IoT Battery Lifetime Enhancement Using Relays: A Large-Scale Analysis

Yue Qi and Mojtaba Vaezi
Department of Electrical and Computer Engineering
Villanova University, Villanova, PA 19085, USA
Email: {yqi, mvaezi}@villanova.edu

***Abstract*—The exponential growth of the Internet of things (IoT) necessitates long-lasting, low-cost, and sustainable green IoT network designs. In this paper, relay deployment is proposed to increase the battery lifetime of IoT devices in smart homes. Then, the effect of this deployment on the battery lifetime of IoT sensors is analyzed and evaluated in large scales using tools from stochastic geometry. Such analysis is more realistic as it captures real-world spatial correlation of IoT devices and reveals better insights to network design. Further, a closed-form expression of the battery consumption model is presented, and its cumulative density function is derived analytically. Numerical and analytic results match and confirm that relay deployment is a promising opportunity that can extend smart homes' IoT battery lifetime from about one year to several years.**

***Index Terms*—IoT, sensor, relay, battery lifetime, Poisson cluster process, stochastic geometry, green communications.**

I. Introduction

The goal of fifth-generation (5G) wireless networks and beyond is to realize connecting "anything, anyone, anytime, anywhere" [1] reliably and energy-efficiently. With this ambition, 5G and beyond cellular networks face unprecedented challenges in terms of required capacity, number of connections, and delay [2]. These are due to various applications including mobile broadband, mission-critical services, and massive Internet of Things (IoT), among others.

IoT devices and networks can be exploited to make human life more convenient. Applications of IoT networks are increasing in various fields such as healthcare, industry, smart homes, energy, and transportation [3]. According to Statista Research, the total number of IoT connected devices will grow up to 75 billion worldwide by 2025 [4], and connection density is expected to be one million devices per km^2 [2]. These devices will generate massive data and consume significant energy. The economic growth of IoT would also be in the range of \$2.7 to \$6.2 trillion [5]. However, efficient exploitation of IoT networks needs frequent communication, which in turn requires considerable energy. On the other hand, IoT sensors commonly run on battery, and reducing the energy consumption of billions of IoT sensors becomes a big challenge, both economically and environmentally.

To address this problem, modeling and analysis of battery lifetime in large-scale networks is a crucial step. Hence, many researchers have studied the lifetime of IoT networks. In [6], a basic energy consumption model for IoT battery is provided. Lately, the battery lifetime with event generation model in cellular networks is considered in [7]–[9]. Network lifetime is analyzed based on stochastic geometry (SG) in [10].

A second step toward reducing the energy consumption of IoT networks is to come up with solutions to increase the battery lifetime of these devices. A big percentage of energy is consumed during communication (transmitting packets). The amount of energy used for communication depends on the number of packets to be transmitted, the success probability of transmission, and the distance between the device and access point. One line of research is focused on reducing the number of packets to be transmitted. Distributed source coding and compressed sensing approaches [11], [12] are in this category. Another line of research is concerned with improving coverage and bringing access points closer to the devices such that less energy is used for transmission.

However, there still exists a long way to improve energy efficiency in reality, and IoT batteries can survive only several months without charging [13]. Frequent replenishing energy such as recharging and replacement for IoT devices seems not a feasible solution in many applications. Numerous sustainable methods such as optical wireless communication, duty-cycling transceivers [14], and signaling flow optimization [15] have been proposed to help IoT devices save energy and extend battery lifetime.

In this paper, we propose relay deployment strategies for IoT battery longevity and analyze it in large scales. Specifically, we explore the effect of relay deployment in IoT battery lifetime extension in large-scale networks in two different settings, namely, the 3rd Generation Partnership Project (3GPP)-based and SG-based cellular networks. The former is extensively used for simulation by standardization groups, whereas the latter gives a more realistic and tractable approach to get insight into the network design [16]–[18].

The contributions of this paper are summarized as

- A rectangle cluster process (RCP) is defined to characterize the spatial coupling of indoor IoTs in smart homes. This model better fits the footprints of homes in practice.
- Relay deployment strategies are proposed to extend IoT battery lifetime in smart homes. The cases with one relay per cell and one relay per smart home are considered.
- An expression for battery consumption of IoT sensors based on event arrival pattern is formed and the cumula-

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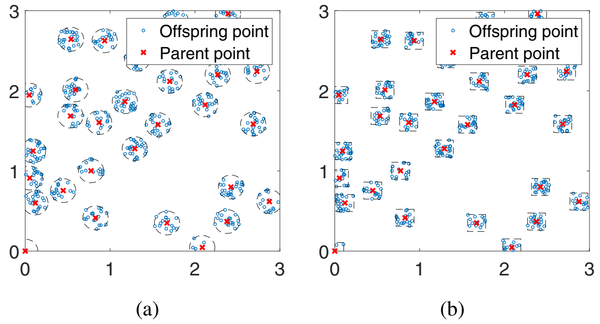


Fig. 1: Graphical illustration of IoT networks with (a) Matérn cluster process, (b) proposed rectangle cluster process in which the number of IoT devices is Poisson distributed, and their locations are uniformly distributed within a rectangle.

tive density function (CDF) of battery lifetime is derived analytically and verified numerically.

- Path loss and battery lifetime performance of the 3GPP-based and SG-based networks are compared using the above baseline model and system-level simulations.

Our analysis and simulation show that with relay deployment, battery lifetime can be extended from one year to several years because IoT sensors can send packets with less energy with the aid of relay. This is as if we bring the access point close to the sensors.

The remainder of the paper is organized as follows. Section II presents the background and system model. Based on the system model, the IoT lifetime probability model is proposed in Section III. System-level simulations and performance evaluation are shown in Section IV and Section V. The conclusion is drawn in Section VI.

II. Background and System Model

In this section, we discuss the large-scale network model and describe the system model. First, a single-tier network modeling the correlation between a smart home and IoT sensors is introduced. To better describe the realistic spatial correlation, a new cluster process called hard-core rectangle cluster process is defined according to SG. Then, we generalize it to multi-tier large-scale networks. In addition, we use IEEE802.16j path loss model, which helps in analysis and system-level simulation.

A. One-tier Spatial Network Model

We first introduce a single-tier network in which indoor IoT devices are uniformly distributed around each smart home within a radius. This network can be modeled as a stationary and isotropic Matérn cluster process [17], [19]. However, a rectangular boundary is better to characterize houses in actual HetNet deployment [18]. We improve the definition by forming a rectangle boundary to match an accurate deployment.

Definition 1 (Poisson cluster process (PCP) [17]): A PCP $\Psi(\lambda_p, f, p_n)$ can be defined as

$$\Psi = \bigcup_{\mathbf{z}\in\Phi_p} \mathbf{z} + \mathcal{C}_{\mathbf{z}} \tag{1}$$

in which Φ_p is a stationary Poisson point process (PPP) formed by parent points with density λ_p and $\mathcal{C}_{\mathbf{z}}$ denotes offspring point process with respective to a cluster center $\mathbf{z} \in \Phi_p$ where random vector $\mathbf{s} \in \mathcal{C}_{\mathbf{z}}$ is scattered independently with probability density function (PDF) $f(\mathbf{s})$ around the cluster center $\mathbf{z}$. The number of points in $\mathcal{C}_{\mathbf{z}}$ is a random vector N with mean intensity p_n ($n \in \mathbb{N}$).

A hard-core Matérn cluster process (MCP) denoted as $\Psi(\lambda_p, f, \lambda_s)$ is realized when N follows a Poisson distribution with density $\bar{c}$, denoted by $N \sim \text{Poisson}(\bar{c})$, the offspring points denoted by random vector $\mathbf{s}$ are uniformly distributed within a disk of radius R around the parent points with the density $\lambda_s = \bar{c}\lambda_p$. Any two of the parent points have a minimum distance r_e in between.

Definition 2 (Rectangle cluster process (RCP)): An RCP $\Psi(\lambda_p, f, \lambda_s)$ is defined uniquely when offspring points are uniformly distributed within a rectangle with length L and width M.

The PDFs of both RCP and MCP follow a uniform distribution but are defined in different coordinate systems. We develop a rectangle boundary since it is a better approximation of houses footprint. Each home is a parent point $\mathbf{z}$ in the network, which includes IoT sensors as offspring points $\mathbf{s} \in \mathcal{C}_{\mathbf{z}}$, where the domain $\mathcal{C}$ is a two-dimension rectangular area. Rectangle hard-core process is defined in this case when minimum distance r_e equals to $\sqrt{L^2+M^2}$, and the PDF of RCP in Cartesian coordinate is system represented as:

$$f(\mathbf{s}) = f(x, y) = \frac{1}{LM}, \tag{2}$$

in which $x \sim U(0, L)$ and $y \sim U(0, M)$.A realization of RCP is shown in Fig. 1(b).

B. Multi-tier Networks

Consider a two-tier HetNet with base stations (BSs) and relays modeled by SGs, as shown in Fig. 2(a). This is a more realistic model than the 3GPP hexagonal grid cellular network [20], illustrated in Fig. 2(b). In the 3GPP case, the location of outdoor IoTs and smart homes are randomly generated within which indoor IoTs are randomly scattered. This regular model is not rich enough to capture actual spatial deployment compared to SG-based networks, in which the distribution of relays and outdoor IoTs follow PPP, and indoor IoTs as the offspring points are distributed around their smart homes following RCP.

C. Path Loss Model - IEEE802.16j Model

IEEE802.16j model was developed by IEEE802.16 relay task group in 2007 to evaluate multi-hop relay system [21]. This evaluation methodology covers parameters and methods related to the channel model, path loss model, performance metrics, etc. It introduces nine categories of path loss models for relay systems based on terrain type, location of transmitters and receivers, and building distribution circumstances. We apply Types C for outdoor-to-outdoor (O2O) cases which includes BS to outdoor IoT, relay to outdoor IoT, BS to relay. Type J is a non-line-of-sight (NLOS) path for outdoor-to-indoor (O2I) case, such as BS to indoor IoT and relay to indoor IoT.

The basic IEEE 802.16 path loss model for type C is expressed as [21], [22]

$$PL_C = \begin{cases} 20\log(4\pi d/\lambda_c) & \text{for } d \le d_0^{'} \\ A + 10\gamma\log(d/d_0) & \\ +\Delta PL_f + \Delta PL_{ht} & \text{for } d > d_0^{'} \end{cases} \tag{3}$$

where,

$$\gamma = a - bh_1 + c/h_1 \tag{4a}$$

$$\Delta PL_f = 6\log f_c/2 \tag{4b}$$

$$\Delta PL_{ht} = \begin{cases} -10\log(h_2/3) & \text{for } h_2 \le 3m \\ -20\log(h_2/3) & \text{for } h_2 > 3m \end{cases} \tag{4c}$$

$$A = 20\log(4\pi d_0^{'}/\lambda_c) \tag{4d}$$

$$d_0^{'} = d_0 10^{-\frac{\Delta PL_f + \Delta PL_{ht}}{10\gamma}} \tag{4e}$$

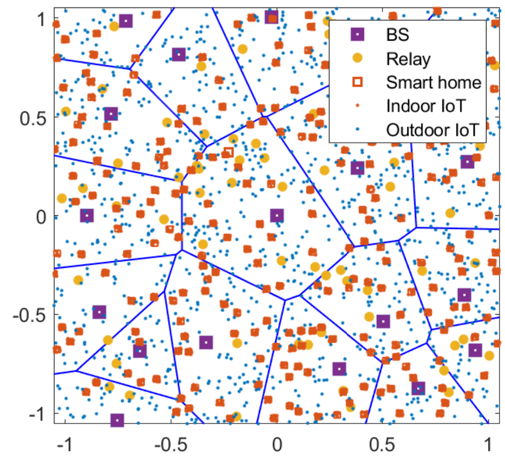
d is the distance between transmitter and receiver, $\lambda_c = \frac{c}{f_c}$ is the wavelength in meter, c is the speed of light, f_c is carrier frequency, γ is path loss exponent, h_1 is the height of the BS/relay above rooftop antenna, $a = 3.6$, $b = 0.005\text{m}^{-1}$, $c = 20\text{m}$, d_0 is set as 100 m, and h_2 is the height of relay/IoT bellow rooftop. The path loss of Type J is written as

$$PL_J = PL_C + \mathcal{N}(21, 8), \tag{5}$$

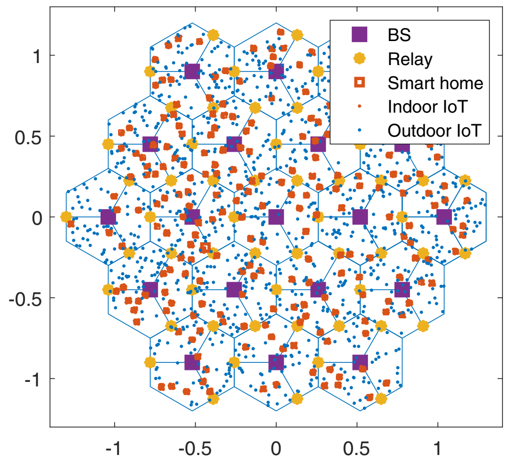
in which $\mathcal{N}(21, 8)$ is a Gaussian distribution with mean 21dB and standard deviation $\sqrt{8}$dB. With the path loss, we can obtain the received signal power through the link budget [23].

III. Battery Lifetime Analysis in Large Scale Network

In this section, a mathematical model of battery lifetime without considering the charging process is built, and the probability of battery lifetime based on the spatial location is derived. Battery internal resistance consumption and battery discharge consumption are considered as the battery properties and are taken into account in our study. In addition to the above factors, IoT battery consumption via wireless communication mainly depends on two patterns. One pattern is that sensors are used for regular events, such as recording temperature, fire and security alerts. Another pattern is due to emergent irregular events and follows Poisson process. For example, fire sensors will constantly inspect or sound when a microwave oven starts working or density of smoke is high, and illuminating sensors will be more brightened than the default if detecting someone appears [24]. Both patterns require energy if IoT devices ask for communication with the BS, which results from a high transmission loss, especially for those smart homes far away from the BS, while a relay can assist IoTs packet transmission with little energy.



(a) SG-based cellular network



(b) 3GPP-based cellular network

Fig. 2: The SG-based and 3GPP-based cellular networks. Purple squares denote the BS, yellow dots denote relays, red squares represent smart homes, red dots depict indoor IoTs, and blue dots are outdoor IoTs.

The number of events generated (n_k) by time t is an independent and identically distributed Poisson process with density λ. The probability that k events occur is [7],

$$\mathbb{P}(n_k = k) = \frac{e^{-\lambda t}(\lambda t)^k}{k!}. \tag{6}$$

The remaining energy can be written as an iterative formula,

$$R^{(\text{d}+1)} = R^{(\text{d})}(1-\gamma) - E_R^{(\text{d})} - E_I^{(\text{d})} - R_b^{(\text{d})}, \tag{7}$$

where $\gamma \in [0, 1]$ is discharge rate [25], $E_R^{(\text{d})}$ is regular event energy consumption at day d, $E_I^{(\text{d})}$ is irregular events energy dissipation, and $R_b^{(\text{d})}$ is battery internal resistance consumption. Assume E is the initial battery capacity in mWh

and $R(0) = E$. To simplify the derivation, we set discharge rate $\gamma = 0$. Then we have the recursive form of residual energy

$$
\begin{aligned}
R^{(\mathrm{d})} &= E - \sum_{\mathrm{m}=1}^{\mathrm{d}} E_R^{(\mathrm{m})} - \sum_{\mathrm{n}=1}^{n_k} E_I^{(\mathrm{n})} - R_b^{(\mathrm{d})} \\
&= E - \sum_{\mathrm{m}=1}^{\mathrm{d}} P^{(m)} T_r^{(\mathrm{m})} n_r - \sum_{\mathrm{n}=1}^{n_k} P^{(\mathrm{n})} T_i^{(\mathrm{n})} - R_b^{(\mathrm{d})} \\
&= E - \mathrm{d}P(s_i)T_r n_r - n_k P(s_i) T_i - \mathrm{d}R_b, \qquad (8)
\end{aligned}
$$

in which T_r is dissipated duration per packet, n_r is the number of regular packet per day, $P(s_i)$ is the uplink transmit power for the IoT sensor s_i, where $s_i \in \Psi$, and T_i is the irregular event duration. The lifetime T is achieved when $R(T) = 0$, s is the point set of stochastic geometry-based IoTs, scattered in spatial domain. Then, the CDF of T given each IoT location is derived as,

$$
\begin{aligned}
&\mathbb{P}(T \geq \tau | \{P(s_i), s_i \in \mathbf{s}\}) \\
=&\mathbb{P}\left(\frac{E - n_k P(s_i) T_i - R_i(T)}{R_b + P(s_i) T_r} \geq \tau \right) \\
=&\mathbb{P}\left(n_k \leq \frac{E - \tau [R_b + P(s_i) T_r]}{P(s_i) T_i} \right) \\
=& \sum_{j=0}^{f(\tau, s_i) - 1} \frac{e^{-\lambda\tau} (\lambda\tau)^j}{j!} \qquad (9)
\end{aligned}
$$

in which

$$
f(\tau, s_i) = \left\lfloor \frac{E - \tau [R_b + P(s_i) T_r]}{P(s_i) T_i} \right\rfloor, \qquad (10)
$$

where $\lfloor \cdot \rfloor$ rounds a number to the next smaller integer. Here, we can have the upper bound and lower bound of the system when the transmit power is at the minimum threshold $P_{\min}$ and maximum threshold $P_{\max}$. The upper bound of the most energy-saving system can be considered as an ideal case each smart home is equipped with a relay, while the lower bound is achieved when each IoT device needs to keep transmitting at the maximum power to the BS, which is the most energy-consuming case.

IV. System-level Simulations

In this section, we verify the analytically driven CDF of battery lifetime in (9) through simulations. Then, we characterize the results of battery lifetime with and without relays in large scale networks.

TABLE I: Parameters of battery lifetime model.

Notation	Parameter description	Value
E	Battery initial capacity	1000 mWh
n_r	The number of regular packets	300 times per day
T_r	Dissipated duration per packets	$0.01s$
R_b	Internal resistance consumption	0.1 mWh
n_k	The amount of irregular data	$n_k \sim$ Poisson(λ)
λ	Density of events	5 or 20
T_i	Irregular duration	6 min
P	Sensors uplink transmit power	15dBm or 20dBm

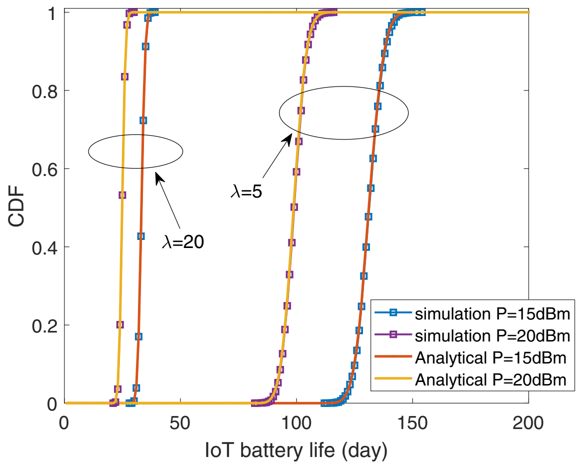


Fig. 3: CDF of indoor IoT battery lifetime in days.

A. Battery Lifetime Simulation

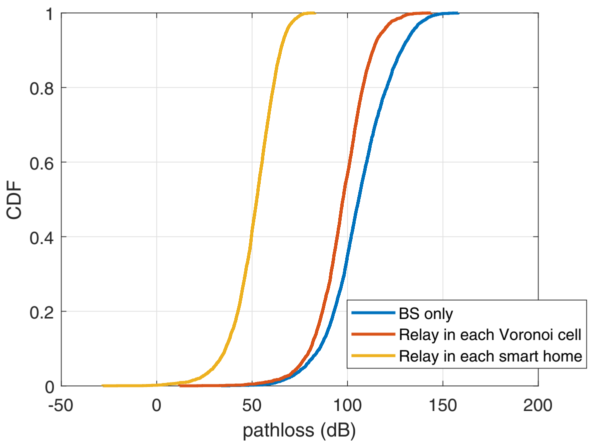
To verify the analytical results in (9), it is worth to note that using cyclic superposition and multiplier is much easier for factorial function because it may be too large for numerical calculations. The simulation parameters are shown in Table I. From Fig. 3, we can see that the derived expression for battery lifetime and simulation results match very well. A small λ can extend battery life. For example, when $P = 20\mathrm{dBm}$ and $\lambda = 20$, the battery lifetime is around 100 days compared with 25 days when $\lambda = 5$, as shown in Fig. 3. This is because reducing the frequency of using batteries can save more energy. Besides, less transmit power can also help to prolong battery life. The system simulation is introduced next.

B. Path Loss Simulation

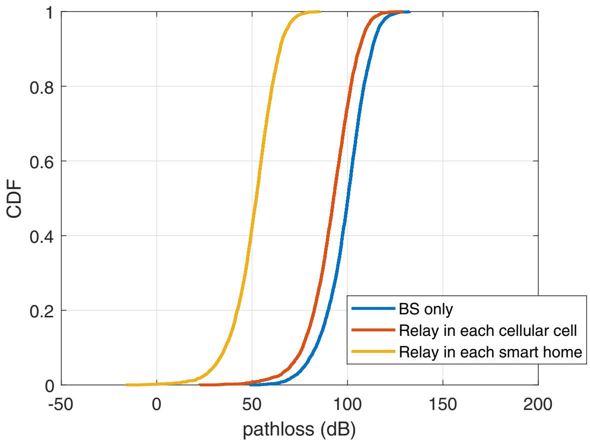
To understand the system-level performance, we consider three sorts of network deployment, 1) BS only; 2) Relay in each Voronoi cell; 3) Relay on the top of each smart home. Each case will result in different path loss for IoT sensors. The height of the BS, building, and IoT devices are $35\mathrm{m}$, $5\mathrm{m}$, and $1.5\mathrm{m}$, respectively. Carrier frequency f_c is $7\mathrm{GHz}$. Simulations are shown in Fig. 4, which demonstrates that the shorter transmit distance, the less path loss.

C. Relay-aided Networks Simulation

We realize the system-level simulation for the 3GPP-based and SG-based models. For each model, we study the three cases mentioned in the path loss simulations above. The parameters of the two networks are listed in Table II and are basically equivalent. All the house is towards one direction, no rotation in this case for simplification. λ is chosen to be 30 events per day. The CDFs of battery lifetime for the three networks discussed above are shown in Fig. 5. The lower bound is the case that each IoT sensor transmits at the fixed maximum power. We can draw a conclusion from the results that relay deployment can extend IoT battery lifetime from about one year to almost ten years.

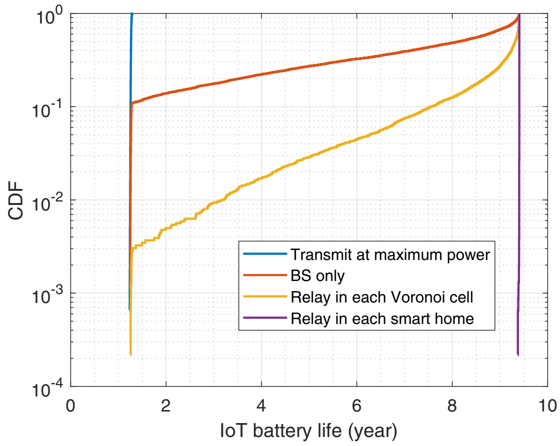


(a) CDF of pathloss in SG-based networks

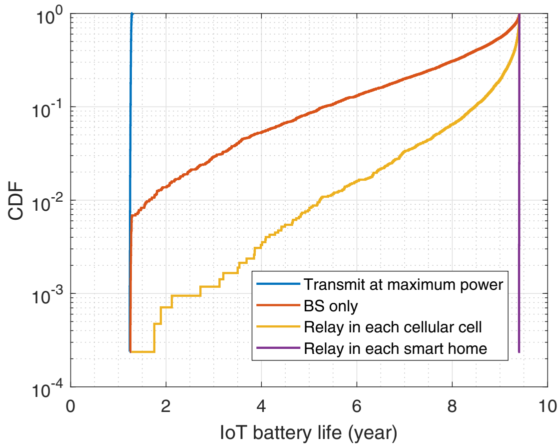


(b) CDF of pathloss in 3GPP-based networks

Fig. 4: CDF of path loss.



(a) CDF of battery lifetime in SG-based networks



(b) CDF of battery lifetime in 3GPP-based networks

Fig. 5: CDF of battery lifetime.

V. Performance Evaluation and Analysis

We analyze the simulation results in this part. First of all, the 3GPP-based network results in a lower path loss compared to the SG-based case. The CDF of path loss usually has a large range in the SG-based network than that of the 3GPP-based network, which means variance is larger. This is because the SG brings in the randomness to the deployment. Deployment of BSs, relays, and IoT sensors cannot always follow a regular grid; many unpredictable issues such as terrain, original building, forest, and wetland can affect it. The SG-based path loss is closer to reality, see Fig. 2 in [18] and [26], and the 3GPP-based network with less loss is closer to ideal performance.

Besides, the path loss of the case when the relay is installed in each smart home is much lower compared to the case where a public relay installed in each cell or the case without relay, and they are almost the same for both networks. This is because indoor IoTs can communicate with the relay in each smart home directly instead of transmitting to outdoor BS or relay outside somewhere. Thus, the path loss gets lower and will not be affected by long-distance transmission.

For the battery lifetime, relay deployment can increase longevity for both networks, especially the case of relay in each smart home. In the SG-based network, 99% IoT batteries is improved by relay from nearly 15 months to 38 months. 90% of IoT batteries can be extended from one year to seven and a half years. While in the 3GPP-based network, 99% IoT batteries can be extended by relay from about 19 months to 63 months. 90% of IoT batteries can be prolonged from five years to eight and a half years. The relay in smart home deployment for both cases nearly reaches the upper bound in which 99% of the batteries are still alive after nine years. The SG-based network is more convincing because the design and structure are more accurate compared to the cellular network [16], [17].

It is worth pointing out that the battery lifetime converges to a point finally because of the discharge rate and daily consumption. Many parameters also influence longevity; for example, the number of regular and irregular events and their corresponding duration. The fewer packets, the shorter the duration, and the longer the battery can live.

By increasing the scale of the network, the transition from city to suburban area is realized, while the trend of the results is nearly unchanged. A suburban area is usually covered by a large amount of vegetation. BSs and homes are more unplanned in which SG fits better. Due to a smaller density of people and BSs, sometimes the quality of communication is poor. With relay deployment strategies, people can have better communication.

TABLE II: Parameters of large scale networks.

3GPP-based Network	
Radius of each cell	0.3km
Intersite distance (ISD)	0.5196km
Number of wrap-around cells	57
Average number of IoT devices per cell	100
Average number of buildings per cell	4
Percentage of indoor IoT devices	80%
SG-based Networks	
The area of square	$4.4427\ \mathrm{km}^2$
The intensity of the BS λ_b	$4.2767/\mathrm{km}^2$
The intensity of relay λ_r	$12.83/\mathrm{km}^2$
The intensity of smart home λ_{home}	$51.32/\mathrm{km}^2$
The intensity of indoor IoT λ_{in}	20 per home
The intensity of outdoor IoT λ_{out}	$256.6/\mathrm{km}^2$
Battery Lifetime Parameters	
The area of each building	$30\mathrm{m} \times 30\mathrm{m}$
Maximum transmit power $P_{\max}$	10dBm
Battery initial capacity	$3\mathrm{V} \times 1000\mathrm{mAh}$
Irregular events duration T_i	60s
Discharge rate γ	0.001
Receiver antenna sensitivity for BS	-114dBm [23]
Antenna gain of IoT	-1dB [27]

VI. Conclusion

We have proposed two relay-aided strategies for IoT battery lifetime enhancement in smart homes. An SG-based RCP model has been defined for modeling the smart home and indoor IoTs correlation in large scales. System-level simulations verify that relay deployment, especially having one relay in each smart home can significantly extend the battery lifetime of IoT devices in smart homes. In our future work, we will apply non-orthogonal multiple access to ensure access to all IoT devices in high-density deployments, and improve the security of communication in the physical layer.

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