Probabilistic Model for the Lifetime Prediction of IoT Devices

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Abstract The development of new electronics and communications technologies allows the Internet of Things (IoT) concepts to be put into practice. A large amount of information is expected to travel over the internet from intelligent objects to many different kinds of software and cloud computing applications. However, there are still several challenges to be overcome. Among them, management of devices energy consumption is intriguing. Therefore, a model to estimate the range of probabilities of the energy spent by IoT equipment is presented in this work. The results include the formulation of probability distributions and discrete event simulations. The proposed method can be applied to design and evaluate IoT applications.

Keywords Internet of things · smart objects · energy consumption · stochastic

1 Introduction

The expression Internet of Things (IoT) defines the communication between objects and human beings. For this paradigm, everyday objects can connect to intelligent computer systems to capture data from the physical environment or transmit control and action commands. Applications in this field involve resource management, productivity increase and quality of life improvement [1][2].

Advances in microelectronics and communications, in the last decades, have enabled the development of sensors, controllers and radios with different functionalities and lower costs, allowing usual things to interact with information and communication technologies [3][4]. These intelligent objects are connected to embedded systems, equipped with microcontrollers or microprocessors, sensors and actuators, and communication units. The hardware that makes up a smart object is called a node, mote or end device [5][6].

In the coming years, IoT-related applications are expected to overload networks with many packets containing little data [7]. Therefore, the ecosystem of pervasive applications depends on infrastructures and technologies capable of guaranteeing quality of service [3]. The devices have limited resources, mainly due to communication technologies used [5]. In addition, the IoT solutions proposed in a more comprehensive way are built with several different technologies making their design and management relatively complex tasks [6][2].

Energy savings are still a challenge for IoT applications [8][9]. The devices are usually powered by batteries or energy collectors (for example, solar panels). Batteries need to be recharged, or replaced, and energy collectors, despite having a longer life, have restrictions related to the environment. Beyond that, the power supply may malfunction. Thus, energy efficiency is one of the most important design factors for extending network lifetime and reducing maintenance costs [10][11].

This paper proposes a statistical model to analyze power consumption of end devices, based on the fact that the time the nodes remain in different modes of operation can be described by exponential distributions,

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which is controlled by different parameters. In this sense, the objective is to assess energy consumption, in order to plan the network so that the cost of maintaining the network of intelligent objects can be mitigated.

The results obtained opens a wide range of possible experiments and field tests that can be done with commercial radios and devices. The contributions include the formulation of an expression for the most likely intervals of energy consumption for smart objects. Furthermore, the derivation of maximum and minimum consumption distributions for a group nodes is essential to establish the intervals of the worst and best cases of network nodes consumption. This methodology can be used to design and evaluate IoT applications, as well as dimension the parameters of intelligent devices.

The rest of this paper is organized as follows: In Section 2, basic concepts of IoT and smart objects are presented along with recent works available in research databases. Subsequently, in Section 3, the model for energy consumption during one duty cycle is derived together with the maximum and minimum consumption for a group of nodes. Afterwards, simulation using the obtained equation is done in Section 4. Finally, Section 5 presents conclusions and possible future work.

2 Internet of Things

The IoT is formed by an ecosystem of intelligent objects that have sensors and actuators, integrated by one or more communication systems. Environments that use this type of technology are called smart environments, such as cities, houses, universities, industries, farms and hospitals [10][12]. Networks formed with this range of resources will be part of next phases of Internet evolution. Moreover, new global network technologies are being researched to make IoT available in the coming years, including cloud computing, edge computing and fog computing [13][14][15][16].

Some characteristics are common to objects that form an IoT application, such as being identifiable and having the ability to communicate and interact between them and the end users. Identification can be implemented with readable names and addressing patterns; communication is carried out by different protocols and means of transmission; and interaction between objects and users rely on protocols and applications for personal computers and mobile devices [6][4].

2.1 Smart Objects

Some technologies are available to implement smart objects [5]. Microcontrollers (MCUs) are more flexible when it comes to application development. On the other hand, Application-Specific Integrated Circuits (ASICs) perform better. There are also Field Programmable Gate Array (FPGA) platforms that provide superior performance to MCUs and the ability to be reconfigured, providing greater flexibility in relation to ASIC circuits. In recent years, FPGA manufacturers have been integrating processors in order to increase the flexibility of these devices. These new motes are called Field-Programmable Systems-on-Chips (FPSoCs).

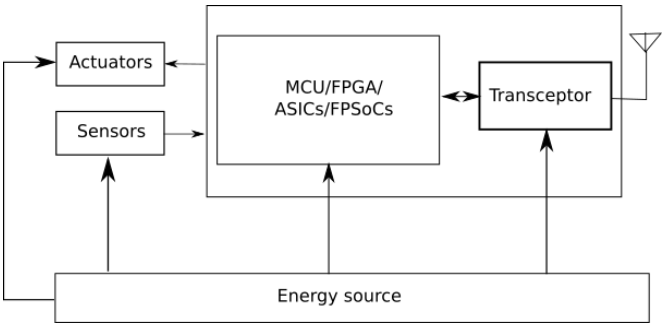

Fig. 1 Diagram of a typical end device.

In addition to microelectronics technologies, it is usually necessary to use telecommunications systems to make data reach the end user. Short-range technologies can be used in scenarios with a smaller coverage radius, such as ZigBee and Bluetooth. Cellular architectures, such as 4G and 5G, provide greater coverage with higher energy consumption. Finally, Low Power-Wide Area Network (LPWAN) technologies have larger reach with low consumption, such as SigFox, Long Range (LoRa) and Narrow Band in IoT (NB-IoT) [17].

Figure 1 shows a diagram of a typical end device. Generally, the node has a microcontroller or microprocessor to perform local processing and act as the interface between sensors and actuators and the RF module. One or more sensors can be connected. Furthermore, a mote has a communication module that allows the transmission of data collected from the sensors, the receipt of action commands and the determination of its position in the environment monitored by the application [18].

Some nodes have an operating system that uses an architecture to make implementation faster, and minimize code size. A software layer is needed to manage communication functions, such as routing, packet management, topology maintenance and medium access control. Moreover, some encoding and physical layer modules manage the details of the link, such as synchronization, signal encoding, bit retrieval and modulation. Small size applications can be developed for data processing. These applications manipulate, store signals and apply numeric functions to the data. They are used for processing within the network [19].

2.2 Energy Consumption

There are, in literature, recent studies that investigate the energy consumption by wireless end devices in order to predict node and network lifetime. The proposed models present some assumptions regarding the duty cycle, transmission and reception power. There are more generic and more specific formulations that take into account details of hardware implementation and communication protocols, apart from evaluating the possible network topology configurations. Validations are performed by experiments and simulations.

The work developed by [20] proposes an analytical model to estimate the lifetime of wireless device networks considering the remaining energy, the quality of the link and the position of the network nodes in the environment. The experimental results achieved indicate the accuracy of the proposed model. Another work [21] discusses a methodology that combines contributions communication tasks consumption, data acquisition and data processing activities. The article considers Time Slotted Channel Hopping (TSCH) access method, for networks with LoRa Semtech devices and Guidance and Inertial Navigation Assistant, GINA, platform developed by Wireless Autonomous Robot Platform with Inertial Navigation and Guidance (WARPwING) project.

The studies carried out by [22] lead to a power consumption model for devices that use IEEE 802.15.4e standard, in TSCH mode, identifying the activities and state changes performed by the processing unit and the communication unit. The authors conclude that the model is accurate for OpenMote nodes that run OpenWSN (Open Wireless Sensor Network) firmware. The work of [23] describes an energy consumption model based on LoRa and LoRa Wide Area Network (LoRaWAN) technologies. Three configurations of the SX1272 LoRaWAN transceivers were evaluated, allowing to establish the impact of the hardware and software choices.

In [24], a method for predicting LoRa Ra-01 modules lifetime is presented. Experiments were performed to obtain the battery discharge and energy consumption curve in relation to package size, and a probabilistic approach based on Markov chains was adopted to evaluate simultaneous transmissions. A stochastic model using Gradient Based Routing (GBR) techniques was developed by [25]. The formulation considers the random effects of the wireless communication channel, random change of device operating states and the duration of operations. Simulations were performed to compare three different forms of the protocol: EA-GBR, generic GBR and GBR-C. Stochastic methods to analyze and estimate energy consumption for data transmission in networks with different topologies were presented in [26]. The author assumes that the devices are positioned at random locations and the packages take random paths to the central node.

Based on the formulations, the work suggests some scenarios to minimize energy consumption. Each device in the network can remain in four states (i.e. fully active, two semi-active states, and one low consumption state) in the model proposed by [27]. A joint probability distribution for the number of packages and the device states was obtained from a multi-dimensional Markov process. Several performance measures were established and a numerical analysis was performed to validate the model.

All these models are able to predict energy consumption of IoT motes, however they are not general enough, they have some specificities, or they do not take into account the cases in which time events are random. This work presents a more general formulation for the problem, considering its stochastic nature and its independence from the hardware platform.

3 Energy Consumption Model

Generally, the evolution of energy consumption over time is modeled considering that the transmission rate, packet size, collision rate and retransmission rate are proportional to the operating time. Some typical parameters are [28,29]:

- t_b: time the node remains in low consumption state;
- t_m: time the node remains in measurement state;
- t_p: time the node remains in processing state;
- t_r: time the node remains in receiving state;
- t_t: time the node remains in transmission state;
- c_b: consumption per unit of time in low consumption state;
- c_m: consumption per unit of time in measurement state;
- c_p: consumption per unit of time in processing state;
- c_r: consumption per unit of time in receiving state;
- c_t: consumption per unit of time in transmission state;

The sequence in which the states occur can be deterministic or random. Furthermore, the operating time in each state can be constant or random, as well as, the energy consumption per unit of time.

Each period of time t_k that a network node remains in a state referring to the mode of operation can be modeled as a random variable with Probability Density Function (PDF) given by [30]

$$f_k(t) = \begin{cases} \alpha_k \exp[-\alpha_k t], & t \geq 0 \\ 0, & \text{otherwise,} \end{cases} \tag{1}$$

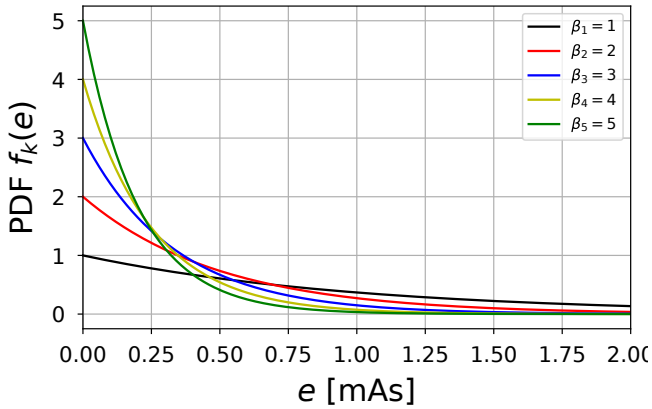

Fig. 2 PDF graph of energy consumption for different values of β_k.

in which $\alpha_k = 1/\mu$ is the inverse of the distribution average.

On the other hand, the energy consumed E can be estimated as a function of time periods that a sensor node remains in each state, according to the equation

$$E = \sum_{k=1}^{M} t_k c_k, \tag{2}$$

in which M is the number of sensor nodes possible states and c_k are the costs related to energy consumption per unit of time. Therefore, the energy consumed in each state can be expressed by

$$e_k = t_k c_k \tag{3}$$

Applying a PDF transformation [31], the probability density function of the energy spent in each state is given by

$$f_k(e) = \frac{f_k(t)}{|\frac{de}{dt}|} = \frac{\alpha_k \exp[-\alpha_k e/c_k] u(e/c_k)}{c_k}.$$

Making $\beta_k = \alpha_k/c_k$ and using the unit step function property,

$$f_k(e) = \beta_k \exp[-\beta_k e] u(e). \tag{4}$$

Figure 2 shows the PDF graph for the energy consumption in each state for different values of β_k. The $u(\cdot)$ function is the unit step function.

3.1 Consumption Distribution in One End Device Work Cycle

Let $e_1, e_2, ..., e_M$ be independent random variables with exponential distribution given by

$$f_k(e) = \beta_k \exp[-\beta_k e] u(e), \tag{5}$$

and E the sum of these random variables denoted by

$$E = \sum_{k=1}^{M} e_k. \tag{6}$$

It is possible to obtain distribution for E, assuming that the random variables that represent the end device states are independent. According to [32], the sum of these variables leads to the convolution of their respective distributions,

$$f_E(e) = f_1(e) * f_2(e) * \cdots * f_M(e).$$

The Laplace transform of this expression is given by

$$\mathscr{L}\{f_E(e)\} = \mathscr{L}\{f_1(e)\}\mathscr{L}\{f_2(e)\} \cdots \mathscr{L}\{f_M(e)\}.$$

To obtain the final expression, the case in which the state number M is equal to 2 is considered first. The Laplace transform of the probability distribution of any state is given by

$$\mathscr{L}\{f_k(e)\} = \mathscr{L}\{\beta_k \exp[-\beta_k e]\} = \frac{\beta_k}{\beta_k + s}.$$

Therefore, for $M = 2$, and using partial fraction expansion to obtain the inverse of Laplace transform,

$$\mathscr{L}\{f_E(e)\} = \frac{\beta_1}{(\beta_1 + s)} \frac{\beta_2}{(\beta_2 + s)}$$

$$\mathscr{L}^{-1}\Big\{\frac{\beta_1}{(\beta_1 + s)} \frac{\beta_2}{(\beta_2 + s)}\Big\} = \beta_1\beta_2\Big[\frac{\exp[-\beta_1 e]}{(\beta_2 - \beta_1)} - \frac{\exp[-\beta_2 e]}{(\beta_1 - \beta_2)}\Big].$$

Applying from the same procedure, for $M = 3$,

$$\mathscr{L}^{-1}\Big\{\frac{\beta_1}{(\beta_1 + s)} \frac{\beta_2}{(\beta_2 + s)} \frac{\beta_3}{(\beta_3 + s)}\Big\} = \beta_1\beta_2\beta_3$$
$$\times\Big[\frac{\exp[-\beta_1 e]}{(\beta_1 - \beta_2)(\beta_1 - \beta_3)} - \frac{\exp[-\beta_2 e]}{(\beta_1 - \beta_2)(\beta_2 - \beta_3)}$$
$$-\frac{\exp[-\beta_3 e]}{(\beta_1 - \beta_3)(-\beta_2 + \beta_3)}\Big].$$

Observing the numerators and denominators of the partial fractions, it is possible to obtain, by induction, the probability distribution for M states as follows

$$f_E(e) = \sum_{i=1}^{M} \frac{\beta_1 \cdots \beta_n}{\prod_{\substack{j=1 \\ j \neq i}}^{M} (\beta_j - \beta_i)} \exp[-\beta_i e] u(e). \tag{7}$$

From the values provided by the ESP32 datasheets [33], it was possible to obtain the estimated values for c_k described in Table 1. The values for α were estimated based on the average time that the mote stays in each state. The graphs in Figure 3 present the PDFs for the energy consumption of five states for the ESP32, considering different values of operation average time in low consumption mode.

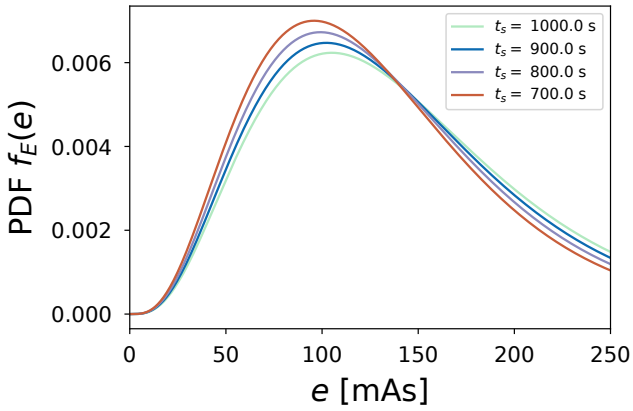

Fig. 3 Graph of energy consumption PDFs of an end device configured to operate at different times the node remains in low power mode.

β_k	c_k	α_k
$\beta_1 = 2$	$c_b = 5\mu$A	$\alpha_b = 0.001$
$\beta_2 = 0,2632$	$c_m = 38$mA	$\alpha_m = 1$
$\beta_3 = 0,0294$	$c_p = 68$mA	$\alpha_p = 2$
$\beta_4 = 0,05$	$c_r = 100$mA	$\alpha_r = 5$
$\beta_5 = 0,0417$	$c_t = 240$mA	$\alpha_t = 10$

Table 1 Parameters of a sensor node built with an ESP32 radio [33].

3.2 Maximum and minimum consumption

Operators min and max are useful to evaluate pessimistic and optimistic scenarios of energy consumption [34]. If $E_1, ..., E_N$ are random variables that represent energy consumption per N nodes in a network, during an operating cycle, $W = \min(E_1, ..., E_N)$ and $Z = \max(E_1, ..., E_N)$ can be used to estimate the greatest and the least energy consumption for a group a nodes, respectively.

3.2.1 Maximum of N Independent Random Variables

In order to compute the maximum energy consumption, let

$$Z = \max(X_1, X_2) = \begin{cases} X_1, & X_1 > X_2 \\ X_2, & X_1 \leq X_2 \end{cases}$$

be the distribution of two random variables maximum. Therefore,

$$\begin{aligned} F_Z(z) &= P\{\max(X_1, X_2) \leq z\} \\ &= P\{(X_1 \leq z, X_1 > X_2) \cup (X_2 \leq z, X_1 \leq X_2)\} \end{aligned}$$

Since $\{X > Y\}$ and $\{X \leq Y\}$ are mutually exclusive and form a partition,

$$F_Z(z) = P\{X_1 \leq z, X_1 > X_2\} + P\{X_2 \leq z, X_1 \leq X_2\}$$

Thus, the $F_Z(z)$ distribution is given by

$$P\{X_1 \leq z, X_2 \leq z\} = F_{X_1 X_2}(z, z).$$

Assuming that X_1 and X_2 are independent,

$$F_Z(z) = F_{X_1}(z) F_{X_2}(z)$$

$$f_Z(z) = \frac{dF_z(z)}{dz} = \frac{d[F_{X_1}(z) F_{X_2}(z)]}{dz}.$$

Applying the chain rule, one obtains

$$f_Z(z) = F_{X_1}(z) f_{X_2}(z) + f_{X_1}(z) F_{X_2}(z).$$

Using the same idea for three random variables:

$$\begin{aligned} \frac{dF_z(z)}{dz} &= \frac{d[F_{X_1}(z) F_{X_2}(z) F_{X_3}(z)]}{dz} \\ &= f_{X_1}(z) F_{X_2}(z) F_{X_3}(z) + F_{X_1}(z) f_{X_2}(z) F_{X_3}(z) \\ &+ F_{X_1}(z) F_{X_2}(z) f_{X_3}(z) \\ &= \begin{bmatrix} f_{X_1}(z) & f_{X_2}(z) & f_{X_3}(z) \end{bmatrix} \begin{bmatrix} F_{X_2}(z) F_{X_3}(z) \\ F_{X_1}(z) F_{X_3}(z) \\ F_{X_1}(z) F_{X_2}(z) \end{bmatrix} \end{aligned}$$

Generalizing, by induction, for M random variables

$$f_Z(z) = \begin{bmatrix} f_{X_1}(z) & f_{X_2}(z) & \dots & f_{X_N}(z) \end{bmatrix} \begin{bmatrix} \frac{F_{X_1}(z) \dots F_{X_N}(z)}{F_{X_1}(z)} \\ \frac{F_{X_1}(z) \dots F_{X_N}(z)}{F_{X_2}(z)} \\ \cdot \\ \cdot \\ \cdot \\ \frac{F_{X_1}(z) \dots F_{X_N}(z)}{F_{X_N}(z)} \end{bmatrix}$$

The expression can also be written as follows,

$$f_Z(z) = \sum_{i=1}^{N} f_{X_i}(z) \prod_{\substack{j=1 \\ j \neq i}}^{N} F_{X_j}(z). \tag{8}$$

On the other hand, let

$$W = \min(X_1, X_2) = \begin{cases} X_1, & X_1 \leq X_2 \\ X_2, & X_1 > X_2 \end{cases}$$

be the distribution of two random variables minimum.

In a similar manner, it is possible to obtain for Z,

$$\begin{aligned} F_W(w) &= P\{\min(X_1, X_2) \leq w\} \\ &= P\{X_2 \leq w, X_1 > X_2\} + P\{X_1 \leq w, X_1 \leq X_2\} \end{aligned}$$

Therefore, the $F_W(w)$ distribution is given by

$$\begin{aligned} 1 - P\{W > w\} &= 1 - P\{X_1 > w, X_2 > w\} \\ &= 1 - [1 - F_{X_1}(w)][1 - F_{X_2}(w)] \end{aligned}$$

Following the same idea used to obtain $f_Z(z)$, the PDF of W is obtained for N random variables

$$F_W(w) = 1 - [1 - F_{X_1}(w)][1 - F_{X_2}(w)] \dots [1 - F_{X_N}(w)]$$

$$\frac{dF_W(w)}{dw} = \sum_{i=1}^{N} f_{X_i}(w) \prod_{\substack{j=1 \\ j \neq i}}^{N} [1 - F_{X_j}(w)] = f_W(w). \tag{9}$$

3.2.2 Maximum and Minimum Distribution of $E_1, ..., E_N$

The Cumulative Distribution Function (CDF) of a random variable E, whose PDF is the sum of independent random variables with exponential distribution, is given by

$$\begin{aligned} F_E(e) &= \int_{-\infty}^{e} p_E(\tau)d\tau \\ &= \int_{-\infty}^{e} \sum_{i=1}^{M} \frac{\beta_1 \cdots \beta_M}{\prod_{\substack{j=1 \\ j\neq i}}^{M} (\beta_j - \beta_i)} \exp[-\beta_i \tau] u(\tau) d\tau \\ &= \sum_{i=1}^{M} \frac{\beta_1 \cdots \beta_M}{\prod_{\substack{j=1 \\ j\neq i}}^{M} (\beta_j - \beta_i)\beta_i} [1 - \exp[-\beta_i e]] u(e). \end{aligned} \tag{10}$$

In order to obtain $Z = \max(E_1, ..., E_N)$, one assumes that $E_1, ..., E_N$ are independent random variables. Replacing Equations 7 and 10 in Equation 10, it is possible to obtain

$$\begin{aligned} f_Z(z) = \sum_{i=1}^{N} \Bigg[\Bigg(\sum_{j=1}^{M} \frac{\beta_{i1} \cdots \beta_{iM}}{\prod_{\substack{k=1 \\ k\neq j}}^{M} (\beta_{ij} - \beta_{jk})} \exp[-\beta_{ij} z] u(z) \Bigg) \\ \times \Bigg(\prod_{\substack{l=1 \\ l\neq i}}^{N} \sum_{m=1}^{M} \frac{\beta_{l1} \cdots \beta_{lM}}{\prod_{\substack{n=1 \\ n\neq m}}^{M} (\beta_{lm} - \beta_{ln})\beta_{ln}} [1 - \exp[-\beta_{ln} z]] u(z) \Bigg) \Bigg]. \end{aligned} \tag{11}$$

A special case occurs when $E_1, ..., E_N$ are independent and identically distributed. Therefore, the expression for Z becomes

$$\begin{aligned} f_Z(z) = N \Bigg[\Bigg(\sum_{i=1}^{M} \frac{\beta_1 \cdots \beta_M}{\prod_{\substack{j=1 \\ j\neq i}}^{M} (\beta_j - \beta_i)} \exp[-\beta_i z] u(z) \Bigg) \\ \times \Bigg(\sum_{i=1}^{M} \frac{\beta_1 \cdots \beta_M}{\prod_{\substack{j=1 \\ j\neq i}}^{M} (\beta_j - \beta_i)\beta_i} [1 - \exp[-\beta_i z]] u(z) \Bigg)^N \Bigg] \end{aligned} \tag{12}$$

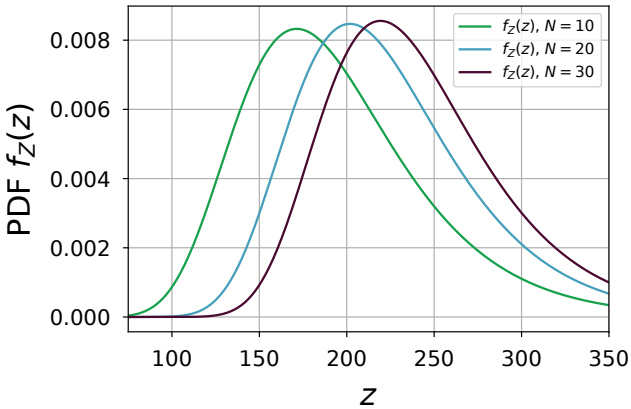

Fig. 4 Graph of maximum energy consumption for N i.i.d. nodes. The PDF is configured with parameters β_k from Table 1.

To obtain $W = \min(E_1, ..., E_N)$, Equation 9 is applied, thus,

$$\begin{aligned} f_W(w) = \sum_{i=1}^{N} \Bigg[\Bigg(\sum_{j=1}^{M} \frac{\beta_{i1} \cdots \beta_{iM}}{\prod_{\substack{k=1 \\ k\neq j}}^{M} (\beta_{ij} - \beta_{jk})} \exp[-\beta_{ij} w] u(w) \Bigg) \\ \times \Bigg(\prod_{\substack{l=1 \\ l\neq i}}^{N} \Bigg[1 - \sum_{m=1}^{M} \frac{\beta_{l1} \cdots \beta_{lM}}{\prod_{\substack{n=1 \\ n\neq m}}^{M} (\beta_{lm} - \beta_{ln})\beta_{ln}} [1 - \exp[-\beta_{ln} w]] u(w) \Bigg] \Bigg) \Bigg]. \end{aligned} \tag{13}$$

In case $E_1, ..., E_N$ are independent but β_i parameters are the same,

$$\begin{aligned} f_W(w) = N \Bigg[\Bigg(\sum_{i=1}^{M} \frac{\beta_1 \cdots \beta_M}{\prod_{\substack{j=1 \\ j\neq i}}^{M} (\beta_j - \beta_i)} \exp[-\beta_i w] u(w) \Bigg) \\ \times \Bigg(1 - \sum_{i=1}^{M} \frac{\beta_1 \cdots \beta_M}{\prod_{\substack{j=1 \\ j\neq i}}^{M} (\beta_j - \beta_i)\beta_i} [1 - \exp[-\beta_i w]] u(w) \Bigg)^N \Bigg] \end{aligned} \tag{14}$$

4 Simulation Results

The stochastic process $E_i(t)$ is formed by the family of functions that establish N network nodes energy consumption over time. Therefore, a discrete event simulation algorithm was developed to evaluate the performance of an IoT application. The devices have identical configurations, that is, with the same parameters β_k and α_k (Table 1). Each node has an initial amount of

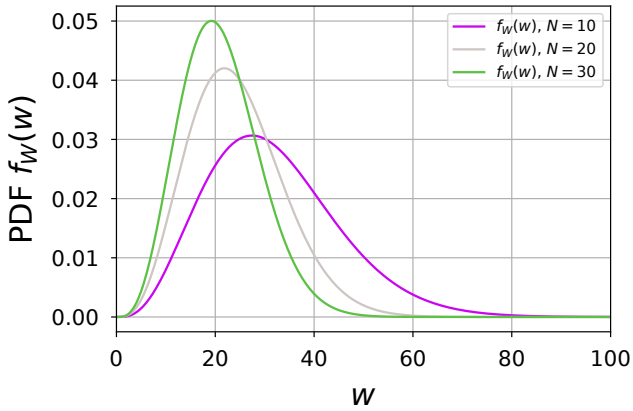

Fig. 5 Graph of minimum energy consumption for N nodes i.i.d PDF configured with parameters β_k from Table 1.

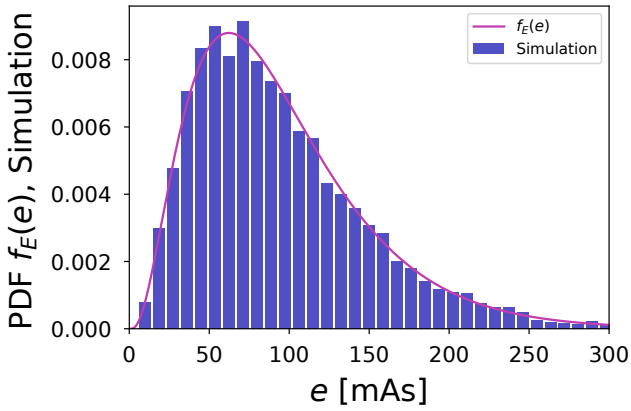

Fig. 6 Histogram graph of simulation data and theoretical energy consumption curve during an operating cycle.

energy which is spent by the equipment depending only on time they remain in each state. The energy extracted from the battery is consumed linearly, following Equation 15. This simple formulation allows to compute the remaining capacity after a discharge period.

$$C = C' - It_d. \tag{15}$$

The capacity at the beginning of an operation is denoted by C', t_d the duration of the operation and I the discharge current. The relaxation effect is not considered in this model. The simulation algorithm for the operation of one node (Algorithm 1) was implemented in the Python language. It has as input the vectors $\boldsymbol{\alpha}$ and $\boldsymbol{c}$, which make up the parameters β_k of the consumption distribution. C' represents the initial capacity of the battery, and N_s and N_c are the number of device states and the maximum number of simulation cycles, respectively. The output is formed by a vector $\boldsymbol{W}$n that stores the amount of energy consumed in each operation cycle, $\boldsymbol{C}$ how much was consumed in each state, and T_v refers to the sum of times that one node remains in each state, resulting the lifetime.

The first pair of nested loops (lines $1-5$) fills the vector $\boldsymbol{t}$ with random time intervals. These intervals have an exponential distribution with an average of $1/\alpha_k$. The second pair of loops (lines $6-20$) discharge the battery as time progresses. It is observed that the instructions are executed while there is load available. The vectors $\boldsymbol{C}$ and $\boldsymbol{W}$ are filled with the mote consumption. The lifetime is increased with time intervals in which the node remained in the state k.

Algorithm 1: Simulation of one node lifetime and consumption during for one duty cycle.

Input: $\boldsymbol{\alpha}$, $\boldsymbol{c}$, C', N_s, N_c
Output: $\boldsymbol{W}$, $\boldsymbol{C}$, T_v

1 **for** $i = 1, ..., N_c$ **do**
2 **for** $k = 1, ..., N_s$ **do**
3 $\boldsymbol{t}_i$ =random.exponential($1/\boldsymbol{\alpha}_k$)
4 **end**
5 **end**
6 $j = 1$
7 **for** $i = 1, ..., N_c$ **do**
8 $\boldsymbol{W}_i = 0$
9 **for** $k = 1, ..., N_s$ **do**
10 **if** $C' \geq \boldsymbol{t}_i c_k$ **then**
11 $\boldsymbol{C}_j = \boldsymbol{t}_j \boldsymbol{c}_k$
12 $C' = C' - \boldsymbol{C}_j$
13 $\boldsymbol{W}_i = \boldsymbol{W}_i + \boldsymbol{C}_j$
14 $T_v = T_v + \boldsymbol{t}_j$
15 $j = j + 1$
16 **else**
17 break
18 **end**
19 **end**
20 **end**

Figure 7 presents the histogram of energy consumption per operating cycle for $N_c = 10000$, as well as the theoretical curve, $f_E(e)$. The χ^2 test did not rule out the hypothesis that $f_E(e)$ describes the phenomenon. Accordingly, it is possible to observe, graphically, that the curve and the histogram have similar behavior. This indicates a good adherence of the simulation samples to the PDF curve which indicates that the model (Equation 7) is a valid option to anticipate the probability density of energy consumption during an operating cycle.

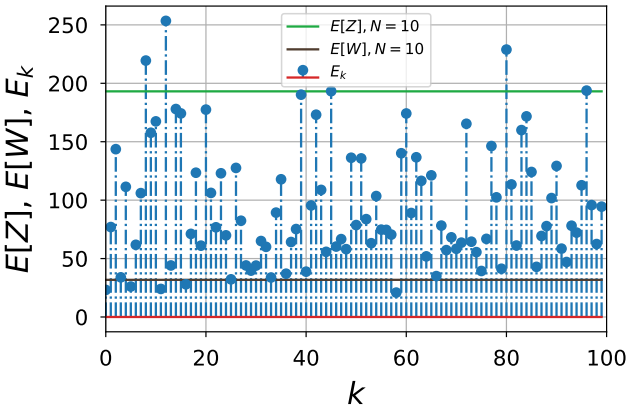

Fig. 7 Graph of limits established by $E[Z]$ and $E[W]$, and energy consumption per cycle during 100 operating cycles.

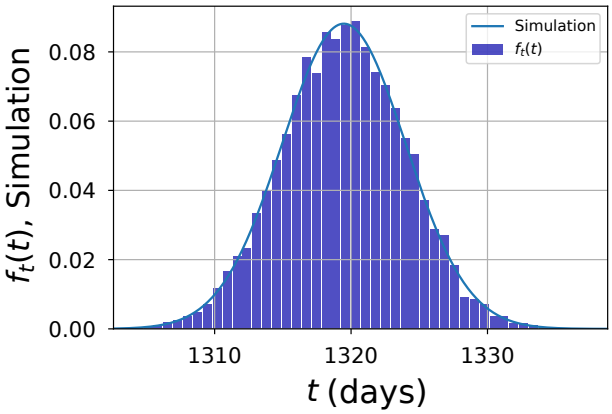

Fig. 8 Histogram graph of data from simulation and adjustment curve for lifetime distribution of 10000 network nodes.

The expected value of $f_Z(z)$ provides the average of the largest energy consumption for a group of devices during an operating cycle. Since the simulation was performed with identical devices,

$$E[Z] = \int_{-\infty}^{+\infty} z f_Z(z) dz =$$
$$\int_{-\infty}^{+\infty} zN \left[\left(\sum_{i=1}^{M} \frac{\beta_1 \cdots \beta_M}{\prod_{\substack{j=1 \\ j \neq i}}^{M} (\beta_j - \beta_i)} \exp[-\beta_i z] u(z) \right) \right.$$
$$\left. \times \left(\sum_{i=1}^{M} \frac{\beta_1 \cdots \beta_M}{\prod_{\substack{j=1 \\ j \neq i}}^{M} (\beta_j - \beta_i)\beta_i} [1 - \exp[-\beta_i z]] u(z) \right)^N \right] dz \quad (16)$$

On the other hand, the average of the lowest consumption of a group of nodes in the network is given by

$$E[W] = \int_{-\infty}^{+\infty} w f_W(w) dw =$$
$$\int_{-\infty}^{+\infty} wN \left[\left(\sum_{i=1}^{M} \frac{\beta_1 \cdots \beta_M}{\prod_{\substack{j=1 \\ j \neq i}}^{M} (\beta_j - \beta_i)} \exp[-\beta_i w] u(w) \right) \right.$$
$$\left. \times \left(1 - \sum_{i=1}^{M} \frac{\beta_1 \cdots \beta_M}{\prod_{\substack{j=1 \\ j \neq i}}^{M} (\beta_j - \beta_i)\beta_i} [1 - \exp[-\beta_i w]] u(w) \right)^N \right] dw \quad (17)$$

The integrals were solved numerically for a group of 10 nodes. Furthermore, a consumption simulation was performed during 100 operating cycles of one node. Figure 7 presents a graph with the limits established by $E[Z]$ and $E[W]$, and the evolution of consumption in each cycle, E_k, for the k-th operating cycle.

The network lifetime was evaluated from the simulation with 10000 devices equipped with batteries having initial capacity $C' = 3000$ mAh. In fact, the simulation was repeated 10000 since devices were considered independent. Figure 8 shows the result of the simulation and the adjustment of the normal distribution to the lifetime histogram, t_v. In the considered scenario, the average lifetime of the network nodes is 1319.47 days with $\sigma = 4.53$.

5 Conclusions and Future Work

In this work, a stochastic model for energy consumption in IoT applications was proposed. It was possible to obtain a generic expression for the PDF of energy consumption during a work cycle as a sum of exponential random variables. It is a theoretical model for IoT/WSN, so that adjustments can be made to reflect reality. Several authors have already proposed energy consumption models in which the sum of consumption in each state results in total consumption in each cycle. Thus, a generalization is proposed based on the premise that the time in each state is random. The model was developed considering consumption of each device individually. It is an abstraction that incorporates internal and external effects to the device. The model can be adjusted by means of its $beta_k$ parameters and by unfolding the formulation (e.g. it can be considered that the time in the low consumption mode is deterministic or that the $beta_k$ parameters change over time). The lifetime simulation was repeated 10000 times (e.g. 10000 nodes) in order

to obtain the distribution of the lifetime of the network. Beyond that, the PDFs for the maximum and minimum consumption were derived, allowing to analyze extreme scenarios for a group of nodes. With the estimated β_k parameters of ESP32 radio, the following theoretical curves of the model were drawn:

1. PDFs of consumption during a cycle for the devices configured to operate with different sleep mode times;
2. PDFs of the maximum energy consumption for N nodes i.i.d configured with the parameters β_k;
3. PDFs of the minimum energy consumption for N nodes i.i.d configured with the parameters β_k.

Based on the obtained model, a simulation algorithm was developed to determine the consumption during one duty cycle, in addition to obtaining the lifetime of end devices, based on the linear battery discharge model. Then, a simulation data histogram and a theoretical curve of energy consumption during an operating cycle were obtained, indicating a good fitting of the theoretical model to the simulation data. Finally, the limits established by the expected values of the maximum and minimum, and the energy consumption per cycle were obtained numerically. It is possible to observe that most of the simulated consumption values are within the established limits. The simulation developed is widely known in the literature. This is a discrete event simulation. As there is no need to simulate the interaction between devices, this type of simulation seems to be adequate. The model abstracts the routing and interference interactions by adjusting the $beta_k$ parameters of the distribution.

The proposed model has wide applicability in the area of IoT and wireless networks in general. The presented methodology can be used in application projects in which energy consumption is a determining factor, considering that the time that RF devices remain in each operational state is random. The motes performance can be evaluated and performance tests can be carried out to compare different technologies and configurations, in order to analyze the relationship between cost and benefit. The IoT application is justified by the fact that this device represents a single node in a network of devices.

Some advantages of the approach can be enumerated, such as its simplicity and flexibility, which is valid for any package size, low consumption operation time, processing time and any other parameter related to the time that the designer can extract from the end device. Also, the model is generic and precise, allowing to evaluate the most probable lifetime interval of a specific node or a group of independent nodes.

Future work may involve conducting field tests with commercial devices, simulating and experimenting with other parameters, such as the mote position, the transition time between states, control signals and the impact of the signal strength. It is also possible to simulate energy consumption using a nonlinear discharge model. The development of a closed expression to calculate the expected value of the maximum and minimum energy consumption of a group of nodes can be accomplished.

Declarations

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