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RESEARCH ARTICLE

Carbon Footprint vs Energy Optimization in IoT Network Deployments

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ABSTRACT We are witnessing the full integration of the Internet of Things (IoT) into many social and economic sectors. Part of this unprecedented growth is due to the emergence of new communication technologies such as Low Power Wide Area Networks (LPWAN), which have been the catalyst for previously unfeasible smart applications. Efforts to optimize energy consumption in these types of networks have been necessary to extend their lifetime. However, not much attention has been paid to the study and optimization of the carbon footprints (CF) of these network deployments. In general, it has always been understood that minimizing energy consumption should also minimize the carbon footprint. In this work, the carbon footprint of a generic IoT network that uses renewable energy sources and communicates via LoRa is explored, and an optimization framework is proposed. We have found that minimizing energy consumption and the carbon footprint are two different things. In fact, we show that it is not possible to minimize the carbon footprint without greater energy consumption, and vice versa. This is due to the placement of gateways in the network. Our findings could be extrapolated to other networks with similar topologies. These results suggest that a fresh perspective on the optimization of IoT networks is needed to seriously consider environmental sustainability criteria that has been ignored up to now.

INDEX TERMS Carbon footprint, LPWAN, IoT networks, optimization.

I. INTRODUCTION

A wireless IoT network deployment consists of a large group of autonomous low-cost devices (end devices or nodes) distributed throughout a given arbitrary area. End devices monitor one or several environmental variables and submit their sample values wirelessly to one or more gateways (sink nodes), which, in turn, deliver the information to network servers for further processing according to a specific application (e.g., precision agriculture, home automation, smart cities, e-health, Industry 4.0, etc.). There is a huge number of real examples that have proven the IoT utility [1], [2], [3]. This architecture has been studied extensively to evaluate general performance capabilities, such as economic cost [4], maximum lifetime [2], [5], [6], packet loss [7], energy consumption [3], [4], [6] or the Human Toxicity Parameter [4], among others. In this context, suitably planning IoT networks before deployment is a major factor in determining the viability and operation of the final application. This is extremely complex due to the many possible configurations and scenarios that can be established depending on the target objectives. Moreover, IoT network deployments produce a significant environmental footprint. However, there is scarce literature about the sustainability of IoT and, more explicitly, the carbon emissions associated with IoT networks. This paper analyzes the different elements that generate a carbon footprint in IoT network deployment and proposes an optimization framework to minimize the environmental impact of IoT networks. Through this optimization problem, we empirically demonstrate (somewhat counter-intuitively) that minimizing the carbon footprint is one thing, and minimizing energy consumption is another. In fact, minimizing the

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carbon footprint requires increasing the energy consumption of IoT devices.

The concept of a carbon footprint refers to the total emissions of carbon dioxide (and sometimes other greenhouse gases) emitted directly and indirectly by an activity or product [8], [9]. Recently, this concept has been attracting significant attention from the scientific community, as the emission of carbon dioxide and other greenhouse gases is a standardized measurement of environmental impact. Therefore, it is a simple way to understand the effect of a determined process on the environment.

Given that most IoT networks take samples from the real world and need to collect data from selected places [1], [2], [3], [5], end device (or node) location is unavoidably bound to where sensing is needed. Furthermore, one of the most popular ways of connecting IoT nodes is through LPWANs. In principle, LPWAN deployments follow a star or connected-star topology. Consequently, the network needs gateways, or sink nodes, that gather the information sent by the end devices and forward it through long-range technology to data centers to process the acquired data. The number and placement of these gateways will greatly impact the performance of the network. Many specifications are available for LPWAN networks, including LoRa, Zigbee, and SigFox. The operating process of LoRa will be detailed in Section III.

Although those devices consume very little power, the deployment of these networks is increasing substantially. The Information and Communications Technology (ICT) industry is estimated to be responsible for at least 2–3% of Global Greenhouse Gas (GHG) emissions, and this will continue to increase in the future [10], [11]. Even though there is not enough data to estimate the part of these emissions that are produced by IoT, their impact should not be disregarded [11], [12]. The importance of optimizing the carbon footprint of IoT networks is undeniable. For this reason, we propose an optimization framework to place sink nodes or gateways in LPWANs to minimize carbon emissions.

Renewable energies are usually suggested as green alternatives to feed IoT devices, especially in large outdoor deployments. However, there are also carbon emissions associated with the use of these so-called greener technologies, from production to the end-of-life of their components [13], [14]. Furthermore, renewable power supplies are irregular, meaning that a battery is also required to provide continuous operation. The optimization under study could reduce the carbon emissions of IoT networks, even in a network completely fed by photovoltaic panels, as we assume in our model.

In this context, the main contributions of this paper are summarized below:

- An optimization framework to minimize the carbon footprint in IoT network deployments using LPWAN technology and applying renewable energy sources.
- An analysis of the trade-off between the carbon footprint and energy consumption in IoT networks.
- The empirical demonstration that minimizing energy consumption significantly increases the carbon footprint. Conversely, the empirical evidence shows that enabling IoT devices to consume more energy has a positive effect on reducing the network's carbon footprint.

The rest of the paper is organized as follows. Section II reviews some relevant works on IoT network optimization and some studies measuring the carbon footprint of an IoT network. Section III introduces the linear model and problem formulation proposed, and Section IV discusses the numerical results obtained. Finally, in Section V, we conclude the paper.

II. RELATED WORK

In the past few years, IoT networks powered by photovoltaic panels have been shown to have great advantages. The improvement in performance obtained by an optimal setting and deployment of the network, from gateway location to the throughput achieved, has also been proven. The authors of [2] reported that, theoretically, a network fed with photovoltaic energy would work indefinitely until the components wore out. They also concluded that these networks would perform better if their nodes consumed more energy. This was also confirmed in the study conducted in [4], where the authors used an Integer Linear Programming (ILP) approach to understand network behavior with varying objective functions or problem conditions. They assumed that (i) the nodes were powered by either one of the two models of battery presented in the article and (ii) the environmental waste came from the Li-ion batteries of the end devices after all their recharge cycles were over. The experiment was tested with a discrete number of gateway locations available and a maximum of 400 end devices connected to each gateway. They concluded that increasing the number of gateways could decrease the chemical waste up to a certain threshold and showed the existence of a trade-off between the environmental footprint, energy, and cost. They also concluded that the use of long-life batteries achieved better performance in terms of reduced chemical waste (as the lifetime of the node, and therefore the network, is increased) at the expense of increasing the deployment cost of the entire network. However, their contribution was focused on the configuration of a deployed network, not on planning the optimal deployment beforehand.

The authors of [5] also proposed a novel optimization framework to maximize the lifetime of the network. Their approach to the problem was to assign renewable energy sources to the nodes with greater energy consumption. In addition, based on the results offered by the optimization problem, they designed an algorithm that maximized the life-time of the network while minimizing the number of hops. To this end, they envisioned a mesh multi-hop topology, meaning that a set of end devices worked as sink nodes and, as such, their location could not be changed. In contrast, our paper investigates the effects of free gateway placement.

Others approaches to minimize the energy consumption of IoT networks include [3], where the authors study the effect of reducing the traffic of a ZigBee IoT network. They concluded that an estimated annual saving of up to 99% can be achieved by removing seemingly crucial identifier fields from packets and reducing the frequency of data polling interval. It is clear that a wide range of approaches can be made to optimize a LPWAN. However, there are different perspectives that have not been studied in detail, and energy is usually selected as optimization function over CF. Consequently, in this paper the gateway placement is studied because there is few literature about it, and it can offer a significant reduction in environmental impact if the carbon footprint is considered while deploying the network.

The carbon footprint of wireless networks has also been studied by authors in [15]. They estimated the carbon emissions associated with the deployment and use of a Fourth Generation Long Term Evolution (4G LTE) network in six different demographic areas. They concluded that the ''annual carbon emissions generated by the larger ICT networks catering for high density urban and suburban areas and comparatively greater (up to three orders of magnitude) than those produced by smaller networks,'' and most of these emissions came from the manufacturing of mobile phones. Additionally, they discovered a linear correlation between annual carbon footprints and number of subscribers. However, this link was not maintained with small ICT systems due to the network's less efficient operation. Consequently, their conclusions cannot by applied to our work, and the findings of our work may be untrue for very large networks. Should a LPWAN with tens of thousands of nodes be considered, new investigations would be necessary to understand the behaviour of its CF.

There is vast literature addressing the consumption of IoT end devices and their energy models. Authors in [6], [16], [17], [18], and [19] broke down the functions of an end device, determining the electric current needed to accomplish every task. Data from manufacturers is also available online [20]. The three major functions are transmitting, receiving, and the idle state. In comparison, all the other tasks, from sensing to computing, can be considered negligible.

On the other hand, gateways have greater energy demands as they must be continuously listening according to the long-range technology requirements (nodes are assumed to only transmit, without listening requirements). In [21], the authors studied the power consumption of front-end LoRaWAN gateways, including backhaul wireless technology. They provided a simplified model for gateways, assuming the device is always-on with a fixed number of channels. In this case, power consumption depended on two factors: the LoRaWAN gateway vendor and the backhaul technology.

Concerning the carbon emissions of gateways and end devices, we shall start by providing a formal definition of the term carbon footprint since its definition seems to be a point of debate among the scientific community. The work presented in [8] defined a carbon footprint as ''a measure of the exclusive total amount of carbon dioxide emissions that is directly and indirectly caused by an activity or is accumulated over the life stages of a product.'' This approach has been followed by some studies, such as the work in [22], while other studies also considered other GHGs [9], [13]. Our paper follows the first approach and considers only CO_2 emissions, as the equivalency of other GHGs depends on the number of years used to calculate global-warming potential. After GHGs have been converted to their equivalence in CO_2, the carbon footprint is measured in CO_2eq. Given that this paper only considers CO_2, both units will be equivalent.

The emissions of producing IoT nodes are calculated in [12]. However, as we consider the number of end devices a constant and their CF is invariable, it can be disregarded during the ILP. Authors in [13] estimated the carbon emissions of photovoltaic panels and the percentage of emissions coming from carbon dioxide. In the work presented in [14], the authors calculated power consumption during the production process of a 1 kW photovoltaic system. Therefore, they calculated the carbon footprint by using the emissions of energy production. They considered both the efficiency of a photovoltaic grid connected power station and the degradation of this efficiency over time at the rate of 2% annually. Using these figures, they deduced the amount of energy that a 1 kW photovoltaic panel exposed to the effective illumination time of 3000 h could produce. Finally, authors in [23] stated that crystalline-silicon solar panels ''dominate 80% of the market globally,'' and the authors in [24] and [25] concluded that there was still not enough information to calculate the average emissions from the disposal of photovoltaic panels, as there are many options for disposal and few panels have reached their end-of-life.

Finally, regarding batteries, in [25], the authors assessed the life cycle of batteries. They obtained the carbon footprint for each of the phases of lithium iron phosphate batteries: raw materials, production, and use. And, according to [27] and [28], lithium-ion cobalt based batteries offer 500 recharge cycles.

III. MODEL AND FORMULATION OF THE PROBLEM

The network model to develop the optimization problem is based on LPWAN topologies. For this purpose, the LoRaWAN specification, one of the most popular LPWAN technologies today, will be taken as a reference. LoRaWAN is a wireless communication technology based on a one-hop radio system and designed to achieve long ranges while consuming little power. A LoRaWAN network uses a star-of-stars topology consisting of three basic elements, as shown in Figure 1: end devices, gateways, and a central network server. End devices, which may be sensors or actuators, communicate with the network server through the backhaul of the gateways. End devices use the LoRa physical layer to exchange messages with the gateway, whereas the gateway and the network server communicate using an IP-based protocol stack.

LoRaWAN comprises three communication classes: Class A, Class B, and Class C. Class A, also known as basic LoRaWAN, schedules the transmissions based on the behavior of the end device. In this operating mode, downlink transmissions (i.e., from the network server to the end device)

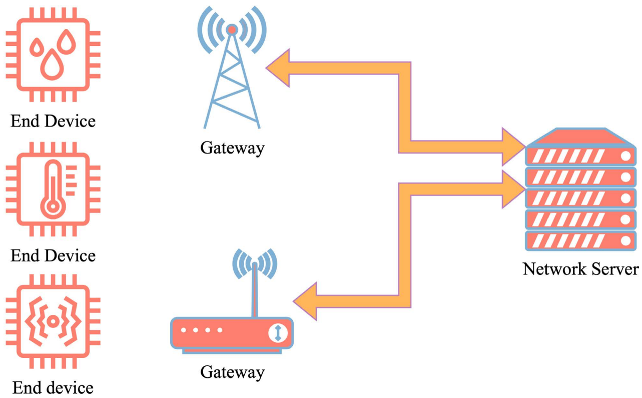


FIGURE 1. LoRaWAN basic architecture.

can only occur after an uplink transmission (i.e., from the end device to the network server) has taken place. Since this class offers the lowest energy consumption, all the end devices will work under these characteristics.

Class B introduces additional functions. It supports additional downlink transmission opportunities at prescheduled times. Class C allows downlink transmissions at any time, except when the end device is transmitting. A Class C device consumes more power but is ideal for the gateways since they are always listening.

Thus, based on the LoRaWAN topology specification, we develop a linear programming formulation for the minimization of the IoT network carbon footprint. Basically, we consider the IoT network as a set, $\mathcal{N}$, of n connected nodes randomly and uniformly distributed over a square surface. We assume an end device density of d, meaning the area of the experiment is n/d. We also assume that all the nodes transmit directly to one of the network gateways (or, in other words, there must always be a gateway within the coverage area of any end device), which is always listening and backhauling.

Regarding the gateways, both their total amount and placement are parameters to be optimized. To this end, we create a mesh grid with a finite number of points (a set $\mathcal{G}$ of p points) where a gateway can be located and define a variable vector G, whose size matches the number of possible gateway location points. One of the two optimization variables is the logical vector G, containing elements with a value of one if there is a gateway situated in that point, or zero if the point is empty. The sum of the elements of G indicates the number of gateways in the IoT network under consideration. The size of G, that is, the number of points that make up the grid, is p. Although the number of potential gateway locations is limited, a custom algorithm has been designed to determine the optimal area for gateway location. More details on this issue are explained in Section III-B2.

The second variable of optimization is L, a logical matrix where $L_{i,j}$ takes the value of 1 if a connection is established between end device i-th and the gateway located at point j-th. The link can only be established if the distance

TABLE 1. Spreading factor and related configuration for LoRa devices in Europe in the 868 MHz band.

Spreading factor	Bitrate (bit/s)	Receiver sensitivity (dBm)
SF7	5470	-124
SF8	3125	-127
SF9	1760	-130
SF10	980	-133
SF11	440	-135
SF12	250	-137

between them is less than or equal to the transmission range. Transmission power is fixed at 14 dBm (the maximum allowed by the LoRa specification in Europe in the frequency band of 868 MHz [20]), but the spreading factor can be reduced to minimize energy consumption, or it can be increased to extend transmission range. The spreading factor is a LoRa parameter that determines the bit rate. A spreading factor of 7 (SF7) offers the highest data speed rate of 5470 bit/s, whereas a spreading factor of 12 (SF12) only transmits at 250 bit/s. However, lower physical bit rates are associated with increased sensitivity in the receiving antenna. This information is outlined in Table 1.

Receiver sensitivity corresponds to the spreading factor, ranging from -124 dBm for a spreading factor of 7 to -137 dBm for a spreading factor of 12. Finally, without loss of generality, we consider the energy consumption of non-radio components, such as the sensing of end devices, as negligible.

All devices (both end devices and gateways) are powered using a photovoltaic panel and a battery with enough capacity to operate the device for 24 hours. The photovoltaic panel is big enough to power the device all year long given the number of hours of solar incidence a year. With the combination of battery and panel, the device can work uninterruptedly 24 hours a day. For the sake of simplicity, we do not consider periods of time without sunlight longer than a night or seasonal daylight differences.

The gateway consumption model is based on [21], which provides power consumption as a constant, regardless of the number of end devices connected to it. This study is based on the assumption of pure aloha-based channel access, which only considers 3 and 6 LoRa channel configurations of 125 kHz each. We have selected a Lorrier LR2 gateway with backhaul implemented with LTE (worst-case scenario out of those covered in [21]). This energy consumption will be referred to as E_G.

We have calculated the carbon footprint as the sum of the carbon emissions generated during the manufacturing of the photovoltaic panel and the battery for both the end devices and the gateways. Solar photovoltaic panel end-of-life management is an evolving field that requires further research and development, as mentioned in [24] and [25]. As such, and given that the life expectancy of photovoltaic panels is about 25 years [13], [14], [23], [24], [28], we have disregarded the end-of-life emissions.

TABLE 2. Problem parameters.

Parameter	Description
α	The maximum number of end devices connected to one gateway. In our case, a very large number, $\alpha \gg 1$.
E_G	Energy consumption of a gateway for one year in kWh/year.
$E_{i,j}$	Energy consumption by the link between end device i and point j for one year, or ∞ if the link cannot be established in kW h.
$\mathcal{G}$	Set of end potential gateway locations in the IoT network.
G_j	Optimization variable representing whether point j from the grid contains a gateway, $G_j \in G$.
K_b	Carbon footprint of 365 recharge cycles of a battery that provides a total of 1 kW h in CO_2eq/kWh.
K_p	Carbon footprint of a photovoltaic panel for every kW it produces in a year in CO_2eq/kW.
$L_{i,j}$	Optimization variable representing whether a link between end device i and point j exists.
$\mathcal{N}$	Set of end devices in the IoT network.
n	Number of end devices in the IoT network.
p	Number of points where a gateway could be placed in the IoT network.
T_p	Lifetime of a photovoltaic panel.
C_p	The carbon footprint generated when making a photovoltaic panel of 1 kW in CO_2eq.
C_b	The carbon footprint generated when making a Li-ion rechargeable battery of 1 kW h in CO_2eq.
C_T	The total carbon footprint of the network in CO_2eq/year.
R	The number of battery recharge cycles.
T_i	Number of hours of solar incidence in a year in h/year.
η_p	The efficiency of the solar panel, $0 < \eta_p < 1$.

A. LINEAR PROGRAMMING FORMULATION

The first step is to model the total carbon emissions of a generic device (end device or gateway). Thus, expression (1) allows us to obtain K_p, the carbon footprint of a photovoltaic panel for every kW h it produces during a year:

$$K_p = \frac{C_p}{T_p\, T_i\, \eta_p} \tag{1}$$

where C_p represents the CF generated where producing a photovoltaic panel depending on its power. T_p and T_i represent, respectively, the lifetime of the panel and the number of hours of solar incidence, and η_p is the efficiency of the panel.

Expression (2) represents the carbon footprint of 365 recharge cycles of a battery that provides a total of 1 kW h for one year, K_b. C_b represents the CF generated where producing a battery depending on its capacity, and R its number of recharge cycles.

$$K_b = \frac{C_b}{R} \tag{2}$$

Then, the total emissions of a generic device with an annual consumption of 1 kW h would be $K_p + K_b$. Note that all the equation parameters are defined in Table 2

The second step is to model the energy consumption of the end devices. Thus, $E_{i,j}$ represents the link energy consumption between end device i-th and point j-th for one year, measured in kW h, while $L_{i,j}$ represents whether a link between end device i-th and point j-th exists (recall that a point j is a potential location for a gateway). Moreover, G_j denotes whether there is a gateway located at point j. From these considerations, it is easy to obtain the expressions for the energy consumption of an end device and a gateway, expressions (3) and (4), respectively.

$$\sum_{i=1}^{n}\sum_{j=1}^{p} L_{i,j}\, E_{i,j} \tag{3}$$

$$\sum_{j=1}^{p} G_j\, E_G \tag{4}$$

Combining expressions (1) to (4), the carbon footprint, C_T, of the network can be obtained as formulated in (5). This function expresses the carbon emissions in kgs for one year (CO_2eq/year), and it is the optimization function of the problem.

$$C_T = \left(\frac{C_p}{T_p\, T_i\, \eta_p} + \frac{C_b}{R}\right)\left(\sum_{i=1}^{n}\sum_{j=1}^{p} L_{i,j}\, E_{i,j} + \sum_{j=1}^{p} G_j\, E_G\right) \tag{5}$$

Then, the problem of gateway and link assignment is equivalent to that of minimizing the carbon footprint of the network, as follows:

$$\text{minimize } C_T \tag{6a}$$

$$\text{subject to: } \sum_{j=1}^{p} L_{i,j}\, G_j = 1,\ \forall i \in \mathcal{N}, \tag{6b}$$

$$L_{i,j} \in \{0, 1\},\ \forall i \in \mathcal{N},\ \forall j \in \mathcal{G}, \tag{6c}$$

$$G_j \in \{0, 1\},\ \forall j \in \mathcal{G}. \tag{6d}$$

Table 2 defines the parameters employed for the programming formulation. Expressions (6b) to (6d) are the problem constraints for the carbon footprint problem:

- Expression (6b) ensures that every end device is connected to a gateway.
- Expressions (6c) and (6d) model that problem variables ($L_{i,j}$ and G_j) can take zero or one logical value.

Note that expression (6b) is a non-linear constraint, as it multiplies two optimization variables. However, the problem can be expressed as a mixed-integer linear programming (MILP) optimization. To this end, expression (6b) must be rewritten. Consequently, it is subdivided into two different constraints, namely expressions (7b) and (7c). The linear problem formulation is thus expressed as follows.

$$\text{minimize } C_T \tag{7a}$$

$$\text{subject to: } \sum_{j=1}^{p} L_{i,j} = 1,\ \forall i \in \mathcal{N}, \tag{7b}$$

TABLE 3. Different settings under which the experiment has been done.

End device density (node/m^2)	2×10^{-3} node/m^2, 1×10^{-3} node/m^2, 5×10^{-4} node/m^2, 3.3×10^{-4} m^2, 2.5×10^{-4} m^2
Surface (m^2)	6×10^4 m^2, 1.2×10^5 m^2, 1.8×10^5 m^2, 2.4×10^5 m^2, 3×10^5 m^2, 3.6×10^5 m^2, 4.2×10^5 m^2, 4.8×10^5 m^2

TABLE 4. Problem parameter values.

Parameter	Value	References
E_G	153.6504 kWh/year	[21]
T_p	25 years	[13], [14], [23], [24], [28]
C_p	2024.823 CO_2eq/kW	[13], [14]
C_b	0.0279 CO_2eq/kWh	[25]
R	500 recharge cycles	[26], [27]
T_i	1400 h	[21]
η_p	0.8	[13], [14]

$$\sum_{i=1}^{n} L_{i,j} < \alpha\, G_j,\ \forall j \in \mathcal{G}, \tag{7c}$$

$$L_{i,j} \in \{0, 1\},\ \forall i \in \mathcal{N},\ \forall j \in \mathcal{G}, \tag{7d}$$

$$G_j \in \{0, 1\},\ \forall j \in \mathcal{G}. \tag{7e}$$

Expression (7b) ensures that every end device is connected to a potential gateway location point. Additionally, expression (7c) represents that every link to a potential gateway location point is made to a point where there is a gateway (meaning there is no connection to an empty point), and no gateway receives more than α connections. Both expressions together guarantee that every node is connected to a gateway and that no gateway receives more than α connections. Given that α is a very large number, the second condition is irrelevant.

Ultimately, the combination of both restrictions achieves the same behavior as expression (6b): guaranteeing that every node is connected to a gateway. However, using expression (6b) as a constraint would make it a non-linear optimization problem.

B. EXPERIMENT DESIGN

We have planned 40 different settings for the experiment by varying the density of the nodes and the total area of the problem. We selected 1 node every 500 m^2, 1000 m^2, 2000 m^2, 3000 m^2, and 4000 m^2 as the possible end device densities, and 6×10^4 m^2, 1.2×10^5 m^2, 1.8×10^5 m^2, 2.4×10^5 m^2, 3×10^5 m^2, 3.6×10^5 m^2, 4.2×10^5 m^2, and 4.8×10^5 m^2 as the values for the area under evaluation, as shown in Table 3. We have studied every possible combination of these two factors by running every scenario with 20 different seeds. The values given to the problem parameters, and the references from where they were taken, are expressed in Table 4. Given that equations (2) and (3) model the energy source, and every device is powered by the same technology, most of the parameters included in Table 4 are directly or inversely proportional to the total carbon footprint of the LPWAN, and changing the values selected would appropriately change the CF of the network. However, variations in E_G could result in changes in the network deployment, and consequently the network emissions would change unpredictably.

To solve the problem, the following considerations should be made. The most important one is that the problem is NP hard and if the number of potential locations for the gateways is too wide (an overly dense grid of points), it would take too long to solve the problem. On the other hand, defining a grid with fewer points would result in having less precision than desired. Therefore, we propose a series of simplifying steps to reduce the time necessary to solve the linear integer problem. These steps are shown in Sections III-B1 and III-B2.

1) REDUNDANT POINTS

Let i and j be two points of the grid, where both are potential locations for a gateway. Then, if for each given node b contained in $\mathcal{N}$, $\forall b \in \mathcal{N}$, it is true that either $E_{b,i} < E_{b,j}$ or $E_{b,i} = E_{b,j} = \infty$. j would never be selected as a location for a gateway (mathematically, it means that $G_j = 0$ in vector G) because it would always be better to place it in i: for every node in the grid, either none of them can offer coverage, or i is closer, therefore consuming less energy.

Narrowing down the size of the number of points where a gateway could be placed, p, by using this criterion has shown to reduce the computational burden of the problem, mainly by eliminating check points located on the borders of our working area. Consequently, the processing time needed to solve the problem is shorter. An example is shown in Figure 2, where the number of points has been reduced from 324 to 163.

2) REFINING THE GRID

Even after removing redundant points, as explained above, it has been proven that problems with more than 60 nodes are still hard to solve, as they require large amounts of computational/memory resources and time. Therefore, we have resorted to an additional simplifying strategy based on solving the optimization problem iteratively. In the first iteration, the starting point is a low density of potential gateway locations that will increase in successive iterations. As a result of each iteration, areas to place the gateways will be discarded and we will check whether the carbon footprint is lower than in the previous iteration. The iterative process will stop when the carbon footprint does not significantly improve. Below, we provide more details about this iterative process.

As previously indicated, we first solve the problem for a considerable distance between points (e.g., 60 m). This problem contains fewer points and, as such, is easier to solve. Therefore, it produces an approximate location for every gateway in the ideal network. Then, we start iterating around these points to refine the outcome. In this way, we calculate the exact solution faster.

To do so, we calculate the cost of the objective/optimization function of the network for every node when we move a gateway to an adjacent position. If the cost increases,

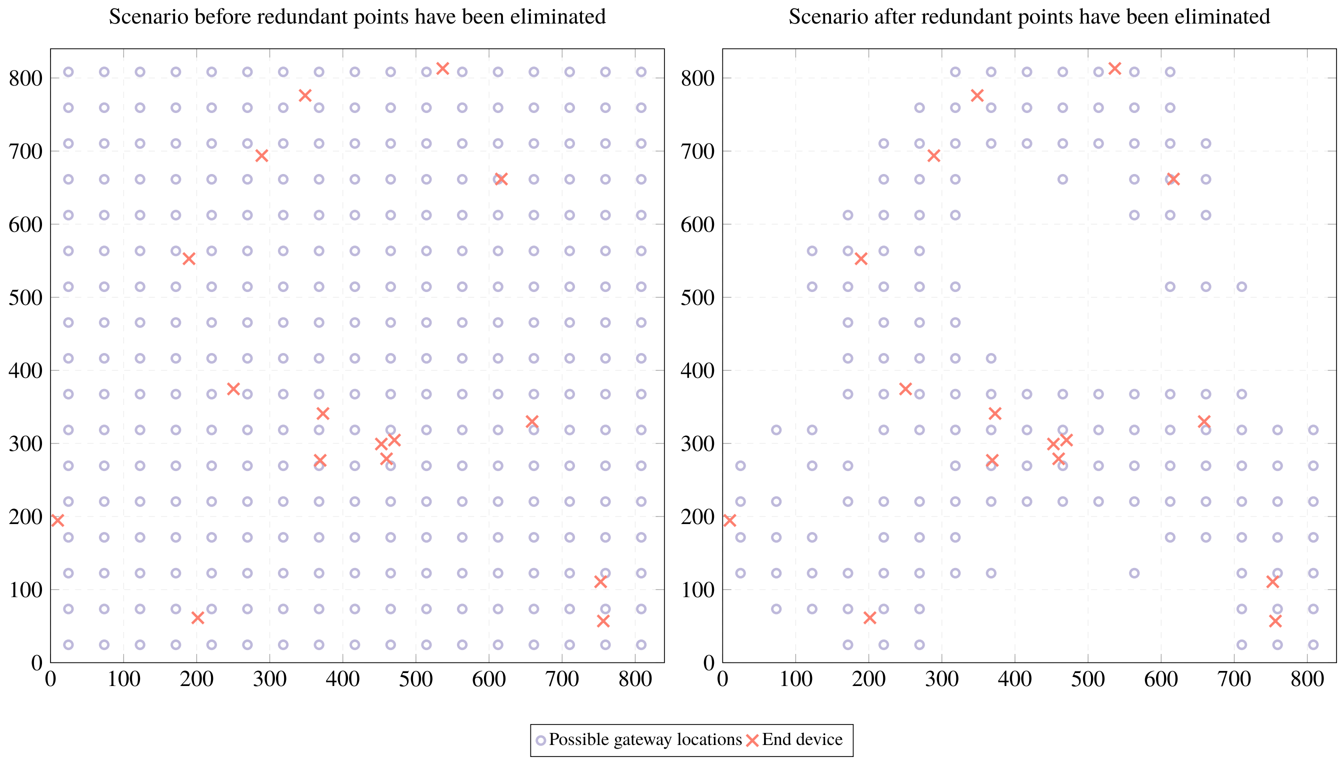


FIGURE 2. **Removing of redundant points for an example with 16 end nodes and 324 points where a gateway could be located. In the second image, 161 points have been eliminated according to the criteria in Section III-B1. Circles represent the possible positions and crosses mark the placement of each end node.**

we are moving away from the optimal location. If the cost remains the same, we have found a target area where the gateway could be placed. We run over this target location in all the four possible directions, calculating a squared area where the gateway could be placed. Then, we reduce the distance between points to half and place the points only around the target area. Next, we eliminate the redundant points, as explained in Section III-B1, and we solve the MILP again. We repeat these iterations until the cost of the objective function is not reduced any more, as shown in Figure 3.

"Refining the grid" is an experience-based simplifying approach, thereby allowing us to solve time-consuming device-placing problems faster. For instance, in the example shown in Table 5, we can observe that the problem has been solved in only 4.67 s, on average, when the original distance was 60 m and "refining the grid" was applied. Using a fixed distance between points has proven to take longer. Moreover, if "refining the grid" is not used, setting a large distance between potential points leads to less precise solutions with higher carbon emissions, while placing the points closer means a more complex problem.

IV. NUMERIC RESULTS

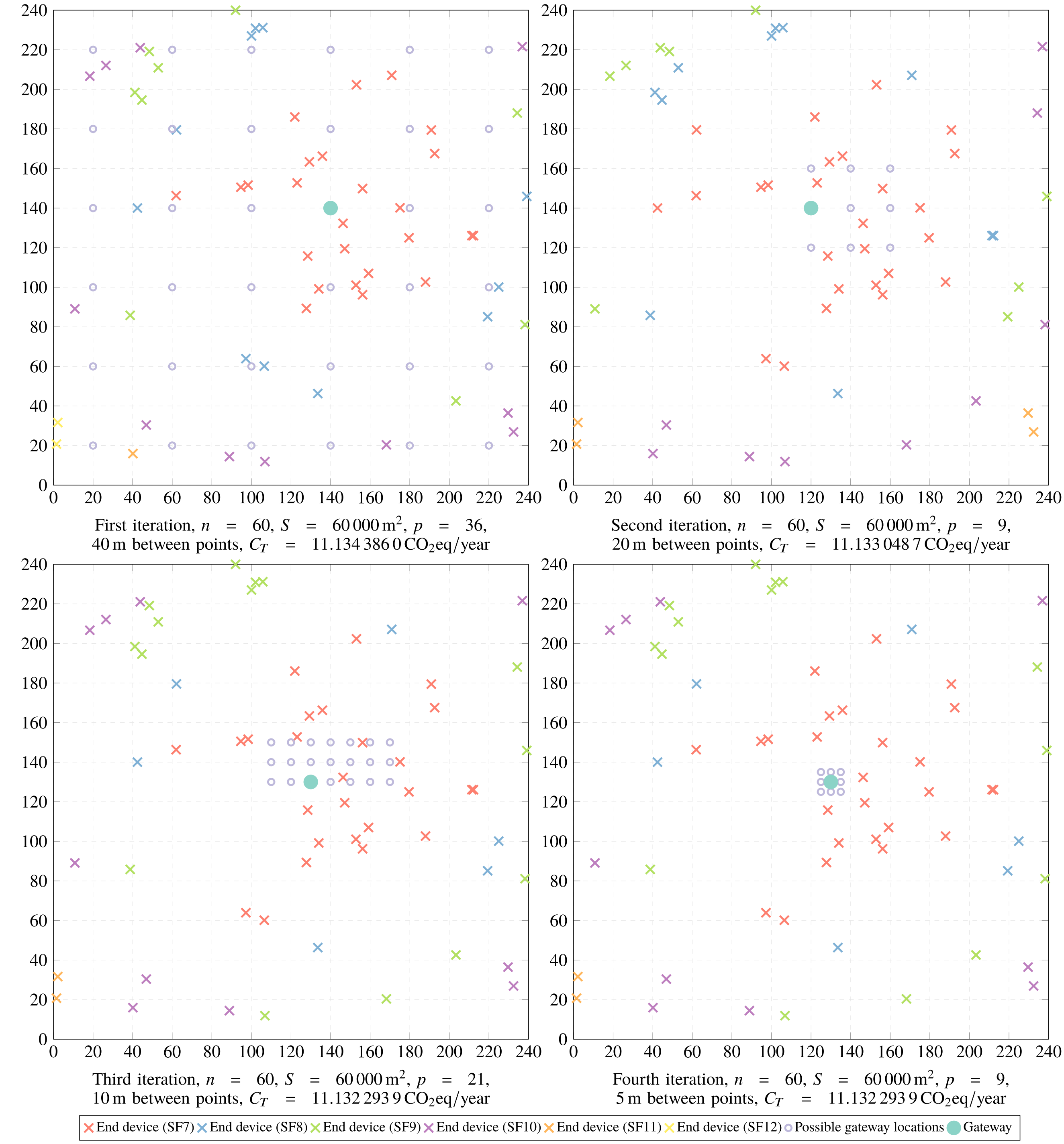
This section discusses our results and provides some examples to show the benefits of the optimization process.

There are two factors that have been considered when analyzing the numerical results: the density of the end device nodes and the area of network deployment. Figure 4 shows the emissions obtained for every optimization scenario tested after the algorithm minimized the carbon footprint.

Increasing the density of end devices in the network barely increases emissions, and thus, the carbon footprint. For instance, increasing the number of end nodes 4 times, from 1 for every 4000 m^2 to 1 for every 1000 m^2, the carbon footprint increases by only 29.6% in the worst-case scenario, i.e., an 300% increase in the number of nodes entails an increase in the CF of one order of magnitude lower. However, enlarging the area covered by the network increases the carbon footprint at a higher rate.

In order to make perceptible the reduction in carbon emissions that can be achieved, we have calculated the CF for the same scenarios without optimizing the gateway placement. Instead, gateways have been reasonably placed forming a grid that guarantees that every point in the network has coverage, and every end device has been connected to the closest gateway. Results are shown in Figure 5. Without optimization, the CF grows rapidly for certain scenarios where the number of gateways is significantly higher than needed.

In classical problems, one common optimization goal has been to minimize energy consumption. Thus, to better understand our model and assess the relevance of the carbon footprint optimization, we also formulate the energy optimization framework. Specifically, we apply the same constrains while minimizing the amount of energy consumed by



First iteration, $n = 60$, $S = 60\,000\,\mathrm{m}^2$, $p = 36$, 40 m between points, $C_T = 11.134\,386\,0$ CO_2eq/year

Second iteration, $n = 60$, $S = 60\,000\,\mathrm{m}^2$, $p = 9$, 20 m between points, $C_T = 11.133\,048\,7$ CO_2eq/year

Third iteration, $n = 60$, $S = 60\,000\,\mathrm{m}^2$, $p = 21$, 10 m between points, $C_T = 11.132\,293\,9$ CO_2eq/year

Fourth iteration, $n = 60$, $S = 60\,000\,\mathrm{m}^2$, $p = 9$, 5 m between points, $C_T = 11.132\,293\,9$ CO_2eq/year

FIGURE 3. Step by step carbon footprint emissions optimization example results for a scenario with 60 end device nodes. Note that since the fourth iteration does not offer an improvement over the third iteration, we assume that the optimal cost has been found.

the end devices:

$$\sum_{i=1}^{i=n}\sum_{j=1}^{j=p} L_{i,j}\,E_{i,j} \tag{8}$$

Expression (8) denotes the optimization function. This allows us to confirm the findings in [4], whose authors concluded that energy optimization leads to greater waste since "optimizing each variable leads to different network configurations." As will be shown below, optimizing energy consumption leads to a larger number of gateways placed closer to the end devices.

As observed in Figure 6, we found that when minimizing energy consumption by increasing the number of

TABLE 5. Comparison of the required time to complete optimization according to the experiment settings and whether the "refining the grid" technique is used.

	Original distance between points	Distance between points (m)	Nodes	Average time (s)	Difference with optimal C_T
Distance between points is reduced progressively	60	Variable	60	4.67	0%
Distance between points is constant	Fixed	15	60	9.49	0.05%
	Fixed	10	60	21.93	0.02%
	Fixed	5	60	379.05	0%

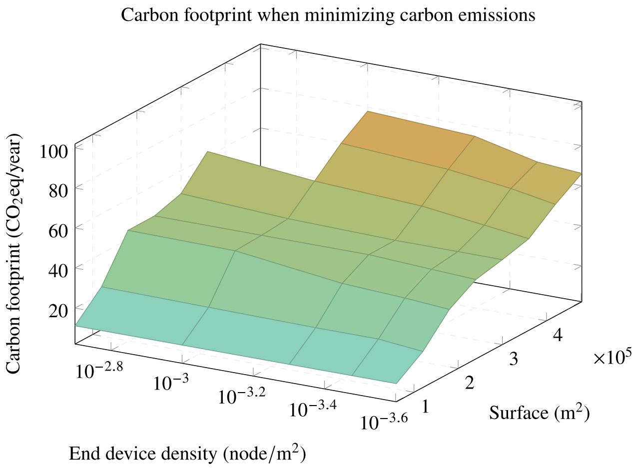


FIGURE 4. Carbon footprint optimization.

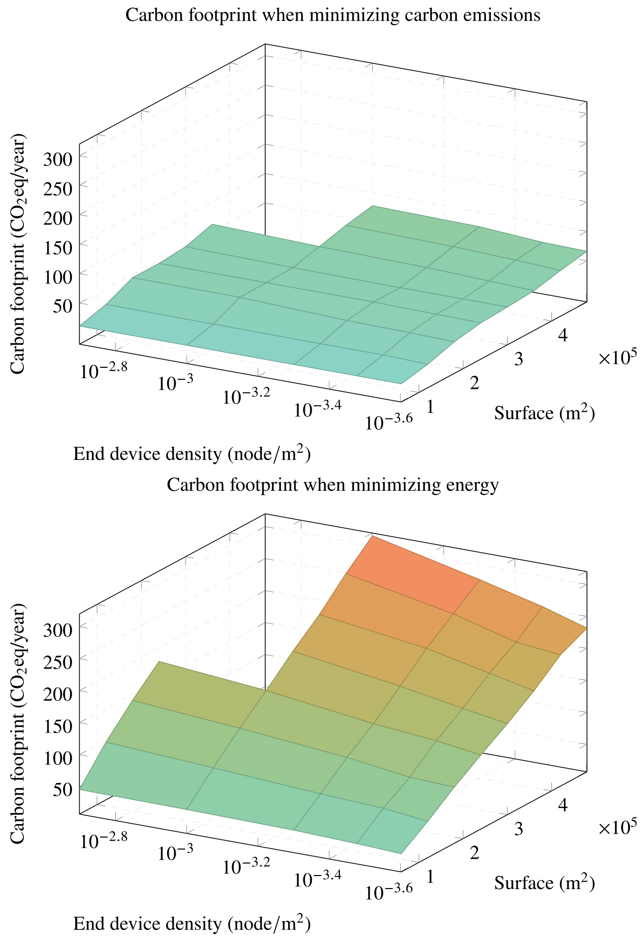


FIGURE 6. Carbon footprint obtained by optimizing (top) carbon emissions or (bottom) energy consumption. Each plot represents the average result for each of the 40 different scenarios tested.

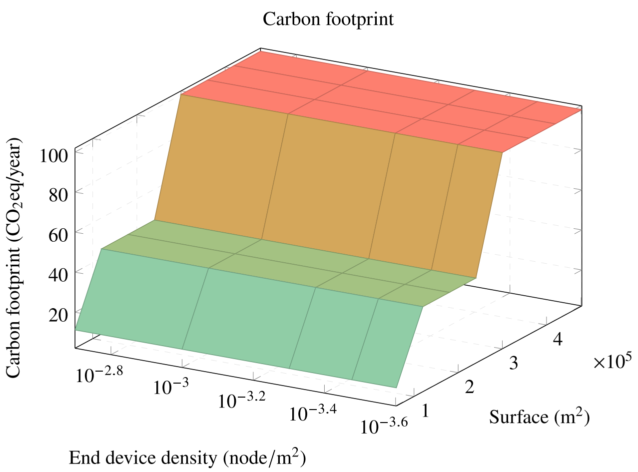


FIGURE 5. Full coverage carbon footprint (gateways deployed in a grid layout).

nodes 4 times, from 1 for every 4000 m^2 to 1 for every 1000 m^2, the carbon footprint increases 36.55% in the worst-case scenario, slightly higher than in the previous case (29.6%). The larger coverage area in this case causes the carbon footprint to increase faster. So, Figure 6 shows that for the largest studied scenario with a density of only 1 node per 1000 m^2, the carbon footprint is up to 4 times bigger if we try to minimize energy consumption instead of carbon emissions.

Another way of measuring emissions is by calculating the carbon footprint per node or end device, as represented in Figure 7. The fact that the carbon footprint remains constant for a given node density establishes that an increase in surface intensifies carbon emissions at the rate that the number of nodes grows.

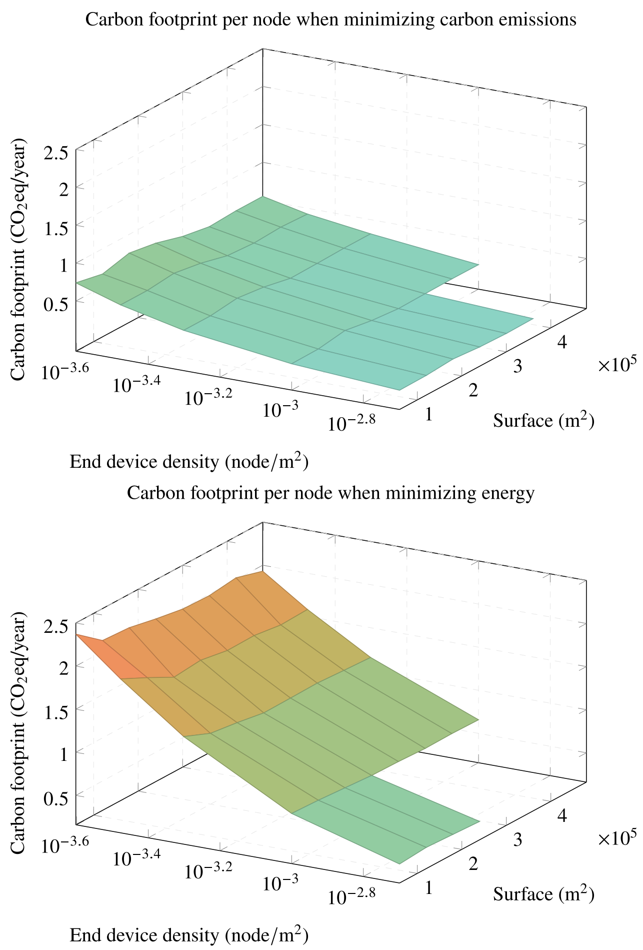


FIGURE 7. Carbon footprint per end device obtained by optimizing (top) carbon emissions or (bottom) energy consumption. Each plot represents the average result for each of the 40 different scenarios tested. Notice that the *x* axis has been inverted to better observe the plot.

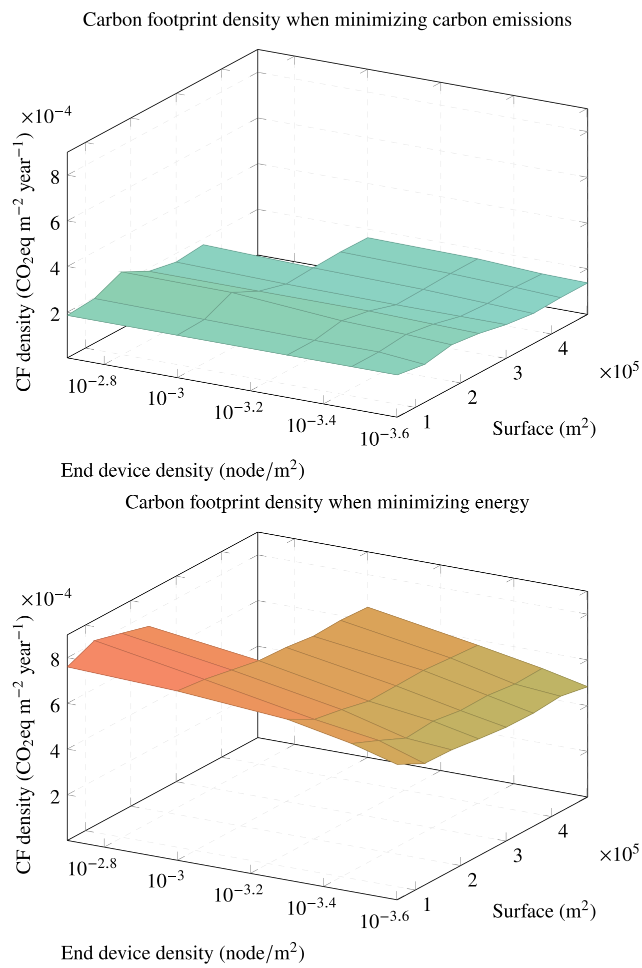


FIGURE 8. Carbon footprint density obtained by optimizing (top) carbon emissions or (bottom) energy consumption. Each plot represents the average result for each of the 40 different scenarios tested.

In Figure 7, we can see that increasing the surface covered by the network does not increase the carbon emissions per node, but it acts like a constant: in the worst-case scenario, the carbon footprint only decreases 37.61% from the maximum value for a given density of end devices while minimizing the carbon footprint, or 19.39% while minimizing energy consumption. Alternatively, measuring the carbon footprint per square meter (as illustrated in Figure 8) reveals that an increase in the surface covered by the IoT network leads to a decrease in emissions per surface.

Therefore, we have validated the fact that minimizing energy consumption leads to a bigger carbon footprint. On the other hand, optimizing carbon emissions results in greater energy consumption, as shown in Figure 9.

One of the main outcomes of this paper is that when using optimal deployments, there is a trade-off between the carbon footprint and energy consumption. This means that minimizing one of the two parameters will increase the other. Thus, we have studied the same ILP adding an additional restriction: minimizing the carbon footprint while limiting the maximum energy that can be consumed by end devices. This constraint is expressed as follows:

$$\sum_{i=1}^{n} \sum_{j=1}^{p} L_{i,j} \, E_{i,j} < E_M , \tag{9}$$

where E_M is the maximum amount of energy that can be consumed

Figure 10 shows the results for two test scenarios with 240 nodes. These results show that it is not possible to minimize the carbon footprint without allowing an increase in minimum energy consumption. This does not mean that carbon footprint minimization and energy minimization are opposites. In fact, the carbon footprint partially depends on energy consumption. So, reducing energy consumption only reduces the carbon footprint to a certain extent. From this point on, it is no longer possible to further reduce the carbon footprint without increasing energy consumption. What happens in this case is that to further reduce the carbon footprint, it is necessary to eliminate network equipment (gateways) and force the nodes to transmit at greater distances, increasing energy consumption to a lesser extent than the reduction in the

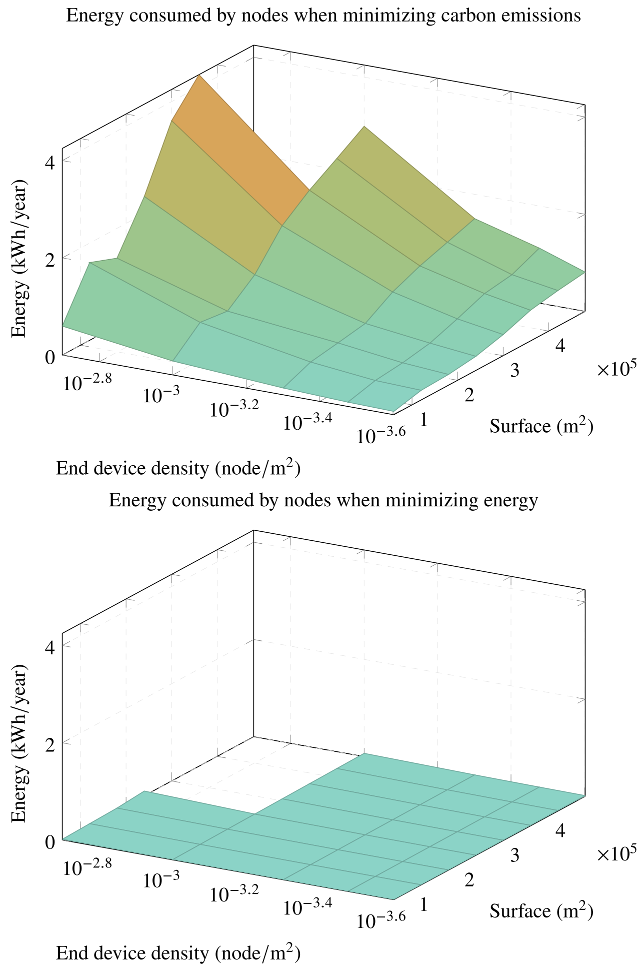


FIGURE 9. **Energy consumed by the end devices, obtained by optimizing (top) carbon emissions or (bottom) energy consumption. Each plot represents the average result for each of the 40 different scenarios tested.**

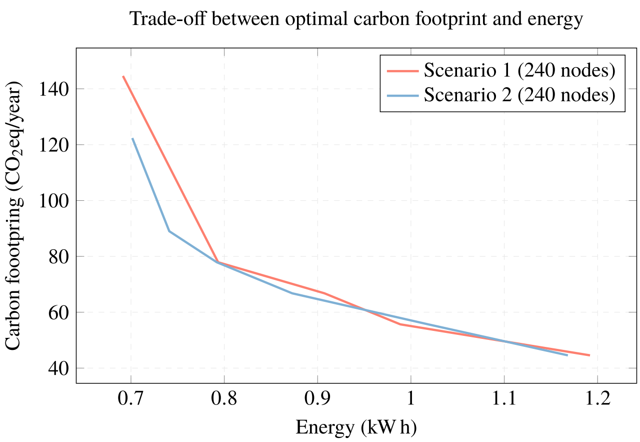


FIGURE 10. **Trade-off between the optimal carbon footprint and energy for an IoT network of 240 nodes.**

carbon footprint achieved. This can be verified in Figure 10, where a minimal reduction in energy consumption allows significant reductions in the carbon footprint.

The general behavior of energy consumption is similar to the carbon footprint, growing if we increase either the surface covered by the network or the density of the end devices. These variances in the carbon footprint and energy consumption are caused by changes in the network configuration. The first and most obvious change affects the number of gateways placed in the covered area. The average number of gateways required to achieve optimization in each experiment is represented in Figure 11.

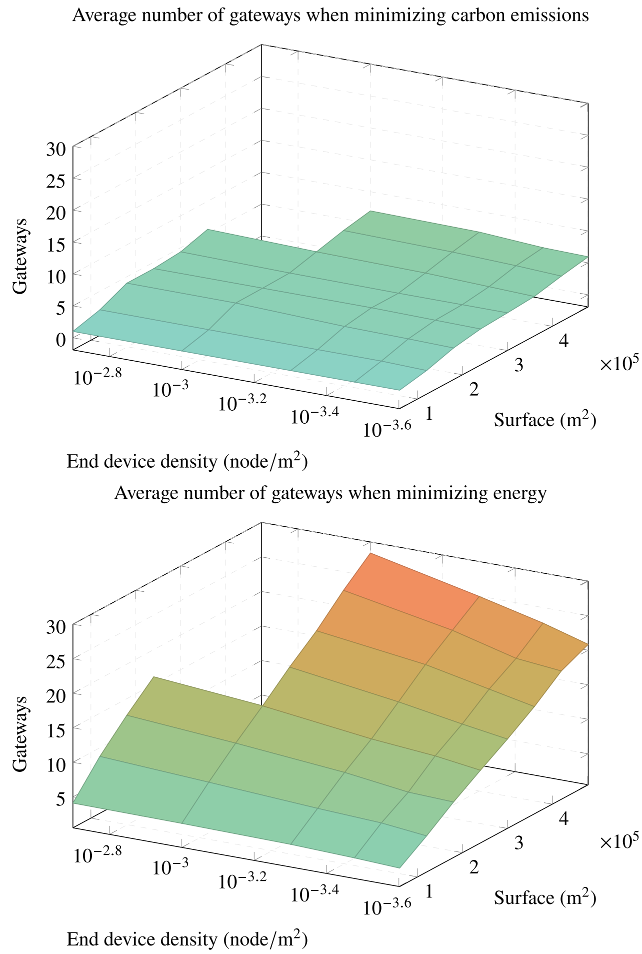


FIGURE 11. **Average number of gateways placed when optimizing (top) carbon emissions or (bottom) energy consumption. Each plot represents the average result for each of the 40 different scenarios tested.**

As can be observed, minimizing energy consumption instead of carbon emissions in the IoT network means deploying many more gateways at their corresponding places. Accordingly, other key parameters in the LPWAN network have noticeably decreased, like the total time that the network is transmitting.

To represent the total transmission time of the network, we will use Time-on-Air (ToA). This parameter represents the percentage or time that the end devices are transmitting data, as shown in Figure 12. Since there may be several gateways working in different channels and different spreading factors, the transmission time can exceed 100%. As previously explained, minimizing carbon emissions leads to fewer gateways, but also to an increased distance between end nodes

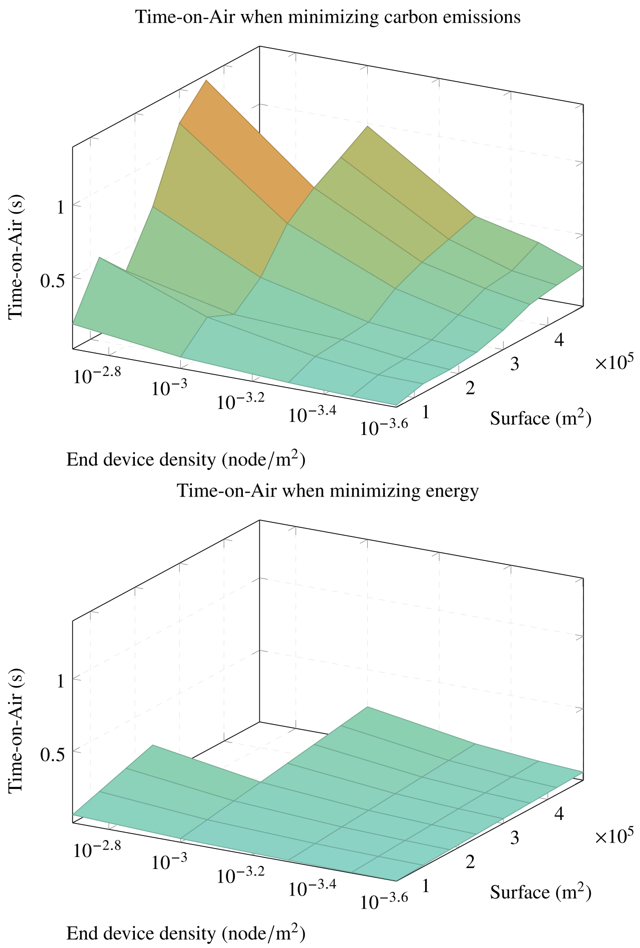


FIGURE 12. Time-on-Air measured in seconds of transmission per natural second when optimizing (top) carbon emissions or (bottom) energy consumption. Each graph represents the average result for each of the 40 different scenarios tested.

and gateways, thus forcing the use of a lower transmission bit rate. This means the spreading factor employed is increased and, as a consequence, the ToA is also increased.

V. CONCLUSION

The optimal planning of IoT networks is a complex problem due to the openness of their deployment and final settings to fulfill the goals of a particular IoT application. In this paper, we justify and develop an optimization framework to minimize the carbon footprint in IoT network deployments. The impact on the environment of these types of networks by optimizing their carbon footprint when LPWAN technology and renewable energy sources are in use is also explored.

Interestingly, we have found and confirmed that in an IoT network, energy optimization does not equal carbon footprint optimization. In fact, energy minimization has proven to incur in significantly higher carbon emissions. Therefore, we can accomplish a more sustainable IoT network deployment if the network planning takes gateway placement into account to minimize carbon emissions.

This result is significant since the classical literature has always assumed that the optimization of energy consumption is the most sustainable option from the environmental point of view. However, the reduction in energy consumption not only produces an increase in the carbon footprint, but this relationship is non-linear. As a general conclusion, allowing end device nodes to consume more energy in an IoT network can contribute to reducing its carbon footprint.

As future work, we are focusing on cases where a portion of the end nodes are allowed to use third end nodes as relays instead of having to be directly in the reception range of a gateway. Even a small portion might lead to a substantial reduction in the carbon emissions of the network. Moreover, the MILP problem could be turned into a very reliable instrument by modifying it to consider other effects, such as 3D terrain or a more complex model to characterize gateway consumption.

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