"GREEN ICT @ FMD" – Center of Excellence for Environmentally Sustainable ICT

Reducing the CO_2e Footprint of Sensor-Edge-Cloud Systems for Condition Monitoring

A white paper by "HUB 1 – Sensor-Edge-Cloud"

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1. Summary

The digitization of public spaces (Smart City), production environments (Industry 4.0), or home environments (Smart Home) is, in most cases, based on continuous monitoring of the status of objects like machines and systems or environmental conditions. This data is collected via sensors, often aggregated via a gateway or an edge device, and ultimately processed in the cloud via an internet connection (e.g., via wireless networks). It is precisely these systems that make a significant contribution to Industry 4.0 by enabling continuous condition monitoring of machines and equipment. However, as these sensor-edge-cloud systems become more widespread, their environmental footprint also grows - quantified in terms of their climate impact as units of carbon dioxide equivalents (CO_2e). To date, however, these aspects have been largely overlooked in system design.

This white paper examines the key CO_2e drivers in sensor-edge-cloud chains using two case studies and derives concrete recommendations for action from them. The first case study assesses a vibration-based monitoring system for a milling machine that has been implemented in a laboratory setting, while the second case study examines a commercial asset-tracking module from the industrial sector. The investigation focuses on sensor nodes and edge devices, as the cloud component is difficult to quantify from a metrological perspective.

The results of the first case study show that targeted optimization measures can achieve energy savings of nearly 50% across the entire system chain, which translate linearly into CO_2e reductions. The biggest lever here is the optimization of the edge device, which consumes up to 50 times more energy than the sensor node. In particular, the use of lightweight operating systems and disabling unused peripherals such as LEDs or HDMI interfaces lead to significant savings across the entire chain. At the communication level, local data preprocessing further reduces energy requirements. In the commercial asset tracking module of the second case study, energy savings of up to 95% are possible by adjusting the communication strategy to transmit data in significantly reduced transmission cycles. For the battery-powered device, manufacturing emissions are the primary driver of the CO_2e footprint. However, energy-efficient operation extends the service life, thereby spreading the emissions from the production phase over several years and reducing the annual CO_2e share.

The strategies identified in this study - such as application-specific hardware sizing, reduction of the baseline load, early data processing, and minimized communication - are transferable to other IoT-based systems and provide guidance for the systematic reduction of the CO_2e footprint during the design and operation of sensor-edge-cloud systems.

2. Introduction

In Industry 4.0, digitalization plays a crucial role, with Sensor-Edge-Cloud (SEC) systems increasingly being implemented for condition monitoring of machines and plants to enable predictive maintenance [1], [2]. In typical architectures, a sensor node collects the desired data, and an edge device handles communication with the cloud for data storage. There, the data is then processed, visualized, and analyzed to determine the condition of the monitored system [3]. As these systems become more widespread, attention is shifting not only to functionality, latency, and costs but also to their environmental footprint. The resulting emissions arise from both manufacturing and operational phase [4], [5]. In practice, however, these aspects are often not yet addressed in the design and application of SEC systems, even though even simple adjustments could have measurable effects.

The aim of this study is to identify and quantify the key CO_2e drivers in SEC chains using two case studies, in order to derive concrete, practical optimization strategies. The study examines a self-built system for vibration-based tool monitoring on a milling machine, as well as a commercial battery-powered asset-tracking module for filling containers. Since the cloud component cannot be directly measured, it is not included in the assessment; the focus of the study is on the sensor nodes and edge devices.

The study first describes the assessment framework for the CO_2e accounting of the measurement objects. Subsequently, the two case studies are presented, accounted for, and evaluated. Finally, general observations are summarized, recommendations for the design and operation of SEC chains are derived, and the limitations of the investigations are discussed.

3. Assessment Framework for Carbon Footprint Assessment

When quantifying the CO_2e footprint of SEC chains, two components must be considered separately: the initial portion associated with the manufacturing of hardware components, and the ongoing portion resulting from the device's continuous energy consumption. These two components are determined separately using different methods. The assessment covers the sensor node and the edge device; for the cloud, both the hardware and energy consumption are difficult to measure and attribute to the influence of the SEC chain.

3.1. Determination of Manufacturing CO_2e

To estimate the CO_2e emissions generated during manufacturing, a bill of materials is first created for each measured object under consideration, if not already provided. This describes the essential assemblies and components, such as printed circuit boards (PCBs), integrated circuits (ICs), passive components, or batteries, and serves as the basis for component-based accounting. The CO_2e estimate was performed using an internal Fraunhofer accounting tool based on datasets from the Sphera "LCA for Experts" database. For this purpose, the components are divided into categories and evaluated using appropriate influencing factors such as design, size, mass, and similar parameters. In this way, the manufacturing footprint can be approximated even when no manufacturer-specific emission data is available for individual components.

The manufacturing assessment is limited to the cradle-to-gate scope; thus, CO_2e generated up to the point of leaving the factory gates is taken into account. Not included are all subsequent parameters such as transport routes, packaging, or disposal. The results should therefore be understood as an estimate, which is particularly suitable for classifying orders of magnitude and identifying dominant components.

3.2. CO_2e during the use phase

To determine the CO_2e emissions generated during the usage phase, the energy consumption of the devices is measured and correlated with the respective operating profile. The measurements were conducted in a laboratory environment at room temperature. To measure power consumption, two different measurement systems were used depending on the device type: a compact Nordic Power Profiler Kit 2 for recording current profiles during long-term measurements, and a more precise Joulescope J220 measurement system for detailed power consumption measurements. The latter also offers the option of current limiting, which is necessary to prevent overcurrent, particularly when measuring battery-powered modules.

Power consumption under realistic operating conditions, particularly for edge devices running an operating system and during communication events, can fluctuate significantly over time. Therefore, a time-averaged power value is used for evaluation. To this end, the measurement series were recorded over defined measurement windows and evaluated as an arithmetic mean over the respective duration.

The operational CO_2e emissions from the measured energy consumption are calculated using an emission factor for the electricity mix; in Germany, this is set at approximately 0.4 kg CO_2e/kWh. The CO_2e value is derived from the average power consumption P, the operating duration t, and the emission factor EF using the following formula:

$$CO_2e = P * t * EF$$

For the overall assessment, the operating time of the respective applications is included in order to determine absolute savings value.

4. Case Study 1: Milling Machine Monitoring in the Laboratory

4.1. System Description

The first case study examined the application of vibration-based condition monitoring for a milling machine. The goal is to draw conclusions about the tool's condition like the wear status from vibration data, thereby supporting predictive maintenance. For the investigation, a corresponding SEC chain was set up in the laboratory and characterized metrologically across defined operating conditions.

The system architecture follows the typical SEC pattern and is shown in *Figure 1*. A microcontroller board equipped with a vibration sensor serves as the sensor node, transmitting vibration data via Bluetooth Low Energy (BLE). The edge device receives this data and forwards it to the cloud via Wi-Fi using MQTT. The cloud was primarily implemented to complete the transmission chain; from there, the data could be read, visualized, and evaluated. For the assessment, a conservative worst-case operating profile was assumed, in which the system runs continuously, with measurements taken 24 hours a day, 7 days a week.

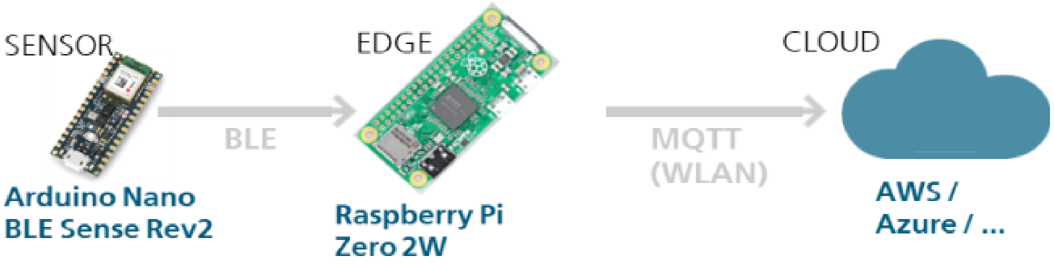


Figure 1 : Architecture of the sensor-edge-cloud chain in the laboratory for vibration-based condition monitoring of a milling tool

4.2. Manufacturing CO_2e

For condition monitoring, an Arduino Nano 33 BLE Sense Rev2 was selected as the sensor node and a Raspberry Pi Zero 2W as the edge device; both have technical specifications that meet the requirements for the use case. To ensure comparability, an Arduino Nicla Sense ME was included as an additional sensor node, and a Raspberry Pi 4 was included as an alternative edge device. Figure 2 shows the CO_2e footprint of the sensor nodes and edge devices in the SEC chain. At 0.6 kg (Nicla Sense ME) and 1.0 kg (Nano BLE Sense Rev2), the sensor nodes generate significantly fewer emissions than the edge devices, which emit 2.6 kg (Pi Zero 2W) and 9.4 kg (Pi 4). This difference appears plausible given the differing size factors and higher complexity. In all cases examined, a smaller form factor was also associated with lower CO_2e.

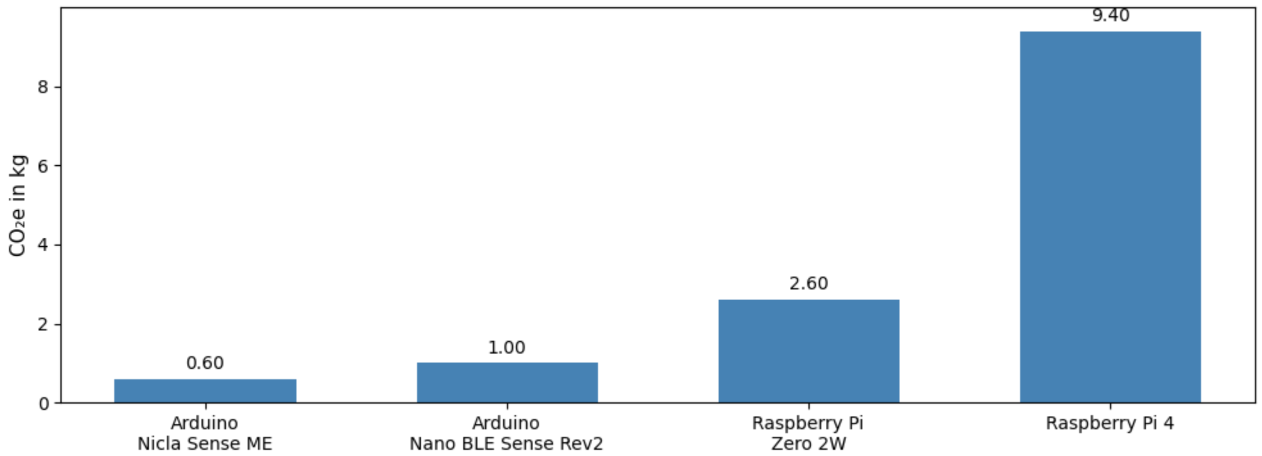


Figure 2 : Manufacturing CO_2e footprint of two sensor nodes and two edge devices

Figure 3 breaks down the components' contribution to the CO_2e footprint of the two sensor nodes. In both cases, the PCB accounts for the largest share, at 86% for the Nicla Sense ME and 78% for the Nano BLE Sense, followed by the chips (ICs) at 13% each. The remaining component categories, each accounting for less than 5%, have been combined into a single category for clarity.

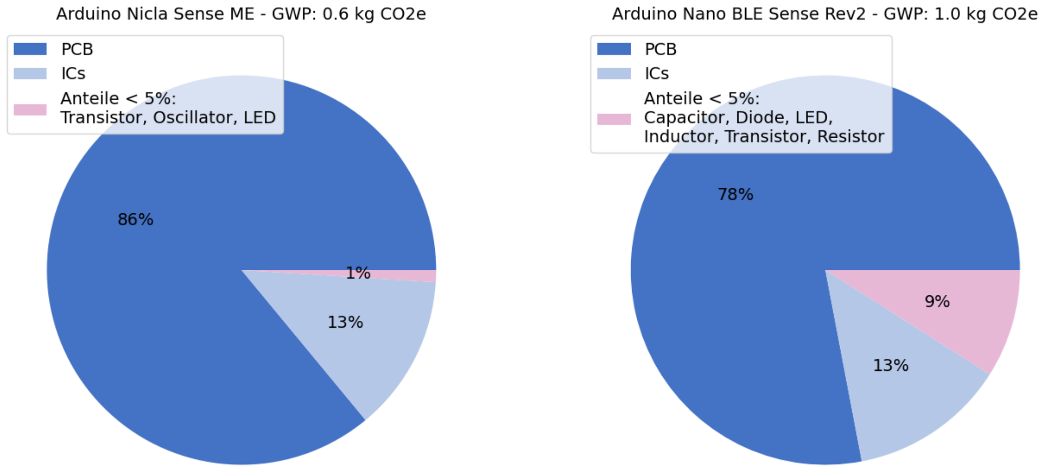


Figure 3 : Comparison of CO_2e component shares between the Arduino Nicla Sense ME (left) and the Arduino Nano BLE Sense Rev2 (right)

4.3. Usage Phase

To determine the operational CO_2e emissions, the power consumption of the devices used was first examined. Here, a distinction can be made between individual analysis and the overall system.
In the individual analysis, the measurement objects are systematically measured independently of one another, i.e., not yet considered in the end application. The purpose of this approach is to first identify the influences of the various configurations in isolation without having to account for many different dependencies. In the analysis of the overall system, the SEC chain is considered as a unit, and relevant findings from the previous individual analysis are applied to measure their impact on the overall system.

Individual Analysis of the Sensor Node and the Edge Component

The sensor node offers various approaches for optimizing power consumption. These can be categorized into disabling peripherals, microcontroller settings, and accelerometer configurations. The results of the investigations are shown in *Figure 4*. The original power consumption without optimization was 13.5 mW in sleep mode and 35.5 mW during data acquisition at an acceleration sensor sampling rate of 200 Hz. Turning off the power LED resulted in a power reduction of approximately 10 mW in both cases. Using the built-in step-down converter

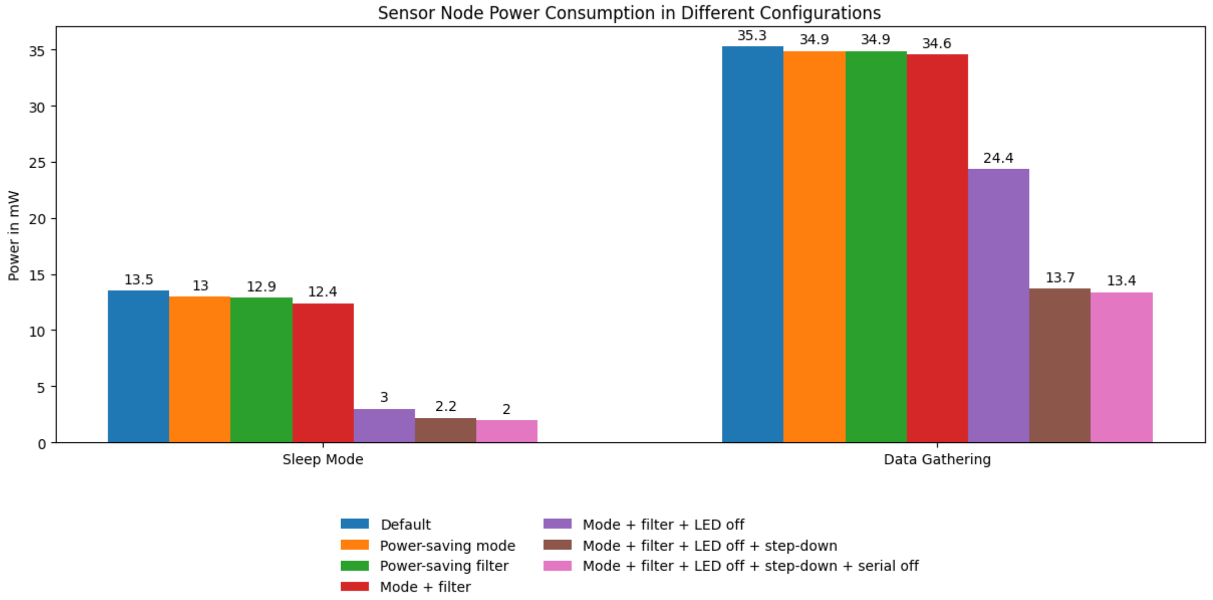


Figure 4 : Power consumption of the sensor node for various configurations in sleep mode and during data acquisition

instead of the low-dropout regulator (LDO) resulted in a power reduction of about 25-45%. The various options available on the sensor element itself for implementing power-saving modes and filter optimizations had little effect on power consumption, as did disabling serial communication.

The Raspberry Pi Zero 2W is more complex and less deterministic due to its operating system. Key options included disabling the HDMI port and LED. Additionally, a firmware called DietPi was tested [6], which is optimized for operation without a graphical user interface (headless). It can be understood as a minimalist operating system in which only the most essential background services run. All tests were conducted in idle mode, i.e., the Edge device was powered on but not performing any active operations. The average power consumption was approximately 1100 mW. Disabling the LED resulted in power savings of 20 mW, while disabling the HDMI port saved 170 mW. The DietPi firmware reduced power consumption by a total of 250 mW to 850 mW, here the disabling of the LED and HDMI port is already implemented at the operating system level.

Total Sensor-Edge(-Cloud) System

When examining the entire chain, the energy consumption of both components (edge and sensor) was recorded in parallel using two PPK2 measuring devices and added together in the following analyses.

Data preprocessing can generally be performed on both the Edge and the Sensor. The placement of computational operations along the SEC chain influences energy consumption in several ways; a change in energy costs is caused both by the computational operations of preprocessing and by the reduced data volume at the transmitter and receiver.
To investigate the impact of sensor-near data preprocessing on power consumption, raw data streaming was compared as a reference to classification using neural networks on the sensor node. A sensor sampling rate of 1600 Hz was used, as higher sampling rate increases the accuracy of the classification results. To compensate for operating system-dependent fluctuations in power consumption at the edge, measurements were recorded over extended periods and the arithmetic mean was calculated.

The DietPi firmware was identified as the most influential factor, with savings under load reaching up to 800 mW. Classification on the sensor further reduced the power consumption of the edge device to 1150 mW, while the sensor node showed no significant change (approximately 47 mW for raw data stream and classification).
The power consumption of the edge device exceeds that of the sensor node by nearly a factor of fifty (2200 mW versus 47 mW); therefore, sensor optimizations had only a minor effect on the overall chain and were neglected in the following calculations. For the overall system, this results in a 47% reduction in power consumption from 2.25 W to 1.20 W, corresponding to a power saving of 1.05 W.
All the optimization measures mentioned are summarized in *Table 1* for the various scenarios.

Table 1 : Optimization measures for power savings in the sensor, edge, and total chain

Optimization	Component	Savings
LED off	Sensor	10 mW
Step-down converter instead of LDO	Sensor	25–45% (power-dependent)
HDMI off	Edge (idle)	170 mW
Edge LED off	Edge (idle)	20 mW
Headless firmware (DietPi)	Edge (idle)	250 mW
Classification on sensor instead of cloud	Total chain (under load)	250 mW
Headless firmware (DietPi)	Total chain (under load)	800 mW

4.4. Impact on CO_2e

From the optimization measures examined (operating system and classification on sensor nodes), the energy savings in CO_2e can be directly derived from the reduction in the average power consumption of the SEC chain and the assumed operating profile. Continuous operation (i.e., 24 hours/day, 365 days/year) is assumed as the reference value for the use of the condition monitoring electronics. This calculation results in an annual savings of 9.2 kWh, which corresponds to just under 3.7 kg of CO_2e. Over a standard service life of 5 years, the more efficient operation would save 18.4 kg of CO_2e. When comparing the CO_2e of component manufacturing (3.6 kg) with that of the usage phase (38.5 kg over 5 years) across the entire lifecycle, it becomes clear that energy consumption is the decisive driver of emissions in the SEC system under consideration starting as early as the first year.

4.5. Lessons learned

The measurement results from the laboratory SEC chain show that, in the architecture under consideration, the edge device clearly dominates the energy consumption of the entire chain and thus the operational CO_2e emissions. While the sensor node operates in the milliwatt range, the power consumption of the edge device is in the watt range, meaning that optimizations on the edge represent the greatest systemic leverage. What is decisive here is not so much the momentary computational demand of individual algorithms as the edge device's constant baseline load, which in continuously operated condition monitoring applications translates directly into energy consumption and CO_2e emissions. It follows that the selection and sizing of edge hardware, as well as the consistent reduction of unnecessary system services, should be considered as early as the design phase. The greatest lever for energy savings would be to completely bypass the edge level and connect the sensor nodes directly to the cloud, provided the use case allows for this.

Measures that reduce the base load without functional limitations have proven particularly effective. These include disabling unused peripherals such as HDMI outputs and status LEDs, as well as operating the edge device in a headless configuration. In this context, the operating system has been confirmed as a key influencing factor: A minimalist operating system with reduced background services not only lowers idle power consumption but is particularly effective under load, as less background activity leads to lower power consumption. From a system-wide perspective, this service minimization, combined with peripheral shutdown, was the primary driver of the observed reduction in power consumption across the SEC chain.

In addition to reducing the base load, the location of data processing significantly influences the energy requirements of the chain. Early preprocessing of measurement data, such as classification at the sensor level, reduces the volume of data to be transmitted and thus lowers communication overhead. This effect is particularly relevant when raw data streaming generates high data rates and the energy requirements of wireless transmission dominate over local computing operations.

5. Case Study 2: CO_2e Footprint of an Asset Tracking Module

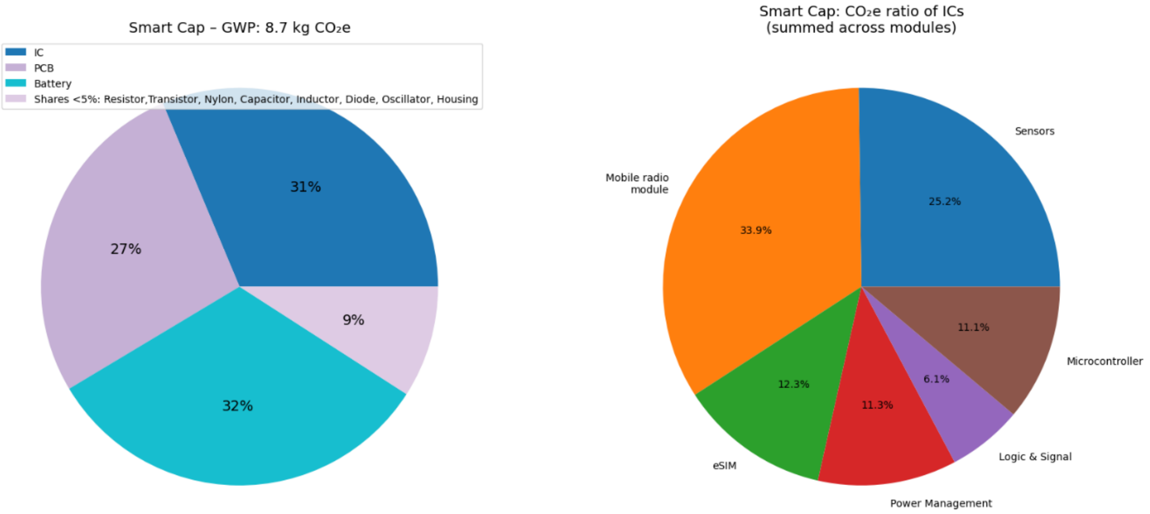
5.1. System Description

In the second case study, a commercial, battery-powered IoT module ("Smartcap" from Packwise) combines sensor nodes and edge computing in a single device [7]. The module is attached to, for example, refillable chemical containers and is used to monitor the condition of the transport container. Unlike the SEC chain in the laboratory from the first case study, this is a largely closed system in which the hardware and firmware are fixed, and optimizations can primarily be made via configurable operating parameters. The module under investigation features sensors for measuring temperature, acceleration, and fill level, as well as a cellular connection for the direct transmission of measurement data to a cloud platform. Both data access and device configuration are controlled via this platform.

The system's operating conditions have a significant impact on the environmental assessment during the operational phase. The battery is neither rechargeable nor replaceable; consequently, no direct emissions are generated during operation, and energy consumption instead has an indirect impact via the device's achievable lifespan. Once the battery is depleted, a new device must be deployed for continued monitoring, the manufacture of which further increases the carbon footprint of the technological solution.

5.2. CO_2e from the manufacturing phase

The CO_2e footprint was derived from the manufacturer's bill of materials. This results in a manufacturing footprint of 8.7 kg CO_2e for the module. *Figure 5 (left)* presents a diagram showing the breakdown of emissions across the different component categories. The battery is the largest single item at 32%, followed by ICs (31%) and the printed circuit board (27%). Other components, such as passive or mechanical components, account for a combined share of approximately 9%. *Figure 5 (right)* also shows which components are primarily responsible for IC emissions. Mobile communications components (communication module and eSIM) account for the largest share at around 46%, totaling approximately 1.3 kg CO_2e. The built-in sensor technology accounts for the next largest share at about 25%, while microcontrollers and power management each contribute about 11%. The smallest category consists of the remaining components, accounting for about 6% in logic and signal processing.


Smart Cap – GWP: 8.7 kg CO_2e

Smart Cap: CO_2e ratio of ICs (summed across modules)

Figure 5 : CO_2e footprint of the IoT module. Left: Breakdown of total CO_2e into various categories such as ICs, PCBs, batteries and others. Right: Proportions of the various ICs to the total IC footprint.

5.3. Usage phase

Since the module does not draw power from the mains, no additional consumption-related CO_2e emissions are accounted for at the point of use during the usage phase. The device's energy requirements are nevertheless critical, as they determine the achievable battery life and thus the frequency of replacement. If the battery is depleted, a new device must be deployed to continue monitoring, thereby incurring manufacturing CO_2e emissions once again. To make different operating strategies comparable, this effect is allocated to annual CO_2e emissions over the expected lifespan by dividing the manufacturing CO_2e emissions by the estimated lifespan and distributing them across the years of use.

Manufacturer specifications regarding battery life are used as a reference for classifying the influencing factors. Packwise notes that battery life depends in particular on activated functions, the number of measurements and transmission cycles, the cellular connection (availability and signal strength), and the ambient temperature. As guidelines, depending on the transmission interval, battery lives of 10.7 years (daily transmission), 4.3 years (three transmissions per day, every 8 hours), and 2 years (six transmissions per day, every 4 hours) are provided. These numbers serve as a plausibility framework in the following, as radio conditions and temperature influence energy consumption and can vary significantly in the field.

Energy measurements taken on the module show a standby power consumption of approximately 0.1 mW during steady-state laboratory operation. Accordingly, the minimum daily energy consumption is approximately 2.4 mWh. The additional energy requirement arises on an event-by-event basis due to measurement and transmission cycles. Significant fluctuations occurred during cellular communication, which is why the values provided were evaluated as averages over repeated cycles. A transmission cycle in the standard configuration, including level measurement, requires approximately 9 mWh; without level measurement, approximately 6.5 mWh. Additional measurement cycles between transmissions are significantly lower, at around 2.5 mWh per measurement. *Figure 6* shows the daily energy consumption for various transmission intervals, broken down into the portions for baseline consumption, radio, and level measurement. All measurements were performed in a stationary state. In real-world scenarios, movements caused by different positioning methods - such as GPS instead of Wi-Fi-based location estimation - could trigger additional radio activity and increase energy consumption.

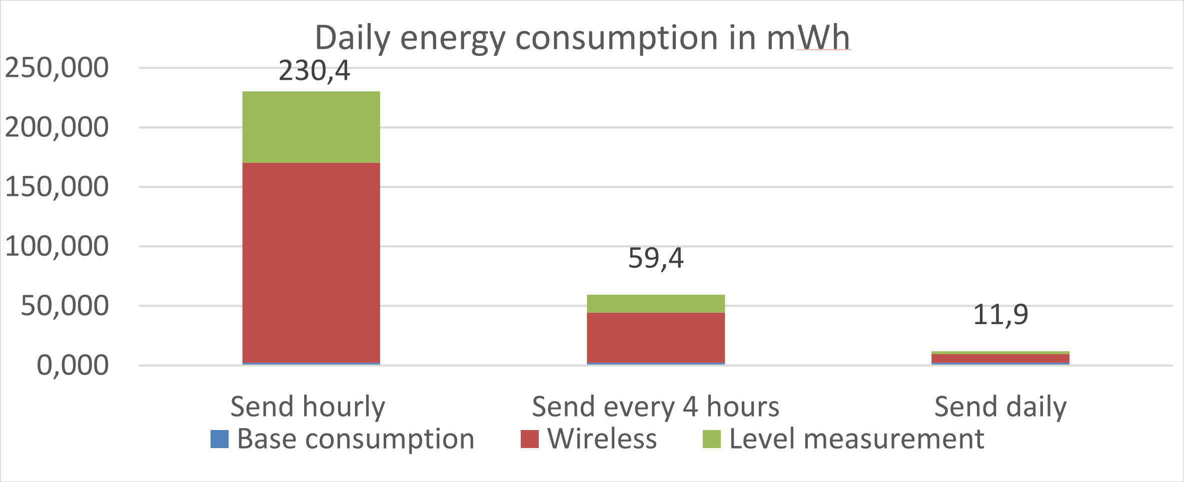


Figure 6 : Daily energy consumption in mWh of the IoT module for different transmission intervals

5.4. CO_2e Impact

In *Table 2*, the respective lifespans were derived based on the measured energy consumption for the various operating profiles, and the manufacturing emissions were converted into annual CO_2e emissions accordingly. For hourly transmission, the expected lifespan is 0.8 years, resulting in annual emissions of 10.8 kg CO_2e. With a 4-hour interval, the service life is 3.5 years (2.5 kg CO_2e/year); with daily transmission, it is 15.7 years (0.6 kg CO_2e/year). With a 4-hour transmission interval without level measurement, CO_2e emissions are already reduced by 28% to just 1.8 kg/year. A similar reduction is achieved by aggregating the measured values every 4 hours, when the data is transmitted only once a day instead of regularly immediately after recording. Comparing emissions with an hourly transmission interval to daily transmission results in a 95% reduction in emissions.

Table 2: Lifespan and annual CO_2e emissions of the IoT module under different operating profiles

Transmission interval	Lifespan [years]	CO_2e emissions [kg/year]
Hourly	0.8	10.8
Every 4 hours	3.5	2.5
Daily	15.7	0.6
Every 4 hours (without level measurement)	4.8	1.8
Daily (aggregated measurements every 4 hours)	4.7	1.8

The deviations in battery life from the manufacturer's projections are plausible, such as radio conditions (cellular network availability, signal strength), temperature, and motion-induced events (varying position determinations, GPS or Wi-Fi-based location estimation) can increase energy consumption, whereas the available measurements reflect a stationary laboratory profile. Additionally, the study did not account for self-discharge or battery aging.

5.5. Lessons learned

In the battery-powered, cellular-based asset tracking system, the CO_2e savings from operation arise primarily from the increase in the service life or usage duration and thus from the replacement rate of the device, not from directly accounted-for grid power consumption. Mobile data transmissions account for the dominant share of energy consumption during use; consequently, transmission frequency is the most reliable lever for extending service life and reducing the annual CO_2e contribution from manufacturing. Strategies that reduce the number of transmissions are particularly effective; this is possible without losing any information content - for example, by aggregating multiple measurements per transmission or using event-based transmission. Functions such as level measurement also influence the energy consumption per transmission and should, where the application allows, be carefully sized and configured. The same principle applies to the use of alarms: if information is sent only when relevant changes occur - such as a change in position or the exceeding of temperature or shock thresholds - frequent transmission of redundant information can be avoided.

In addition, there are further opportunities for optimization at the system design level. Processing the raw data locally on the device to determine the fill level would also make it possible to trigger an alarm in the event of a significant change in the container's fill level. Furthermore, this would reduce data communication and thus energy consumption per data transmission. Additionally, a more compact PCB design would contribute to a further reduction in CO_2e emissions from the manufacturing process. The use of an energy harvester to extend the service life or reduce the size of the battery is also conceivable.

6. Recommendations for reducing the CO_2e footprint

The two case studies illustrate that the most effective levers for reducing the CO_2e footprint depend heavily on the system type. In the grid-connected SEC chain, the CO_2e footprint is determined by energy consumption during the use phase, whereas for the battery-powered, non-serviceable IoT module, manufacturing emissions dominate, and operation primarily affects the annual CO_2e allocation over the product's lifespan. To reduce CO_2e in SEC systems, the respective optimization approaches must always be tailored to the specific use case.

If emissions from energy consumption during the operational phase account for the majority of total emissions, reducing the base load is crucial. In the laboratory SEC chain, the edge component was the dominant consumer because it operates continuously in the watt range, while the sensor node operates in the milliwatt range. It follows that the selection and sizing of the edge platform during the design phase is a primary factor influencing the resulting CO_2e emissions - under suitable conditions, an energy-efficient edge platform should therefore be chosen. If a Linux-based system is used here, continuously running background services are a major consumer and should be optimized by operating in a headless configuration with minimal background services and deactivation of unnecessary peripherals.

At the sensor node level, optimizations are particularly relevant when they reduce the baseline power consumption or make the power supply more efficient without compromising functionality. The first case study suggests that turning off the LED and selecting the voltage converter often offers more leverage than configurations at the sensor element. At the same time, it is to be expected that sensor-level optimizations are often secondary in the overall system as soon as a continuously operating edge device is included in the chain.

Communication strategy is another key factor influencing the energy-efficient and resource-conscious use of the SEC chain. Since data communication involves significant energy consumption, it should be kept to a minimum. Early data processing not only reduces the data stream to be transmitted and the energy required for it but also enables the use of event-driven communication, whereby only non-redundant information would be transmitted. Depending on the use case, significant energy savings can already be achieved without loss of information simply by aggregating measurement data and transmitting it at longer intervals.

Across both use cases, the following guidelines can be formulated: The choice of platform and its sizing must be based on actual demand, as oversizing increases manufacturing and operational costs. The baseline load must be consistently minimized through measures such as reducing peripherals and services, particularly on edge systems. Furthermore, communication should be reduced to the necessary minimum, preferably state- or event-driven, which is primarily supported by early data processing. These principles are broadly applicable but must be balanced against requirements such as information needs and system constraints.

7. Discussion

In this study, CO_2e emissions from manufacturing and usage for sensor nodes and edge devices were quantified. The cloud component was not considered, as reliable metrological measurement and unambiguous attribution in shared cloud infrastructures are only possible to a limited extent. At the same time, it is plausible that the data reduction measures examined in both case studies also result in savings on the cloud side, as less data is transmitted, stored, and processed. The reported CO_2e values should therefore be interpreted as a partial assessment.

Manufacturing CO_2e emissions were estimated on a component-by-component basis within the cradle-to-gate scope and serve primarily to classify orders of magnitude and identify dominant assemblies. Neither were manufacturer-specific process data available, nor were transport, packaging, and end-of-life taken into account. Consequently, the absolute values are subject to uncertainties; however, the relative contributions of key categories (such as battery, ICs, and printed circuit board) remain useful as a guide for design decisions.

For the usage phase, power consumption was measured under laboratory conditions and applied to simplified operating profiles. In real-world applications, temperature, radio conditions, and application-specific activity patterns can significantly alter average power consumption. This applies in particular to mobile communication-based systems, where signal strength, network availability, and retransmissions can strongly influence energy requirements per transmission. The derived absolute annual values should therefore be understood as a reference, while the dominant influencing factors and optimization approaches are transferable.

The practical feasibility of the optimizations also depends on the system type: In open platforms, software, peripherals, and data processing can be specifically adapted, whereas commercial, closed systems often allow only parameterization via measurement and transmission intervals as well as activatable functions. Furthermore, use-case-specific requirements may limit data aggregation and infrequent transmission. Accordingly, the measures presented should be validated with realistic operating profiles wherever possible.

8. Conclusion and Outlook

The two case studies suggest that significant energy and CO_2e savings can be achieved in SEC chains through relatively simple measures. In the grid-powered laboratory SEC chain, savings of nearly 50% across the entire chain were achieved by reducing the edge baseline load and through data-reduction preprocessing. The edge device proved to be the dominant consumer and thus a key lever for operational emissions. In the battery-powered asset tracking module, however, manufacturing dominates the footprint, while during the usage phase, device lifespan is the primary determinant of annual emissions. Here, the communication strategy proved to be the most effective lever: Fewer transmissions significantly reduce the annual CO_2e allocation, with savings of up to 95%.

Across both use cases, the following practical guidelines can be derived: Hardware should be appropriately sized for the application, the baseline load should be consistently reduced, data should be processed as early as possible, and communication should be minimized. These principles are broadly applicable but must be weighed against requirements for latency, data quality, and system constraints in each case.

Future work should systematically incorporate the cloud component to enable a complete end-to-end assessment. Furthermore, field measurements under real-world environmental and radio conditions are useful to validate the transferability of laboratory results. Complementary studies on energy harvesting approaches and low-CO_2e hardware designs are also recommended to investigate further reduction potentials in manufacturing and operation.

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