# EGDC Case study - Ericsson & Kiona: Edge AI Steering Function for District Heating Optimisation in Residential Buildings

March 2026

Case Study Methodology

EUROPEAN GREEN DIGITAL COALITION

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# 1 Introduction

The European Green Digital Coalition (EGDC) is an initiative of companies, supported by the European Commission and the European Parliament, based on the request of the EU Council, which aims to harness the enabling emission-reducing potential of digital solutions on all other sectors.

The main aim of the EGDC is to maximise the sustainability benefits of digitalisation within the ICT sector, while supporting sustainability goals of other key sectors such as energy, transport, agriculture, and construction. The Coalition recognises the need for science-based methods to estimate the reduction and avoidance of greenhouse gas (GHG) emissions by specific ICT solutions across sectors. This will accelerate the sustainability and circular transitions of these sectors while contributing to an innovative, inclusive, and resilient society.

To support the EGDC, a set of case study calculators are developed to provide a practical example of calculating the net carbon impact of a green digital solution in line with the European Green Digital Coalition (EGDC) methodology. This work aims to support the members of the EGDC with Action 2 of the EGDC Declaration.

This case study methodology accompanies the "Ericsson & Kiona – Edge AI Steering Function for District Heating Optimisation" case study calculator and provides further details, additional context and transparency around the case study calculator to ensure the outcomes of the case study are interpreted and used correctly.

EUROPEAN GREEN DIGITAL COALITION

## Disclaimer for European Parliament Pilot Project – European Green Digital Coalition (EGDC) Case Studies

The following disclaimer is intended to provide clarity and context for the case studies prepared as part of the EP Pilot Project, which have showcased the net carbon impact of specific digital solutions using the EGDC ICT Methodology developed during the project:

**1. Purpose of the Case Studies:**
The case studies served multiple purposes, including:

- **Development of the Methodology:** They contributed to the development of the EGDC ICT Methodology. These case studies were conducted concurrently with the methodology's creation and served as a valuable testing ground for its initial formulation.
- **Application Examples:** They provided practical examples of how the methodology can be applied to real-life use cases. These case studies were essential in demonstrating the practicality and effectiveness of the methodology when applied to concrete situations.
- **Identification of Improvement Areas:** By conducting these case studies, we aimed to highlight parts of the calculation in need of improvement. They shed light on the challenges and limitations inherent in using available data and indicated the necessary steps to move towards best practices in assessing net carbon impacts.

**2. Data Quality as a Key Determinant:**
It is imperative to emphasize that data quality is a fundamental determinant of the quality and reliability of the case studies. The accuracy and completeness of the data used significantly influence the outcomes and findings of these case studies.
It is essential to acknowledge that the data available for each case study may differ in terms of accuracy, granularity, and coverage. As a result, the case studies may not necessarily represent the best practice application of the EGDC ICT Methodology. Instead, they reflect the application of the methodology at various stages of data availability.

**3. Liability for Errors/Omissions:**
While reasonable steps have been taken to ensure that the information contained within the case studies is correct, the EGDC gives no warranty and makes no representation as to its accuracy. We accept no liability for any errors or omissions that may be present in the case studies, methodology, or related information. Users and readers are advised to exercise their judgment and seek further clarification if needed, as the information provided may evolve over time and depend on external factors beyond our control.

**4. Appropriate Use of the Case Study Calculators:**
The case study calculators are intended for educational and informational purposes. They rely on certain assumptions and input data to generate results.
The results of the calculators are specific to the implementation of the ICT solution and may not be representative for other implementation contexts.
As such, it is imperative for users to refrain from directly extrapolating these results to ICT solutions or implementation contexts that may seem conceptually similar.
Instead, users are advised to use the calculators as a means to understand the practical application of the EGDC ICT Methodology, thereby equipping themselves with the knowledge required to develop customized calculators specifically tailored to their unique ICT solutions and implementation circumstances.

In conclusion, these case studies provide valuable insights into the calculation of the net carbon impact of digital solutions through the practical application of the EGDC ICT Methodology. However, it is vital to exercise caution when interpreting the results, considering the variances in data quality and the evolving nature of the methodology. The findings are indicative of the methodology's potential and its room for refinement as we work towards more accurate and comprehensive assessments of net carbon impacts.

## 2 Results

**ICT Solution and assessment overview**

The Kiona Edge AI Steering Function solution is a digital building energy optimisation solution that uses temperature and humidity sensors, Edge Hubs, connectivity networks, and a cloud-based AI platform to optimise district heating in residential buildings. The AI steering function predicts forward heating demand based on building physics, weather conditions, and thermal capacity, enabling more efficient heat supply and improved indoor climate comfort. This case study is an expost assessment covering 356 residential buildings located in Sweden and Finland, all heated by district heating, using one year of operational data (2022). The assessment compares actual energy consumption with AI steering to a hypothetical reference scenario without the solution.

**Quantified impacts**

| | |
|---|---|
| Assessment period: | 1 year (rolling 12-months) |
| Net carbon impact: | -1,113 tCO2e (location-based) |
| Net carbon impact range: | -1,027 to -1,199 tCO2e (location-based) |
| Net impact per sqm: | -0.87 kgCO2e/m2/year |

**Organisational contribution**

Kiona is responsible for developing, deploying, and operating the Edge AI building management solution, while Ericsson enables the deployment and operation of the solution through the provision of ICT infrastructure and connectivity. The contributions of both organisations align with A-level and B-level classification respectively under ITU-T L.1480, reflecting their role in implementing and enabling the integrated ICT solution within a real-world deployment context.

**Other identified impacts**

The optimisation of building heating results in significant energy cost savings for building owners and tenants. Potential rebound effects associated with the use of financial savings were identified. However, these were not quantified and were addressed through sensitivity and scenario analyses. The solution also enables more stable indoor temperatures, reduces peak heating demand, and may contribute to peak load shifting, potentially lowering reliance on fossil fuel-based reserve generation during high demand periods. These additional system level benefits were identified and assessed qualitatively but not quantified due to data limitations.

# 3 Methodology

**Abbreviations**

| | |
|---|---|
| **AI** | Artificial Intelligence |
| **BAU** | Business-as-usual |
| **EF** | Emission Factor |
| **GHG** | Greenhouse Gas |
| **ICT** | Information and Communication Technologies |
| **IoT** | Internet of Things |
| **ISO** | International Organization for Standardization |
| **LCA** | Life Cycle Assessment |
| **T&D** | Transport and Distribution |
| **W** | Watt |
| **WTT** | Well-to-Tank |

# 1. The goal of the assessment

## 1.1. Assessment aim and type

This assessment aims to assess the effect the implementation of Kiona Edge's Artificial Intelligence (AI) Steering Function has on the district-heating energy consumption of 356 residential buildings located in Finland and Sweden. The assessment takes an ex-post perspective, i.e., aims to assess the impact of the solution for a past period.

The specific guidance provided by the Rec. ITU-T L.1480 for assessments of the greenhouse gas (GHG) emissions of a specific ICT solution implemented in a specific context is followed for the development of this case study and this report has been aligned to the EGDC methodology.

This case study accompanied by communications material on the avoided emissions of the Edge AI district heating steering solution was developed with the purpose of communicating the solution's net avoided emissions impact, capturing actual contextual conditions, and detailing the methodology applied to players along the solution's value chain. This case study is accompanied by an MS Excel document with all the supporting calculations.

The results of the original study published in 2023 differ marginally to those outlined in this EGDC methodology and accompanying calculator. However, the difference is not material. The difference is due to the underlying emission factors having been updated to use public sources for EGDC as the EGDC calculator will be published. The original study relied on EcoInvent emission factors, which are subject to licensing restrictions and therefore could not be used in the publicly available EGDC model.

Since the original study publication in 2023, the case study has been reviewed for the purposes of EGDC to ensure the assumptions estimation methods and data within the calculation remain valid.

# 2. The scope of the assessment

## 2.1. Edge AI Steering Function for building heating management

Kiona Edge is a cloud platform for technical property management and energy optimisation with an integral Artificial Intelligence (AI) steering function. The AI steering function within Edge contains a mix of data and smart algorithms which constantly improve the energy optimisation of individual properties. The AI steers buildings by calculating the forward temperature and energy needs using an ENLOSS model (Taesler & Andersson, 1984,). The ENLOSS program accounts for outdoor temperature, wind and solar radiation to calculate heat losses and gains, which in turn are used to predict future heating energy demand and control buildings' heating system (Kalagasidis A. S., 2006). Kiona has developed a function, with the help of building physicists, to convert the energy needed for heat into a simulated outdoor temperature. This is done via a heating curve graph that correlates forward temperature, or the estimated supply temperature needed, and building energy as a function of the outdoor temperature. The outdoor temperature is simulated and used by buildings' heating centre to set the forward temperature for heating. This optimised forward temperature results in more efficient building heating. The main second order effect is, therefore, the optimised building heating needs, and the consequent reduction in GHG emissions from the decreased energy use sourced from district heating. The building optimization solution is directly related the use stage emissions of the buildings sector.

The geographical coverage of the assessment is Finland and Sweden, as this is where the bulk of Kiona's clients have residential buildings. All buildings in the case study consistently and exclusively used district heating as their heat source, which remained consistent throughout the evaluation period. This also impacted the emission reduction potential. Ninety five percent of Kiona's customers in Sweden and Finland use district heating showing district heating is a representative heating source. The remaining five percent of Kiona customers were not included in the sample due to lower data quality.

The temporal coverage of the assessment considers a rolling 12-month baseline for the year of 2022, consisting of hourly measurements for the preceding 12 months. Thus, the assessment covers a full year's data.

For this assessment, primary data was collected from the actual implementation of the Edge AI steering function in Kiona's customers' buildings and, where necessary, secondary data from other reliable sources was used to supplement data gaps.

The solution assessment takes an LCA approach in which associated life cycle processes are considered.

Kiona is the building management solution provider and is responsible for developing and deploying the solution. This aligns with A-level classification as defined by ITU-T L.1480 (contribution of implementing the integrated solution or the innovation of the solution). Ericsson enables the deployment and operation of the solution through the provision of ICT infrastructure and connectivity. This aligns with B-level classification as defined by ITU-T L.1480.

**Table 1. Solution characteristics for Case Study**

| Characteristic | Description |
|---|---|
| **Main function** | A heating energy optimization solution in buildings delivered using a cloud platform with an integrated AI steering function. For this case study the source of heating is exclusively district heating. |
| **Baseline** | A theoretical baseline is established by calculating the quantity of district heating required to heat a home from a simulated outdoor temperature without the AI steering function.<br>Note: The simulated outdoor temperature is the one calculated by the AI steering function itself. |
| **Measured data** | Primary data on the actual district heating required to heat homes with the AI steering function and simulated data on the district heating consumption without the AI steering function.<br>Primary data on the Kiona solution itself, including its components and material composition. |
| **Calculated reductions** | The difference between the simulated district heating energy without the AI from the theoretical baseline and the actual measured district heating energy consumed with the AI.<br>To calculate the net carbon impacts, the aggregated first order effects of the Kiona solution are subtracted from the second order effects. |
| **Building Type** | This case study only includes residential buildings. |
| **Geographical coverage** | Sweden (275 buildings), Finland (81 buildings) |
| **Coverage of heating types** | This case study only includes district heating. |

## 2.2. Functional Unit

The functional unit is one square meter ($m^2$) of residential building area heated by district heating in Sweden and Finland in 2022.

The reference flow represents the energy from heating (kWh) per square meter of residential building area and the GHG emissions arising from the district heating used ($kgCO_2e$) per square meter for 2022.

## 2.3. Assessment perspective

The assessment applies an ex-post perspective to calculate the estimated actual effect via a hypothetical reference scenario and the actual solution scenario. This perspective has been chosen due to the retrospective nature of the assessment as the solution has been implemented so actual data on its deployment and operation are available. These actual measurements are used to develop the hypothetical reference scenario which represents the before implementation scenario of the solution.

The assessment's sole focus is on the effect of using the Edge AI steering function.

## 2.4. Composition of the Edge AI Steering Function

The Edge AI steering function is part of the Kiona Edge System which is comprised of three main building blocks: building connectivity, AI-based optimisation and data consolidation.

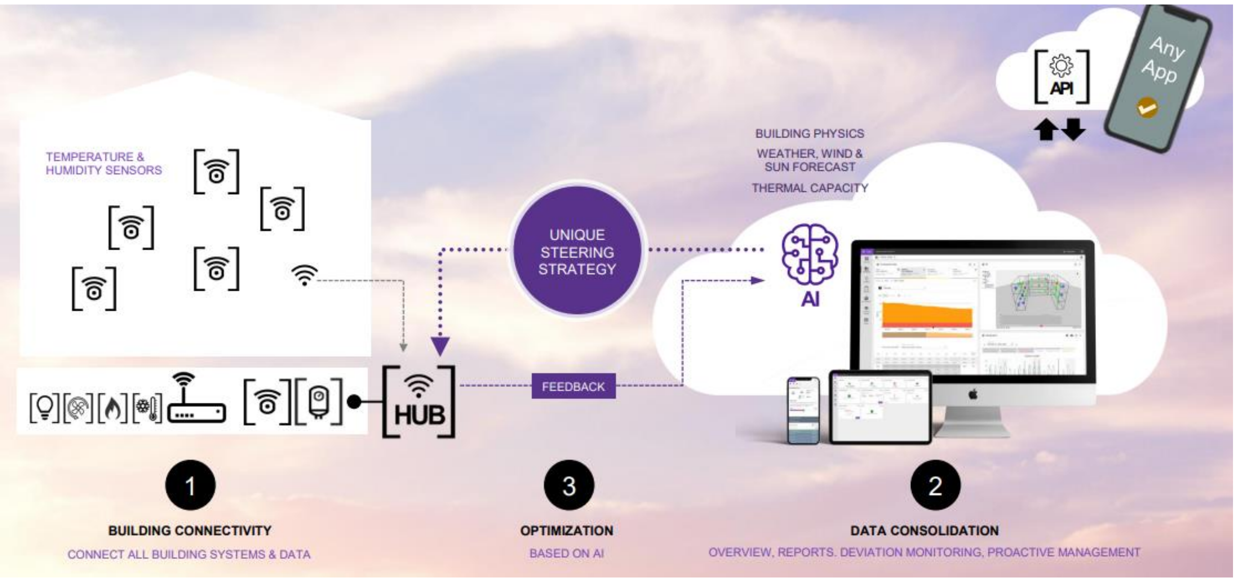


Figure 1. The Kiona Edge System

The building connectivity encompasses all the systems within the building and the data these provide that are necessary for the Edge AI Steering functionality. This includes temperature and humidity sensors which measure the indoor building temperature and humidity.

AI-based optimisation relates to the hardware that makes up the AI system, and the AI software that develops a unique steering strategy, which accounts for building physics, weather, wind and sun forecasts, and buildings' thermal capacity. A feedback loop is created which further optimises the steering. These functionalities are enabled through Edge Hubs which act as gateways to connect the data transmissions between the building sensors, the network, and the Edge platform.

Data is consolidated, analysed, and communicated on Kiona's cloud-based Edge platform. End-users access the platform through devices such as personal computers or phones.

**Table 2. Edge AI components**

| Component | Description | Life cycle stages | Comments |
| --- | --- | --- | --- |
| **Edge Hubs** | Edge Hubs are gateways that are installed in the buildings that transmit the building data to the Edge platform. | Raw materials acquisition | Included in the calculation of the component's embodied emissions. |
| | | Production | Included in the calculated embodied emissions of the component. |
| | | Usage and end-of-life treatment | Edge Hubs have a 15-year lifetime, which is used to allocate the component's lifecycle stages to yearly emissions.<br>Installation of Edge Hubs are simple and do not require any special tools or expertise. It is assumed that emissions from installations are negligible and so are excluded. |
| | | Transportation | Included in the calculated embodied emissions of the component. |
| | | Use of energy | The Edge Hub's maximum daily energy consumption (10W) is assumed in the part's use-phase calculations. |
| | | Waste treatment | It is conservatively assumed that no material of the sensors is recycled. |
| **Sensors** | Temperature and humidity sensors are installed inside | Raw materials acquisition | Included in the calculated embodied emissions of the component. |

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| | the buildings to monitor the building indoor climate. | Production | Included in the calculated embodied emissions of the component. |
| | | Usage and end-of-life treatment | Installation of sensors are simple and do not require any special tools or expertise. It is assumed that emissions from installations are negligible and so are excluded.<br>Temperature and humidity sensors are battery operated so it is assumed there are no additional use-phase emissions.<br>It is assumed batteries do not need to be replaced during sensors' lifetime.<br>Sensors have a 10-year lifetime, which is used to allocate the component's lifecycle stages to yearly emissions. |
| | | Transportation | Included in the calculated embodied emissions of the component. |
| | | Use of energy | Battery-powered, and batteries are assumed to last throughout the lifetime, so no charging or use-phase emissions are accounted for. |
| | | Waste treatment | It is assumed that no material components of the sensors are recycled. |
| **IoT Accelerator Platform** | The IoT accelerator platform is a connectivity management platform service. It is made up of a core network (including data centres) through which all IoT devices, including Kiona's are connected, enabling the | Raw materials acquisition | The embodied emissions have been derived based on the estimated relation between embodied and use stages globally 2020 (based on a submitted research paper by Ericsson and Telia), recalculated with the Swedish electricity mix. |
| | | Production | |
| | | Usage and end-of-life treatment | |
| | | Transportation | |
| | | Use of energy | The electricity consumption of the IoT accelerator has been derived based on actual electricity usage for Stockholm site for 2022, and Amsterdam |

| | | | |
|---|---|---|---|
| | transmission of data between the enterprises and communication service providers within the network. | | site has been derived based on comparison of HW setup between the two sites. Kiona's share of the IoT accelerator has been derived after allocating the electricity consumption based on subscriptions and data traffic and of which the highest value was selected based on conservativeness. |
| | | Waste treatment | Excluded |
| **Radio Network** | The radio network encompasses the network energy consumption from mobile core networks, base stations and other network components which are necessary for Kiona's devices to communicate. | Raw materials acquisition | Kiona's share of the operator´s embodied emissions have been derived based on estimated relation between embodied and use stages globally 2020 (submitted research paper by Ericsson and Telia), recalculated with Swedish electricity mix[1]. |
| | | Production | |
| | | Usage and end-of-life treatment | |
| | | Transportation | |
| | | Use of energy | For the use-phase, Kiona users have been recalculated into a corresponding number of typical network subscriptions and the typical electricity intensity per user in Sweden has been applied for both Sweden and Finland as a proxy but applying the Finish electricity emission factor. Typical Swedish electricity and traffic intensity values are derived based on PTS statistics[2]. Publicly available |

[1] https://energyplaza.vattenfall.se/blogg/epd-ger-forutsattning-for-klimatneutralitet

[2] PTS, The Swedish Post and Telecom Authority, Statistics Portal, 2022, https://statistik.pts.se/svensk-telekommarknad/tabeller/marknadenfor-elektronisk-kommunikation/tabell-1-nyckeldata/

| | | | |
|---|---|---|---|
| | | | electricity emission factors for Sweden[3] and Finland[4] are used. |
| | | Waste treatment | Excluded |
| **Google cloud platform** | Google's cloud platform is a suite of cloud computing services. Kiona's Edge platform runs on Google cloud. | Raw materials acquisition | For the cloud emissions, Kiona's share of the cloud platform footprint is apportioned based on its amount of Edge Hubs. The footprint is provided by Google Cloud following a location-based approach, its figures are used in the calculations. |
| | | Production | |
| | | Usage and end-of-life treatment | |
| | | Transportation | |
| | | Use of energy | |
| | | Waste treatment | Excluded |

**Usage scenario**

Typically, a new Kiona client will set up their Edge AI solution by installing an Edge Hub and temperature and humidity sensors in their building. These devices are interconnected via an existing wireless meter bus which enables the sensors to transmit data to the Edge Hubs. The Edge Hubs communicate the sensor data to the cloud platform via IoT accelerator platform and underlying radio network. Based on the building physics, weather, wind and sun forecast, and thermal capacity, the AI steering function calculates a forward temperature based on a simulated outdoor temperature. The heating centre effectuates a building-specific steering strategy based on the calculated forward temperature, and continually steers the building's heating energy supply to an optimised level. A feedback loop is created with the historic and current data which further optimises the steering of the building. The Kiona Edge platform consolidates, analyses, and communicates the optimal building temperature and presents this through the platform interface which is accessed by end-users.

[3] https://energyplaza.vattenfall.se/blogg/epd-ger-forutsattning-for-klimatneutralitet

[4] https://www.fingrid.fi/en/electricity-market-information/real-time-co2-emissions-estimate/

## 2.5. The reference scenario

The reference scenario is the hypothetical building heating consumption of each of Kiona's residential buildings with district heating in Sweden and Finland in 2022, the baseline year, without the presence of the AI steering function. The theoretical baseline is back-calculated on a rolling 12-month basis by Kiona's Edge AI.

Note: This is a special situation where the baseline is dependent on the solution itself. Ideally those should have been independent.

District heating networks supply energy sourced from heat to buildings in which its residents/building managers can control their heating energy usage through a heat interface unit (HUI). Adding the AI system to the district heating network allows for the heating energy usage to be optimized by measuring the outdoor temperature to calculate the expected outdoor temperature which manages the heating energy supplied to the building.

The forward heating consumption that represents the reference scenario is based on a simulated outdoor temperature. This theoretical outdoor temperature is compared to the actual outdoor temperature collected from meters. Both the reference and actual heating consumption is normalised for heating degree days and cooling degree days to capture a comparative representation of buildings' heating consumption. A rolling 12-month baseline is used for the comparison of the actual heating energy consumption and theoretical baseline.

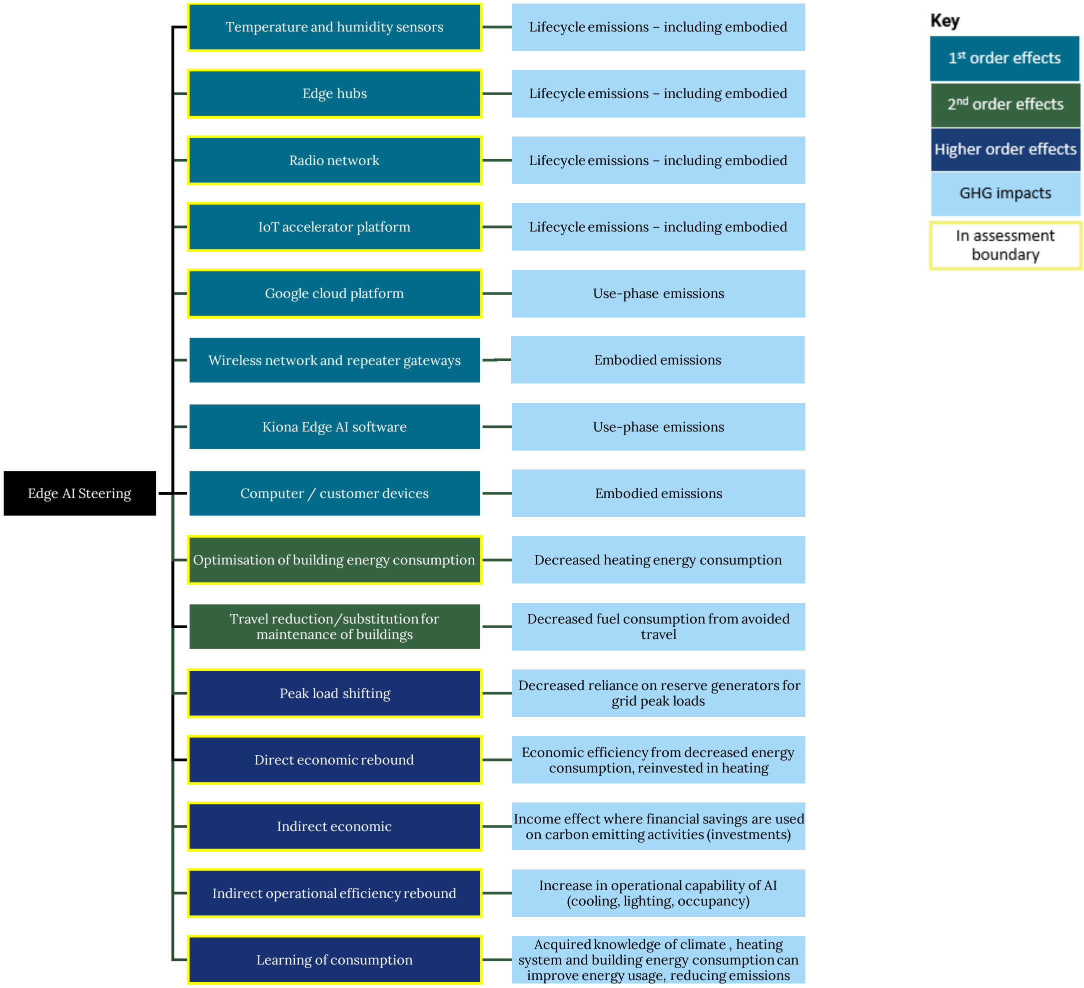
Data is collected on the buildings' build year, glazing type and ventilation type as these variables impact heating usage. The building characteristics provide further context around the variables that impact potential avoided emissions and add a level of analysis to the assessment in terms of identifying trends and patterns amongst the dataset and create an additional lens through which to analyse the buildings.

For the uncertainty analysis, Kiona provided data on 5 buildings that had undergone little to no refurbishments. These buildings and their corresponding savings were used as a control to compare and sense-check the savings experienced in the dataset. The savings from the AI in the control group (hypothetical building consumption) underestimated the savings relative to the baseline with primary 'before AI installation' data. This approach provides confidence in the reference scenario, as the savings relative to the baseline are underestimated and there is only an approximate 7% variation across the five reference buildings, as demonstrated in the uncertainty analysis in section 5.4.

## 2.6. Consequence Tree

First order effects, second order effects, and higher order effects of the Edge AI Steering Function have been identified and documented as a Consequence Tree:

### Figure 2. The Consequence Tree




In Table 4 the effects visualised in Figure 2, the consequence tree, are outlined. The effects are categorised by type of effect and are described and assessed based on the timespan of their impact where short is immediate, medium is over multiple years and long is over many years (more than 10).

**Table 3. Assessment of effects in the consequence tree**

| Effect type | Effect | Description | Timespan |
|---|---|---|---|
| **First Order Effects** | Edge Hubs | The first order effect includes the Edge Hubs' lifecycle emissions. | Short |
| | Sensors | The first order effect includes the sensors' lifecycle emissions. | Short |
| | IoT accelerator platform | The first order effect is the platform's energy use and embodied emissions. | Short |
| | Radio network | The first order effect is the network's energy use and embodied emissions. | Short |
| | Google cloud platform | The first order effect is the platform's lifecycle emissions. | Short |
| | Kiona Edge software | The first order effect is the software's lifecycle emissions. | Short |
| | End-user device interface (e.g., PCs, tablets, smartphones) | The first order effect is the device's use-phase emissions. | Short |
| | Wireless network and repeater gateways | The first order effect is the device and network's lifecycle emissions. | Short |
| **Second Order Effects** | Decreased building heating energy consumption | The second order effect is the change in greenhouse gas emissions related to the change energy consumption due to the Edge AI. | Short |
| **Second Order Effects** | Decreased fuel consumption from avoided travel | The second order effect is the change in greenhouse gas emissions related to the change in fuel consumption. | Medium |
| **Higher Order Effects** | Decreased reliance on reserve generators for grid peak loads (when using electricity for heating) | The higher order effect is the change in greenhouse gas emissions related to the change in usage of reserve generators. | Medium/Long |
| **Higher Order Effects** | Tenants paying for utilities gain economic efficiency and use saved income on | The higher order effect is the greenhouse gas emissions related to activities undertaken because of the economic efficiency. | Medium |

| | | | |
|---|---|---|---|
| | carbon emitting activities (indirect rebound) | | |
| **Higher Order Effects** | Property owners paying for utilities use extra income on carbon emitting activities (indirect rebound) | The higher order effect is the greenhouse gas emissions related to activities undertaken because of the economic efficiency. | Short/Medium |
| **Higher Order Effects** | Potential increase in operational capacity of AI (cooling, lighting, occupancy) | The higher order effect is the greenhouse gas emissions related to the increased operational capacity of the AI and its energy usage. | Long |
| **Higher Order Effects** | Improved building energy consumption, heating system and climate knowledge | The higher order effect is the greenhouse gas emissions related to the activities or operations impacted by the knowledge gained. | Medium/Long |

The consequence tree reflects the case study and actual solution effects, not the general use of this type of solution. For example, the direct economic rebound effect is related to which stakeholder has the burden of the utilities (property owner or tenant) in residential buildings.

Higher order effects deemed improbable or of low materiality, such as the need to expand network infrastructure, were excluded.

Below are the contextual factors, the factors that impact the reference scenario and future use of the ICT solution. The factor and perspective are detailed as well as an assessment of the factor, including the importance, probability of occurring and addressability.

**Table 4. Contextual factors**

| Factor | Perspective | Assessment |
|---|---|---|
| Economic downturn will incentives tenants/building owners to reduce emissions | Party responsible for utility bill (tenant or building owner) | Importance: high (will affect use)<br>Probability: high<br>Addressability: medium (impact effect when it occurs) |
| Increased heating cost due to political factors (e.g., natural gas crisis stemming from Ukraine war) incentivising tenant/building owners more to reduce emissions | Party responsible for utility bill (tenant or building owner) | Importance: high (will affect use)<br>Probability: high<br>Addressability: medium |
| More stringent environmental laws will incentivise tenants/building owners to reduce emissions | Party responsible for utility bill (tenant or building owner) | Importance: high<br>Probability: medium<br>Addressability: medium |
| Heating energy generation and supply mix in the region depending on how low the emission factor is will incentivise more or less use | Party responsible for utility bill (tenant or building owner) | Importance: high<br>Probability: medium<br>Addressability: low |
| Tenant/building owner interest in climate beneficial activities | Party responsible for utility bill (tenant or building owner) | Importance: medium<br>Probability: medium<br>Addressability: low |
| Decreased energy usage/demand due to the economic environment, as economy-wide impacts, such as an increase in heating prices and financial constraints, can impact tenant/building owners' behaviour. | Party responsible for utility bill (tenant or building owner) | Importance: low<br>Probability: medium<br>Addressability: low |
| Decreased need for energy/heating due to environmental changes, such as an increase in temperature due to climate change can impact tenant/building owners' behaviour. Higher outdoor temperatures can lead to | Party responsible for utility bill (tenant or building owner) | Importance: medium<br>Probability: low<br>Addressability: low |

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|---|
| decreased need and use of heating. The effect’s coverage is likely to be large, resulting in a greater impact. |

## 2.7. Effects to be quantified

**Table 5. First order effects**

| Effect | Relative Magnitude | Inclusion / Exclusion | Justification for exclusion |
|---|---|---|---|
| **Edge Hubs** | Medium/High | Included | |
| **Temperature and humidity sensor** | Medium/High | Included | |
| Wireless network and repeater gateways | Low | Excluded | Uncommonly, an additional or repeater gateway is needed for the sensors and Edge Hubs to transmit data correctly. These repeater gateways connect to an existing wireless network within the building. This additional installation of components is not usual and expected to have very low materiality. |
| **Google cloud platform** | Medium/Low | Included | |
| **Radio Network** | Medium | Included | |
| **IoT Accelerator platform** | Medium | Included | |
| Personal Computers | Low | Excluded | Data availability is low due to the difficulties in quantifying the energy use of PCs solely for accessing the Edge platform. The relative magnitude related to the use of computers to access the interface by end-users is also expected to be low as it is not expected the platform will be accessed frequently and for long periods of time. Therefore, the materiality of the emissions impact of the PCs is expected to be low and so excluded on de minimis. |

Table 6. Second order effects

| Effect | Relative Magnitude | Exclusions |
|---|---|---|
| **Optimisation of building energy consumption** | High | |
| Travel reduction/substitution for maintenance of buildings | Medium | Not considered in the assessment boundary because the study focuses on the building energy consumption. |

The quantification of higher order effects goes beyond the specifications of this assessment's depth.

## 2.8. Solution and reference scenario boundaries

The reference scenario boundary is the theoretical heating energy consumption of the residential buildings in Sweden and Finland without the AI steering function in 2022. The assessment focuses on buildings heated by district heating.

In setting the solution boundary it was important to isolate the impact of the solution and ensure the different features that could potentially influence the GHG emissions impact within the boundary were identified (e.g., building glazing and ventilation type).

The consequence tree displays a thick yellow outline around the effects that fall within the boundary of the assessment. The boundary of the first order effects includes the components' lifecycle emissions based on primary data for the device material make-up and energy use, supplemented by secondary sources for the material, electricity, and disposal emission factors. The second order effects focus on the heating energy consumption of buildings before and after the solution, for which primary data was provided by Kiona from its Edge platform.

Higher order effects fall outside of the solution boundary for this assessment.

# 3. Modelling, data collection and calculation

## 3.1. Overall usage of Edge AI steering function

The scenario under assessment concerns the heating energy consumption of buildings with and (assumed) without the solution for a defined data set of 356 buildings in Finland and Sweden. The hypothetical baseline scenario has been normalised to account for variations of usage, by using degree days to account for temperature changes over time.

## 3.2. Quantifying the aggregated first order effect

The first order effects are calculated based on the life cycle emissions of the Edge Hubs, temperature and humidity sensors, the Google cloud network, radio network and the IoT accelerator. An underlying assumption for all first order effects is that the embodied emissions include the raw material acquisition and production life cycle stages.

For the sensors, the material breakdown and corresponding material weights were provided by Kiona. The appropriate emissions factors were applied to each material to calculate the component's embodied emissions. As the installation of the sensors is simple and does not require any special tools or expertise, it is assumed that emissions from installations are negligible and are excluded. As the sensors are battery powered, the embodied and disposal emissions of the batteries are accounted for, but the use-phase emissions are zero. It is also assumed that no materials that make up the sensors are recycled and that 100% of materials go to landfill. The corresponding disposal emission factors (EF) are also applied to obtain the total lifecycle emissions of the device. Dividing the total lifecycle emissions by the sensor lifetime provides the annual emissions per sensor. To calculate the lifecycle emissions of the Edge Hubs, a similar approach is taken for the embodied, installation and disposal emissions, however use-phase emissions are also calculated assuming a maximum daily energy consumption of 6 Watt/day and that Hubs operate 24/7. The specifications around the energy consumption and material breakdown of the Edge Hubs were provided by Kiona. Annual use-phase emissions are calculated for both Sweden and Finland by applying the corresponding emission factors, following the location-based approach for both geographies. The annual emissions per Edge Hub therefore include the embodied, disposal and use-phase emissions to account for the device's whole lifecycle. Installation is considered to be simple and so installation emissions are assumed to be zero.

The radio network's emissions were derived from operators' embodied emissions and use stages globally in 2020 (submitted research paper by Ericsson and Telia). Kiona's share of the radio network emissions was estimated based on the relationship between the embodied and uses stages and recalculating it to apply the Swedish and Finish electricity mix where appropriate[5]. For the use-phase, Kiona users have been recalculated into a corresponding number of typical network subscriptions and the typical electricity intensity per user in Sweden. Typical Swedish electricity and traffic intensity values are derived based on PTS statistics[6]. The Swedish figures were used as proxies for Finland. Multiplying the total number of Kiona subscriptions recalculated to average subscriptions by the electricity intensity per subscription, results in Kiona's share of the network electricity consumption in kilowatt hours. This value is then multiplied by the Swedish or Finish grid factor when taking the location-based approach. A multiplier of 9.3 was derived based on literature to calculate the embodied emissions of the radio network based on the network's electricity related emissions. For the use-phase, Kiona users have been recalculated into typical network subscriptions and the typical electricity intensity per user in Sweden[7] and Finland was applied using the countries' electricity mix to follow a location-based approach respectively.

For the IoT accelerator, Kiona's share has been derived based on the actual electricity usage of Ericsson's Stockholm site for 2022, and that of the Amsterdam site has been derived based on a comparison of the hardware setup between the two sites. Allocation based on subscriptions, data and revenue was performed and the highest value was selected based on conservativeness. Each sites' annual electricity consumption was multiplied by its corresponding electricity emission factor based on the sites' location, applying the grid mix to follow the location-based approach. For the embodied emissions, the same 9.3 factor was used as that for the radio network embodied emissions, is multiplied by the sum of the annual electricity emissions of both sites to obtain the embodied emissions of the IoT accelerator.

Google provided Kiona's total usage share of the cloud's footprint emissions. Kiona provided the total amount of Edge Hubs in operations as well as the number of Edge Hubs in the assessment dataset. Using the total number of Edge Hubs, the google cloud

[5] https://energyplaza.vattenfall.se/blogg/epd-ger-forutsattning-for-klimatneutralitet

[6] PTS, The Swedish Post and Telecom Authority, Statistics Portal, 2022, https://statistik.pts.se/svensk-telekommarknad/tabeller/marknadenfor-elektronisk-kommunikation/tabell-1-nyckeldata/

[7] PTS, The Swedish Post and Telecom Authority, Statistics Portal, 2022, https://statistik.pts.se/svensk-telekommarknad/tabeller/marknadenfor-elektronisk-kommunikation/tabell-1-nyckeldata/

emissions were apportioned to reflect the percentage of Edge Hubs in the dataset. Then, the annual emissions per Edge Hub were calculated using the location-based approach.

The radio network, IoT accelerator and Google Cloud emissions were allocated to the buildings based on their number of Edge Hubs, as the Edge Hubs are connected to the network and platforms and are the central devices that gather and retain the buildings' data.

The aggregated first order effect is the sum of all the first order effects, namely the annual emissions from the sensors, Edge Hubs, network, IoT accelerator platform and Google Cloud. These are calculated for each individual building for all buildings in the dataset. The location-based approach was used as it was deemed most appropriate, specifically as the first order effect involved calculating use-phase emissions. There was supplier specific information available for the district heating suppliers, however, no such data was requested or publicly available for the radio network or IoT accelerator.

## 3.3. Quantifying the second order effect

The change in GHG emissions representing the second order effect is the difference between the reference scenario and the scenario in which the solution has been implemented. The data provided included the district heating energy consumption (kWh) of each building with the AI steering, representing the solution scenario, as well as without the AI steering to represent the reference scenario. The area of each individual building in the dataset was also provided in square meters.

To derive the reference scenario district heating energy consumption per square meter, the hypothetical building district heating energy consumption without the AI (see section 2.5) was divided by the building area.

The district heating energy savings per square meter of each building are calculated as the difference between the building district heating energy consumption with and without the steering function, divided by the area of the building. The district heating energy savings are multiplied by the corresponding country specific emission factor to derive the second order effect per square meter of each building. The change in greenhouse gas emissions per square meter is the difference between the emissions of the reference scenario and the emissions of the scenario with the AI steering.

## 3.4. Deriving the net carbon impact

The net carbon impacts, i.e., the remaining second order effect once the first order effect has been taken into account, are calculated using a location-based approach by subtracting the annual aggregated first order effects from the change in GHG emissions of each building. Moreover, the net annual second order effect per square meter is calculated.

Note: In reality the first order effect may not scale with building area, but the intensity is calculated this way to follow the logic of the second order effect.

In addition to calculating the total net annual second order effect per building and per square meter of each building, building profiles were developed based on the buildings' characteristics. This enabled further analysis and scenario building of the potential average net carbon impacts a building with certain characteristics may achieve based on the dataset used for the assessment.

Overall, the AI steering function resulted in a positive net carbon impact, where a reduction in GHG emissions was experienced due to the implementation of the AI steering function. For the 356 buildings in Finland and Sweden provided in the dataset, the average net carbon impact per square meter as well as the average kWh savings per square meter were -0.87 and -10.97 respectively. The total net carbon impact of the dataset was found to be 1,113 $tCO_2e$ following the location-based method and the total net avoided energy consumption was 17,325 MWh for 2022.

## 3.5. Assessment of higher order effects

Higher order effects were identified by considering the effects associated with potential changes in the behaviour of the solution's users. These are depicted in a consequence tree (see section 2.6.). The identified higher order effects are described and assessed in Table 13. The magnitude of impact considers the expected materiality in terms of relative emissions impact and probability in terms of how realistic it is for the higher order effect to occur given the contextual factors, such as those described in Table 5.

**Table 7. Assessment of higher order effects**

| Higher order effect | Direct or indirect | Description | Magnitude of impact |
|---|---|---|---|
| **Decreased reliance on reserve generators for grid peak loads** | Direct | A decreased reliance on fossil-fuel sustained grid peak loads, would directly impact the GHG emissions produced. Less carbon-intensive heating sources such as district-heating would be sufficient in peak loads due to increased efficiencies. This is dependent on the location and alternative power sources used, and on | Low/Medium |

| | | | |
|---|---|---|---|
| | | the frequency of peak loads and need for reserve generators. | |
| **Tenants paying for utilities gain economic efficiency and use saved income on carbon emitting activities** | Indirect | Economic efficiencies experienced by tenants who pay their utilities may lead to the expenditure of the savings on other carbon emitting activities such as travel. | Low |
| **Property owners paying for utilities gain economic efficiency and use extra income on carbon emitting activities** | Indirect | Economic efficiencies experienced by landlords who pay their utilities may lead to the expenditure of the extra income on carbon emitting activities. | Low |
| **Potential increase in operational capacity of AI (cooling, lighting, occupancy) increases energy consumption and related emissions** | Direct | The increased operational capabilities of AI and its application across buildings can target other building energy management systems and lead to greater energy savings. | Medium |
| **Improved building energy consumption and heating system knowledge** | Indirect | Improved knowledge around building energy consumption and climatic patterns could inform decisions around building energy management and result in savings. If consumer behaviour is impacted on a large scale this could impact the reference scenario (e.g., the solution becomes part of the reference scenario, or it becomes common for buildings to undergo energy-saving reforms). | Low/Medium |

## 3.6. Data selection and quality

The selection of the buildings included in the dataset was mainly based on data availability and the application of the Edge AI Steering function. The buildings in the dataset are present in two geographical locations, Sweden and Finland, and represent Kiona's three biggest customers.

The selected dataset only includes residential buildings with the AI steering functionality and with district heating as their heating source. Buildings were disqualified based on two further criteria: lack of energy statistics or lack of information (incomplete data in the system, such as building parameters) as this would increase the uncertainty of the results.

After removing all buildings that did not fit these requirements, the total number of buildings in the dataset was 358. Two further buildings were later excluded from the data set as these were found to not have sensors installed which would prevent the creation of a feedback loop for the indoor climate and consequently affect the steering function. This would in turn cloud the correlation between indoor climate, the steering function and the resulting GHG emissions impact.

The final dataset of buildings is composed of 356 residential buildings, with district heating, operating in Finland or Sweden.

Data of the solution components tend to be of high quality as their material composition is provided by Kiona who assembles the Edge Hubs and by the supplier for the sensors. Emission factors from BEIS 2022 are used to calculate the first order effect of the solution's components. The emission factors applied are those that most accurately match the materials provided for each component. For a few specific materials it was not possible to find an exact emission factors, so a more general factor was used, slightly reducing the accuracy of the calculation.

For the data from Google Cloud on its footprint, data quality is assessed as medium as little insight is provided on the footprint's methodology and, for example, how robust the scope 3 emissions are.

Data completeness was evaluated from 1 – 10 with 9 - 10 meaning all/almost all primary data was available, 7 - 8 all secondary data was available, 5 - 6 data was able to be derived using good approximations, up to 3 - 4 data was derived based on adequate approximations and 1 - 2 very rough approximations were made.

**Table 8. Data selection analysis**

| Data point | Data type | Data quality | Completeness | Uncertainty | Representativeness | Time coverage | Data provider |
|---|---|---|---|---|---|---|---|
| Building energy consumption | kWh | High | 10 | Sensor (+/- 2C), | Good | 12 months rolling average | Kiona |
| Building energy consumption w/o Kiona AI | kWh | Medium | 8 | Theoretical baseline – estimated 7% (see section 5.4) | Good | 12 months rolling average | Kiona |
| Sensor material composition | kg | High | 9 | Low – composition provided by supplier | Good | 10 years | Kiona |

| Data point | Data type | Data quality | Completeness | Uncertainty | Representativeness | Time coverage | Data provider |
|---|---|---|---|---|---|---|---|
| Sensor emission factors | $kgCO_2e/kg$ | Medium | 8 | Some general material emission factors allocated to specific materials | Medium | Lifecycle | BEIS |
| Edge Hub material composition | kg | High | 8 | Low – Kiona assembles the Edge Hubs in-house | Good | 10 years | Kiona |
| Edge Hub emission factors | $kgCO_2e/kg$ | Medium | 8 | Some general material emission factors allocated to specific materials | Medium | Lifecycle | BEIS |
| Google Cloud emissions | $kgCO_2e$ | Medium | 8 | Google allocated Scope 1, 2, 3 emissions shares. Unclear how accurate footprint is and what allocation rules are applied. | Medium | 12-month February 2022 – February 2023 | Google Cloud |
| IoT Accelerator use-phase emissions | $kgCO_2e/m^2$ | Medium | 6 | Derived based on actual electricity usage for the Stockholm site, for the Amsterdam site this has been derived based on a comparison of the HW setup. Allocation based on subscriptions. | Medium | 12 month – 2022 | Ericsson |
| IoT Accelerator embodied emissions | $kgCO_2e/m^2$ | Low | 4 | Derived based on estimated relation between embodied and global use phase emissions 2020 (recalculated | Low | 12 month – 2022 | Ericsson |

| Data point | Data type | Data quality | Completeness | Uncertainty | Representativeness | Time coverage | Data provider |
|---|---|---|---|---|---|---|---|
| | | | | with Swedish electricity mix). Factor of 9.3 applied. | | | |
| Network use-phase emissions | $kgCO_2e/m^2$ | Low | 4 | Kiona users have been recalculated into typical network subscriptions and the typical electricity intensity per user in Sweden has been applied.[8] | Low | 12 month – 2022 | Ericsson |
| Network embodied emissions | $kgCO_2e/m^2$ | Low | 4 | Derived based on estimated relation between embodied and global use phase emissions 2020 (recalculated with Swedish electricity mix). Factor of 9.3 applied.[9] | Low | 12 month – 2022 | Ericsson |

## 3.7. Emission Factors

Table 15 displays all publicly available electricity emissions factors used for the location-based approach which applies country specific grid mix factors. Where relevant, the electricity emission factors are used in the calculation of the use-phase of first order

[8] Note: There is no exact way of measuring network usage by a certain customer at this point, so a more exact number seems difficult to derive. However, the typical network subscription and typical electricity intensity per user in Sweden is considered to be of medium quality.

9 Note: There is no exact way of measuring embodied emissions of network usage by a certain customer at this point.

effects and second order effects when converting electricity consumption in kilowatt hours to emissions. Other emission factors are embedded within the annual emissions of the first order effects.

**Table 9. Electricity emission factor sources**

| Emission Factors | Source - Scope 2 Emissions & Scope 3 Transport and Distribution (T&D) losses |
|---|---|
| Electricity: Finland | (Fingrid, 2023) |
| Electricity: Netherlands | ((AIB), 2022) |
| Electricity: Sweden | (Climatiq, 2025) |

## 3.8. Assumptions

Quantifying Effects

- Life cycle emissions include raw material acquisition, production, use, and end-of-life treatment.
- Installation of Edge Hub's and sensors are simple and do not require any special tools or expertise. It is assumed that emissions from installations are negligible and are excluded.
- Temperature and humidity sensors are battery operated so it is assumed there are no additional use-phase emissions.
- The lifetime of batteries is assumed to be 10 years and does not need to be replaced during sensor lifetime.
- It is assumed that no material component of the Edge Hubs and sensors are recycled.

Data

- It is assumed the IoT accelerator energy consumption and lifecycle emissions can be allocated based on buildings' number of Edge Hubs.
- It is assumed the Radio network energy consumption and lifecycle emissions can be allocated based on buildings' number of Edge Hubs.
- It is assumed the cloud platform energy consumption emissions can be allocated based on buildings' number of Edge Hubs.
- Buildings with no sensors are excluded from the data set as the lack of a feedback loop from the indoor climate are assumed to heavily affect the steering function and consequent savings.

Emission Factors for district heating

- For supplier specific district heating emissions factors, if the utility provider does not explicitly state that the factors are Well-to-Tank (WTT), it is assumed WTT is included in the figure to be conservative with regards to the savings.

- Electricity residual mix factors from the AIB[10] are uplifted using 2018 values to convert from emissions in $CO_2$ to $CO_2$ equivalents to include all other GHG's.
- When calculating the emissions from electricity consumption using the market based-approach, country-specific electricity residual mix factors from AIB were used.
- If no supplier specific emission factor was available, the Swedish or Finish country average district heating emission factor was used.

Sensitivity analysis

- For the sensitivity analysis conducted, first order effects are assumed to have an uncertainty range of +100% as a conservative approach assuming that the number of sensors and equipment would have to be doubled. A further sensitivity analysis of the equipment's lifetime is also conducted.
- For the sensitivity analysis conducted, average rebound effects assumed to be 35% for the with a range of -9 - 91% applied[11]. These residential building rebound effects are not specific to AI steering and district heating as a heating source. As such the rebound effects may be an over estimation.

# 4. Results

Overall, the AI steering function resulted in a positive net carbon impact, where a reduction in GHG emissions was experienced due to the implementation of the AI steering function. For the 356 buildings in Finland and Sweden provided in the dataset, the average net carbon impact per square meter as well as the average kWh savings per square meter were -0.87 and -10.97 respectively. The total net avoided emissions for the dataset were found to be 1,113 $tCO_2e$ for the location-based method and the total net avoided energy consumption was 17,325 MWh for 2022.

Further, an analysis was done on the 16 building archetypes identified in the building sample. The archetypes were developed based on the following building characteristics: build year, window glazing type and ventilation type. The 16 building categories were assessed to identify trends and calculate the net avoided emissions of each type of

[10] https://www.aib-net.org/facts/european-residual-mix/2018

[11] https://www.ipcc.ch/report/ar6/wg3/downloads/report/IPCC_AR6_WGIII_Chapter_09.pdf

building profile. As the net avoided emissions calculations were done for each individual building, 'average' values were extracted for each building profile.

The results indicate buildings with the profile '1920-1944-Double Glazed-Natural Ventilation', which describes buildings in the sample built between 1920-1944, have double window glazing and natural ventilation, demonstrate the greatest emissions reductions in comparison to the reference scenario emissions (11%) and had an average net carbon impact of -0.91 $kgCO_2e/m^2$/year. Buildings with the profile '1995-2020-Triple Glazed-Exhaust' had a 4% reduction in net emissions in comparison to the reference scenario and an average net avoided emissions of -1.44 $kgCO_2e/m^2$/year.

Meanwhile, the building profile with the highest net avoided emissions per $m^2$ is the '1970-1994 – Triple Glazed – Exhaust', whose emissions reduction is 5%. The '1995-2020-Double Glazed-ESX' profile demonstrated the lowest net carbon impact per $m^2$ at -0.24 $kgCO_2e$ but has a 10% emissions reduction from the reference scenario.

The mirroring of the average percentage reduction from the reference scenario for both the emissions and energy consumption demonstrate an overall downward trend. This is due to building improvements, such as more efficient systems and processes and ameliorations in design, that can affect building's energy retention and consumption. Due to this, buildings built more recently, as they have more efficient heating energy systems, experience savings to a lesser extent as the reference scenarios is increasingly efficient as time passes. Therefore, though the energy savings and emissions savings per square meter vary from year to year, the most significant data point is the relative percentage reduction from the BAU.

# 5. Interpretation of results

## 5.1. Discussion on the applied method and future enhancements

The calculations conducted show the reference scenario emissions, first order effect, second order effect and net carbon impact for all buildings in the dataset. The 356 buildings in the dataset were then grouped according to their building profiles (building year, ventilation type and exhaust type) into 16 distinct categories. In addition, calculations were done as an average for all buildings in the dataset.

A calculator was set up that allows for building year, ventilation type, exhaust type and area to be input and that estimates the average net carbon impact.

The data evaluated only looks at residential buildings located in Finland and Sweden that are heated by district heating. This is a limitation of the case study as it will not apply directly to other geographies and heating types. A further limitation is that the study uses a theoretical baseline to compare its savings which is calculated by the Kiona AI steering solution itself. Consequently, the reference scenario is not independent from the assessed solution which is a methodological drawback. As many buildings are refurbished it is difficult to take the energy vs temperature profile before the Kiona AI heating system was installed as a fair comparison to the situation after Kiona AI installation. To evaluate the relevance of the calculated reference value in relation to actual conditions five buildings with no or minimal refurbishments were taken as a check. An improvement would be to have a real baseline vs AI comparison in the first year of the AI installation for all buildings.

The energy and net carbon impact were evaluated across the 16 building profiles. These building profiles were grouped based on three characteristics (build year, ventilation type and glazing type) however, there are many further factors that can impact the buildings savings and could be incorporated into a future evaluation.

A further second order effect that could be evaluated is the decrease in travel for maintenance. Due to remote monitoring from the Kiona platform issues can be either resolved remotely or allow for quicker and timely resolution of issues. This could be evaluated by a log of maintenance for a set period of time (such as a year) for properties before installation and after installation of Kiona Edge AI.

Rebound effects were identified but not evaluated in this report. Rebound effects that could be evaluated going forward include tenants and property owners' response to reduced heating energy consumption from Kiona AI. Direct economic rebound for tenants/property owners that pay utilities that pay utilities could be evaluated through measuring whether set temperatures and other building parameters are changed. A survey could also be conducted to understand whether extra income leads to further carbon emitting activities.

The rebound effect of peak load shifting could be evaluated going forward to understand if Kiona AI leads to a decreased reliance on generators for grid peak loads. This would require access to regional data on peaker plant utilisation and the information on the reduction of energy consumption from buildings in a concentrated area using energy from the same grid.

## 5.2. Data quality analysis

**Table 10. Qualitative analysis of data source quality**

| Data point | Primary or secondary data | Weakness | Strength |
|---|---|---|---|
| Building energy consumption | Primary data – direct data from utilities | | Exact primary data used as the solution enabled scenario as reported by the utilities in kWh. |
| Building energy consumption w/o Kiona AI | Primary data from Kiona | This data point is a theoretical baseline that estimates what the building energy consumption would have been based on estimated temperature if there had been no AI steering installed. A more robust data point would have been to use the energy to temperature profile of the building combined with measured (not calculated) temperature. | For five buildings with no or little refurbishments done that were used as a reference with actual energy consumption to temperature profile before and after Kiona AI installation there was a low discrepancy that showed that the AI steering slightly (~7%) underestimated the emission reductions. |
| Sensor material composition | Primary data Kiona suppliers | Could have a more granular breakdown (indicating if virgin or recycled materials were used). | Good quality data with a good volumetric breakdown of materials. |
| Sensor emission factors | Secondary data BEIS 2022 | Some emission factors for general material types used instead of specific factors for the exact material specification. | All upstream emissions are included in the factor, the database is a reputable source that follows LCA best practices. |
| Edge Hub material composition | Primary data Kiona | Could have a more granular breakdown (indicating if virgin or recycled materials were used). | Good quality data with a good volumetric breakdown of materials. |
| Edge Hub emission factors | Secondary data BEIS 2022 | Some emission factors for general material types used instead of specific factors for the exact material specification. | All upstream emissions are included in the factor, the database is a reputable source that follows LCA best practices. |
| Google cloud emissions | Secondary data from | Google allocated Scope 1, 2, 3 emissions to Kiona's share. | Google has submitted their emissions to the CDP and |

| | | | |
|---|---|---|---|
| | google cloud | Unclear how accurate footprint is and what allocation rules are applied. | most of their top suppliers have verified footprints indicating high accuracy. |
| IoT Accelerator use-phase emissions | Extrapolated primary data and secondary data from Ericsson | Use phase emissions for the Amsterdam site have been derived based on comparison of the Stockholm set up and does not include primary data. | Derived based on actual electricity usage for Stockholm and allocated Kiona's portion based on subscriptions. Evaluated different ways of allocating emissions and chose the most conservative estimate. |
| IoT Accelerator embodied emissions | Secondary data from Ericsson | A proxy uplift factor of embodied emissions from use-phase emissions is applied. This is derived based on the estimated relation between embodied emissions and global use phase emissions in 2020 (recalculated using the Swedish electricity mix).<br>This assumes that this ratio holds true for the IoT accelerator. | Even though the embodied emissions are small, and no primary data was available, a good effort was made to include them, and a conservative estimate uplift factor was used. |
| Network use-phase emissions | Secondary data from Ericsson | Kiona users have been recalculated into typical network subscriptions based on data traffic and the typical electricity intensity per user in Sweden has been applied. A number of approximations were made to allocate network emissions. | Even though the use-phase emissions are small and difficult to calculate per user, a good effort was made to include them, and a conservative estimate uplift factor was used. |
| Network embodied emissions | Secondary data from Ericsson | Derived based on estimated relation between embodied and global use phase emissions 2020 (recalculated with Swedish electricity mix).<br>Factor of 9.3 applied. | Even though the embodied emissions are small and difficult to calculate, a good effort was made to include them, and a conservative estimate uplift factor was used. |

## 5.3. Sensitivity analysis

Three approaches were taken to undertake a sensitivity analysis. The first approach was to change the variables used in the net annual second order effect calculations to see the sensitivity of the net carbon impact. The second approach was conducting a scenario analysis, looking at varying the rebound effect and overall first order effects. The third approach was conducting a market-based calculation as a comparison to the location-based calculation.

### 3.1.1 Sensitivity of variables approach

A sensitivity analysis was performed on the variables used in the net carbon impact calculations. The following variables were varied to see the effect on the net carbon impact (kg $CO_2e/m^2$/year), as illustrated in Fig. 9-13:

**Table 11. Variables in Sensitivity Analysis**

| Parameter | Parameter in model | Parameter variation | Variation in overall result (%) |
|---|---|---|---|
| **Sweden district heating emission factor** | 45.80 $gCO_2e$/kWh | 0– 2,000 $gCO_2e$/kWh | -47%- 2,006% |
| **Finland district heating emission factor** | 190.00 $gCO_2e$/kWh | 0– 2,000 $gCO_2e$/kWh | -48% - 454% |
| **Sensor lifetime** | 10 years | 1 – 20 years | -2.1% - 0.1% |
| **Edge Hub lifetime** | 15 years | 1 – 20 years | -0.94% - 0.02% |
| **Edge Hub maximum daily energy consumption** | 6 W/day | 3 – 100 W/day | -0.06%- 0.002% |
| **Electricity consumption Stockholm site IoT accelerator** | 1.26 MWh/year | 0.50 – 10 MWh/year | -0.2%-0.02% |
| **Electricity consumption Amsterdam site IoT accelerator** | 0.48 MWh/year | 0.48 – 10 MWh/year | -5.6% - 0% |
| **Electricity intensity /subscription radio network** | 37 kWh/subscriber | 10–200 kWh/subscriber | -0.3%-0.04% |

The net carbon impact varies greatly with the Sweden district heating emission factor. As the emission factor increases from 45 to 2000 $gCO_2/kWh$ the net carbon impact increases 2000%. The net annual second order effect emissions also vary with the Finish district heating emission factor, however, to a lesser extent. For both cases, as the emission factor increases, the net annual second order effect increases.

The sensor and Edge Hub lifetime's have a very small impact on the overall net carbon impact. As the lifetime increases there is a slight increase in net carbon impact, however it is negligible and seems to flatten out.

As the Edge Hub maximum daily energy consumption in Watt per day increases the net annual second order effect slightly decrease. There is a very minimal effect from varying the Edge Hub energy consumption.

The energy consumption at the Swedish and Amsterdam sites for the IoT accelerator increase, the net carbon impact slightly decreases. The rate of decrease is slightly greater for the Amsterdam site, as the Netherland emission factor is higher. In both cases there is a minimal effect on net carbon impact.

As the electricity intensity per subscription for the radio network increases, the net carbon impact decreases. For this variable too, there is a minimal effect.

In general, all variables relating to the aggregate first order effects have a very small impact on the overall net carbon impact. District heating emission factors play a big role and thus results are very sensitive to their change.

### 3.1.2 Rebound and first order effect scenario approach

A sensitivity analysis of the net avoided emissions when varying rebound effects and overall first order effects was conducted on the data. Since:

*net avoided emissions = second order effects − (the aggregated first order effects + rebound effects)*

Three buildings scenarios were evaluated for the sensitivity analysis: average building, lower bound, and upper bound. For the scenarios we have evaluated the change in net carbon impacts based on changing the rebound effects and the aggregated first order effects.

The aim of the scenario assessment is to understand worst- and best-case scenarios for the avoided emissions, taking first order and rebound effects into consideration. The scenario analysis parameters can be seen in Table 18 below.

**Table 12. Scenario analysis parameters**

| Scenario | Second order effects | First order effects | Rebound effects |
|---|---|---|---|
| **Lower bound** | Average of all buildings | Average of all buildings | -9% |
| **Average** | Average of all buildings | Average of all buildings | 35% |
| **Upper bound** | Average of all buildings | 200% of an average building | +91% |

**Average building**: Assume average reference scenario emissions, first-order and net-second order effects across all buildings. The direct rebound effects for residential energy consumption, which includes heating are assumed to be 35% for Europe (IPCC, Intergovernmental Panel on Climate Change, n.d.) (Galvin, 2015).

**Lower bound:** Assume average reference scenario emissions and net-second order effects across all buildings. The average first order effects are assumed to be the same as for an average building. The reasoning being that the first order effects would be maximized to reduce costs by the suppliers. A more detailed analysis of individual components was done above in section 'Sensitivity of variables approach'. The rebound effects are assumed to be -9% (IPCC, Intergovernmental Panel on Climate Change, n.d.).

**Upper bound:** Assume average building reference scenario emissions and have evaluated the net-second order effects across all buildings. The average first order effects are assumed to be double that of an average building (e.g. all sensors etc. are doubled as a conservative estimate).The rebound effects are assumed to be +91% (IPCC, Intergovernmental Panel on Climate Change, n.d.).

The rebound effects considered in the scenario analysis are not specific for district heating and therefore most likely over estimate the negative rebound effects, which is a major limitation.

Below are the results of the scenario analysis.

**Table 13. kWh energy savings scenario analysis**

| Energy savings | Average building | Lower bound | Upper bound |
|---|---|---|---|
| **Average building BAU energy consumption per $m^2$ (kWh)** | 149.04 | 149.04 | 149.04 |

| | | | |
|---|---|---|---|
| **Average building aggregated first-order effects energy consumption per m² (kWh)** | 0.01 | 0.01 | 0.02 |
| **Average building rebound effects per m² (kWh)** | 3.84 | 0.99 | -9.99 |
| **Average building avoided emissions per m² (kWh)** | 10.97 | 10.95 | 10.97 |

The effect on the net carbon impact from varying different parameters can be seen by selecting from a drop-down in the results tab of the accompanying excel sheet.

From the scenario analysis, it is concluded that the aggregate first order effects have a minimal effect on net carbon impacts while the rebound effects lead to a great variation in net carbon impacts between the upper and lower bound. As mentioned above, the rebound effects found in literature may be an over estimation so for future study it would be important to evaluate rebound effects through primary data.

### 3.1.3 Location-based and market-based approach sensitivity

All calculations and results follow the location-based approach as it was deemed most appropriate and representative of the emissions relating to the district heating energy consumption of the buildings. The market-based approach was carried out to assess the sensitivity of the results.

Kiona provided the utility providers of each individual building in the sample of 356 buildings. In total there were 14 different utility providers, two Finnish and 12 Swedish providers. For nine of these utility providers, supplier-specific district heating emission factors were found. Given the availability of this data, to make the calculations more robust a market-based calculation was carried out.

The location-based approach employs emission factors that are based on the average emissions factor in the operating country, usually this is the national gird. The market-based approach employs an emission factor specific to the energy purchased, usually this is supplier specific. To follow the market-based approach, the energy consumption of each individual building was multiplied by its supplier's district heating emissions factor or, where this was not available, the country average district heating emission factor. For electricity consumption in the first order effects, the grid emission factor was taken in the location-based approach as no supplier specific factors were available and residual mix factors were taken for the market-based approach. This follows the data hierarchy as set forth in the GHG Protocol.

The residual mix factors for Sweden, Finland and the Netherlands were taken from AIB. Since the AIB factors for residual mix are only provided in $kgCO_2$ and not in $CO_2$ equivalents, an uplift was applied. The uplift applied to the $CO_2$ values of the countries shown in Table 20, is the percentage difference between the 2018 AIB residual mix (AIB, 2018) $CO_2$ and $CO_2$ numbers available. Further details can be found in the accompanying calculations.

**Table 14. Residual mix electricity emission factors**

| Country | 2022 ($gCO_2$/kWh) | 2022 ($kgCO_2$/kWh) | 2022 ($kgCO_2e$/kWh) |
|---|---|---|---|
| Finland | 520.77 | 0.52 | 0.53 |
| Netherlands | 438.97 | 0.44 | 0.44 |
| Sweden | 38.95 | 0.04 | 0.04 |
| European Attribute Mix | 531.21 | 0.53 | 0.54 |

Emission factors for the materials used in the first order calculations, as well as for waste and disposal can be found in the accompanying calculations on tab 'Emission Factors'. Sources are BEIS 2022.

The market-based first order effect, second order effect and net carbon impact for an average building can be seen in the accompanying excel, as well as the market-based calculations for all building types.

## 5.4. Uncertainty analysis

Kiona provided data of five buildings heating energy consumption before Kiona AI was installed and after Kiona AI was installed. The actual energy consumption was compared to the theoretical baseline that was calculated by the AI platform.

The five buildings that were used as a reference were selected because they had no, or very few, refurbishments conducted on the buildings. This was assumed to be a fair representation of a baseline without AI steering. For these the 'energy consumption without AI' (a function of the outdoor temperature) which is the theoretical reference scenario was compared to the actual energy consumption expected in kWh. The absolute percentage difference is calculated and the average percentage difference for the buildings is found to be 6,63%. It is important to note that the energy consumption without AI kWh data was weather normalised using heating degree days and cooling degree days.

This percentage difference was used to apply error bars to the difference of the average second order effect per $m^2$ and the uncertainty on the average energy consumption in kWh per $m^2$ for the 16 different building profiles. Assuming a 6.63% uncertainty on the second order effect per m2, and extrapolating this to the full building dataset derives an uncertainty range for the net carbon impact of -1,027 to -1,199 tCO2e.

There are additional uncertainties that arise from the use of the components such as the sensor sensitivity, which is estimated to be +/- 2 degrees Celsius, however, these uncertainties have not been included in the analysis.

### 5.5. Key considerations for usage of results

List of considerations to have when using these results for other use cases:

- Corresponding climate regions will affect the outdoor temperature and Edge AI Steering, and therefore likely affect the scale of observed savings.
- District heating may not be the only energy source in the building.
- Building characteristics (window glazing, ventilation type and build year) can impact potential avoided emissions.
- Emissions factors will vary by location.
- Average heating energy consumption depends on climate region and building size.
- The results are specific to the 356 residential buildings with district heating, located in Finland and Sweden.

### 5.6. Do no significant harm

This assessment focuses on GHG impacts and identifies (and qualitatively assesses) higher-order effects such as rebound and behavioural changes. No evidence was assessed that the solution causes significant adverse environmental or social effects; however, broader contextual factors (e.g., energy prices, policy, energy supply mix) may influence outcomes and rebound risks. Users should ensure responsible deployment practices including data governance, cybersecurity, and responsible sourcing/end-of-life management of hardware, noting that conservative assumptions in the study include zero recycling for sensors and Edge Hubs. No negative impacts are foreseen on any of the EU Taxonomy’s environmental nor social objectives and strongly supports objective 1: Climate change mitigation. The Kiona AI Building Heat Optimisation solution is scalable, while also having the potential to improve quality of life and human comfort.

## 6. Conclusions

The aim of the study was twofold, to develop a case study of the effect of Kiona Edge’s Artificial Intelligence (AI) Steering Function on the building heating energy consumption.

The net carbon impact from the optimised heating energy consumption, because of the Edge AI steering function is 1,113 $tCO_2e$ using the location-based approach. The net carbon impacts are specific to the 356 Finnish and Swedish residential buildings' using district heating. In relation to the overall reference scenario emissions of all the buildings in the assessment, the implementation of Kiona Edge's AI resulted in an average percentage decrease of 7% in building heating energy consumption.

Based on the building profiles that were developed from the dataset's characteristics, buildings built between 1970-1994 experienced the greatest heating energy savings with the implementation of the Edge AI steering function. Additionally, double-glazed windows are correlated with greater energy savings compared to triple-glazed windows, and buildings with ESX ventilation demonstrated the greatest net carbon impacts, followed by natural ventilation, and then exhaust ventilation.

The assessment and calculations are representative of the conditions of the sample buildings and cannot be used to make conclusions regarding other buildings or other building management systems or other heating systems without further analysis. The case study results are only valid under the conditions of the study. The second order effect of the solution is the reduced greenhouse gas emissions related to the decreased building heating energy consumption due to the Edge AI. However, the second order effect is always hypothetical as it's compared to a reference scenario and given the reference scenario is theoretical this increases its uncertainty.

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