Leakage-Aware Lifetime Estimation of Battery-Free Sensor Nodes powered by Supercapacitors

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ABSTRACT

Battery-free sensor nodes rely solely on energy harvested from the environment and thus employ supercapacitors as energy storage to allow perpetual operation in absence of ambient energy. To guarantee that the sensor nodes can survive in periods where no harvested energy is available, it is crucial to accurately estimate the lifetime of these devices. However, as we show experimentally in this paper, an accurate lifetime estimation is non-trivial due to the supercapacitors' complex discharge characteristics (e.g., leakage currents) and large capacitance tolerances. After showing that empirical data capturing the supercapacitors' characteristics is essential towards an accurate estimation of the system's lifetime, we introduce an enhanced leakage model that is computationally lightweight and evaluate its accuracy experimentally.

CCS CONCEPTS

• **Computer systems organization → Embedded systems**.

KEYWORDS

Battery-Free Systems, Sensor Nodes, Supercapacitors, Leakage

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1 INTRODUCTION

Recently, battery-free sensor nodes are emerging as a viable alternative to conventional battery-powered devices and are used to build maintenance-free and sustainable Internet of Things (IoT) applications. Equipped with an energy harvester and a capacitor as energy storage, battery-free sensor nodes are powered from environmental sources (e.g., light, vibration, or temperature) and promise to overcome the shortcomings of batteries, which are often costly both in terms of maintenance (i.e., battery replacement) and environmental impact (i.e., battery disposal). As the amount of harvested energy strongly varies over time, battery-free devices often operate *intermittently*, i.e., they shut down after depleting the accumulated energy and wait until the capacitor has recharged [1, 19, 20]. While these devices are suitable for designing reactive systems (where events of interest occur if harvested energy is available), they are not feasible in many real-world applications that require *perpetual* operation (e.g., alarm or monitoring systems).

In order to provide continuous, battery-free operation despite fluctuating incoming energy, *supercapacitors* can be employed as energy storage [8, 9, 21]. Supercapacitors offer a magnitude higher capacities than conventional capacitors and can thus store enough energy to power the devices in absence of ambient energy. At the same time, they provide an effectively unlimited life cycle, as, in contrast to batteries, they are not constrained in the number of (re-)charge cycles [13]. These properties make supercapacitors a promising candidate to design maintenance-free, long-lasting battery-free sensor nodes. The deployment of supercapacitor-powered devices, however, introduces several challenges, including the proper dimensioning of the storage capacitance.

Importance of accurate lifetime estimation. In fact, the provided capacitance largely affects the systems' lifetime (i.e., how long the sensor node can operate from the supercap's power without incoming energy), which is a parameter of utmost importance. Overestimating the lifetime can lead to *underprovisioning* of the storage capacity and hence to accidental power-failures, leading to unreliable operations and limited applicability. Underestimating the lifetime and *overprovisioning* the capacity, on the other hand, limits the efficiency of the system, as higher capacitances typically come paired with larger form factors, increased costs, and disadvantages in the (dis-)charging behavior, such as higher leakage currents and longer charging times. An accurate lifetime estimation is hence important to determine the optimal capacitance for a specific application, such that (i) the capacity is minimized to avoid costs and inefficiencies, and to (ii) ensure sustained operation for a given time in which no harvested energy is available. Furthermore, it is a necessary basis for energy-aware scheduling, where devices adapt their duty-cycles according to the incoming energy [4, 24].

Supercapacitor ≠ supercapacitor. In existing works, the supercapacitor is often treated as an ideal component [8, 9, 12], i.e., the lifetime (or energy budget) estimation is based on the rated capacitance, without considering any supercapacitor characteristics such as leakage or charge redistribution effects. This simplistic approach, however, is insufficient in practice. To illustrate this, we experimentally obtain the lifetime of two sensor nodes powered by five different off-the-shelf supercapacitors listed in Tab. 1. More specifically, we charge each supercapacitor for 15 minutes to 3.3 V and derive each sensor node's lifetime by monitoring its operating voltage (i.e., assuming it can operate from 3.3 V to 1.8 V). Fig. 1 shows

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Model	C. rated (mF)	C. meas. (mF)	Diff (%)	Voltage (V)	ESR (Ω)
Kemet FT	220[a]	333	+51,4	5.5	10[e]
Kemet FM	220[b]	179	-18,6	5.5	100[e]
Maxcap	220[b]	195	-11,4	5.5	6-14[d]
Eaton KR	220[c]	263	+19,5	5.5	75[e]
Eaton PM	100[c]	149	+49,0	5	2[d]

Cap. measurement method according to datasheet: [a]Discharge method, [b]Charge method, [c]Not given.
ESR value given in datasheet: [d]Typical, [e]Maximum.

Table 1: Supercapacitors studied in this work. The rated capacitance (C) according to the datasheet can be obtained using either the charge or discharge method and shows significant deviations from the actual measured capacitance.

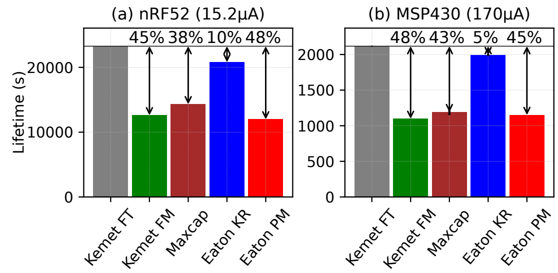

Figure 1: Measured lifetime of an nRF52 (a) and MSP430 (b) sensor node powered by five different supercapacitors. The two sensor nodes have an average current consumption of $15.2\mu A$ and $170\mu A$, respectively.

that there are significant differences in the observed lifetimes of the sensor nodes. Although four of the five supercapacitors have the *same* rated capacitance (220 mF) and voltage (5.5 V), the differences in lifetime amount to up to 48%. Such a difference translates into a lifetime range between 3.5 and 6.5 hours for the nRF52-based sensor node and between 18.3 and 35.3 minutes for the MSP430-based sensor node. Moreover, the `Eaton PM` supercapacitor, with a rated capacitance of only 100 mF, achieves a similar lifetime than `Kemet FM` and `Maxcap`. As we show experimentally in this paper, these deviations stem from differences in the actual capacitances and diverse discharge characteristics, such as charge distribution effects or leakage currents. Interestingly, there are also relative deviations between Fig. 1(a) and (b), which hints a dependency of the discharge characteristics on the load current. In fact, the nRF52-based node (with an average power consumption of appr. 15 µA) runs 10% shorter when powered by an `Eaton KR` rather than a `Kemet FT` supercapacitor, whereas for the MSP430-based node (170 µA) the difference amounts to only 5%.

Existing work. Previous studies have indeed shown that supercapacitors exhibit complex discharging characteristics due to leakage and charge-distribution effects that largely affect the actual energy budget and lifetime of the sensor node [3, 7, 15, 18, 22, 23]. In a large number of these works, the supercapacitor's behavior is reflected by means of equivalent circuit models [7, 18, 22], which often require laborious measurements to extract the required parameters and are complex to compute. Ultimately, the lifetime estimation should also be performed on the sensor nodes at run-time (i.e., to adapt the operation according to the available energy budget) and thus a light-weight modelling is necessary. Other works propose an iterative lifetime estimation based on the leakage behaviour of supercapacitors [14, 23]. While the suggested leakage models are simple to derive and also applicable on resource-constrained devices, they have been developed and evaluated for larger capacitors (e.g., 22 F [23]) and do not consider that the discharge characteristics change depending on the load current.

Our contributions. In this paper, we highlight that empirical data of a given supercapacitor is necessary to perform an accurate lifetime estimation. More specifically, we show experimentally that the differences observed in Fig. 1 stem from differences in capacitance and leakage characteristics. Based on these observations, we propose an enhanced leakage model considering the load current that is computationally lightweight and requires only two measurements, integrate it in the lifetime estimation process, and evaluate it based on experimental data. The remaining paper is organized as follows:

- We discuss how existing work tackles lifetime estimation and highlight its shortcomings experimentally (§ 2).
- We introduce an enhanced leakage model (§ 3).
- We evaluate the leakage model as well as its suitability in estimating the system's lifetime experimentally (§ 4).
- We discuss limitations and future work (§ 5).

2 THE NEED OF REVISITING THE LIFETIME ESTIMATION PROCESS

An accurate lifetime estimation is crucial to ensure that sensor nodes can survive periods where no ambient energy is available. As discussed in existing work and emphasized in Fig. 1, it is necessary to consider the supercapacitor's characteristics in this process. We explain next how to estimate a sensor node's lifetime in an iterative process based on [23] and discuss the shortcomings of this approach.

Iterative lifetime estimation. Zhu et al. [23] propose to estimate the lifetime iteratively based on (i) the *available energy* stored in the capacitor, (ii) the *consumed energy* of the sensor node, and (iii) the energy lost due to *leakage*, while assuming zero incoming energy.

Starting at $t_0 = 0$ with the currently stored energy $E_{cap}(0)$, the remaining energy can be computed in each iteration using Eq. 1.

$$E_{cap}((n+1)T) = E_{cap}(nT) - (P_L(nT) + P_C(nT))T \tag{1}$$

where T is a given time-window and P_L and P_C correspond to the leaked and consumed power, which are assumed to be constant within T. The iteration process stops once E_{cap} reaches its minimum value, such that the next iteration would lead to a power failure of the sensor node (i.e., if $E_{cap}((n+1)T < E_{min})$ and nT yields the expected lifetime. E_{min} can be calculated using $\frac{1}{2}CV_{min}^2$, where V_{min} is the minimum operating voltage of the sensor node.

Revisiting $E_{cap}(0)$. The available energy stored in the supercapacitor depends on its capacitance C and voltage V_{Cap}, and is given by $\frac{1}{2}CV_{Cap}^2$. Zhu et al. [23] as well as other related works [8, 9, 12] commonly rely on the *rated* capacitance when computing the initial

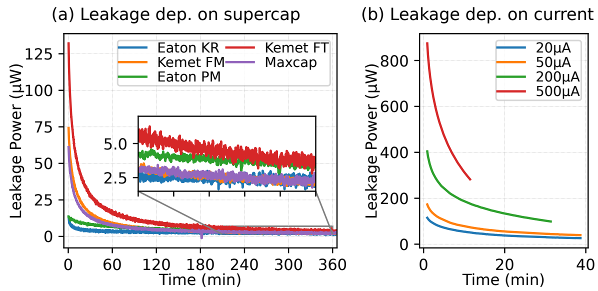

Figure 2: Leakage profile over time for different supercapacitors at $I_C = 0$ (a) and for a single capacitor (Kemet FT) at different load currents (b). The leakage power is not only highly dependent on the supercapacitor model, but increases with larger discharge currents.

energy budget. However, the capacitance of commercial supercapacitors typically has large tolerances from -20% to +80% and the given capacitance value strongly depends on the measurement procedure [10, 11, 17]. We obtain the capacitances of the five supercapacitors from Tab. 1 using the discharge method. As shown in Tab. 1, the actual capacitances indeed differ greatly (e.g., Eaton PM and Kemet FT exceed their rated capacitance by 50%) and we thus argue that empirically determining the capacitance is a necessary step to accurately estimate the lifetime.

Revisiting $P_L(t)$. Apart from the diverse capacitances, the self-discharge characteristics (i.e., leakage currents) of the supercapacitor play a vital role in the sensor nodes' achievable lifetime. Supercapacitors can exhibit leakage currents that range from tens of nAs to several µAs and might exceed the average power consumption of the sensor node itself [15]. Such leakage currents strongly depend on the capacitor model, operating voltage, capacitance, and typically decay over time, before settling at an equilibrium value [13]. Unfortunately, datasheets provide only limited information: details about the leakage characteristics are either omitted [6, 11], specified rather vague (e.g., "if charged to 5V, the terminal voltage remains >4.2V after 24h" [10]), or the leakage current is determined after long charging and discharging periods (i.e., >24h [5]), which is not realistic for energy-harvesting devices.

The leakage behavior must thus be modelled from empirical data, based on the measured capacitor voltage and consumed energy [22, 23]. By observing the terminal voltage V_{Cap} for a given time-window T, the difference in capacitor energy can be computed as:

$$\Delta E_{cap} = E_{cap}(0) - E_{cap}(T) = \frac{C}{2}(V_{cap}(0)^2 - V_{cap}(T)^2, \quad (2)$$

while the consumed energy amounts to

$$E_C = \int_0^T P_C(t)\,dt \approx P_C T = \frac{V_{cap}(0) + V_{cap}(T)}{2} I_C T, \quad (3)$$

given a constant discharge current I_C. The leaked energy is the energy that was dissipated from the capacitor ($E_L = \Delta E_{cap} - E_C$) and thus the leakage power can be computed using:

$$P_L = \frac{\Delta E_{cap} - E_C}{T}. \quad (4)$$

Leakage depending on supercapacitor model. We obtain the leakage profile over time for the five supercapacitors studied previously according to Eq. 4. To this end, we charge them for 15 minutes to 3.3V and discharge them at a given discharge current I_C to 1.8V using a constant current sink. At the same time, we monitor and record the supercapacitors' terminal voltage to obtain the leakage profile over time accordingly. Fig. 2(a) shows that there are differences among the supercapacitor models both in the time behavior (i.e., in how fast the leakage power decays after charging), and in the steady value obtained once the leakage current reaches an equilibrium state. In the following, we will refer to these different leakage shares as *transient* and *constant* part, respectively. [1] For example, the losses due to charge redistribution processes are clearly pronounced for the Maxcap and Kemet FM model, which exhibit increased leakage within the first 60 and 120 minutes, respectively, that settles to approx. 2.2 and 3.5 μW after 6 hours. The Eaton KR and Eaton PM models, on the other hand, show a rather constant leakage behavior which decreases minimally over time and amounts to approx. 2.3 and 3.4 μW (see zoom in Fig. 2(a)). As we will show in Sec. 3, these leakage curves can be expressed by fitting the experimental data to an exponential or linear function, similar to the piecewise linear approximation by Zhu et al. [23].

Leakage depending on load current. While it is widely known that the leakage is highly dependent on the capacitor model and typically increases with larger capacitances [13, 15], we observe also a dependency on the discharge current that has not been considered in previous work [23]. To illustrate this behavior, we obtain the leakage power of the studied supercapacitors using different discharge currents. Fig. 2(b) shows the leakage profile for the Kemet FT supercap and highlights that the capacitors' losses increase with higher loads. Note that, for each measurement, the capacitors have been charged equally to 3.3V for 15 minutes, and that a similar trend applies to each supercapacitor model (but are omitted because of space constraints).

3 AN ENHANCED LEAKAGE MODEL

Based on the empirical data obtained in Sec. 2, we model the leakage power using the exponential function

$$P_{L,exp}(t) = ae^{-bt} + c \quad (5)$$

where a, b, and c are the model parameters that can be obtained by means of curve fitting. To this end, we make use of the Python *SciPy* library and give an example in Fig. 3(a), showing the measured leakage profile of the Kemet FT supercapacitor at $I_C = 300\mu A$ (grey) along with its fitted exponential curve (red). While this approach reduces the storage requirement for one curve to only three parameters, we observe that for some supercapacitor models (e.g., Eaton KR and Eaton PM), the transient part of the leakage power is minimal and their profile can thus simply be expressed using the single constant

$$P_{L,lin}(t) = c \quad (6)$$

as shown in Fig. 3(b).

[1] The transient leakage is due to ions in the carbon electrodes diffusing into the pores [13] and sometimes referred to as 'charge redistribution' [15], while the constant leakage is based on ohmic leakage pathways [22].

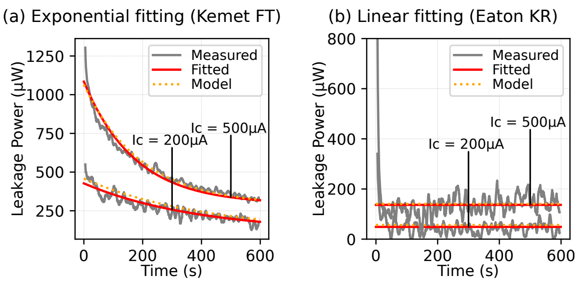

Figure 3: Leakage profiles for the `Kemet FT` (a) and `Eaton KR` (b) supercapacitors at I_C = 200 μ and I_C = 500μA. The measured leakage can be modelled using exponential (a) or linear (b) curve fitting.

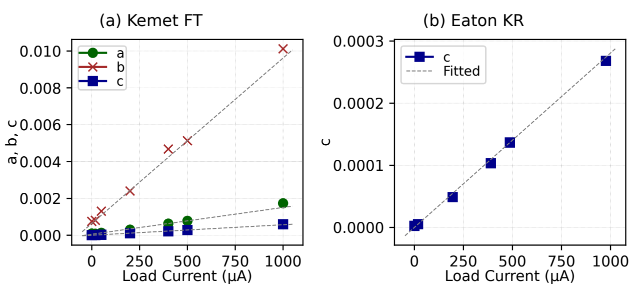

Figure 4: Linear interpolation of curve-fitted parameters (a, b, and c) to derive a single leakage model depending on the discharge current. The linearity of the parameters allows to derive the model using only two distinct measurement points.

Generalization for different discharge currents. In order to consider the discharge current dependency of the leakage power (see Fig. 2(b)), it would be necessary to obtain and store the corresponding leakage curve for *every* load current. This would not only increase the measurement efforts and storage requirements, but renders the model inflexible, as the sensor node's expected load currents must be known beforehand. However, our empirical study reveals that the parameters a, b, and c can be interpolated linearly, as shown exemplarily for the `Kemet FT` and `Eaton KR` supercapacitors in Fig. 4. Equations 5 and 6 can thus be rewritten to the final leakage power model by

$$P_{L,exp}(t, I_C) = a(I_C)e^{-b(I_C)t} + c(I_C) \tag{7}$$

$$P_{L,lin}(t, I_C) = c(I_C) \tag{8}$$

where $a(I_C)$, $b(I_C)$, and $c(I_C)$ are derived using the linear form

$$x(I_C) = x_0 \cdot I_C + x_1. \tag{9}$$

The exponential and linear model are hence reduced to three (or one) parameter pairs $\{(a_0, a_1), (b_0, b_1), (c_0, c_1)\}$ and are applicable regardless of the discharge current. Furthermore, to obtain the model, minimal measurement effort is required, as the linear interpolation of the parameter pairs requires only two measurements. The generalized model matches the initial curve-fitted leakage profiles accurately, as shown by the red and yellow lines in Fig. 3 and will be evaluated more thoroughly in Sec. 4.

4 EVALUATION

In this section, we evaluate the accuracy of the enhanced leakage model (Sec. 4.1) and the lifetime estimation process (Sec. 4.2).

To this end, we obtain the leakage profiles as described in Sec. 2 at $I_C = \{20, 100, 200, 400, 500, 1000\}\mu A$ for the five studied supercapacitors listed in Tab. 1. We then use the measurements at $I_{C0} = 20\mu A$ and $I_{C1} = 500\mu A$ to derive the linear and exponential leakage model according to Eq. 7, Eq. 8, and Eq. 9, while the remaining measurements are used for evaluation.

4.1 Enhanced Leakage Model

We first evaluate how well the generalization of the leakage curves for different discharge currents (i.e., the linear interpolation of the parameters a, b, and c) matches the actual obtained leakage power.

Towards this goal, we compare the initial curve fitted leakage function $P_{L,exp}(t)$ obtained at a given I_C with the generalized function $P_{L,exp}(t, I_C)$ and compute the *absolute* and *relative* error using Eq. 10 and Eq. 11, respectively:

$$E_{exp,abs}(t) = P_{L,exp}(t) - P_{L,exp}(t, I_C) \tag{10}$$

$$E_{exp,rel}(t) = \frac{E_{exp,abs}(t)}{P_{L,exp}(t)}. \tag{11}$$

In addition, analogue to Eq. 10 and Eq. 11, we compute the error functions $E_{base}(t)$ for the existing leakage model. Recall that in this model, only a single leakage curve is obtained at a given discharge current. In our evaluation, we use the leakage profile obtained at $I_C = 200\mu A$, and hence define $E_{base,abs}(t) = P_{L,exp}(t) - P_{L,exp}(t)|_{I_C=200\mu A}$. Fig. 5 shows the average relative (a) and absolute (b) leakage model error for the `Kemet FT` supercapacitor at different discharge currents. The existing leakage model is only accurate at the discharge current it has been obtained from (i.e., at $200\mu A$). At smaller currents, the leakage is highly overestimated (e.g., the average relative error amounts to more than 800% at $I_C = 20\mu A$). Larger currents, on the other hand, lead to an underestimation (e.g., the average absolute error is as low as $-754\mu W$ at $I_C = 1000\mu A$). Instead, the leakage model error of the exponential model remains rather constant across all evaluated discharge currents, as the average relative error never exceeds 9.8%. Furthermore, we obtain comparable results across all five supercapacitors, with maximum average errors between 9.8% and 17.5%.

4.2 Lifetime Estimation

We evaluate next the accuracy of the lifetime estimation process using the enhanced leakage model, compare it to the existing approaches, and verify its applicability for actual sensor nodes.

Comparison to existing work. We first compare the accuracy of different lifetime estimation approaches by emulating a sensor node that exhibits a constant load current. Specifically, we calculate the lifetime estimation iteratively as shown in Sec. 2 using the experimentally obtained capacitance, the given discharge current, and by applying the *existing*, our enhanced *exponential*, and our enhanced *linear* leakage model. Additionally, we compute the expected lifetime in a *naïve* way neglecting any leakage currents, i.e., considering an ideal capacitor with the (i) rated and (ii) measured capacitance and using $T_{naive} = \frac{C(V_0 - V_{min})}{I_C}$. We finally derive

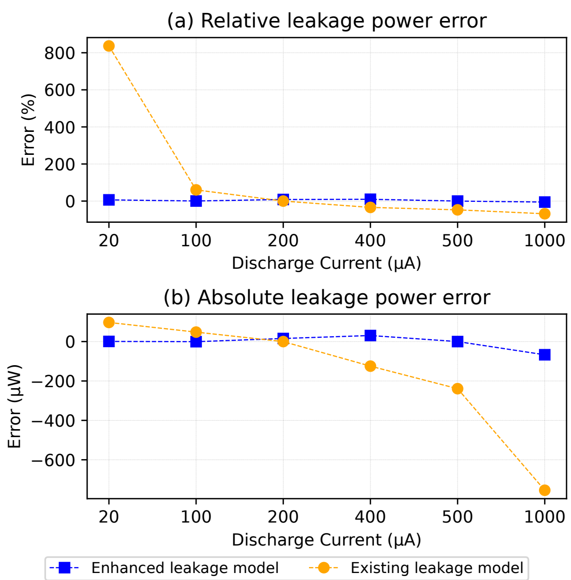

Figure 5: Relative (a) and absolute (b) error of the enhanced exponential and existing leakage model for the `Kemet FT` supercapacitor. The enhanced exponential model matches the observed leakage regardless of the used discharge current.

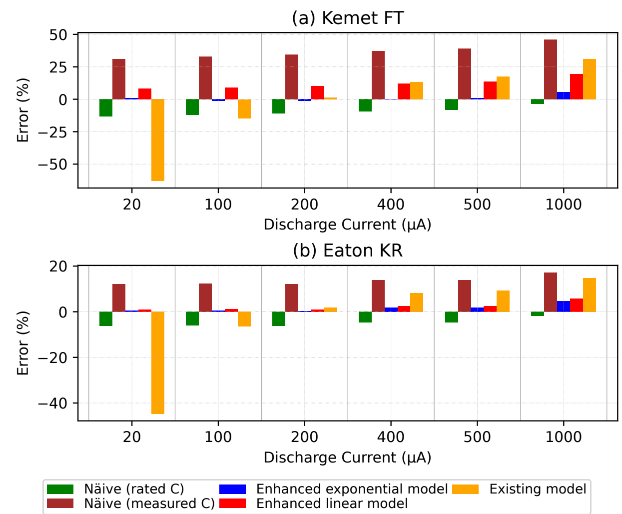

Figure 6: Comparison of different lifetime estimation approaches for the `Kemet FT` (a) and `Eaton KR` (b) supercapacitor depending on different constant discharge currents. The naïve approach over- or underestimates the lifetime consistently, while the error of the lifetime estimation based on the enhanced exponential model stays below 6.9% in all experiments.

the accuracy of these estimates by comparing them against the experimentally measured lifetimes of the five studied supercapacitors (assuming $V_0 = 3.3V$ and $V_{min} = 1.8V$). As shown in Fig. 6, the *naïve* approach based on the measured capacitance falls short when estimating the lifetime, as neglecting the supercapacitors' leakage power results in an (over)estimation error from 31 to 46% and 12 to 17% for the `Kemet FT` and `Eaton KR` supercapacitor. The *naïve* approach based on the rated capacitance leads to an underestimation of the lifetime of up to -13% and -6%, respectively, as the actual capacitance is considerably higher (see Tab. 1). In contrast, including the supercapacitors' leakage profile can indeed improve the estimation accuracy significantly. At a discharge current of $I_C = 200\mu A$, the estimation error for the *existing* and the enhanced *exponential* model stays below 2% for both capacitors. However, as anticipated from the results in Fig. 5, the *existing* model fails at other discharge currents, while the *exponential* model remains accurate with errors ranging from 0.8 to 5.5% and 0.43 to 4.8% for the `Kemet FT` and `Eaton KR` supercapacitor, respectively. Furthermore, the enhanced *linear* model proves to be an adequate fit for the `Eaton KR` supercapacitor (see Fig. 6(b)), as the transient part of the leakage remains minimal and modelling the constant leakage is sufficient. For the `Kemet FT`, on the contrary, the transient leakage is more pronounced and hence the linear model leads to an overestimation of the lifetime.

Lifetime of sensor nodes. We finally compare the different lifetime estimation approaches against the measured lifetime of the two off-the-shelf sensor nodes used in Fig. 1, when powered by the different supercapacitors. To determine the lifetime, we first observe the load current of both sensor nodes using a power profiler [16]. Although the sensor nodes exhibit periodic current spikes (e.g., during BLE transmissions) of up to $8.5mA$ (nRF52) and $2.5mA$ (MSP430), we perform the lifetime estimation based on the *average* current consumption. As the current consumption depends on the operating voltage, we obtain the currents at $V_{node} = \{3.3, 3, 2.5, 2\}V$ and use their mean value amounting to $I_{C,nRF52} = 15.2\mu A$ and $I_{C,MSP430} = 170\mu A$, respectively. Fig. 7 shows that the introduced lifetime estimation process based on the enhanced leakage model gives accurate results despite these simplifications. Across all five supercapacitors, the absolute estimation error remains below 3.3% for the nRF52 and below 3.4% for the MSP430 using the exponential model, while the naïve approach would overestimate the lifetime by up to 27.1 and 36.8%, respectively. Note that the estimation based on the linear model is only feasible for certain supercapacitor models and works best for the `Eaton KR` and `Eaton PM` supercapacitors with estimation errors of up to 0.3 and 3.3% for the nRF52-based node and up to 0.3 and 3.5% for the MSP430-based node.

5 DISCUSSION & FUTURE WORK

In this paper, we have shown that considering the real capacitance of the supercapacitor as well as its leakage behavior is crucial to obtain an accurate lifetime estimation of a supercapacitor-powered sensor node and propose a model that requires only three measurements in total (i.e., one to determine the capacitance and two to derive the leakage model). In the following, we discuss the limitations of our approach and give an outlook on future research directions.

Generalization for different voltages and architectures. This work considers sensor nodes that are powered *directly* by the supercapacitor (i.e., converterless). Hence, the leakage characteristics between 3.3 and 1.8V have been investigated, as this operating

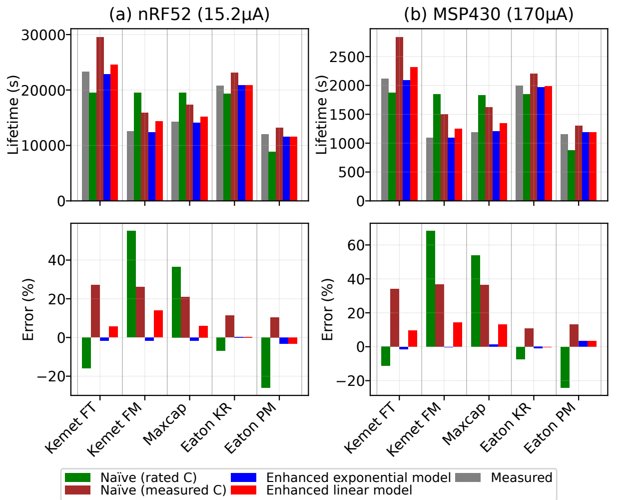

Figure 7: Comparison of lifetime estimation approaches for two sensor nodes based on nRF52 (a) and MSP430 (b) powered by five different supercapacitors. The enhanced linear model leads to an overestimation of the lifetime for supercapacitors with large transient leakage, but is an adequate fit for the `Eaton KR` and `Eaton PM` supercapacitor.

range is common for popular microcontrollers. Since supercapacitors also offer higher rated voltages (e.g., 5.5V), one can charge them further to make use of the entire capacity and employ a linear converter to provide the required supply voltage. To support such an architecture, it is necessary to include the converter efficiency in the lifetime estimation process and to consider the voltage dependency of the leakage currents in the model. Note that we have confirmed the linearity of the model parameters (a, b, and c) also for different charging voltages and thus aim to derive an overall model that is applicable to any voltage in future work.

Generalization for (large) load currents. As discussed in Sec. 4.2, our lifetime estimation approach is based on the *average* current consumption of the sensor node. While this has proven to be feasible for current peaks of several mA (e.g., up to $8.5mA$ for the nRF52), it is not sufficiently accurate if large load currents are required. We show this in Fig. 8, which shows the measured and estimated lifetime of an MSP430-based LoRa node exhibiting current peaks of more than $40mA$ during transmission. The error of the lifetime estimation stays below 7.6% for the `Eaton PM` supercapacitor only, but is severely degraded for all the others. This is due to neglecting the equivalent series resistance (ESR), which introduces considerable drops in the supercapacitor's terminal voltage. The ESR values reported in the supercapacitors' datasheets (see Tab. 1) roughly correlate with the observed lifetime estimation errors and their influence will be investigated in more detail in future work.

Furthermore, using a constant load current for the lifetime estimation can be a pitfall for certain sensor nodes. As pointed out by Ahn et al. [2], MCUs based on digitally-controlled oscillators show a large variation in the power consumption depending on their supply voltage. As supercapacitor-powered sensor nodes have to deal with large variations in operating voltage (e.g., due to the depletion of the stored energy), it might be necessary to model this dependency to achieve an accurate lifetime estimation and is an interesting direction for future work.

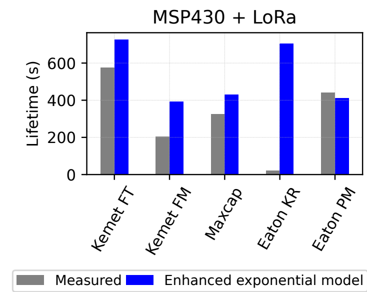

Figure 8: Comparison of the measured and estimated lifetime for an MSP430-based LoRa node. Due the ESR and its effect at large load currents, the accuracy of the lifetime estimation is severely degraded.

Considering different charging currents. This work focuses on the impact of the *discharge* characteristics of supercapacitors on the sensor node's lifetime estimation. However, previous work has shown that the amount of *charging* current (and charging time, respectively) also affects the available energy in the supercapacitor [3]. For large charging currents (or short charging times), the amount of energy at a given terminal voltage is reduced due to charge redistribution (i.e., $E \neq \frac{CU^2}{2}$). As the currents provided by small energy harvesters (e.g., solar panels) are typically low and charging times are often rather long, we consider this effect to be negligible in our experiments, but will investigate its impact in future work w.r.t. common energy harvesting scenarios.

Modelling after deployment and during run-time. In the future, we aim to implement our work in a way that allows on-device modelling of the supercapacitor-powered node. This way, an accurate lifetime estimation is possible after deployment and during run-time, so to enable reliable energy-aware scheduling. We deem this a necessary step for accurate estimations, as in our experiments we could observe differences in the capacitance and leakage behavior even for the same type of supercapacitor. We will investigate the variability across the same model of supercapacitor (e.g., due to manufacturing differences) in future work. To realize on-device modelling after deployement, simplifications of the leakage model and estimation process as well as measurement procedures that can be realized on constrained embedded devices will be explored.

6 CONCLUSION

The deployment of supercapacitors enables perpetual operation of battery-free sensor nodes despite varying energy income. However, as shown experimentally in this paper, supercapacitors have large tolerances and exhibit considerable leakage currents. Modelling of these characteristics is crucial to perform an accurate lifetime estimation, so to ensure that the sensor nodes can operate in periods where no energy is available. We thus propose a lifetime estimation approach including a leakage model that can be derived with little measurement efforts and evaluate its accuracy experimentally using five different supercapacitor models.

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