Energy Dynamics of Green IoT Nodes with Time-Varying Energy Harvesting, Leakage, and Consumption Patterns

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***Abstract*—The growing proliferation of Internet of Things (IoT) devices has intensified the need for sustainable energy solutions, particularly in resource-constrained deployments where non-rechargeable batteries and supercapacitors are the primary energy sources. Green IoT (G-IoT) frameworks address this challenge by combining energy-saving techniques with energy harvesting from ambient sources such as solar power. However, the intermittent nature of renewable energy and the non-ideal behavior of energy storage systems—such as energy leakage and capacity degradation—complicate reliable energy provisioning. This paper presents a novel Markovian framework for modelling the coupled dynamics of time-varying solar energy harvesting, time-dependent energy consumption, and state-dependent energy leakage in G-IoT systems. Unlike traditional steady-state models, our approach uses Discrete-Time Markov Chains (DTMCs) to capture the stochastic variability in both energy harvesting and consumption processes. We also introduce a refined leakage model in which the leakage rate is dynamically dependent on the stored energy level, enabling a more realistic characterization of energy losses due to energy leakage. Through extensive analytical evaluation, we examine how key parameters—such as storage capacity, leakage rate coefficient, and energy harvesting and consumption patterns—affect critical performance metrics, including the mean stored energy and energy-related service outage probability. Furthermore, we propose a parameter tuning strategy to optimize energy reliability and storage efficiency. The proposed model provides valuable insights for the design and optimization of robust, energy-aware IoT systems powered by renewable energy sources.**

***Index Terms*—Green IoT (G-IoT), time-dependent analysis, energy storage systems, time-varying energy consumption and harvesting, and energy leakage**

This paper was supported by the ReACTIVE Too project, which has received funding from the European Union's Horizon 2020 Research, Innovation, and Staff Exchange Programme under the Marie Skłodowska-Curie Action (Grant Agreement No. 871163). Scientific work is published as part of an international project co-financed by the program of the Minister of Science and Higher Education entitled "PMW" in the years 2021–2025, contract no. 5169/H2020/2020/2. Additionally, this scientific work is also published as part of an international project, ReACTIVE Too, co-financed by the program of the Minister of Science and Higher Education entitled "PMW" in the years 2024–2025, contract no.5872/H2020/2024/2. Additionally, this research was funded in part by the National Science Centre, Poland, under the IMPRESS-U competition, project no. 2023/05/Y/ST7/00192.

I. Introduction

The Internet of Things (IoT) is revolutionizing modern infrastructure across a wide range of sectors [1], including healthcare, manufacturing, agriculture, transportation, supply chains, security and defense, environmental monitoring, energy, and construction. With the anticipated deployment of tens of billions of interconnected devices, IoT is poised to become a foundational pillar of Industry 4.0, enabling enhanced efficiency, automation, and intelligent decision-making across diverse domains [2]. Recent advancements in artificial intelligence further amplify the potential of IoT by allowing the vast volumes of data generated by these devices to be processed and analyzed in real time, supporting automated workflows and rapid, data-driven decision-making.

Despite the growing adoption of IoT technologies, energy availability remains one of the most critical constraints. The majority of IoT devices rely on non-rechargeable energy storage systems, such as batteries and supercapacitors, which are inherently limited by finite capacity and gradual performance degradation over time [2], [3]. These systems also exhibit practical non-idealities—including energy leakage, capacity loss due to aging, and internal charge redistribution, particularly in supercapacitor-based designs—which collectively compromise energy reliability and reduce operational lifespan. Therefore, accurate evaluation and optimization of the performance of energy storage systems require taking into account these imperfections [4].

To address the limitations associated with powering IoT nodes using non-rechargeable energy storage systems, Green IoT (G-IoT) [5] strategies have been introduced. These approaches combine energy-saving techniques—such as duty cycling, hardware and software optimization, and communication overhead reduction—with the integration of energy harvesting systems that capture energy from renewable sources like solar, RF, thermal, or wind. The goal of G-IoT is to enhance energy efficiency, reduce environmental impact from emissions and electronic waste, and promote the use of sustainable energy within IoT infrastructures. However, harvesting energy from ambient sources poses significant challenges due to their inherently intermittent and unpredictable nature, which leads to fluctuations in the amount of energy that can be harvested and stored [6]. Additionally, the energy demand of IoT nodes is not constant; it varies depending on how often the device transitions from low-power sleep modes to active operation and on the specific energy-saving mechanisms implemented—further complicating energy management in G-IoT systems.

To analyse and optimise energy performance, a growing number of studies [7]–[9] have proposed abstracting energy dynamics into quantized energy packets. In this modeling approach, the IoT system operates under a harvest-store-consume paradigm, where discrete packets of energy arrive stochastically from an energy harvesting (EH) module, are stored in an energy storage system (ESS), and are later consumed during device operations. The ESS is modeled as a queue of energy packets, with energy packets arriving and being consumed—analogous to the processing of data packets in communication systems. The energy packet size can be calibrated based on the device's operation cycle, encompassing both active and sleep phases. This abstraction enable the analysis and evaluation of energy performance of G-IoT energy systems without focusing on the internal complexities of harvesters and storage systems [10].

Recent works have demonstrated that such systems can be effectively analyzed using Generalized Queueing Networks (G-Networks) [11], which capture both energy delivery and consumption dynamics. This framework allows for modelling energy arrivals as a modulated Poisson process and consumption as an exponentially distributed service time, potentially modulated by external factors such as event-driven sensing. Compared to traditional queueing systems, where stability requires that service rate exceeds the arrival rate, energy harvesting systems must ensure that energy input exceeds or matches consumption to avoid outages [12].

Alternative modelling techniques include continuous-time stochastic models such as fluid queues [13], [14] and diffusion approximations [2], [15]–[18]. Although these approaches offer a fine-grained view of energy dynamics, incorporating inefficiencies of the energy storage system, especially energy leakage, introduces complexities into the model, as energy leakage rates often depend on the energy content of the energy storage system. Consequently, leakage cannot be modeled as a static drain but must be integrated dynamically with the energy arrival and consumption processes [12], [19]–[22].

A. Main Contributions of the Paper

In this paper, we propose a Markovian model to capture the dynamic interactions among time-dependent solar energy harvesting, time-varying energy consumption, and energy leakage processes in green IoT systems. Unlike existing models in the literature, which often assume constant energy harvesting and consumption rates under steady-state conditions, our approach accounts for the inherent variability of real-world environments. Specifically, both the energy delivery to the energy storage system (ESS) and the energy consumption processes are modeled as time-varying and are governed by their respective Discrete-Time Markov Chains (DTMCs). In addition, energy leakage from the ESS is modeled as a state-dependent process, where the leakage rate varies with the amount of stored energy, capturing non-ideal behaviors commonly observed in practical storage technologies.

The main contributions of this paper are as follows:

1) We develop a novel analytical framework that models the coupled dynamics of time-varying solar energy harvesting, energy consumption, and state-dependent energy leakage in green IoT systems.
2) Unlike previous studies that assume constant rates and steady-state conditions, our model incorporates time-varying energy harvesting and consumption behaviors, driven by independent DTMCs. This allows for the realistic representation of scenarios such as event-triggered sensing and intermittently available solar power.
3) We enhance the classical exponential energy leakage model by introducing state-dependent leakage dynamics, offering a more accurate and physically meaningful representation of energy loss in non-ideal ESSs.
4) We conduct a comprehensive analysis of how key system parameters—such as the leakage model and coefficient, energy delivery and consumption rates, and ESS capacity—affect critical performance metrics, including the mean number of stored energy packets and the probability of energy service outage due to depletion.
5) We propose a performance optimization strategy to tune system parameters for enhanced energy reliability and storage efficiency.

II. Markov-Modulated Energy Packet Model with State-Dependent Energy Leakage

Consider the Green IoT node shown in Fig. 1 where the energy harvested by the energy harvester (EH) is stored in an energy storage system (ESS), and then drawn to power the IoT node. Let C_B (in mWh) represent the total capacity of the ESS, which could be a battery or a supercapacitor. The total number of energy packets the ESS can store is:

$$B = \frac{C_B}{E_p}, \tag{1}$$

indicating that the ESS can hold up to B discrete energy packets, with possible energy states $\{0, 1, 2, \ldots, B\}$. Where E_p is the size of an energy packet, which is basically a pulse of power with a finite amount of energy.

Introducing device inactivity periods improves model realism compared to our earlier work [10], where energy consumption—and thus the rate μ—was assumed constant. In this model, both energy harvesting $\lambda(t)$ and consumption $\mu(t)$ rates are modulated by external processes represented as first-order Markov chains.

The weather modulator, with three states (sunny, cloudy, rainy), follows a common approach in weather modeling, as seen in early studies such as [23] and more recent works [24], [25]. More complex models, including higher-order Markov

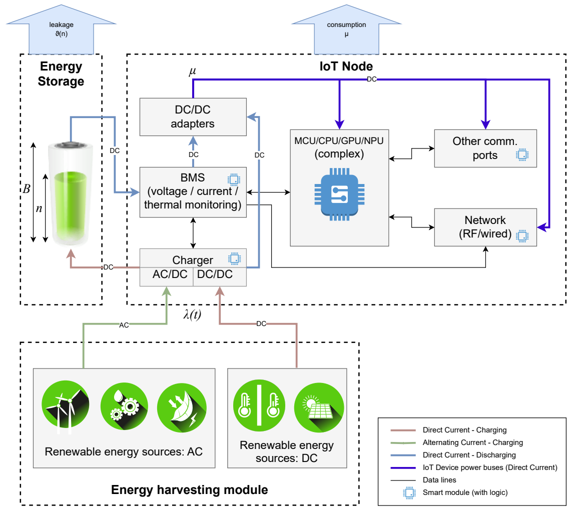

Fig. 1. Architecture of a green IoT node with erratic energy sources.

chains, can also be used [26]. At night, while the weather modulator continues evolving, energy harvesting is inactive ($\lambda = 0$).

The energy consumption modulator has two states—active and sleep. Furthermore, the consumption rate μ is state-dependent, reflecting the impact of energy leakage based on the current ESS content.

Under the above assumptions, the device's energy storage system can be modeled as an $M(t)/M(n,t)/1/B$ queue, where energy packets are harvested, stored, and consumed. Queueing systems with modulated Poisson arrivals and service rates have long been explored in contexts such as teletraffic burstiness and self-similarity, often using ON-OFF and MMPP models with high-dimensional modulators [27]–[30]. However, these studies primarily focused on steady-state behavior using continuous-time modulators, while our interest lies in the transient dynamics of energy storage systems (ESS).

Both modulators are Discrete-Time Markov Chains (DTMCs) that update their states at specific intervals: the modulator for $\mu(t)$ every Δt and the modulator for $\lambda(t)$ every $n\Delta t$. Within each Δt interval, model parameters remain constant with parameters λ and μ, although μ is state-dependent. This results in a transient $M/M(n)/1/B$ queue during each step. While the time-dependent queue distribution can be computed analytically via Laplace transforms and numerical inversion as shown in [31], this approach is complex and error-prone. Instead, we numerically solve model (2), using the resulting queue state at the end of each Δt as the initial condition for the next interval. Modulator state transitions are simulated using random sampling, blending numerical integration with stochastic simulation. The probability of having n energy packets in ESS at time t, $p(n,t) = \Pr\{N(t) = n\}$ is determined by equations

$$\begin{aligned}
\frac{dp(0,t)}{dt} &= -\lambda(t)p(0,t) + \mu(1,t)p(1,t), \\
\frac{dp(n,t)}{dt} &= -(\lambda(t) + \mu(n,t))p(n,t) + \lambda(t)p(n-1,t) \\
&\quad + \mu(n+1,t)p(n+1,t), \quad n = 1, \ldots, B-1, \\
\frac{dp(B,t)}{dt} &= \lambda(t)p(B-1,t) - \mu(B,t)p(B,t). \qquad (2)
\end{aligned}$$

The time-dependent consumption rate $\mu(n,t)$ is defined as:

$$\mu(n,t) = \mu(t) + \vartheta(n), \qquad (3)$$

where $\mu(t)$ is the base energy consumption rate at time t, which is driven by a DTMC that models the active and sleep mode transitions of the device, and $\vartheta(n)$ accounts for state-dependent energy leakage.

In this study, three leakage models—*Constant* ($\vartheta(n,\xi) = \xi$) [20], *Linear* ($\vartheta(n,\xi) = n \cdot \xi$) [12], [32], and *Exponential* ($\vartheta(n,\xi) = \xi \cdot (e^{n/\beta} - 1)$, e.g., $\beta = 20$) [33]–[35]—are utilized to model the nature of energy leakage in energy storage systems, such as supercapacitors or compact batteries. The parameter β in the exponential leakage model moderates the rate of exponential growth, ensuring realistic leakage behavior—slow at low energy levels and steep under high-energy conditions—thus improving both model fidelity and numerical stability for supercapacitor-based systems.

III. Transient Analysis of the Model

Since the mean arrival rate of energy packets to the energy storage system (ESS), $\lambda(t)$, and the mean consumption rate of energy packets, $\mu(t)$, vary over time, a transient analysis is necessary to investigate the influence of time-dependent factors such as solar energy harvesting, leakage, and consumption rates on the energy dynamics of the IoT node. The ESS is modeled as a finite-state Markov process, $\{N(t),\ t \geq 0\}$, where the number of stored energy packets, n, evolves over time based on arrival rates, leakage rates, and service rates. The probability of having n stored energy packets at time t is denoted as:

$$p(n,t) = \Pr\{N(t) = n\}. \qquad (4)$$

The evolution of stored energy packets is influenced by three key time-dependent processes: the energy packet arrival process, the energy packet consumption process, and the energy leakage process. The time-varying arrival rate of energy packets is governed by weather conditions and their durations throughout the day, as well as the length of daytime and nighttime. Similarly, the time-varying energy consumption rate is dictated by the durations of sleep and active modes of the IoT node, while the leakage rate depends on the number of energy packets stored in the ESS at time t.

Consider a three-state Markov chain, S_0, S_1, S_2, representing different weather conditions—sunny, cloudy, and rainy—which influence the state of a solar energy harvester. The corresponding values of λ for each state are given by:

$$\lambda = \{\lambda_0, \lambda_1, \lambda_2\}. \qquad (5)$$

The state transition matrix, $\mathbf{W}$, is given by:

$$W = \begin{bmatrix} p_{00} & p_{01} & p_{02} \\ p_{10} & p_{11} & p_{12} \\ p_{20} & p_{21} & p_{22} \end{bmatrix} \tag{6}$$

where each element p_{ij} represents the probability of transitioning from state i to state j. To capture more complex weather variations, a four-state weather model can be used, as explored in [36]. Once the state transition matrix is defined, the Markov chain can be used to simulate dynamic state changes over time. The state at each time step determines the corresponding value of λ.

Similarly, the time-varying mean energy consumption rate, $\mu(t)$, can be modeled using a Markov process by defining the state transition matrix for the stochastic process governing device mode transitions. If an IoT node randomly switches between active and sleep modes, its state transitions can be represented by a two-state Markov process with states S_0 and S_1, corresponding to the active (on) and sleep (off) modes, respectively. The mean number of energy packets consumed during active and sleep modes are μ_a and μ_s, respectively. The state transition matrix is given by:

$$S = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix}, \tag{7}$$

To solve for the transient state probabilities in the system of differential equations above, we rewrite the system the matrix form as follows

$$\frac{d\mathbf{p}(t)}{dt} = \mathbf{Q}\mathbf{p}(t), \tag{8}$$

where: $\mathbf{p}(t) = [p(0,t), p(1,t), \ldots, p(B,t)]^T$ is the transient state probability vector and the matrix $\mathbf{Q}$ is the transition rate matrix (or generator matrix) that captures the rates at which probabilities move between states. The transition rate matrix for this system is given by:

$$\mathbf{Q} = \begin{bmatrix} -\lambda & \mu & 0 & \ldots & 0 \\ \lambda & -(\lambda+\mu+\xi) & (\mu+\xi) & \ldots & 0 \\ 0 & \lambda & -(\lambda+\mu+2\xi) & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \lambda & -(\mu+B\xi) \end{bmatrix}. \tag{9}$$

The general solution of the above system can be expressed in the following form

$$\mathbf{P}(t) = e^{\mathbf{Q}t}\mathbf{P}(0), \tag{10}$$

where, $\mathbf{P}(0)$ is the initial probability distribution vector. If we start with zero energy packets in the ESS, then the system starts in state $n = 0$ at time $t = 0$ with state probability $p(0,0) = 1$ and all other state probabilities are zero. That is the initial probability distribution vector is

$$\mathbf{P}(0) = [1, 0, 0, \ldots, 0]^T. \tag{11}$$

Also, if the energy storage system is filled to its full capacity at time $t = 0$ with state probability $p(B,t)$, then the initial probability distribution vector is

$$\mathbf{P}(0) = [0, 0, 0, \ldots, 1]^T. \tag{12}$$

For any time, having the current distribution $p(n.t)$ we may compute the distribution of the time after which the queue becomes empty (ESS is depleted). For this purpose we make the state $n = 0$ the sink of the Markov chain, i.e. the rate between 0 and 1 is no longer λ but zero. The transition intensity $p(1,t)\mu(t)$ gives the densituy of ending the process at time t. if the initial condition is $p(B,0) = 1$, i.e starting from full energy content it gives us the density of ending the process at time t. It is only a representation of the process, as it depends on the sequence of modulator's changes that happened during discharging.

The system is solved using Python libraries such as NumPy, SymPy, and SciPy. First, we define the transition rate matrix, $\mathbf{W}$, which governs the energy harvesting process $\lambda(t)$ and specify the corresponding values of λ. Similarly, the transition matrix $\mathbf{S}$, which governs the switching of the device between different energy consumption modes, is defined along with the corresponding mean energy packet consumption rate per time unit.

With the time-varying mean energy packet delivery rate $\lambda(t)$ and the mean energy packet consumption rate $\mu(t)$, we formulate the system of equations governing the time evolution of the number of energy packets (EPs) in the energy storage system (ESS). The initial conditions are specified, such as $p(0,0) = 1$ if the ESS is empty at $t = 0$, or $p(B,0) = 1$ if the ESS initially contains B energy packets. SciPy is then used to numerically solve the system.

To determine the distribution of transient state probabilities $\mathbf{P}(t)$ in the next time interval, the transient probabilities from the current interval serve as the initial probability distribution vector $\mathbf{P}(0)$. In other words, the probability distribution of the number of energy packets stored in the ESS at the next time interval depends on its current distribution before any state transition that modifies λ and μ occurs.

To track the evolution of the mean number of energy packets in the ESS, we compute the expected value of the system at each time step. At each time interval Δt, the values of $\lambda(t)$ and $\mu(t)$ are obtained using the Markov processes presented earlier. These computed values for each interval are then plotted using Matplotlib. The expected number of energy packets at time t is given by:

$$E[N(t)] = \sum_{n=0}^{B} np(n,t). \tag{13}$$

IV. Numerical examples

The transition probabilities of the weather states are determined by the Markov chain transition matrix:

$$W = \begin{bmatrix} 0.7 & 0.2 & 0.1 \\ 0.3 & 0.5 & 0.2 \\ 0.2 & 0.3 & 0.5 \end{bmatrix}. \tag{14}$$

The proposed weather transition matrix aims to represent simplified yet realistic dynamics of weather changes using a discrete-time Markov chain. Each row of the matrix corresponds to a current weather state—sunny, cloudy, or

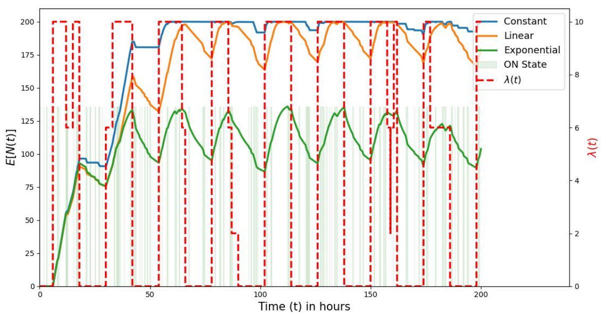

Fig. 2. Evolution of the mean energy level $E[N(t)]$ under different leakage models (Constant, Linear, Exponential) and fixed leakage coefficient $\xi = 0.01$, over a time-varying arrival process $\lambda(t)$ influenced by weather conditions. Also, the ESS is initially empty (i.e, p(0,0) = 1).

rainy—and contains probabilities of transitioning to each possible next state. The highest probabilities lie on the diagonal, indicating that the current weather condition is likely to persist (e.g., sunny remains sunny with 70% probability). This reflects the natural tendency of weather patterns to exhibit temporal correlation.

Transitions between different weather states are modeled to follow typical meteorological trends. For example, sunny weather is more likely to become cloudy than directly turn rainy, while rainy conditions are more likely to shift to cloudy rather than abruptly clear up. These directional preferences lend realism to the model while maintaining computational simplicity. Importantly, the matrix ensures that each row sums to one, satisfying the conditions of a valid stochastic process.

This type of transition matrix is useful for simulations involving solar energy systems, environmental modeling, or queueing systems influenced by weather variability. While the current matrix is heuristic, it can easily be refined using historical weather data for specific geographic locations to increase the fidelity of simulations. The energy delivery rates for the various states are $\lambda_0 = 10$, $\lambda_1 = 6$, and $\lambda_2 = 2$.

We model the energy consumption behavior of the IoT node using a two-state discrete-time Markov chain (DTMC), governed by the following transition probability matrix S:

$$S = \begin{bmatrix} 0.90 & 0.10 \\ 0.02 & 0.98 \end{bmatrix}, \tag{15}$$

where the first row corresponds to transitions from the **ON** (active) state and the second row to transitions from the **OFF** (sleep) state. Based on this DTMC, the steady-state probabilities are computed as $p_{\text{on}} = 0.1667$ and $p_{\text{off}} = 0.8333$, indicating that the IoT node spends approximately 83.33% of its time in sleep mode and 16.67% in active mode. This aligns with the duty-cycling behavior typically observed in energy-constrained IoT systems. The mean energy consumption rate in the on or active state is $\mu = 5$ energy packets per time unit, and in the off state is 0. The capacity of the ESS is $B = 200$ energy packets.

Figs. 2-5 demonstrate how different leakage models—constant, linear, and exponential—affect the energy dy-

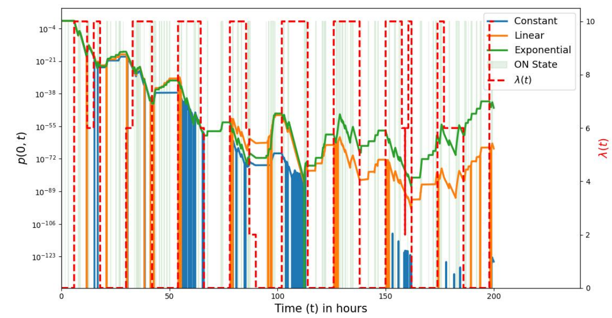

Fig. 3. Evolution of the service outage probability, $p(0,t)$ (in logscale) under different leakage models (Constant, Linear, Exponential) and fixed leakage coefficient $\xi = 0.01$, over a time-varying arrival process $\lambda(t)$ influenced by weather conditions. Also, the ESS is initially empty (i.e, p(0,0) = 1).

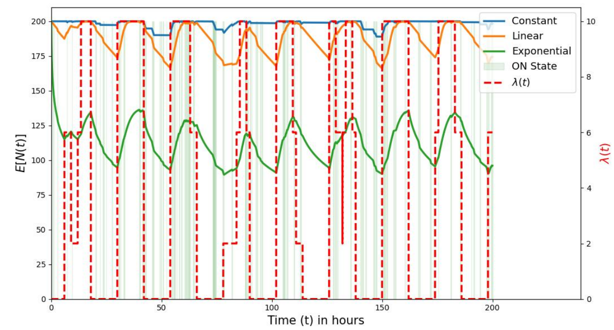

Fig. 4. Evolution of the mean energy level $E[N(t)]$ under different leakage models (Constant, Linear, Exponential) and fixed leakage coefficient $\xi = 0.01$, over a time-varying arrival process $\lambda(t)$ influenced by weather conditions. Also, the ESS is initially filled (i.e, p(B,0) = 1).

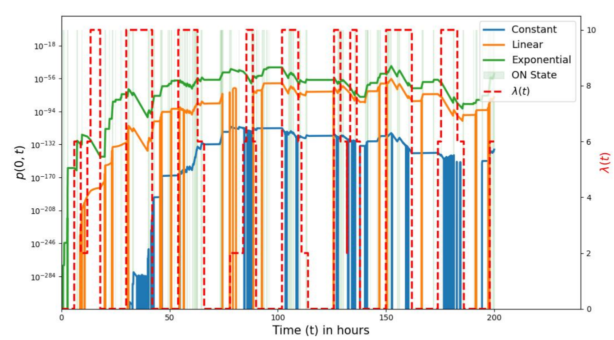

Fig. 5. Evolution of the service outage probability, $p(0,t)$ (in logscale) under different leakage models (Constant, Linear, Exponential) and fixed leakage coefficient $\xi = 0.01$, over a time-varying arrival process $\lambda(t)$ influenced by weather conditions. Also, the ESS is initially filled (i.e, p(B,0) = 1).

namics of an energy-harvesting IoT system under stochastic solar input and duty-cycled operation. As expected, the constant leakage model leads to the most stable energy behavior, as the leakage rate remains constant regardless of the energy content of the storage system. In contrast, the linear model introduces a moderate increase in energy depletion as the energy storage system fills, reflecting storage systems where leakage scales proportionally with stored energy (e.g., battery or capacitor-based storage) [12], [32]. The exponential leakage model, however, amplifies energy loss at higher storage levels, simulating non-linear leakage or instability in energy storage systems such as supercapacitors where it has been shown that energy leakage increases exponentially as its energy content increases [33]–[35].

These leakage dynamics have a clear impact on both the average number of stored energy packets $E[N(t)]$ (see Figs. 2 and 4) and the probability of energy starvation $p(0,t)$ (see figs. 3 and 5). Systems governed by exponential leakage exhibit a sharper decline in energy availability and higher chances of entering energy-depletion (when all the stored energy packets are consumed) states, especially during low solar input periods or prolonged OFF durations. Conversely, the constant leakage model supports longer energy retention and reduces the frequency of $p(0,t) > 0$, thereby ensuring more reliable operation. These results underscore the importance of selecting appropriate storage technologies and modeling assumptions based on application needs, as the leakage profile critically influences the energy sustainability and operational robustness of IoT devices. In Figs. 2 and 3 storage system is empty at the beginning (i.e., $p(0,0) = 1$) while in Figs. 4 and 5 is it filled to its full capacity.

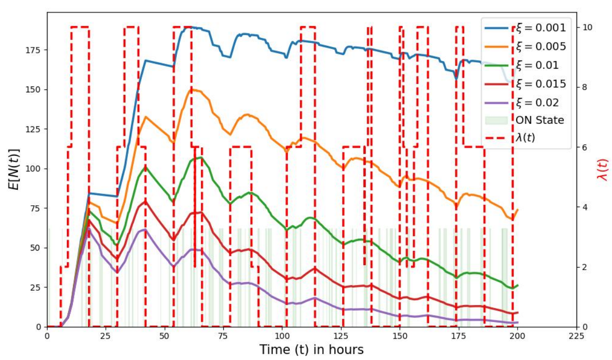

Fig. 6. Time evolution of the expected number of stored energy packets $\mathbb{E}[N(t)]$ under different leakage rates ξ. The solar energy harvesting rate $\lambda(t)$ varies based on weather conditions (sunny, cloudy, rainy) and time of day. Also, the ESS is initially empty (i.e, p(0,0) = 1) and linear leakage is assumed.

Figs. 6 illustrates the dynamic behavior of an energy-harvesting IoT system under varying energy leakage coefficient ξ. As shown in Fig. 6, the expected number of stored energy packets $\mathbb{E}[N(t)]$ fluctuates in response to the time-varying energy delivery rate $\lambda(t)$, which depends on weather conditions and diurnal cycles. Lower leakage rates allow the system to accumulate and retain more energy, especially during prolonged sunny periods, while higher leakage rates lead to faster depletion and reduced energy availability. Overall, the result emphasizes the critical role of the leakage coefficient in determining the energy sustainability and reliability of IoT systems operating under intermittent solar energy and energy consumption conditions. Also, it is that the ESS is initially empty (i.e, p(0,0) = 1) and the energy leakage model is linear.

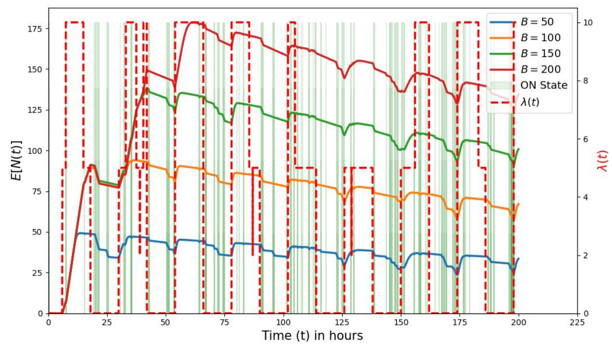

Fig. 7. Time evolution of the expected number of energy packets $\mathbb{E}[N(t)]$ for different buffer capacities B. The system is subject to stochastic weather conditions, ON/OFF activity states, and diurnal solar harvesting. Also, the ESS is initially empty (i.e, p(0,0) = 1). The red dashed line indicates the time-varying solar input rate $\lambda(t)$, while the green shaded regions denote ON activity periods.

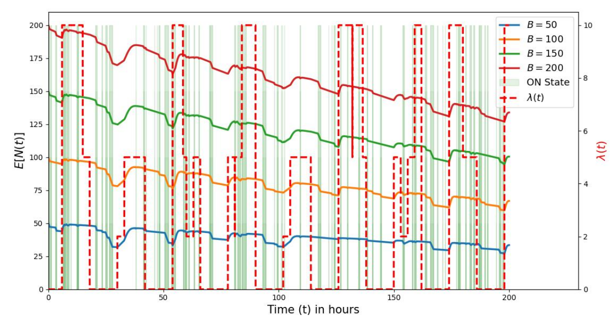

Fig. 8. Time evolution of the expected number of energy packets $\mathbb{E}[N(t)]$ for different buffer capacities B. The system is subject to stochastic weather conditions, ON/OFF activity states, and diurnal solar harvesting. Also, the ESS is initially filled (i.e, p(B,0) = 1). The red dashed line indicates the time-varying solar input rate $\lambda(t)$, while the green shaded regions denote ON activity periods.

Figs. 7 and 8 illustrate the impact of the capacity of the storage system B on the performance of an energy-harvesting IoT system operating under stochastic environmental conditions. As shown in the plots of $\mathbb{E}[N(t)]$ in Figs. 7 and 8, larger buffer sizes allow for greater energy accumulation during periods of solar activity, enhancing the system's ability to endure intervals of low or no energy delivery. In Fig. 7, the storage system is empty at the beginning (i.e., $p(0,0) = 1$) while in Fig. 8, it is filled at time $t = 0$.

In Figs. 2-8, the relatively high value of the energy arrival rate λ results in a negligible probability of energy storage system (ESS) depletion. To better illustrate the system's behavior under reduced energy input conditions, Figs. 9 and

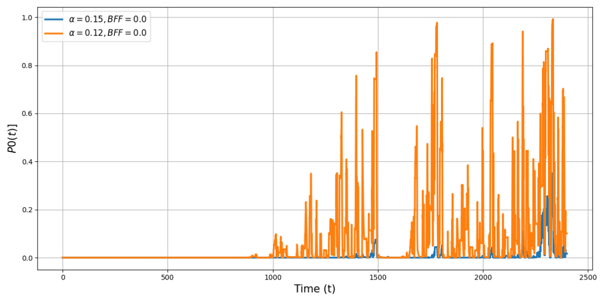

Fig. 9. $p(0,t)$ for various α.

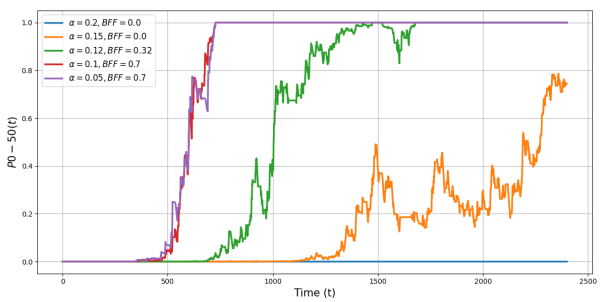

Fig. 10. $p(0-50,t)$ for various α and BFF (percent of time while buffer is full)

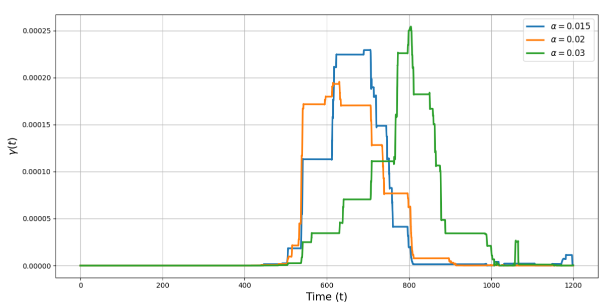

Fig. 11. The probability density function $\gamma(t)$ of the time required to deplete all the stored energy packets

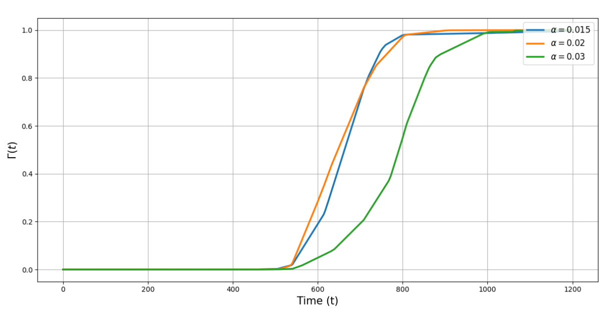

Fig. 12. The cumulative distribution function $\Gamma(t)$ of the time required to deplete all the stored energy packets

10 introduce a scaling factor α applied to all three states of the solar modulator, i.e., $\alpha[\lambda_1, \lambda_2, \lambda_3]$. This adjustment captures the impact of decreased solar irradiance or suboptimal physical parameters of the solar harvesting system on the ESS performance.

Figure 9 highlights the effect of the scaling factor α on the energy service outage probability $p(0,t)$, which denotes the probability that the ESS is completely depleted at time t. Similarly, Fig. 10 presents the probability that the stored energy falls below 25% of the total capacity B. In both scenarios, following an initial period of uninterrupted operation enabled by the fully charged ESS, the risk of depletion escalates more rapidly for lower values of $\alpha\lambda$, indicating the system's growing vulnerability under reduced energy harvesting rates.

This trend is further confirmed in subsequent figures in Figs. 11 and 12, which depict the probability density function and cumulative distribution function of the battery discharge time—defined as the time it takes for the ESS to transition from full capacity B to zero. As shown in Figs. 11 and 12. This allows us to quantify the probability that the ESS will become fully depleted due to insufficient recharging. Consequently, these results support selecting a minimum acceptable value of λ to maintain a desired level of operational reliability.

V. Conclusion

This paper presented a comprehensive Markovian framework to model the energy dynamics in Green IoT (G-IoT) systems, incorporating the coupled effects of time-varying solar energy harvesting, stochastic energy consumption, and state-dependent energy leakage. By employing Discrete-Time Markov Chains (DTMCs) to govern both the energy arrival and consumption processes, our model captures the inherent variability and intermittency of real-world renewable energy sources and IoT device operations. Furthermore, by introducing a state-dependent leakage mechanism, we addressed a critical shortcoming of existing models that overlook the non-ideal behaviors of practical energy storage systems.

Through numerical analysis, we demonstrated how system performance—measured in terms of mean stored energy and energy-related service outage probability—is influenced by storage capacity, leakage characteristics, and the dynamics of energy harvesting and consumption processes. The results underscore the importance of jointly modelling these processes to evaluate and optimise energy reliability in IoT deployments.

This study provides a practical analytical framework for researchers and system architects to assess the energy reliability of Green IoT (G-IoT) systems operating under dynamic environmental conditions. One limitation of the current model lies in its reliance on simplifying assumptions: specifically, that energy arrivals to the storage unit follow a Poisson process and that energy consumption times are exponentially distributed. While these assumptions may not fully capture the nuances of real-world systems, they enable mathematical tractability and yield useful insights into the transient behavior of energy storage systems powered by fluctuating renewable energy sources. In future research, we plan to extend this framework using fluid-flow models, diffusion approximations, and detailed simulation techniques that relax these assumptions. We also intend to explore advanced optimisation strategies to further enhance energy efficiency in highly constrained IoT deployments.

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