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Can energy optimization lead to economic and environmental waste in LPWAN architectures?

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As low-power wide-area network (LPWAN) end devices (EDs) are deployed in massive scale, their economic and environmental costs of operation are becoming too significant to ignore and too difficult to estimate. While LPWAN architectures and protocols are designed to primarily save energy, this study shows that energy saving does not necessarily lead to lower cost or environmental footprint of the network. Accordingly, a theoretical framework is proposed to estimate the operational expenditure (OpEx) and environmental footprint of LPWAN EDs. An extended constrained optimization model is provided for the ED link assignment to gateways (GWs) based on heterogeneous ED configurations and hardware specifications. Based on the models, a simulation framework is developed which demonstrates that OpEx, energy consumption, and environmental footprint can be in conflict with each other as constrained optimization objectives. We demonstrate different ways to achieve compromises in each dimension for overall improved network performance.

KEYWORDS
energy saving, green networking, Internet of things, LPWAN, OpEx, wireless communications

1 | INTRODUCTION

Low-power wide-area network (LPWAN) architectures have been studied extensively to evaluate their general performance limits, such as scalability, range, and penetration in urban environments, and use-case-specific performance limits. Dense deployments of such networks incorporating several thousands of end devices (EDs) have begun to emerge, and billions of these devices are expected to be connected with increased penetration of the Internet of things (IoT) [2–4]. Most LPWAN deployments follow the star or connected-stars topology. This is a departure from the mesh multi-hop topology, which is classically assumed in wireless sensor networks or cellular topology. Radios of LPWAN architectures rely on extremely low bitrate with long-range connectivity reaching several kilometers in urban areas or tens of kilometers in rural areas depending on line-of-sight conditions. Moreover, these devices consume very low power, allowing them to provide connectivity in hard-to-reach areas while being powered by batteries for several years. As this is a nascent technology, state-of-the-art studies have reported several empirical accounts of its performance in different experimental settings. However, the increasing scale of LPWAN, as outlined in [4], creates a demand for metrology to estimate the operational costs of LPWAN architectures. Furthermore, the dependability on various kinds of batteries as primary energy sources necessitates the estimation of the environmental footprint of such massive deployments. In addition, planning the assignment of user equipment to gateways (GWs) is a complex problem, given the heterogeneity of the operational costs of different user equipment EDs. For instance, EDs in a massive LPWAN deployment in a connected-star topology usually have different application configurations, radio configurations, sensor configurations, battery capacities, battery costs, battery recharge cycles (durability), and optionally, operator subscription costs. In such a case, the following questions are of interest:

- How can the real cost of the network be estimated?
- What is the expected environmental footprint of the network, given the chemical properties of ED batteries?
- What is the energy, financial, and environmental impact of changing any of the ED configurations?
- How can nodes be assigned to GWs such that the total network cost is minimized while respecting the minimum quality-of-service (QoS) constraints of the network?
- Does an optimal energy cost always lead to an optimal budget or environmental footprint?

The remainder of this section presents a background of the work related to these questions. The rest of this paper is organized as follows. Section 2 outlines the formal theoretical models for the optimization of network budget and environmental footprint. Section 3 outlines the scenarios and parameters of our experimental setup and the simulation framework implementing the theoretical models in MATLAB (following an ns-3 paradigm). Section 4 presents the results and comparative analysis. The results are discussed in section 5. Finally, the conclusion is presented in section 6.

1.1 | Related Work in LPWAN Performance Analysis and Simulation

Several studies have examined the performance of different LPWANs in real settings. The authors of [5–8] reported LoRa link RSSIs, whereas the authors of [9] reported packet success rates for different link configurations in outdoor settings. The authors of [10–12] performed various measurements of the indoor performance of LoRa EDs. The study in [13] evaluated the LoRa performance for health monitoring with human indoor mobility. The study in [14] evaluated LPWAN schemes for Industry 4.0; the authors investigated the SigFox transmitter in an indoor setting with an attached open-door sensor as a representation of an industrial trigger scenario.

On the optimization front, several clustering approaches have been proposed for optimizing energy saving in the network such as in [15–19]. An optimization model for minimizing network energy consumption was proposed in [20] considering sensor monetary cost, but without providing a comprehensive definition of operational expenditure (OpEx) monetary cost while explicitly ignoring the energy consumption of non-radio components such as sensing of EDs.

On the simulation front, the scalability of LoRaWAN was simulated in [21] using discrete-event simulations in ns-3. The study in [22] proposed an ns-3 simulation extension for LoRaWAN, which provides QoS estimations based on LoRaWAN characteristics.

There is a gap in the literature regarding generic metrics for reporting and optimizing the cost of the network, as existing studies only focus on the energy consumption of EDs; therefore, it is not possible to evaluate the final costs of entire architectures, irrespective of their heterogeneous configurations. Accordingly, the following subsection provides a background on LPWAN costs and economy.

1.2 | Background on LPWAN Economy

The network cost consists of OpEx and capital expenditure (CapEx). A comparative study [23] presented both aspects of LPWAN costs. OpEx generally varies according to the deployment configuration, especially in massive-scale deployments spanning thousands of nodes. Therefore, it is a complex characteristic of network architecture. However, hardware CapEx is generally a one-time cost that varies by manufacturer and market dynamics; therefore, it is out of the scope of this study. OpEx estimation is the focus of this study, assuming a fixed CapEx throughout our analysis.

Batteries are essential cost elements of LPWAN OpEx and the environmental footprint, as LPWAN EDs are powered by batteries. Lithium-ion (Li-ion) rechargeable batteries are often used as energy sources.

Operator subscription fee is another cost element in deployments that rely on operator sinks such as NB-IoT or commercial LoRaWAN operators. Existing solutions that may relay packets from GW to any standard APIs through WiFi, Ethernet, or GSM back haul are available. However, they are only usable if the network owners have their own network servers. Otherwise, the alternative is to utilize third-party applications, which incur an additional license cost.

Furthermore, LPWAN systems are often rolled out as end-to-end solutions where sensor data can be obtained using either subscription to an operator's cloud services (such as SigFox, Senet in the U.S. for LoRaWAN, and LoRIoT) or through a private aggregation GW and server such as Meshlium GW for Libelium. In both cases, the cost of the network includes subscription to the application access, which is the only way to decode and analyze the received data.

1.3 | Novelty compared with State-of-the-art Green IoT Deployment

Concerning the optimization aspect of IoT deployments, the study in [20] represented state-of-the-art green IoT hierarchical deployments using an optimization model that considers budget constraints. The optimization method is formulated as a constrained linear optimization model subject to data rate constraints and budget constraints. The budget model considers only the monetary cost of the IoT devices (ie, CapEx). The network hierarchy is computed as a *Steiner* tree (with link energy consumption as the weights of the edges). The *Steiner* tree formulation determines the least energy-expensive link assignment in the deployment. Furthermore, the approach presumes that any energy consumption apart from radio energy (including sensing) is negligible.

The approach in this study is distinct in three aspects: from realistic, budgetary, and optimization points of view. First, from a realistic point of view, [20] considered abstract IoT layouts and presumed that nodes of each category (ie, EDs or GWs) have the same wireless properties. Non-radio activities (such as sensing) were also excluded from the analysis, thus simplifying the problem. However, in reality, device properties could be heterogeneous in aspects such as application configuration, network headers, battery capacity and durability, subscriber costs, and attached sensor energy consumption. Therefore, such a heterogeneous configuration was not handled by the previous study. In contrast, this study considers a real LPWAN setting with long-range radios and relies on real measurements of energy consumption and a wireless simulation in a realistic geographical setting. Moreover, the object-oriented simulation framework proposed and implemented in this study based on our models offers an optimization model for link assignment by considering heterogeneous *ED configurations*. In addition, both the model and simulation framework consider the comprehensive energy performance aspects of the ED including non-radio components. This study shows that a simple tuning of non-radio components, such as sensing, while possibly having a negligible impact compared with transmission in a sufficiently large network, can have a budget impact equivalent to an employee's monthly salary, as demonstrated in the results in Section 4.

Second, from a budgetary point of view, the optimization model in [20] assumed the monetary cost of devices as the sole factor in the budget. Furthermore, while the *Steiner* tree approach would determine the least energy-expensive topology, there is an implicit assumption that less network energy indicates a lower network budget. However, as GW capacity is constrained, EDs may not always be able to communicate with the closest GW and may use higher energy for longer range modulation. Therefore, the optimization method needs to consider GW capacity as an optimization constraint. In this context, optimal energy consumption in the network does not necessarily indicate an optimal network budget. This is because the real cost of energy depends on the cost of the battery deployed and the cost of battery replacement (the manual labor included), especially for devices located in remote areas, as is common with LPWANs. Such a change in assumption indicates that it is possible to have higher energy consumption in the network but with a lower budget. In contrast, a comprehensive budget model is proposed, including several operational expenses, such as battery change costs, operator subscriber costs, and battery costs. The results in Section 4 show that the optimization model of link assignment provides better budget-efficient planning that considers all the complex budget parameters. Consequently, the optimization model presented here adapts network topology based on more complex and realistic budget factors.

Third, from an optimization point of view, [20] considered the budget parameter as a linear constraint for a *Steiner* tree formulation, which is an NP-hard approach (as explained by the authors). However, the integer linear programing (ILP) model presented in this article, which is an extension of [24], considered the network OpEx as an optimization objective. Therefore, it is guaranteed to determine the network link assignment with the global optimal OpEx budget. Furthermore, approaches for optimizing the performance based on multiple objective optimization (MOO) were discussed [25,26]. While MOO can find the optimal tradeoff among weighted parameters if it exists, our optimization approach is distinct from MOO, as we demonstrate the findings of several optimization objectives separately to provide a panoramic view of the performance under each objective. This separated approach allows gauging the positive or negative correlations among the optimization parameters, as is later demonstrated in the results.

Fourth, this study introduces another metric for measuring the environmental footprint of massive-scale LPWAN architectures. Normally, the quantity of CO_2 emissions is the commonly used metric for measuring the environmental footprint. However, as LPWANs are mostly battery-powered, the hazardous solid waste of disposed batteries is a more direct metric of the footprint of LPWANs, according to the study in [27]. Instead of CO_2 emissions, we refer to the human toxicity parameter (HTP) as an indicator of the environmental footprint, as deduced in this study. Thus, the HTP of the network depends on the battery specifications of each ED, the application configuration of each ED, and the network configuration. Therefore, this parameter can be used for the evaluation and optimization of the network. This can have significant utility in the case of massive LPWAN deployments, which contain batteries with chemical waste of the order of magnitude of tons, as demonstrated in our results section.

1.4 | Contributions

To address the questions and the knowledge gap in the literature, this paper presents the following contributions:

- Mathematical formulations of the OpEx cost model and environmental footprint model for LPWAN architectures are presented. They estimate the total network costs and the environmental footprint considering heterogeneous configurations. The performances of these models are demonstrated by investigating multiple simulation scenarios in a realistic setup.

- An extension of the ILP model in [24] is presented. It is proven to find optimal ED to GW link assignment in terms of minimal link budget in the network; however, we apply it to various cost parameters of the network: OpEx, energy, HTP, and total time-on-air in the network.
- Finally, the analysis shows a conflict among the optimization objectives in our simulated scenarios. Strict energy optimization is shown to lead to potentially higher costs and even environmental footprint of the network. The results also demonstrate that, in a large-scale network, significant budget and environmental savings can be achieved through a minor network configuration such as removing a timestamp, adding a few GWs, or reducing the sensor sampling frequency without changing the transmission configuration.

2 | THEORETICAL FRAMEWORK

This section proposes the main theoretical framework, which consists of 1) the energy model, 2) the environmental cost model, and 3) the budget optimization model.

2.1 | Energy model

A commonly used energy model is considered, adapted from [28]. This considers energy consumption in the four components of a sensor node: processing unit that is, E_{proc}, n I/O tasks, m attached sensors, and k transmissions, each of size b_i bits using the energy per transmission bit E_{Ti}. The total energy E_{ED} is expressed in (1).

$$E_{\text{ED}} = E_{\text{proc}} + \sum_{i=1}^{n} E_{\text{IOi}} + \sum_{i=1}^{m} E_{\text{Si}} + \sum_{i=1}^{k} b_i E_{\text{Ti}}. \tag{1}$$

In the following subsections, we expand this model to a budget estimation model and to an environmental footprint estimation model.

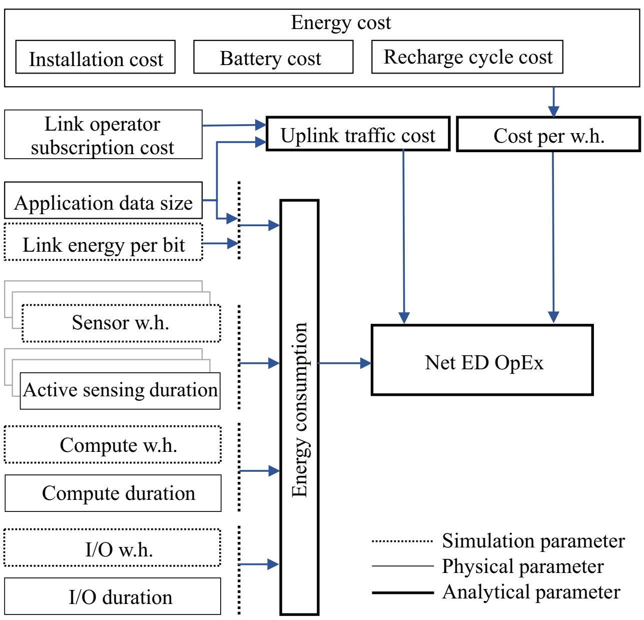

FIGURE 1 Model for estimating ED OpEx

2.2 | Financial cost model

The OpEx model is generally a superposition of the OpEx of the four components of the ED: radio, processing, sensing, and IO, as outlined in Figure 1. While energy consumption is important, the effective ED OpEx depends on battery specifications, price, link subscription cost, and application up-link traffic size. Hence, two main financial cost items are considered in the model: the ED cost per Wh, expressed as C_{Wh}, and the communication cost per bit transmission.

C_{Wh} is expressed in (2) as a function of the battery price B_{cost}, battery recharge cycles (assuming rechargeable battery) B_{rc}, battery installation cost B_{ic}, and battery Wh capacity B_{Wh}.

$$C_{\text{Wh}} = \left(\left(\frac{B_{\text{cost}}}{B_{\text{rc}}} \right) + B_{\text{ic}} \right) / B_{\text{Wh}}. \tag{2}$$

The communication cost is expressed through a function μ that returns the cost invoiced by the provider for the smallest link capacity supporting the throughput requirement represented by $\text{Bits}_{\text{total}}$, the number of bits to be transmitted on the link during the period.

From (1), (2), and the definition of the function μ, an OpEx model for a given ED can be formalized as in (3).

$$\text{OpEx}_{\text{ED}} = E_{\text{ED}} \times C_{\text{Wh}} + \mu \left(\text{Bits}_{\text{total}} \right). \tag{3}$$

The metric OpEx_{ED} expresses the total OpEx of an ED with a given specification as defined in (1). This parameter is used as a network optimization objective to minimize the OpEx budget of the entire network, as shown in Section 2.4.

2.3 | Environmental cost model

This subsection proposes an environmental footprint model based on the hazards originating from the solid waste of Li-ion batteries, which are a main source of energy for EDs. A general outline of how waste is estimated for a given ED configuration is shown in Figure 2.

The expected battery life before disposal is a major determinant of the expected waste. This study aims to estimate this parameter based on E_{day} (energy per day), B_{rc}, and B_{Wh}, as expressed in (4).

$$\text{Battery lifetime} = \frac{B_{\text{rc}} \times B_{\text{Wh}}}{E_{\text{day}}}. \tag{4}$$

The total quantity of expected chemical waste (in grams) resulting from the operation of an ED for a given OpEx duration can be estimated as in (5) as a function of battery weight in grams B_{w} and battery lifetime.

$$\text{Waste}_{\text{ED}} = B_{\text{w}} \times \frac{\text{OpEx}_{\text{Duration}}}{\text{Battery lifetime}}. \tag{5}$$

For a further detailed evaluation, an existing study provides the average estimations of chemical substance waste percentage per Li-ion battery grams [27]. These estimations are expressed in (6).

$$\overrightarrow{BI} = \begin{vmatrix} Ag \\ Tl \\ Pb \\ Ni \\ Li \\ Cu \\ Co \\ Al \end{vmatrix} = \begin{vmatrix} 0.0001 \\ 0.0004 \\ 0.0005 \\ 0.0255 \\ 0.0366 \\ 0.2100 \\ 0.2467 \\ 0.4639 \end{vmatrix}. \tag{6}$$

Based on these percentages, the HTP of an ED can be evaluated as expressed by the authors in [27]. Hence, such a parameter can also be applied to an optimization model to minimize the environmental footprint of the network. This is illustrated in the following subsection.

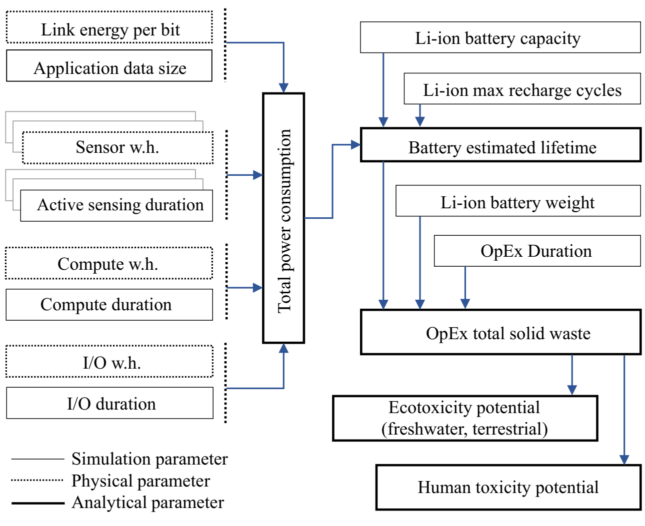

FIGURE 2 Model for estimating ED environmental toxicity

2.4 | Network budget optimization model

After the cost matrix $\boldsymbol{\beta}$ is obtained for all combinations of n EDs and m GWs (eg, OpEx or HTP), the optimal network cost can be obtained according to a certain objective parameter by optimizing the link selection. The typical link assignment procedure considers only the link budget at the ED, as in a recent study [24]. However, we employ the same ILP formulation and use the model to provide the optimal network link selection according to various parameters: minimizing the total network OpEx, P_{Net}; minimizing the total HTP of the network, HTP_{Net}; minimizing the total network energy consumption, E_{Net}, and minimizing the total time-on-air in the network, ToA_{Net}.

Therefore, the model is formulated in (8) and a linear constraint is imposed on the number of EDs per GW $\leq N$ such that no GW will be assigned more than N EDs. Another constraint is imposed such that an ED will be assigned a maximum of one GW.

$$f(E,G,P) = \sum_{i=1}^{E} \sum_{j=1}^{G} \alpha_{ij} \cdot \beta_{ij}, \tag{7}$$

where β_{ij} is the cost parameter of link_{ij} between ED_i and GW_j, expressed as ($\beta_{ij} \in \mathbb{R}$) and is one of the cost parameters: P_{ij}, HTP_{ij}, E_{ij}, or ToA_{ij}. E is the number of EDs, G is the number of GWs, and N_j is the maximum possible capacity of EDs for GW_j. With such a formalization, the global optimal solution for a given LPWAN deployment, if it exists, can be obtained as follows.

$$\begin{aligned} &\min f\ (E,G,P)\,, \\ &\text{subject to} \quad \sum_{i=1}^{E} \alpha_{ij} \leq N_j \ \forall\ \text{GW}_j \\ &\qquad\qquad\quad \sum_{j=1}^{G} \alpha_{ij} = 1\ \forall\ \text{ED}_i, \\ &\text{where } \alpha_{ij} = \begin{cases} 1 & \text{if ED}_i \text{ is assigned to GW}_j \\ 0 & \text{otherwise.} \end{cases} \end{aligned} \tag{8}$$

The following section demonstrates the experimental setup where this optimization model is implemented and deployed. The model performance is tested under different situations and with heterogeneous settings.

3 | EXPERIMENTATION

The setup is shown in Figure 3. We obtain real coordinates of approximately 2000 long-term evolution (LTE) base stations (BSs) of Orange mobile operator in the Paris region, which are available through the Open Data of Île-de-France [29].

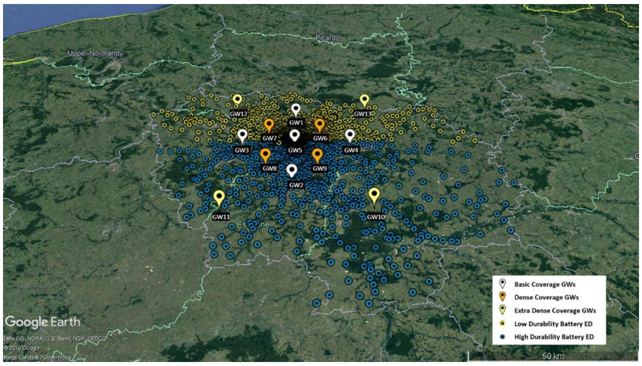

FIGURE 3 Network simulation experiment setup in the Paris region

TABLE 1 Summary of the experiments conducted

Set #	Variable parameter	Values domain
1	ILP optimization objective	{Energy Consumption, HTP, Time-On-Air}
2	Durable battery ratio	{0%, 50%, 100%}
3	Application configuration	{half packet rate, half sensor sampling rate, omit 10 byte timestamp}
4	Number of GWs used in coverage	{5, 9, 13}

The deployment sites are assumed to contain LoRaWAN EDs with CO_2 gas sensors and electric current sensors. A few BSs are selected as GWs (marked by large pins) and the remaining will act as ED locations covering the Paris region (marked by small dots). All the GWs are assumed to have a limited capacity of 400 EDs per GW. Our OpEx model is supported with empirically calibrated link energy profiles for LoRa modulations at the spreading factors (SFs) ranging between 7 and 12, a bandwidth of 125 kHz, and a transmit power of + 14 dBm. The southern half of EDs (in blue dots) is assigned low-durability Li-ion batteries with a weight of 130 gm and a capacity of 27.7 Wh, priced at 6€ with 380 recharge cycles. The northern half (in yellow dots) has high-durability batteries with a weight of 50 gm and a capacity of 12.24 Wh, priced at 22€ with 500 recharge cycles. Both have the same replacement cost.

3.1 | Experiment Design and Setup

The default setup assumes that all the devices transmit electric current sensor readings of some critical equipment every minute (CO_2 measures are provided every hour, a measurement lasting 70*s*). A packet contains a payload of 120 bytes including a timestamp of 10 bytes. The objective of ILP optimization is to minimize the total network OpEx. The area is assumed to be covered by five GWs as a basic setup (marked with white pins).

Four sets of experiments are conducted, as outlined in Table 1. The first set of experiments examines the impact of varying the ILP objective variable as follows: energy consumption, HTP, and time-on-air. The second set examines the impact of using

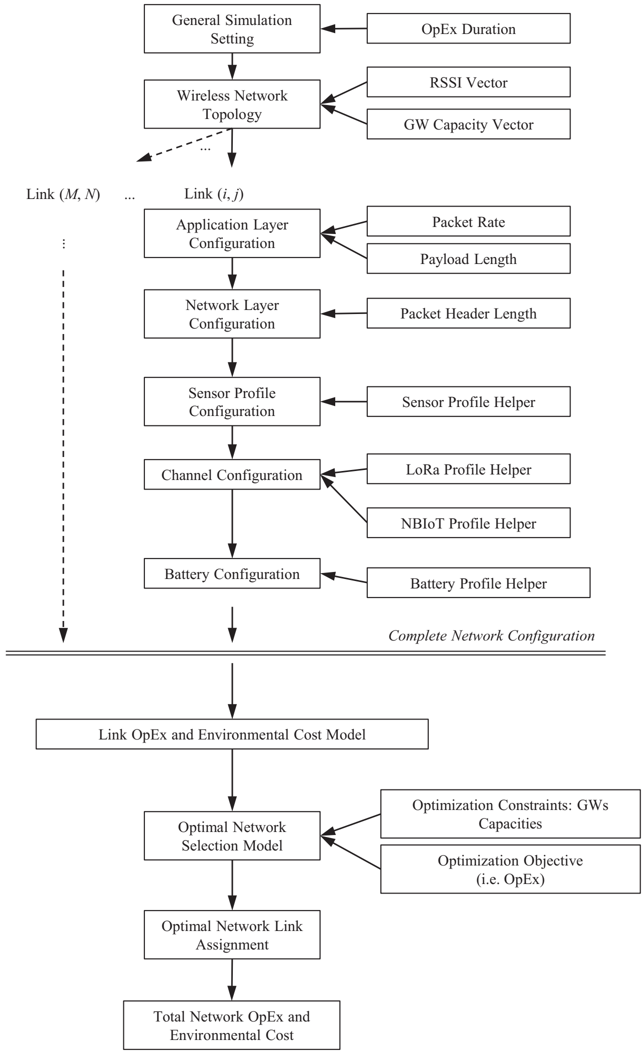

FIGURE 4 Diagram of the flow of the simulation framework to estimate network costs

TABLE 2 Cost of reference architecture for 365 days

OpEx net	388 301.20€
OpEx sensing	30 186.38€
User traffic OpEx	328 271.91€
Management traffic OpEx	60 029.29€
Energy	167.9 kWh
ToA	80.5 years
Chemical waste	1707 gms

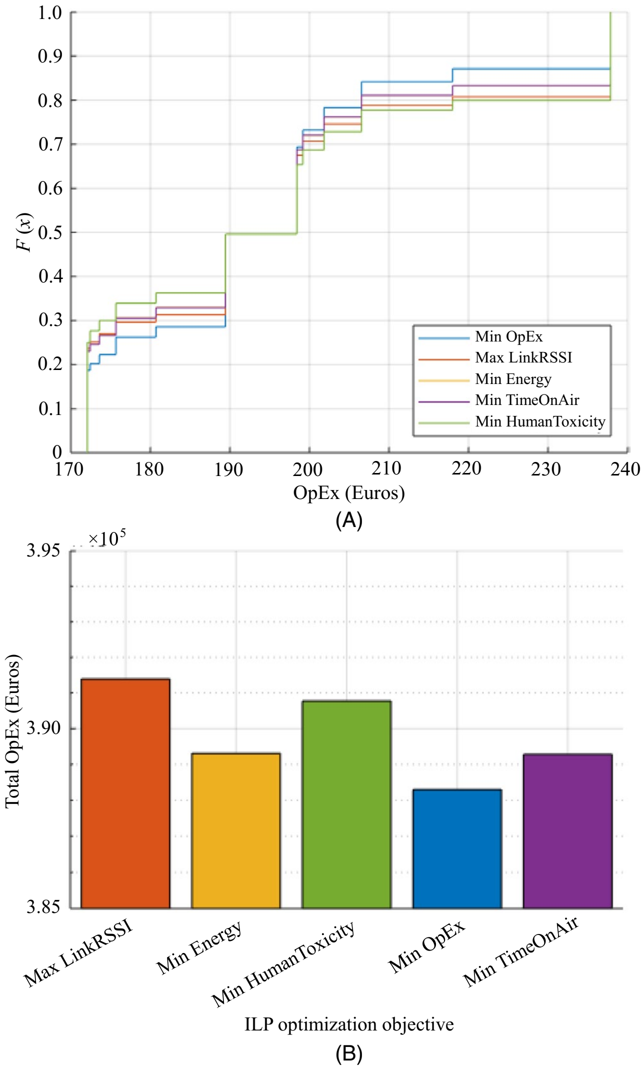

FIGURE 5 OpEx estimations for the network according to different optimization objectives: (A) CDF of ED OpEx of the network with different optimization objectives in the ILP model. (B) Total OpEx of the network with different optimization objectives in the ILP model

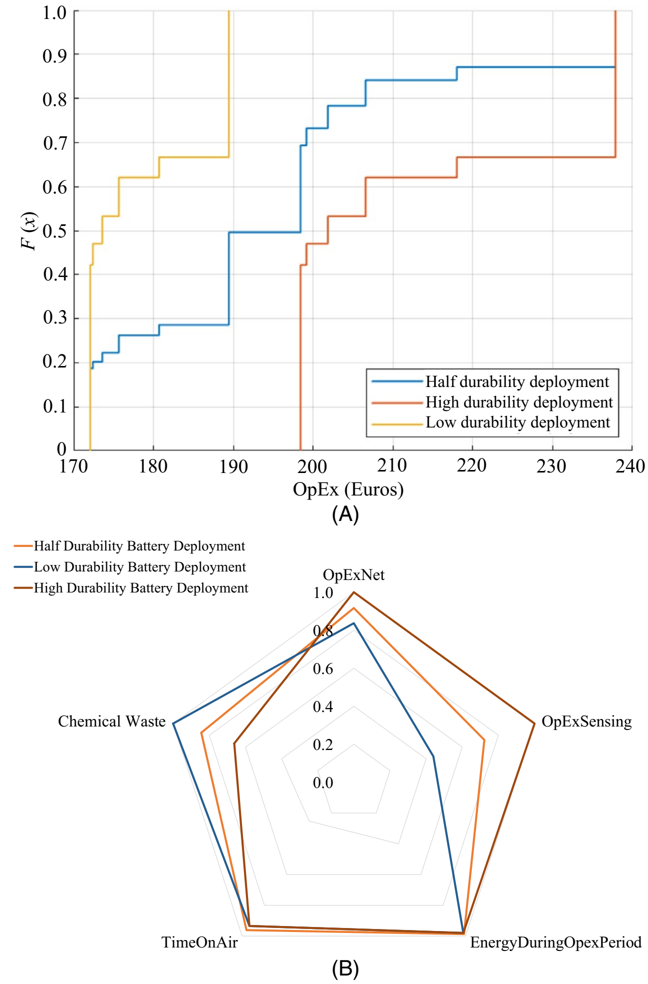

FIGURE 6 Network OpEx for different battery configurations: (A) CDF of ED OpEx of the network for different battery efficiency levels. (B) Impact of battery quality on network budget

fully low-durability batteries or fully high-durability batteries for the entire network compared with the default 50-50 distribution. The third set examines the impact of varying the ED application configuration in three settings: using half the daily packet rate, using half the sensing sampling rate, and omitting the timestamp of 10 bytes from the packet payload (which may not be practical in the case of critical or sensitive applications). Finally, the last set of experiments examines the impact of enhancing radio coverage on the budget components of the network. Three experimental runs are executed with different levels of coverage: basic with 5 GWs (white pins), dense with 9 GWs (white and orange pins), and extra dense with 13 GWs (all the pins).

The propagation loss is simulated using the irregular terrain model [30] and our model assigns the lowest possible SF profile for each ED based on the RSSI of the ED at the GW and based on the RSSI threshold table in [31] for energy saving.

For each set of experiments, the OpEx duration is fixed to 365 days and the normalized estimations are plotted for each architecture in six independent dimensions:

- **OpEx Net (€):** total OpEx of the network,
- **OpEx Sensing (€):** total OpEx consumed in sensing,
- **Energy During OpEx Period (Wh):** total energy consumed by the network,
- **ToA (years)**: sum of the radio time of all the network links, and
- **Chemical Waste (gms):** weight of the total network chemical waste at the end of OpEx duration.

To compare the different scenarios, the cumulative density function (CDF) plots for the OpEx of the network are presented in the following section. Furthermore, the additional savings/

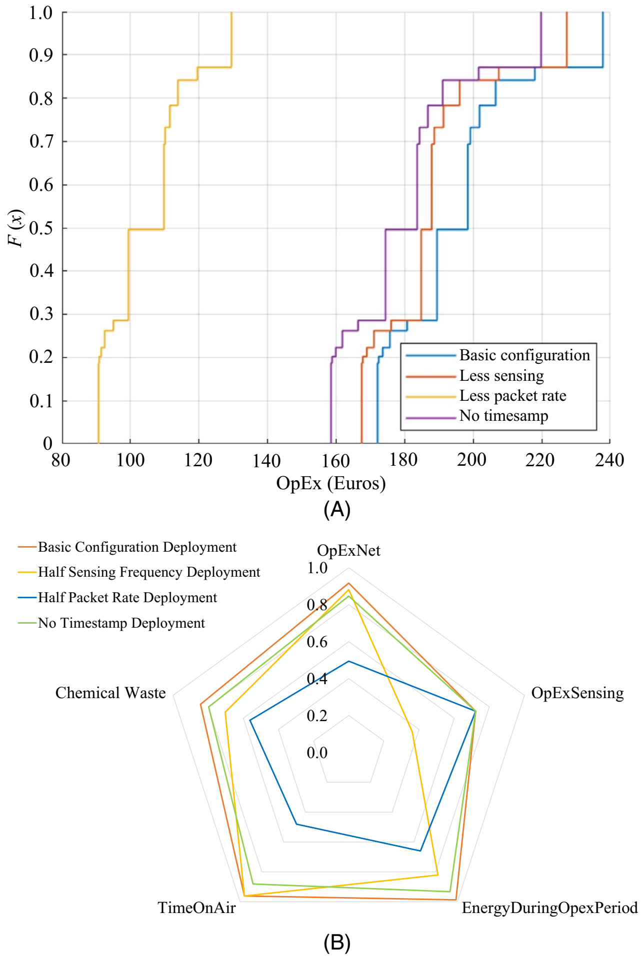

FIGURE 7 Network OpEx for different application configurations: (A) CDF of ED OpEx of the network for different ED configurations. (B) Impact of ED configuration on network budget

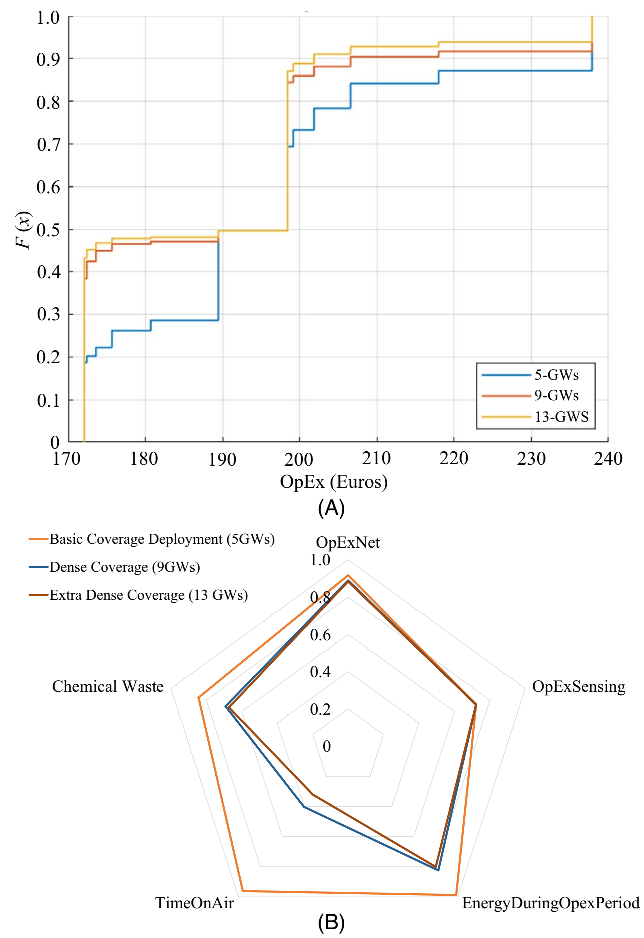

FIGURE 8 Network OpEx for different numbers of GWs: (A) CDF of ED OpEx of the network for different coverage densities. (B) Impact of coverage density on network budget

expenses for each architecture are calculated in relation to the reference architecture in Table 3.

3.2 | Simulation framework

An experimental simulation framework is designed and implemented in MATLAB to simulate the different scenarios in the experiment design. The framework accepts as input basic network topology descriptors: RSSI matrix (between M EDs and N GWs), and the capacity of each GW, expressed as the maximum number of EDs that can be handled by each GW. Therefore, it becomes possible for the simulation framework to be integrated with an existing simulation tool or to be utilized independently.

As shown in Figure 4, the framework considers the profiles for different ED components: application profile, sensor profile, radio channel profile, and battery profile. Helper classes of each profile provide templates that can be applied to multiple EDs in a manner similar to the ns-3 environment and to heterogeneous scenarios.

4 | RESULTS

The cost estimations of the basic setup are presented in Table 2. In the first set of experiments, we vary the optimization variable while computing the resulting OpEx distribution. The results are shown in Figure 5A. The following optimization variables are examined: max-RSSI (as proposed in [24]), min-OpEx, min-energy, min-time on air, and min-human toxicity. An apparent variation in the CDF distribution can be observed, showing how optimizing each variable leads to different network configurations. The total OpEx of the network for the five scenarios is plotted in Figure 5B.

As observed in the plot, minimizing the energy or improving the RSSI can lead to sub-optimal total network OpEx. All the optimization parameters are in conflict with the OpEx

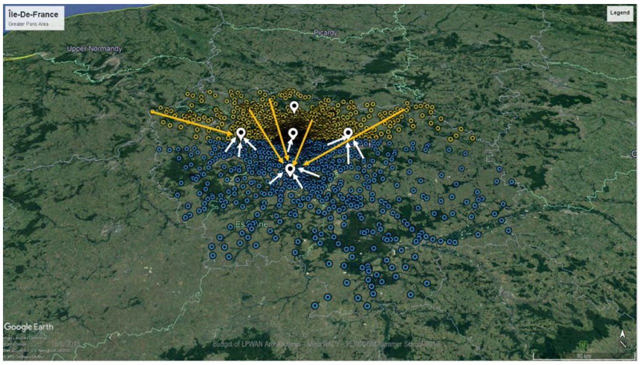

FIGURE 9 Impact of ILP model ED assignment in heterogeneous battery deployment

objective; most notably, an optimal energy consumption in the network leads to sub-optimal OpEx costs.

The second set of experiments demonstrates significant patterns in the impact of battery physical characteristics on the cost of network configurations. The lowest durability batteries lead to a decrease in the network OpEx, as in Figure 6A, saving the OpEx of nearly €34 K. However, this induces higher chemical waste and much shorter battery life-cycle of the network, as in Figure 6B. As expected, high-durability batteries show better performance in terms of reduced chemical waste (as the lifetime of the node—and therefore the network—is increased), at the expense of increased OpEx of the entire network.

In the third set of experiments, the ED configuration is shown to contribute significantly to the network OpEx, as illustrated in the ED OpEx CDF plot in Figure 7A. It also contributes to the overall network performance parameters as shown in Figure 7B. It can be observed that cutting the packet rate by half (to every 120 seconds instead of 60 seconds) induced the highest improvement of the network in terms of all the metrics, leading to the highest savings of €179 K of OpEx, 27 kWh of energy, more than 40 years of ToA, and nearly 600 gm of chemical waste. Similarly, cutting the sensor sampling rate to every 2 hours instead of 1 introduced a significant energy saving of €15 K in the OpEx. This is in contrast to the assumption in [20] that presumes negligible sensing cost. The last experiment reduces the packet size by 10 bytes (eg, by omitting the timestamp). Such a small decrease results in an OpEx saving as high as €30 K per year.

Although the energy consumption in the three networks is the same, the optimal network OpEx varies due to the battery specifications of each network. For an optimal OpEx, the other parameters such as energy consumption, environmental footprint, and air time of each network are compromised.

Reducing the packet inter-arrival rate had the largest impact on OpEx optimization and the various performance parameters. Header compression by timestamp removal showed the next largest impact on OpEx.

In the final experiment, coverage quality is configured by increasing the GW density. This contributed to the network OpEx by allowing the use of less expensive ED radio configurations to account for radio path loss. Deployment of nine GWs instead of five introduced a major enhancement of ED OpEx, as illustrated in the CDF plot in Figure 8A. However, a minor improvement was achieved when the coverage increased to 13 GWs. This suggests that coverage beyond nine GWs in this setting may not be necessary or desirable for a return on investment. Coverage density also contributes to all the financial, environmental, and technical metrics, as illustrated in Figure 8B of normalized metrics. This coverage enhancement saved €12 K of OpEx, 27 kWh of energy, 46 years of ToA, and 300 gm of chemical waste.

OpEx and toxicity are conversely related to GW coverage density. The change from 9 to 13 GWs produces much less improvement than the change from 5 to 9 GWs.

Therefore, the experiments show that the energy optimization of the network can incur a financial cost, as shown in Figure 5 (in the order of €1 K in this setup). It is also shown that RSSI optimization can lead to excess costs (in the order of €3 K in this setup). Finally, the experiments prove that the environmental footprint is in conflict with both energy and cost parameters, meaning this should be independently analyzed while evaluating the network performance.

5 | DISCUSSION

The use of ILP optimization played a significant role in minimizing the network OpEx while inducing occasional unpredictable side effects. For instance, using homogeneous battery deployments (whether high or low durability) resulted in an additional ToA cost of 2.22 years of the network. This is because, in a heterogeneous battery deployment, transmissions from EDs with cheaper (and less durable) batteries require a lower budget than that of highly durable batteries, even at higher SFs. In this case, the ILP assignment model provides the priority of optimal link assignment to EDs with greater OpEx to ensure that they are connected to the closest GWs. The other EDs can still have cheaper connections, even if they consume more energy to reach further GWs, as illustrated in Figure 9.

This results in different radio ToA or network lifetime from homogeneous deployments where all the nodes have the same link OpEx per Joule. In this particular scenario, the savings of ToA were more than the additional ToA in the basic configuration, resulting in a lower network ToA overall.

Deployment\ savings	OpEx (€)	ToA (years)	Chemical waste (grams)	Energy (Wh)
ILP-max-RSSI	(3088.69)	−3.26	−3.02	−2190.34
ILP-min-energy	(1004.67)	2.22	29.02	1239.73
ILP-min-toxicity	(2476.88)	2.11	42.91	1193.23
ILP-min-ToA	(982.6)	2.22	28.80	1239.73
Low-durability battery	33 771.34	2.22	−315.98	1239.73
High durability battery	(35 167.70)	2.22	367.93	1239.73
Half sensing frequency	15 093.19	0.00	284.82	28 278.45
Half packet rate	179 057.41	40.25	568.86	55 672.80
No timestamp	29 842.90	6.71	94.81	9278.80
Dense coverage	11 835.62	46.77	308.92	27 743.51
Extra dense coverage	14 184.34	53.57	347.08	31 743.48

TABLE 3 Savings of each experimental architecture compared with that of basic configuration deployment

Furthermore, all the experiments showed interesting savings from the default basic architecture as listed in Table 3. Significant energy savings were achieved in all the experiments, reaching up to 56 kWh by simply cutting the packet rate by half. Similarly, 31 kWh of savings were achieved by enhancing coverage without changing any of the network or battery configurations.

6 | CONCLUSION AND FUTURE WORK

This study demonstrated how energy saving can be in conflict with the cost saving and environmental footprint of the network. As these optimization parameters are in conflict with each other, the models for OpEx and footprint estimation allow quantifying these complex parameters to enable informed decision-making about network configurations. The study shows that the proposed ILP formulation can at least provide a global optimal solution for the link assignment problem in terms of various objectives to estimate the possible compromises.

The optimization problem can be studied from a multi-objective perspective in the future to determine the best compromise among multiple parameters. Moreover, the OpEx calculations in this study are limited to energy consumption as a fundamental cost. Future work can include the operational costs of manpower, infrastructure, and other overheads. Furthermore, this study does not consider the impact of medium access control (MAC) behavior in terms of acknowledgment or re-transmissions. This model can provide estimations for the OpEx impact using different LoRaWAN classes or generally aloha-based MACs vs allocation-based MACs such as 802.15.4e. This study does not consider the impact of GW OpEx on LPWAN operations, which can be tackled in the future. Further work can also explore the environmental saving of using energy-harvesting modules under different cost parameters and with variable probabilities for energy generation across the year, for example, by using wind and solar sources.

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