not always be at the required levels in the transmitter's battery, possible energy outage may hinder the transmission, especially in weak channel conditions. Herein, we analyze the performance of an energy harvesting communication link by allowing a certain level of energy outage to occur. Such operation is challenging, given that the energy coming into the battery from an uncontrollable source, e.g., solar energy, does not relate to the channel conditions and quality-of-service (QoS) requirement, whereas energy going out of the battery is directly dependent on both. Hence, the incoming energy and outgoing energy become independent of each other. Knowing the exact level of energy that is accumulated in the battery is therefore challenging. To deal with these challenges, a probabilistic energy-outage approach and a virtual battery queuing model are proposed and used to develop the target performance evaluation framework while leveraging the large deviation principle theorem. The derived energy-outage probability of the communication system relates the system parameters, namely, QoS component, channel conditions, and harvested energy. Numerical results are presented to confirm the analytical findings and discuss the performance of energy harvesting based communication with tolerable energy-outage as a function of the system parameters.

INDEX TERMS Energy harvesting, energy outage probability, large deviation principle, QoS.

I. INTRODUCTION

A. MOTIVATION AND RELATED WORK

For industrial internet of things (IIoT) applications, automated networks rely on the seamless integration of innovative self-optimized procedures to increase effectiveness, dependability, and operation economics [1]. Traditional power distribution systems that are dispersed over a vast region are tracked and diagnosed using wired communications with expensive start-up and ongoing costs [2]. Grid monitoring can be carried out using wireless communication techniques to reduce prices. For these applications, by including power fraud, defect detection, outage detection, power line automation, etc., wireless sensor networks (WSNs) are a workable option. WSNs have lower capital and operating costs than traditional cable communication methods [3]. In fact, the paradigm of smart grids is created by the integration of contemporary communication techniques, such as WSNs, as well as monitoring, automation, and control capabilities into the infrastructure of the power grid to increase reliability, productivity, efficiency, etc. [1].

Conventional wireless systems were bound to have batteries with limited capacity, which were used to charge wireless power nodes. In order to eliminate the need for exchanging batteries, environmental energy harvesting (EH) technology is becoming increasingly crucial in many use cases such as today's wireless communication networks, connected devices, and the development of IoT. EH is a

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process where the wireless power or ambient energy from the surrounding environment is scavenged by harvesting equipment, offering the capacity to increase the battery life of communication devices and sustain the continuous operation of low-power sensor nodes [4]. For instance, WSN nodes are usually installed in remote and rugged areas, which can make the recharging or replacement of their depleted batteries difficult and impractical, unless the energy source is renewed or a harvesting mechanism is included to fix the energy deficit [5]. The logical next step in future networks has also been identified as zero-power communication technology, which promises wireless information transmission without the need for changing or charging batteries [6].

Besides, most machine-type communications (MTC) devices are battery-restricted and challenging to recharge. Another crucial area for green MTC is energy harvesting, yet unforeseen environmental conditions and unidentified channel state information (CSI) make it difficult for current models to function in real time. Optimizing security and QoS for energy-harvesting IoT using AI involves leveraging 6G technology to enable energy usage tracking, weather predictions, and intelligent metering. Furthermore, greater security consumes more energy. As a result, it is recommended that IoT sensing devices be equipped with a mechanism for EH [7], [8].

On the other hand hand, the stochastic character of energy sources, in which energy is generated at random times and in variable amounts, may make the amount of harvested energy unpredictable, posing significant challenges for a system operating relying solely on EH [9]. Generally, studies on EH-based systems can be categorized into two kinds, based on the knowledge about the energy arrivals. The first category includes offline methods that call for full knowledge of the arrival energy which is not causal [10]. The second category consists of online approaches. In an online transmission policy, the energy arrival information is only revealed causally over time [11]. Several research works have been carried out to develop efficient power allocation algorithms for better energy management strategies for EH communication systems, see e.g. [12] and [13], and references therein. In [12], the resource allocation problem aims to best use the available harvested energy and transfer the available data to the sink node at the lowest possible cost. Therein, both offline and online transmission policies are put forth. The formulation of the offline problem makes use of non-causal knowledge of the harvested energy and the data arrival. The online policy of the energy harvesting WSN is solved using the model predictive control architecture. In [13], combined hardware and constraint-based models that allow for consistent, opportunistic communication with worst-case latency guarantees, are proposed. Therein, an offline worst-case strategy ensures restricted communication delay between two nodes while permitting locally opportunistic online communication attempts in the event of better-than-worst-case EH. An EH context can be supported offline by a node in the worst-case communication behaviour without violating the offline requirements that ensure bounded latency between two nodes.

In the literature, offline power allocation has received significant attention. Different system models were investigated to improve various performance [14], [15], [16]. Particularly, an offline algorithm based on dynamic programming to minimize the transmission completion time under infinite battery capacity was proposed in [14]. Therein, the random arrival of data packets and the harvested energy at the source were considered. Optimal offline algorithms for EH communication under limited energy storage capacity and energy replenishment constraints are studied in [15]. Particularly, the limits on the energy replenishment process and the battery capacity are used to determine the ideal transmission policy. The work in [15] was also extended to the time selective fading channel in [16], where an iterative approach was used to address the energy allocation problem to maximize the sum-throughput.

The focus of the above-mentioned works is mainly within the scope of having complete knowledge of the arrival time and the amount of harvested energy, which are unrealistic assumptions in practical scenarios. Indeed, one cannot ignore the fact that getting complete information of the dynamics of the EH process is not possible in practice. To make the problems tractable, IoT based wireless sensor systems implementing EH were studied in different papers [17], [18], [19], [20]. Specifically, for different EH system models, various wireless sensor systems were discussed in different industrial and automation areas for planning, monitoring, and managing the system's development and productivity. Particularly in [17], in the field of agriculture, a solar-based WSN with several scattered nodes was introduced to measure humidity and temperature using data received from the sensor nodes. Reference [21] proposed integrating poweredge energy subsystems into a sustainable and energy-efficient smart agricultural system that relies on renewable energy sources. The goal is to ensure cost-effective and efficient energy utilization in all stages, including solar panel production and power generation. A Q-learning algorithm was proposed in [22] to adjust the sampling rate. In IoT and WSN, reinforcement learning has been employed for sequential decision-making under uncertainty. On the other hand, the use of solar EH as a solution to the issue of scarce energy supply was proposed in [23], where each sensor node has a harvesting module to directly recharge its battery. The advantages of the proposed approach in smart agricultural monitoring are improved production and crop quality, as well as effective management and control. In [24], the trade-off between energy usage and delay for mobile edge computing with EH capabilities were investigated. Therein, subject to restrictions on the stability of buffer queues and battery level, an online dynamic task scheduling is provided to minimize the average weighted energy consumption and execution delay.

More recently, advanced works on online transmission policies were carried out [11], [25], [26], [27], [28], [29], [30]. In [25], an optimal power control scheme in a multi-user setting is formulated through a predictive approach, employing the use of a Markov Decision Process (MDP). The MDP framework is particularly suited for addressing decision-making and optimization challenges that arise from sequential actions in uncertain environments. The Bellman dynamic programming equation was solved to minimize the distortion over a fading channel by estimating the energy used to transmit data. In the same work, a practical Q-learning algorithm was proposed, providing a sub-optimal solution for the power management problem. It is to be noted that dynamic programming suffers from limited scalability. In [26], an algorithm based on reinforcement learning is proposed to address the joint optimization compression and transmission control in wireless IoT systems. In [11], minimization of the average age of information (AoI) in EH communication systems with online policy, was analyzed. The AoI denotes the amount of time elapsed since the most recent information is delivered to the end point. The said work tackled the problem by sending an update signal only if the AoI exceeds a certain threshold, and developed an optimal renewal policy by using Lagrangian approach for different system models. For single-user and multi-user channels, the distributed fractional power (DFP) policy is proposed in [27] and shown to be nearly optimal. It is demonstrated that the harvested energy is ideally distributed and decreased until the end of the renewal time, by assuming that a Bernoulli process synchronizes the energy arrival received by the users. With the aid of Markov processes and deviation theory, the authors in [28] investigated an analytical model for a general EH transmitter with energy storage, and formulated the probabilities of outages and overflows. The work in [29] presented the asymptotically optimal online power allocation solution that enhances the performance of the EH communication for infinite time slots and battery capacity. Reference [30] proposed the statistical energy underflow limitation and an energy management method to limit the battery from falling under a certain level. In [31], the effective capacity is derived to analyze the QoS performance of EH wireless links. The system model comprises EH nodes, but the source of energy is not specified. Average delay and energy arrival constraints based on post-decision state-functions to maximize the data packet arrival rate over fading channels is studied in [32], but assuming an infinite storage capacity. The authors of [33] developed statistical QoS-driven power control policies to maximize the spectrum efficiency in EH networks. Therein, the energy outage constraint is ignored.

The aforementioned works in [15], [16], [34], [35] have an underpinning assumption that the resources are allocated in such a way that they guarantee the availability of a sufficient amount of energy in the battery for transmission at a given rate. This assumption is not always feasible, particularly when the fading channel is severely weak, or that energy available for the data transmission is not sufficient. When the transmissions have to be done with significantly high transmit powers, guaranteeing the QoS, e.g., statistic delay, becomes very challenging [36], [37]. Hence, it is inevitable that energy outage will happen, i.e., energy available in the battery is not sufficient. In such scenarios, the EH communication system cannot accommodate the required QoS. However, and as will be detailed shortly, we look at the problem from a different perspective by limiting the energy outage to a very small value.

The energy outage constraint was considered in some works [38], [39], [40], [41]. In particular, in [38], minimization of the outage probability of an EH system with strict delay constraints was studied by providing a fixed threshold transmission (FTT) scheme supporting an online transmission policy. There, it was demonstrated that for practically applicable EH rates, the FTT scheme performed nearly equal to the offline lower bound. However, [38] does not consider scenarios where the wireless channel dynamics influence the energy input process, unlike the proposed work in this paper. The idea in [38] of three power control policies, namely, linear power levels policy, joint threshold-based policy, and disjoint threshold-based policy, was later extended and investigated for minimization of the outage probability in [39]. These policies were investigated to compare the energy arrivals between the source and the destination for finite-sized and infinite-sized batteries. In [40], two power allocation schemes were studied and compared using an exhaustive search, and an upper-bound expression was derived using monotonic optimization for the outage probability of the considered EH system. The work in [40] assumes the availability of information regarding the future energy arrival process, which is not feasible in a practical scenario. The work in [41] uses MDP to reduce the battery outage in the considered EH system. The problem was studied under channel and battery status constraints for high signal-to-noise ratio (SNR). A high SNR denotes a substantial disparity in strength between the signal and the background noise, leading to enhanced clarity and heightened reliability in communication. The system assumed exact knowledge of the state transition probabilities. However, accurately estimating the channel transition probabilities in real-world scenarios is challenging.

Compared to the studies referenced in [38], [39], [40], and [41], the approach presented in this work confronts the difficulties stemming from the energy irregularities within EH systems. The unpredictability and uncontrollability of the harvested energy give rise to a lack of direct correlation with the channel conditions and the stipulated QoS requisites. This study introduces a novel methodology involving a probabilistic energy-outage approach and a conceptual model centered around a virtual battery queue. This approach is harnessed to construct a comprehensive framework for evaluating system performance. Notably, the framework leverages the large deviation principle (LDP) theorem to deduce the probability of energy outages, thereby establishing a coherent connection among the system parameters, the QoS elements, the channel conditions, and the harvested energy profile.

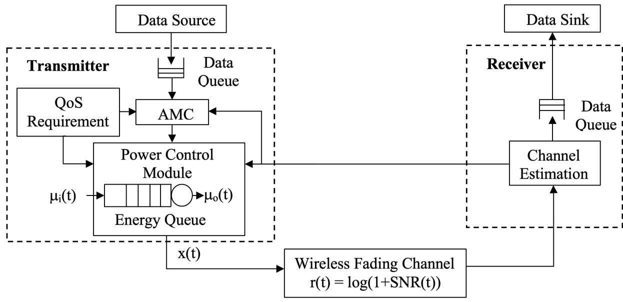
Specifically, we consider point-to-point communication, where direct connection between two nodes can be used to establish back and forth communication between them. This is useful for the analysis carried out in the paper, as our mathematical tool studies the performance of point-to-point EH-based communication, which applies in different energy-constrained networks, including wireless body area networks [42]. The point-to-point radio link can be used to monitor temperature, rainfall, bushfires, etc., where the transmitters are sensors deployed in remote areas without access to the power grid [43], [44], [45], [46].

B. CONTRIBUTIONS

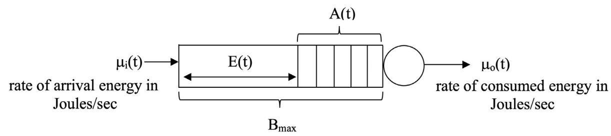
With regard to the previously discussed studies, a mathematical framework that can provide a useful tool to analyze the performance of EH communication systems when considering energy outage at the transmitter is desired. As discussed, developing such a framework is difficult due to the independent randomness in the energy arrival for the harvesting and the fading channel conditions. Motivated by the above discussions, and to obtain more insight for analyzing the performance of EH-based communication, in this work we develop a simple and novel mathematical framework in which we expand the idea of statistical energy-outage constraint. Such an event happens when we need to transmit with a certain amount of energy, but that the battery does not have sufficient resources. To satisfy a target QoS, high transmission power is required. In EH systems, energy consumed from the battery depends on the QoS required by the end user, and on the CSI. At the same time, the energy arrival to the battery depends on the strength of the power source, solar in this case, and is independent of the fading channel conditions and the required QoS. Due to the independence between the energy arrival into the battery and the energy consumed from there, it is challenging to estimate the exact status of the available energy in the battery. In such conditions, energy outage is inevitable. Assuming that the system can tolerate some level of energy outage to take place, we introduce a simple mathematical framework for analyzing the performance of EH communications under QoS constraint, by invoking tools of LDP. In more detail, the major contributions of this work can be summarized as follows:

- A mathematical framework is proposed for the performance analysis of EH communications. The framework is developed based on a concept of energy outage probability. Energy outage is experienced when there is no further energy for the system to utilize for the data transmission.
- The randomness property of the energy outage occurrence in the system is used to develop the mathematical framework. Specifically, the LDP theorem is used to model a queuing system for the EH battery. A virtual battery queuing model is used to facilitate providing the assumptions needed for using LDP.
- Building upon the above two fundamental new ideas, a formulation that relates the channel capacity to the rate of the energy arrival is obtained. This gives a unique mathematical framework that directly relates the two concepts together, which are rather independent by nature. The performance of point-to-point EH communication is investigated using this mathematical tool.
- Simulation results are provided in order to understand how this mathematical framework performs.

The remainder of the paper is organized as follows. Section II explains the system model in detail. The proposed mathematical framework is developed in section III. Then, numerical results are presented and discussed in section IV, followed by concluding remarks provided in section V.



(a) System model.



(b) Battery structure within the power control module in (a).

FIGURE 1. The energy-harvesting based communication system.

II. SYSTEM MODEL AND PRELIMINARIES

A. SYSTEM MODEL

The point-to-point EH-based communication model is illustrated in Fig. 1. At the transmitter, data packets are stored in a data queue, and a battery is used to store the harvested energy. The outgoing energy is stationary and ergodic. Since the fading channel is considered to be stationary and ergodic, and the outgoing energy is a function of the fading conditions, the outgoing energy is also stationary and ergodic. We assume that the channel is Rayleigh block fading, and refer to it by coefficient $h(t)$, where t is the time index. With the block fading model, the channel remains constant during a fading block, but varies independently from one fading block to another. The block duration is denoted by T. With the SNR denoting the ratio of the signal power to the noise power, the function $r(t)$ in Fig. 1, which refers to the instantaneous rate, can be written

$$r(t) = \log(1 + \mathrm{SNR}(t)). \tag{1}$$

At the destination node of the EH-based communication system under consideration, the signal captured by the receive antenna is given by

$$y(t) = h(t)x(t) + n(t), \tag{2}$$

where $x(t)$ is the transmitted signal, and $n(t)$ is the Gaussian random noise, assumed to be of zero mean and unit variance [34], [47]. A similar system model has been considered in [48], where a finite-sized EH battery is considered to measure the performance the EH based communication system.

B. PHYSICAL BATTERY STORAGE MODEL

Physical battery storage model for the EH source is considered. The model has an energy queue, where the arriving (harvested) energy is stored. Energy accumulated in the battery at time t is denoted by $A(t)$, and the empty portion of the battery is denoted by $E(t)$. The physical battery storage model represents the EH as the energy arrival process, and the energy consuming as the departure process. The model is depicted in Fig. 1(b). Accordingly, the empty portion of the battery can be mathematically represented by

$$E(t) = B_{\max} - A(t), \tag{3}$$

where $B_{\max}$, in Joules, denotes the maximum level of energy that the battery can withhold.

Energy accumulated in the battery at time $t + 1$ can be formulated as

$$A(t + 1) = \max\{0, \min\{B_{\max}, A(t) + \mu_{\mathrm{i}}(t)T - \mu_{\mathrm{o}}(t)T\}\}, \tag{4}$$

where $\mu_{\mathrm{i}}(t)$ is the rate of incoming energy into the battery, in the unit of Joules/sec, and $\mu_{\mathrm{o}}(t)$ is the rate of energy spent out from the battery, in the unit of Joules/sec.

With the described model, the instantaneous rate, $r(t)$ in nats/s/Hz, can be expressed as

$$r(t) = \log\left(1 + \frac{h(t)\mu_{\mathrm{o}}(t)}{N_0 B}\right), \tag{5}$$

where N_0 is the noise density per unit bandwidth and B is system bandwidth.

The transmission power of the system is constrained by a maximum permissible level, $P_{\max}$. Therefore, the outgoing power can never go beyond this level. On the other hand, the end-user has a QoS requirement that needs to be met in terms of the minimum rate $R_{\min}$, and this constraint serves as the QoS guarantee for the delay-sensitive user. Since the channel fading is a random process, meeting the target QoS requires that the transmission be done with high transmit power when the channel is severely weak.

However, it is challenging to guarantee that the required amount of transmit power is always available in the EH battery of the transmitter, not to mention that the said amount of power is difficult to measure given that the incoming energy into the battery is harvested from the environment, e.g., solar, and that it is difficult to predict whether it can be sufficient to allow proper adaptation of the data transmission to the variations of the channel so as to meet the user's QoS, or not.

Given that the accumulated energy in the battery is a complex function of all of these parameters, it is challenging to estimate the exact battery status, and guarantee that the required QoS can be maintained during the whole data transmission process. Also, we assume zero battery overflow probability. That is, when the battery is big enough as compared to the arrival energy, it will very unlikely be full. The limiting factor in this work is the risk of the battery becoming empty rather than becoming full. This is very common since solar energy arrives in very small epochs and, since the sensor nodes are small in size, they cannot be equipped with very big solar panels. Therefore, it is very likely that this assumption is valid in real-world applications.

C. PROBLEM STATEMENT AND APPROACH

As discussed above, due to the unknown status of the available energy in the battery, the required QoS cannot be guaranteed all the time. However, it is possible to meet the demand for at least a high percentage of time by allowing a small amount of energy outage to happen in the system. Accordingly, a probabilistic approach is taken in our performance analysis problem, in which we leverage the LDP theorem to examine the probability of energy-outage occurrence in the battery. The large deviation theory is mainly concerned with the study of the asymptotic behavior of probabilities of rare events [49]. The theory proves that the decline of the probability of rare/tail events is exponential [49].

Let us assume $S_1, S_2, \ldots$ to be a sequence of independent and identically distributed (i.i.d.) random variables with mean $m = \mathbb{E}[S_1] < \infty$, and let $M(N) = \frac{1}{N}(S_1 + \ldots + S_N)$ denote the empirical mean. From the law of large numbers and the central limit theorem, we note that $\lim_{N\to\infty} \Pr\{M(N) > b\} = 0$ for any $b > m$. As N grows, the distribution of $M(N)$ converges to the expected value of the random variable. However, the convergence of the tail event probabilities when $N \to \infty$ is not provided by the law of large numbers and the central limit theorem. To fill the gap, convergence when $N \to \infty$ is examined by using the theory of large deviation.

Based on the LDP theorem, for a dynamic queuing system with stationary ergodic arrival and transmission processes [50], the accumulated portion of the queue length process $M(N)$ converges in distribution to a steady-state queue length $M(\infty)$, leading to

$$\lim_{N\to\infty} \frac{\log\big(\Pr\{M(\infty) \geq b\}\big)}{b} = -I, \tag{6}$$

where I is the so-called rate function. The probability decays exponentially as $N \to \infty$ at a rate that depends on b [49], [51].

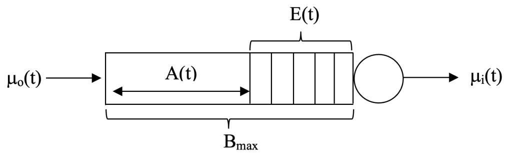


FIGURE 2. The virtual battery queuing model.

In the LDP theorem, the probabilities of events that are exponentially small are taken into account. Hence, invoking the tools of LDP in the current work is useful to find a statistical expression for the energy outage under QoS constraint in the EH-based communication system. This inequality, which is based on the LDP theorem, can be estimated only when the battery capacity threshold is very large, using

$$\Pr\{M(\infty) \geq b\} \approx e^{-Ib}. \tag{7}$$

In our proposed design, we assume that energy outage happens when the amount of energy needed to transmit the data packets is less than the outgoing energy $\mu_o(t)T$.[1] We define the battery's energy-outage status P_{outage} statistically, that is

$$P_{\text{outage}} = \Pr\{A(t) < \mu_o(t)T\}, \tag{8}$$

which explains the condition where the available energy/power is not sufficient to transmit the data, in which case the system suffers energy outage.

III. PROPOSED MATHEMATICAL FRAMEWORK

We aim to develop a simple mathematical framework based on assumptions of the LDP theorem. In order to implement the assumptions, we further propose a virtual battery queuing model. Using the proposed model, we estimate the energy-outage probability under QoS constraint. Also, the theory of effective EH is proposed to derive statistical relations between the QoS component, the Rayleigh fading channel conditions, and the level of incoming energy into the battery of the data transmitter.

A. VIRTUAL BATTERY QUEUING MODEL

The virtual battery queuing model is shown in Fig. 2. This model is basically a representation of the physical battery storage model with interchanged parameters such that tools of the LDP theorem can be invoked.

In the proposed queuing model, the roles of the harvested energy and the consumed energy are reciprocated to have a steady queue. The inputs and outputs of this model are interchanged so that we can invoke the tools of the LDP theorem as compared to the physical battery storage model. Therefore, the rate of the outgoing energy $\mu_o(t)$T is considered as input to the model, and the rate of the incoming energy $\mu_i(t)$T is the output. In this way, the proposed virtual battery queuing model can be implemented to use the inverse inequality so as to make use of the LDP theorem.

Under this setup, the queue length, $E(t)$, can be explained by the energy consumption instead of the level of energy left in the battery. Correspondingly, energy left in the battery is given by

$$A(t) = B_{\max} - E(t). \tag{9}$$

As shown in Fig. 2, the energy arrival to the virtual queue is denoted as $\mu_o(t)$, $\mu_i(t)$ indicates the energy departure from the queue, and the threshold level of the queue is $B_{\max}$. Similar to (9), $E(t)$ for the virtual queue model can be defined as

$$E(t) = B_{\max} - A(t). \tag{10}$$

Also, the number of empty energy slots in the battery at time $t + 1$ can be approximated as follows:

$$E(t+1) = \max\{0, \min\{B_{\max}, E(t) + \mu_o(t)T - \mu_i(t)T\}\}, \tag{11}$$

Our goal is to estimate and analyze the energy-outage probability in the proposed virtual battery queuing model in order to examine the performance of the EH-based communication system under QoS constraint.

B. ANALYSIS OF THE ENERGY-OUTAGE PROBABILITY

We analyze the energy-outage probability to theoretically evaluate the performance of the EH-based communication system.

According to the physical limitation of the system, we define the energy outage condition as the probability when the harvested energy is not sufficient enough to sustain the active power consumption process. That is, situations where the harvested energy is unavailable for data transmission or that the harvested energy is below the outgoing energy $\mu_o(t)T$, should be very limited. Otherwise, the system remains inactive and no data transmission takes place. Specifically, once the accumulated energy, $A(t)$, is below the threshold $\mu_o(t)T$, the transmitter enters into the battery-low status or an energy outage event occurs, and then the system will hibernate until the battery gets recharged to a satisfying level.

With the aid of the proposed virtual battery queuing model by considering the empty side of the battery, the energy-outage probability is estimated with the probability of empty portion of queue at time t. At the same time, the occurrence of energy outage should be minimum, i.e.,

$$\Pr\big\{E(t) \geq (B_{\max} - \mu_o(t)T)\big\} \leq P_{\text{outage}}, \tag{12}$$

[1] If energy accumulated in the battery exceeds the storage capacity, then battery overflow will occur, leading to energy waste. Hence, we need to deal with the problem of an unstable queuing system, which makes the analysis of the system under study, and EH-based communication in general, a challenging task, especially that many powerful tools and results from queuing theory cannot be applied due to the instability. For smooth operation of the system, it is required to avoid energy loss due to battery overflow. Also, the battery overflow probability is equal to the probability of the virtual battery being non-empty. As our focus in this paper is on considering the event of energy outage, situations with battery overflow are left for future investigation.

where P_{outage} is the maximum probability of energy outage that the system tolerates. Here, the left-hand side of the formula in (12) expresses the probability that the virtual buffer is not full at a given time t.

Next, we derive and estimate of the energy-outage probability under QoS constraint by invoking tools of the LDP theorem.

C. STATISTICAL QOS GUARANTEES

Based on the LDP theorem [50], we can show that for a dynamic queuing system, a simpler and tighter formulation can be found to calculate the energy-outage probability. An assumption is made that the battery's maximum power $P_{\max}T$ can be used at each time slot. The empty portion of queue length process, $E(t)$ $(t \geq 0)$, converges in distribution to a finite random variable $E(\infty)$ that satisfies

$$\lim_{B_{\max}\to\infty} \frac{\log\Big(\Pr\big\{E(\infty) \geq (B_{\max} - P_{\max}T)\big\}\Big)}{B_{\max} - P_{\max}T} = -u, \quad (13)$$

which states that the probability of the queue length exceeding threshold $(B_{\max} - P_{\max}T)$ decays exponentially fast as $B_{\max}$ increases.

For large values of $B_{\max}$, we have

$$\Pr\big\{E(\infty) \geq (B_{\max} - P_{\max}T)\big\} \approx e^{-u(B_{\max}-P_{\max}T)}. \quad (14)$$

For small values of $B_{\max}$, a more accurate approximation is given by

$$\Pr\big\{E(\infty) \geq (B_{\max} - P_{\max}T)\big\} \approx \epsilon e^{-u(B_{\max}-P_{\max}T)}, \quad (15)$$

where ϵ denotes the probability of non-empty virtual buffer, i.e.,

$$\Pr\{E(t) > 0\} = \epsilon, \quad (16)$$

which can be approximated by the ratio between the average incoming rate and the fixed outgoing rate pertaining to the virtual battery queue model, namely, as $\epsilon \approx \frac{\mathbb{E}(\mu_{\text{o}}(t))}{\mu_{\text{i}_{\min}}}$ [52].

In the above formulation, the constant u $(u \geq 0)$ is termed the QoS exponent with respect to the outage probability of the battery, which acts as a significant aspect for the statistical QoS guarantee requirement, and shows the exponential decreasing rate of the QoS violation probabilities. A larger value of u results into a faster decay rate supporting a more stringent QoS requirement, while a smaller value of u leads to a slower decay rate, which illustrates that the EH-based communication system can provide a looser QoS requirement. Specifically, when u is close to 0, a longer decay can be tolerated by the communication system. On the other hand, when u is tends to ∞, the system cannot endure any delay [50].

D. THEORY OF EFFECTIVE ENERGY HARVESTING

The proposed theory of effective EH states that the stochastic behaviour of the arrival energy process can be modelled by its effective EH asymptotically.

An arrival energy process to the queue is considered, which gets to the empty side of it, or we can simply say that the empty slot accumulation of the battery, i.e., $\mu_{\text{o}}(t)$, which is defined for $t \geq 0$, represents the rate of outgoing energy or energy spent (in Joules per second) from the battery over the time interval $[0, t)$.

The asymptotic log moment generating function (MGF) of $\mu_{\text{o}}(t)$ is assumed, which is expressed as

$$\Lambda(u) = \lim_{t\to\infty} \frac{1}{t} \log\Big(\mathbb{E}\big[e^{u\mu_{\text{o}}(t)}\big]\Big), \quad (17)$$

and exists for all $u \geq 0$. Here, $\mathbb{E}[\cdot]$ denotes the expectation operator.

Further, assume that $\mu_{\text{i}}(t)$, which is the rate of energy exiting from the virtual queue, i.e., the rate of energy coming into the battery of the physical model, is is minimum and fixed, which is again a common assumption for solar EH and is given by $\mu_{\text{i}_{\min}}$.

The effective EH function of $\mu_{\text{o}}(t)$ can then be defined as

$$\alpha(u) = \frac{\Lambda(u)}{u}. \quad (18)$$

By substituting the asymptotic log-MGF (15) into (16), then defining

$$S(t) = \sum_{i=0}^{t} \mu_{\text{o}}(t), \quad (19)$$

and assuming that the sequence is uncorrelated, we get

$$\frac{\Lambda(u)}{u} = \lim_{t\to\infty} \frac{1}{ut}\log\Big(\mathbb{E}\big[e^{uS(t)}\big]\Big), \quad (20)$$

$$= \lim_{t\to\infty} \frac{1}{ut} \log\left(\mathbb{E}\left[\prod_{i=0}^{t} e^{u\mu_{\text{o}}(i)}\right]\right), \quad (21)$$

$$= \lim_{t\to\infty} \frac{1}{ut} \log\left(\prod_{i=0}^{t} \mathbb{E}\big[e^{u\mu_{\text{o}}(i)}\big]\right). \quad (22)$$

The service process is stationary, ergodic and holds given the block fading nature of the channel. Hence, assuming the independence of $\mu_{\text{o}}[i]$, $i = 0, 1, 2, \cdots$, we get

$$\frac{\Lambda(u)}{u} = \lim_{t\to\infty} \frac{1}{ut}\log\Big(\mathbb{E}\big[e^{u\mu_{\text{o}}(i)}\big]\Big)^{t}. \quad (23)$$

Hence, a simplified expression for the effective EH function is obtained as follows:

$$\frac{\Lambda(u)}{u} = \frac{1}{u}\log\Big(\mathbb{E}\big[e^{u\mu_{\text{o}}(i)}\big]\Big). \quad (24)$$

E. FORMULATION OF AN UPPER BOUND FOR $\mu_{\text{I}_{\text{MIN}}}$

According to the energy arrival process and the expression shown in (5), by assuming the rate of energy $\mu_{\text{i}}(t)$ to be minimum and constant, namely, $\mu_{\text{i}_{\min}}$, the rate of incoming energy to achieve the user's QoS, i.e., the minimum rate $R_{\min}$, is actually the minimum rate of incoming energy $\mu_{\text{i}_{\min}}$. Thus, we can write

$$\mu_{i_{\min}} \leq \frac{\Lambda(u)}{u} = \frac{1}{u}\log\left(\mathbb{E}\left[e^{u\mu_o(t)}\right]\right). \tag{25}$$

Let us recall that the goal is to achieve a minimum required rate $R_{\min}$. Hence, $R_{\min}$, in the unit of nats/s/Hz, can be expressed as

$$r(t) = \log\left(1 + \frac{\mu_o(t)|h(t)|^2}{N_0B}\right) \geq R_{\min}, \tag{26}$$

which leads to

$$\mu_o(t) \geq \frac{(e^{R_{\min}} - 1)N_0B}{|h(t)|^2}. \tag{27}$$

Now, substituting (27) into (25), we find the expression for $\mu_{i_{\min}}$ as

$$\mu_{i_{\min}} \leq \frac{1}{u}\log\left(\mathbb{E}\left[e^{u\left(\frac{(e^{R_{\min}}-1)N_0B}{|h(t)|^2}\right)}\right]\right). \tag{28}$$

The simple and final analytical expression of the large deviation theorem shown in (28) establishes the relationship between the channel $|h(t)|^2$, which is changing all the time, the minimum required rate by the user, $R_{\min}$, which is the user's QoS, and the rate of the fixed incoming solar energy, $\mu_{i_{\min}}$. At the same time, this inequality also satisfies and relates to the energy-outage probability calculated in (15). For a given QoS exponent u, we can find the fixed arrival energy from (15). Also, by using the value of u in (15), we can calculate the probability of energy outage in the EH-based communication system, namely, determining the probability that the battery will not have the required amount of energy for the data transmission.

IV. VALIDATION AND DISCUSSION

With the proposed mathematical framework, numerical results pertaining to the required rate of EH for achieving the target QoS in the EH-based communication system are now presented and discussed. Simulations are used to confirm the analytical findings through the developed framework, particularly with respect to the expressions obtained in (15) and (28), and also to investigate the impact of the energy-outage probability P_{outage}, the QoS component u, and the amount of incoming energy $\mu_{i_{\min}}$, on the system performance.

In the simulations, the number of independent Monte-Carlo runs is 10^5. Unless otherwise stated, the parameter setting is as follows: the noise density $N_0B = 1$, the maximum level of energy that the transmitter's battery can withhold is $B_{\max} = 50$ Joules, the minimum rate requirement $R_{\min} = 0.5$ nats/s/Hz, the maximum transmission power $P_{\max} = 10$ dB,[2] and the time slot duration is $T = 1$ sec.

Firstly, Fig. 3 shows the energy-outage probability, P_{outage}, versus the QoS component, u, for various values of the maximum transmission power $P_{\max}$. As observed, when

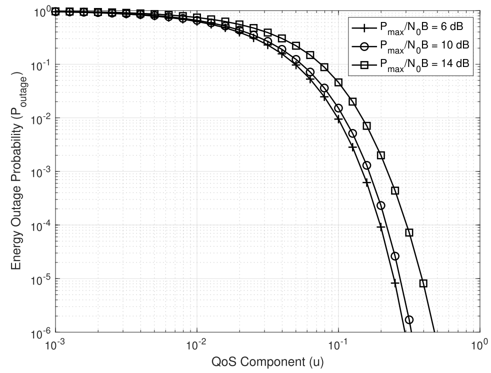


FIGURE 3. Energy-outage probability versus the QoS component for various values of $P_{\max}$.

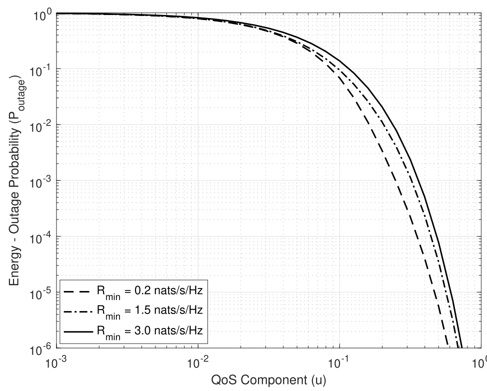


FIGURE 4. Energy-outage probability versus the QoS component for various values of the minimum required rate $R_{\min}$.

the QoS component increases, the energy-outage probability decreases. This confirms the theory that larger u gives a more stringent QoS guarantee, i.e., the system will tolerate less energy outage, which also confirms our design approach. The figure's results also demonstrate that when $P_{\max}$ increases from 6 dB to 14 dB, P_{outage} decreases, which is a favorable condition for the EH-based communication system to be more sustainable.

Fig. 4 illustrates the energy-outage probability versus the QoS component, for different values of the minimum required rate $R_{\min}$. As observed, when u increases, P_{outage} decreases. This confirms the theory that larger u gives a stricter QoS guarantee, i.e., the system will tolerate less energy outage and, as such, it will be more efficient to increase throughput and decrease energy outage as per the required performance measures. The plots also demonstrate that when $R_{\min}$ increases from 0.5 nats/s/Hz to 1.5 nats/s/Hz, then P_{outage} increases, which proves the correctness of our framework design and confirms as well the desired output result according to the paper's analysis.

Fig. 5 plots the rate of the incoming energy, $\mu_{i_{\min}}$, versus the QoS component, for various values of $P_{\max}$. From this figure, we notice that when $P_{\max}$ varies from 5 dB to 15 dB, $\mu_{i_{\min}}$ first remains stable and, then, increases gradually to

[2] Given that N_0B is assumed unity in the simulations, $P_{\max} = P_{\max}/N_0B$. This why unit-less dB unit is used here.

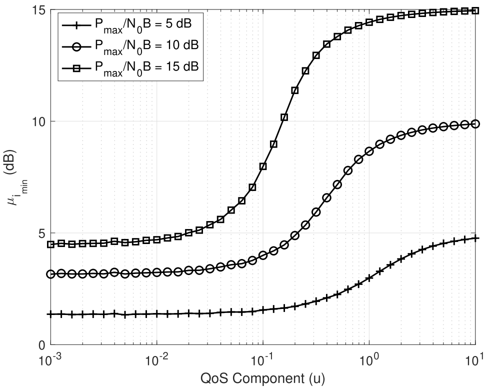


FIGURE 5. Rate of incoming energy versus the QoS component for various values of P_{max}.

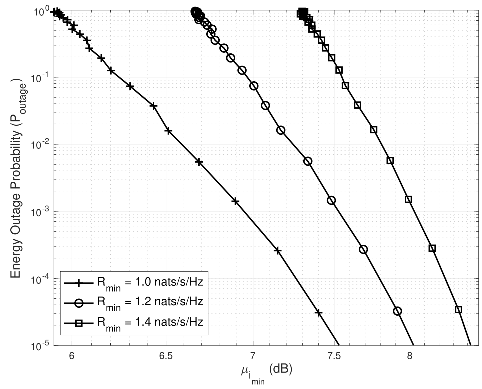


FIGURE 7. Energy-outage probability versus the rate of incoming energy for various values of the minimum required rate R_{min}.

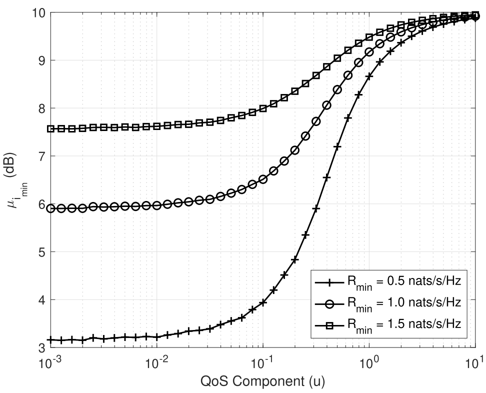


FIGURE 6. Rate of incoming energy versus the QoS component for various values of the minimum required rate R_{min}.

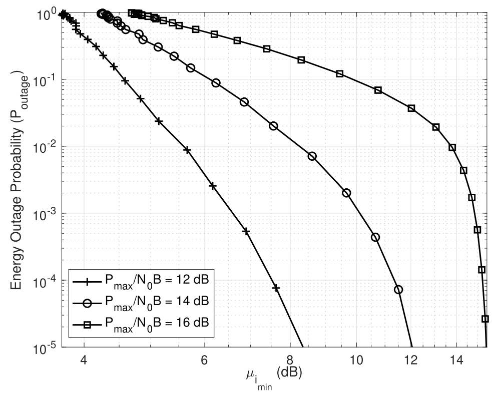


FIGURE 8. Energy-outage probability versus the rate of incoming energy for various values of P_{max}.

become stable eventually after a break-point for increased values of the QoS component. This behavior can be explained by the fact that the amount of the required incoming energy into the battery also increases at higher rate with higher values of P_{max}, for stringent QoS guarantee. That is, higher rate of incoming energy will be required to support maximum transmission power.

Fig. 6 shows the variations of the rate of incoming energy $\mu_{i_{min}}$ versus the QoS component for various values of minimum required rate R_{min}. As observed, $\mu_{i_{min}}$ increases with the increase of the QoS component u as R_{min} increases from 0.5 nats/s/Hz to 1.5 nats/s/Hz. This proves that higher QoS can be guaranteed with the increase in the rate of the incoming energy into the battery of the data transmitter. If we consider the QoS component to be 10^{-2}, then for a minimum required data rate of 0.5 nats/s/Hz, the rate of the incoming energy $\mu_{i_{min}}$ is 3.2 dB. For a minimum required data rate of 1.0 nats/s/Hz, $\mu_{i_{min}}$ is almost 6 dB, whereas for a data rate requirement of 2.0 nats/s/Hz, $\mu_{i_{min}}$ is between 7 dB and 8 dB. This shows that as R_{min} gets higher, the rate of incoming energy $\mu_{i_{min}}$ will also need be higher to satisfy the required QoS.

Fig. 7 shows the energy-outage probability P_{outage} versus the rate of incoming energy $\mu_{i_{min}}$, for various values of the minimum required rate R_{min}. When $\mu_{i_{min}}$ is relatively large, e.g., 7.5 dB, then P_{outage} shows a consistently downward trend with the increase of $\mu_{i_{min}}$ for all the considered rate values. This shows that a higher rate of incoming energy can be harvested and, at the same time, the system will face less energy outage events.

Fig. 8 illustrates the energy-outage probability versus the rate of the incoming energy for various values of the transmission power P_{max}. As it can be noticed, the energy-outage probability decreases rapidly. A higher rate of incoming energy shows that the transmission power can also be increased, which means that more data can be transmitted. With the increase in the incoming energy, the system will face less energy outage, which is obviously beneficial for the system.

Fig. 9 shows the variation of P_{outage} as a function of $\mu_{i_{min}}$, for various values of the battery capacity B_{max}. To explain in detail, if we consider the rate of the incoming energy ($\mu_{i_{min}}$) to be 7 dB, then for a battery capacity of at least 30 Joules, the energy-outage probability lies between 10^{-1} and 10^{-2}. Similarly, for a battery capacity of 40 Joules and 50 Joules, the energy-outage probability lies between 10^{-2} and 10^{-3}, and between 10^{-3} and 10^{-4}, respectively. This indicates that an increase in the battery capacity will allow more energy

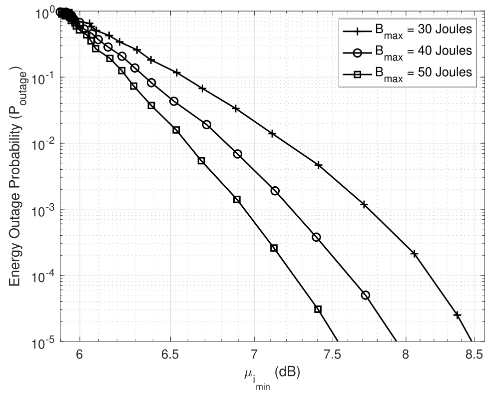


FIGURE 9. Energy-outage probability versus the rate of incoming energy for various values of $B_{\max}$.

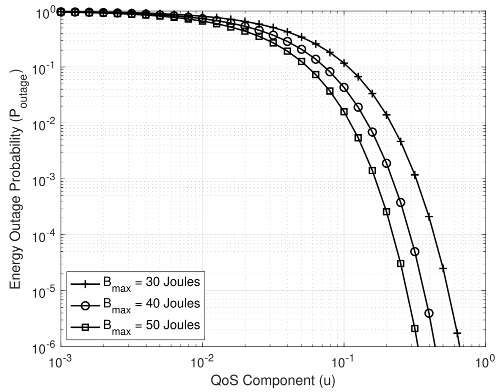


FIGURE 10. Energy-outage probability versus the QoS component for various values of $B_{\max}$.

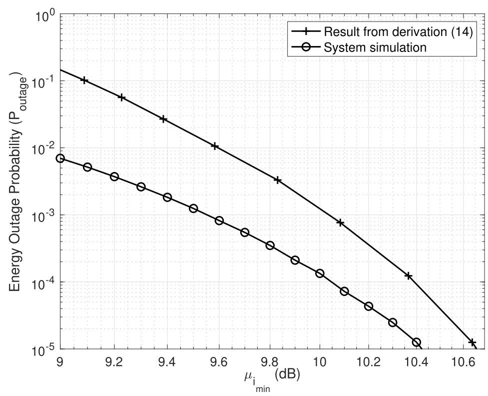


FIGURE 11. Confirmation of the correctness of the proposed mechanism.

to be stored, which will help to reduce the energy-outage probability.

We further plot results of the energy-outage probability versus the QoS component for different values of the battery capacity $B_{\max}$. Here in Fig. 10, $P_{\max} = 10$ dB is considered. The figure indicates that for small values of the QoS component, e.g., $u = 10^{-3}$, different values of $B_{\max}$ will not affect P_{outage}. When u increases, changes in $B_{\max}$ yield energy outage events. This shows that with the increase in battery capacity, the required QoS can be maintained and, also, the system faces less energy outage.

The energy-outage probability is analyzed in Fig. 11 as a function of the rate of incoming energy, $\mu_{\mathrm{i}_{\min}}$. The number of independent Monte-Carlo runs is 10^7. From the result of derivation, we obtained the value of P_{outage} to be approximatively 10^{-1}, and $\mu_{\mathrm{i}_{\min}}$ is approximated as 10.6 dB. From the system simulation output, P_{outage} is approximated as 10^{-2}, and $\mu_{\mathrm{i}_{\min}}$ is approximated as 10.4 dB. Therefore, we can say that the energy-outage probability with the proposed mechanism is less than 10^{-5} in the system simulation. Also, we can see that the value of P_{outage} obtained from the proposed framework is higher than the one obtained with the system simulation, which can be explained by the tighter measure of the outage probability being needed in the framework for the QoS constraint to be satisfied.

V. CONCLUSION

In this paper, a thorough study was carried out to analyze the required energy harvesting rate for satisfying the QoS requirements when a level of energy outage is allowed in point-to-point EH-based communication system equipped with a finite-sized battery. A probabilistic approach was taken, and a novel yet simple mathematical framework using large deviation principle (LDP) was developed. In particular, a virtual battery queuing model was proposed so that the LDP can be used and adapted. Furthermore, an expression relating the rate of the incoming energy with the fading channel conditions and the QoS requirement of the system was provided to analyze the performance of the EH-based communication system under energy constraint. Numerical results were provided to validate the proposed analytical framework and discuss the system performance in different scenarios.

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