Schneider Electric™
Sustainability Research Institute

AI-Powered HVAC in Educational Buildings

A Net Digital Impact Use Case

Rémi Paccou and Gauthier Roussilhe

The Digitalization of Energy Series

December 2024

Life Is On | Schneider Electric

Key Insights from this Research

Rémi Paccou
Director of Sustainability Research,
Schneider Electric™ Sustainability Research Institute

Dear Reader,

I am pleased to present our research on Artificial Intelligence for HVAC optimization in Buildings. As the Schneider Electric™ Sustainability Research Institute, we are dedicated to exploring the intersections of energy, technology, and sustainability. This study arrives at a critical juncture, where AI advancements are rapidly evolving alongside the urgent need to address climate change.

The building sector, a major contributor to global greenhouse gas emissions, presents a significant opportunity for AI-driven HVAC optimization. While AI-powered HVAC systems hold great promise for enhancing energy efficiency and reducing carbon emissions, their comprehensive impact remains understudied.

This is the starting point of our research, which quantifies the Net Digital Impact of AI in a real-world use case in Stockholm, Sweden. The Net Digital Impact considers both direct and indirect effects, providing a holistic view of the technology's potential benefits and drawbacks. Building upon the foundational work of our Research Institute's 'Digital with Impact' and 'AI for Impact' reports, published in 2024, we aim to bridge the knowledge gap and provide a comprehensive understanding.

To achieve this, we conducted a large-scale, real-world study, examining over 87 educational properties over a four-year period. Leveraging a rigorous scientific approach guided by the ITU-T L.1480 standard, we utilized open-source databases, primary measurements, and consequential trees. With an annual energy expenditure of approximately €29.4 million and an energy consumption of more than 250 GWh per year, our case study can be considered a 'meta' use case due to its diversity, comprehensiveness, scale, and potential for deployment in other contexts.

We aimed to transition from a siloed use case to a valuable reference for microeconomic and territorial analysis, facilitating future use of its results for national and international-level quantifications. Moreover, this study can serve as a reference meta-case study, contributing to a large-scale database that systematically collects indirect impact estimates from use case data across various end sectors. This data, standardized based on study design characteristics (e.g., system boundaries) and deployment conditions (e.g., user heterogeneity), will enable statistical analysis of the determinants of variation in indirect impact estimates.

The results of this meta-case study demonstrate a significant positive decarbonization and energy efficiency impact.

First, comparing 2019 and 2023 reveals significant reductions in both district heating and electricity usage: district heating consumption decreased by 2,388 MWh from 76,586 MWh to 74,198 MWh. Electricity consumption dropped by 3,527 MWh from 39,489 MWh to 35,962 MWh. These reductions suggest the effectiveness of the implemented optimization solutions in curbing energy use across the buildings.

Second, relative energy savings, particularly in electricity consumption, show a marked improvement. District heating achieved a 3.12% reduction in total consumption, with an average of 2.84% savings per property. Electricity usage saw an even more substantial decrease of 8.93% in total consumption, averaging 8.66% savings per property. These figures demonstrate the positive impact of the optimization measures, particularly in reducing electricity consumption.

Third, the energy savings have led to a significant reduction in carbon emissions, totaling 259.17 tCO2e between 2019 and 2023. This translates to an average yearly carbon saving of 64.8 tCO2e. The emissions reduction is split between 109.87 tCO2e from district heating and 149.30 tCO2e from electricity savings. Considering the average yearly carbon savings of 64.8 tCO2e, the annual carbon cost-benefit ratio exceeds 60 per year, indicating a highly favorable environmental and economic outcome.

These findings, exemplified by the significant reductions in energy consumption and carbon emissions, underscore the substantial potential of AI-driven optimization strategies, when properly designed and operated with purpose, in achieving decarbonization and energy efficiency goals.

We hope this research represents a step forward in understanding and quantifying the potential of AI in building energy management. We invite critical consideration and further discussion as we present these findings.

Thank you for joining us in this exploration. We look forward to the discussions and further research that this work may inspire.

Rémi Paccou
Director of Sustainability Research,
Schneider Electric™ Sustainability Research Institute

(1) HVAC: Heating, Ventilation, and Air Conditioning

Science Perspectives

Towards Rigorous Net Digital Impacts Assessments

Jan Bieser, PhD in Digitalization & Sustainability
Assistant Professor for Digitalization & Sustainability
Berner Fachhochschule BFH

Foreword

Digitalization, increasingly fueled by the rapid advancement of AI, continues to have unprecedented impacts on our patterns of production and consumption, with enormous potential for environmental protection. After all, digital technologies allow us to understand our environment better, eliminate inefficiencies in systems, and entirely reimagine many parts of our lives. Looking forward, the most significant impacts of digitalization are likely still ahead, as it remains a young and evolving technology.

This study impressively demonstrates the potential of combining smart algorithms, sensor data, and control systems to enable resources and emission savings in buildings. By doing so, we can create "win-win-win"-situations, situations that are beneficial for people, the environment, and organizations alike. However, technology can also have unintended environmental consequences. For example, digital solutions that optimize road transport often increase road traffic and, thus, greenhouse gas emissions. Therefore, it is essential to conduct thorough assessments of the environmental impacts of digital applications so we can identify both positive and negative effects early on and address them effectively.

This case study is an excellent example, assessing the energy, resource and CO2-impacts of AI-based optimizations on HVAC systems. It also incorporates sensitivity analysis to address inherent uncertainties in such types of studies and points to critical areas for future research. In doing so, it directly contributes to reducing the environmental impact of the building sector in Stockholm and beyond.

I hope this study inspires other organizations to follow and systematically assess the environmental consequences of their digitalization journeys. By now, there are many guidelines available that help organizations do so. If so, we will likely see an increasingly positive effect of digitalization on environmental protection. However, this also calls for a more nuanced approach to digitalization and a cultural shift where its actual impacts and perceived benefits are critically scrutinized. For a truly sustainable digital future, we should not start with the question, "What can we do with digital technologies?" but first ask, "What has to change to meet sustainability goals?" and only then explore how digital technologies can help realize these changes. Sound environmental assessments, such as this study, are crucial on this journey.

Jan Bieser, PhD
Assistant Professor for Digitalization & Sustainability
Berner Fachhochschule BFH
https://www.bfh.ch/en/

Berner Fachhochschule
Haute école spécialisée bernoise
Bern University of Applied Sciences

Operational Perspectives

From left to right, Karim Hussain (Schneider Electric), Mats Carlqvist, Erica Eriksson, Niklas Dalgrip (SISAB)

As one of Sweden's leading property managers for schools and preschools, SISAB (Skolfastigheter i Stockholm AB) holds a significant responsibility in creating sustainable, energy-efficient, and healthy learning environments. In alignment with our ambitious climate goals and our commitment to being a role model in the property industry, we have embarked on exploring innovative technological solutions to reduce energy consumption in our properties.

In this endeavor, we have had the privilege of collaborating with collaborating with Schneider Electric and Myrspoven on a study focused on the use of AI for optimizing energy use. This study aims to investigate how AI-based solutions can enhance the efficiency of our property operations, reduce our climate impact, and simultaneously ensure a high-quality indoor climate for students and staff. With AI's ability to analyze vast amounts of data, we can identify inefficiencies and potential improvements that might otherwise go unnoticed.

Our sustainability program is central to this initiative. SISAB is committed to long-term environmental responsibility, continuously working on energy efficiency and reducing climate emissions. We prioritize technologies and decisions that minimize environmental impact during construction and operations, ensuring our schools and preschools are functional, safe, and attractive with the least possible environmental footprint. In 2023, we made significant strides towards our Vision 2040, focusing on creating safe, sustainable, and cost-effective environments. Our efforts include implementing the SOLIDA AI-driven system to optimize building operations, which has shown promising results in reducing energy consumption and improving indoor climate. This aligns with our broader goals of achieving climate positivity by 2030 and contributing to Stockholm's overall sustainability targets.

We are thrilled with the promising results from this study and look forward to integrating these insights into our future work. This new technology paves the way for a more sustainable future, where we can effectively balance energy use with comfort and health. We extend our heartfelt thanks to Schneider Electric for their dedication and expertise, as well as to all employees and partners who have contributed to this important project. Their efforts have been invaluable, and we deeply appreciate their commitment.

Erica Eriksson, Head of Energy and Sustainability
Mats Carlqvist, Head of Operations
Niklas Dalgrip, Director of Operations

Schneider Electric is proud to partner with SISAB in this groundbreaking study. Our collaboration underscores our shared ambition to drive sustainability and innovation in building operations. Both Schneider Electric and SISAB are committed to creating energy-efficient, climate-positive environments that prioritize the well-being of occupants. This project exemplifies how our combined efforts can lead to significant advancements in energy management and sustainability.

By leveraging AI technology, we are not only optimizing energy use but also setting a benchmark for the industry. We commend SISAB for their visionary leadership and dedication to sustainability, and we look forward to continuing our partnership to achieve our mutual goals of environmental stewardship and operational excellence.

We hope this report will inspire other stakeholders in the real estate industry to leverage the opportunities that AI presents in addressing future sustainability challenges. By working together and sharing our insights, we can collectively contribute to creating a better and more sustainable world.

With this foreword, we also emphasize the importance of continuous innovation and collaboration. It is through these principles that we can continue to develop and implement solutions that meet not only today's needs but also those of the future.

Karim Hussain, Product Manager, Digital Buildings

Skolfastigheter i Stockholm AB SISAB

Table of Contents

List of Exhibits

Problem Statement

The impact of digital technologies on carbon emissions and energy efficiency in buildings is a complex and multifaceted issue. While digital solutions offer significant potential for reducing energy consumption and greenhouse gas emissions, their net impact must be carefully considered to create the proper conditions for informed debates and policy decisions[1].

AI-powered HVAC systems in buildings have demonstrated considerable promise in enhancing energy efficiency and reducing carbon footprints. These systems can decrease energy consumption by adapting to usage patterns and integrating lower-carbon sources into the electricity mix[2]. Machine learning approaches, such as deep belief networks, have shown increased accuracy in temperature forecasting with reduced computational expenses compared to traditional physical models[3]. Deep reinforcement learning has achieved notable success in HVAC control, with studies reporting up to 20% reduction in energy use using minimal sensor inputs[4].

Fault detection and diagnosis in HVAC systems have also benefited from AI applications. Wang et al. utilized a one-class classification approach for fault detection using temperature readings[5], while deep autoencoders have been employed to simplify machine operation information, enabling deep neural networks to predict multiple types of faults[6]. These advancements in fault detection can significantly improve system performance and longevity.

Occupancy-based adjustments represent another area where AI can optimize HVAC operations. Systems can adapt based on building or room occupancy, improving both occupant comfort and energy use[7] Machine learning algorithms can help these systems dynamically adapt to changes in occupancy patterns[8], with various techniques such as decision trees(9, 10) and deep neural networks[11] being applied to occupancy detection using data from sensors, WiFi signals, and appliance power consumption.

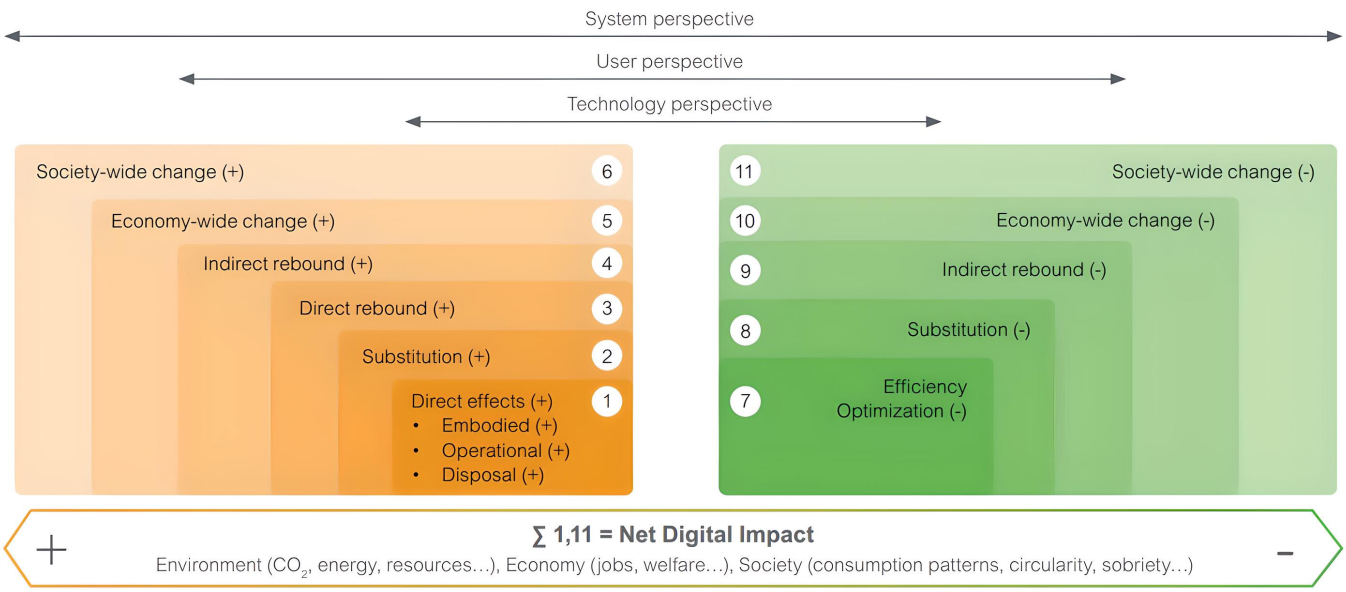
While these advancements are promising, it is important to note that challenges remain in widespread adoption and implementation. Barriers such as lack of awareness, technical expertise, and capital for investment persist. Additionally, the effectiveness of AI-powered HVAC systems may vary depending on building characteristics, climate conditions, and existing infrastructure.

Building upon our research, the Schneider Electric™ Sustainability Research Institute has developed frameworks to quantify the environmental impact of digitalization and AI. Our "Digital with Impact"[12] report introduced the "Net Digital Impact framework," a holistic approach to quantifying digitalization's environmental footprint. Subsequently, our "AI for Impact: A Method for Guiding AI-Energy Applications at Scale"[13] report unveiled the "AI for Impact Compass," tool to assess AI's contribution to climate action has shown AI-Powered HVAC as a potentially promising solution. However, more quantified evidence through use cases is needed.

Hence, we decided to apply the **"Net Digital Impact framework"** to this Stockholm use case. This approach enables us to capture not only the positive outcomes, such as enhanced energy efficiency and reduced carbon emissions, but also any potential negative consequences that may arise from the integration of AI in HVAC systems. We also sought to identify the key local contextual factors which determine whether the impact is solely local or potentially extrapolable to other situations, such as different countries or building segments.

A key challenge lies in combining the rigor of scientific methodologies with the granularity of ground-level data and quantifying them within their respective domains of expertise (IoT, AI, Building Management Systems, HVAC, etc.). Significant effort has been invested in ensuring the solidity of the data and its quantification. To support this work, Gauthier Roussilhe[14], an expert independent researcher, provided guidance by outlining a framework for combining methodologies with practical implementation suggestions. He also critically examined our hypotheses and assumptions, referencing updated databases such as Boavizta[15].

Exhibit 1. The Net Digital Impact Framework. Schneider Electric™ Sustainability Research Institute.



Setting of the Research (1/2)

How does Stockholm lead the way in climate action?

Sweden stands at the forefront of global sustainability efforts, with Stockholm exemplifying this commitment through its ambitious climate action initiatives. The nation's overarching goal of achieving net-zero emissions by 2045 is supported by a robust climate policy framework, while Stockholm's Climate Action Plan 2020-2023 delineates specific strategies to address climate change and foster sustainability[16]. The capital city has demonstrated remarkable progress, reducing greenhouse gas emissions by 25% since 1990, despite economic and population growth. This achievement stems from strategic investments in renewable energy and enhanced energy efficiency across various sectors. Stockholm's vision extends further, with the city aiming to become fossil fuel-free by 2040, emphasizing a transition to electric and renewable energy solutions. This approach underscores Sweden's, and particularly Stockholm's, dedication to sustainable urban development. By setting these targets, the city not only mitigates its environmental impact but also positions itself as a global leader in urban sustainability, providing a model for other cities to emulate in the face of climate challenges.

Stockholm has set ambitious targets for the building sector

The Climate Action Plan for Stockholm lays out clear environmental targets for the building and energy sector, recognizing its significant role in achieving the city's climate objectives. Stockholm's Climate Action Plan aims to achieve net-zero emissions by 2040, with a significant focus on buildings and energy. The city plans to reduce energy consumption in new buildings to 55 kWh/m² and aims to cut overall emissions by at least 240,000 tonnes of CO_2 equivalent through its district heating system[41].

HVAC Systems as a Critical Factor in Efficiency

Heating, ventilation, and air-conditioning (HVAC) systems play a crucial role in the energy consumption and environmental impact of buildings, especially in urban areas like Stockholm. As of 2023, HVAC systems account for a significant portion of total energy use in residential and commercial buildings, ranging from 30% to 50% of overall energy consumption[18]. Hence, in Stockholm, the integration of advanced technologies, including AI and smart controls, has begun to transform traditional HVAC systems into more energy-efficient and responsive solutions.

AI Integration in HVAC Systems: A Game-Changer?

Within this context, AI-powered HVAC systems have emerged as a promising solution for Stockholm's ambitious climate goals. Over the past two decades, HVAC systems have transitioned from conventional mechanical controls and fossil fuel reliance to more efficient designs, driven by regulatory frameworks and incentives promoting energy efficiency. The introduction of AI in HVAC management represents a paradigm shift in addressing the complex control challenges posed by modern and older building structures. Companies like Myrspoven[20] are leveraging AI to optimize HVAC systems in Stockholm, achieving up to 25% reduction in energy consumption and 20% decrease in carbon dioxide emissions in buildings[21].

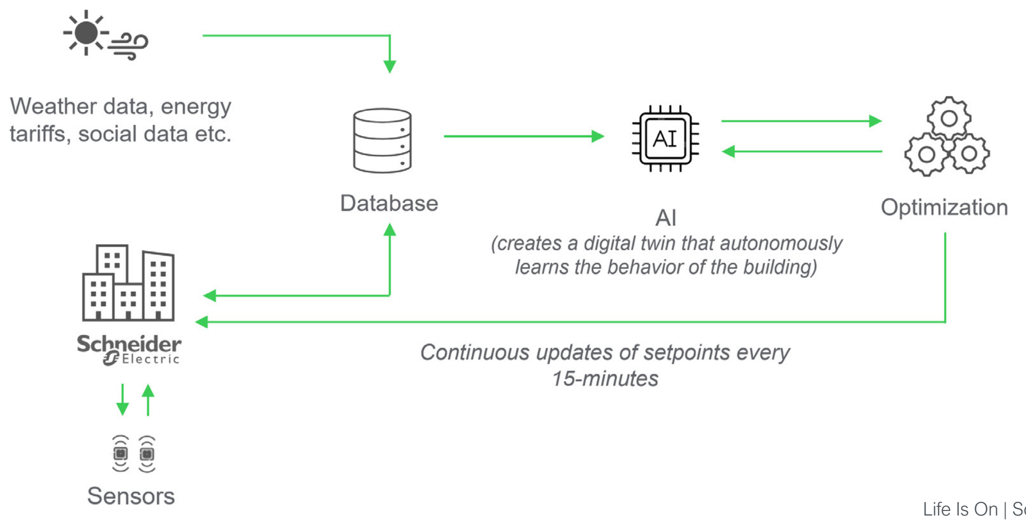
What makes AI-powered HVAC fundamentally different?

AI-powered HVAC systems offer a dual focus on indoor climate control and forecasting, as well as energy savings, utilizing machine learning algorithms to manage multiple factors affecting indoor comfort with unprecedented precision. These systems have demonstrated remarkable capabilities in accurate indoor climate forecasting with reduced computational demands, and in achieving significant energy reductions through techniques such as Deep Reinforcement Learning[22].

The implementation of AI in existing buildings presents an opportunity for substantial energy savings without the need for disruptive renovations, addressing the increasing strain on electrical grids caused by the rising demand for air conditioning and the complexities of integrating on-site generation and energy storage systems[23].

AI-driven HVAC control systems exhibit adaptive learning capabilities, optimizing performance through experiential data and autonomously managing controls across diverse building types. This approach not only enhances energy efficiency but also reduces reliance on skilled engineers, allowing for the reallocation of human resources to more strategic tasks[24]. The integration of AI in HVAC systems offers a promising solution for enhancing energy efficiency in grid-interactive buildings, providing flexible control methods capable of navigating the increasing complexity of modern building systems.

Exhibit 2. High-level illustration of the data flows between the AI-Powered solution and the BMS. Schneider Electric



Setting of the Research (2/2)

What circumstances have led SISAB to invest in AI?

This study investigates the implementation of an artificial intelligence (AI)-based building management solution by SISAB (Skolfastigheter i Stockholm AB), a municipal entity responsible for the operation and maintenance of over 600 educational facilities in Stockholm, Sweden. SISAB is responsible for all electricity and heating, including both HVAC energy and operational energy (appliances, lighting, and plug-loads). The entity manages a heterogeneous portfolio of educational infrastructure, encompassing preschools, primary schools, and colleges, characterized by diverse spatial dimensions (ranging from 100 to 48,000 square meters) and varying ages (7-15 years). With an annual energy expenditure of approximately €29.4 million and annual energy consumption of 250 GWh, even marginal enhancements in efficiency have the potential to generate substantial cost savings.

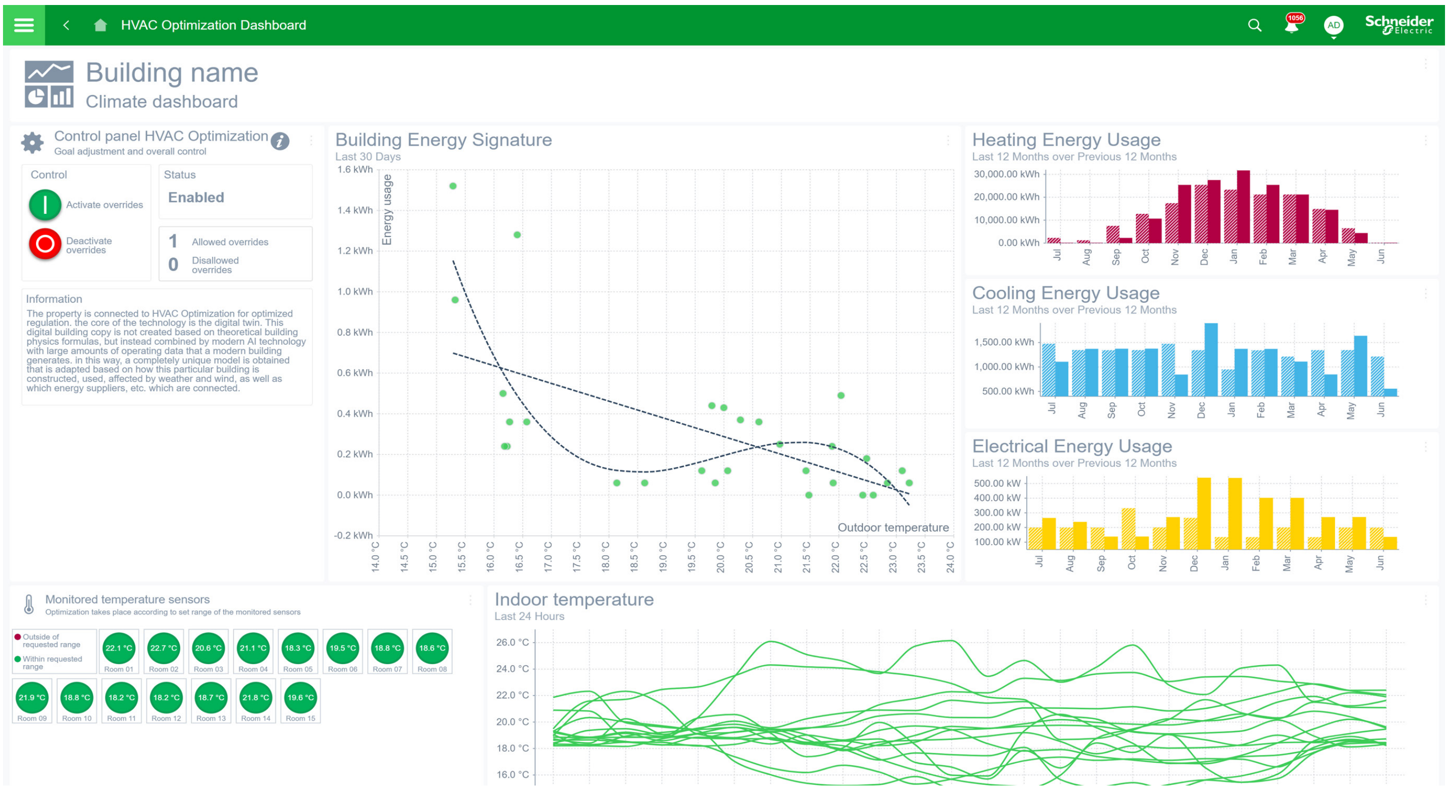
Prior to 2013, SISAB faced operational challenges due to the utilization of multiple building management interfaces from various vendors, resulting in inconsistent control mechanisms and limited supervisory capabilities[25]. The establishment of a centralized operations center in 2013 represented a significant advancement towards achieving unified building control. Furthermore, SISAB had invested in a comprehensive network of over 20,000 temperature and CO2 sensors across their facilities, generating an estimated one million data points daily. This extensive data collection presented both opportunities and challenges for effective building management.

Why did SISAB decide to implement an AI-powered HVAC?

SISAB identified three primary objectives: (1) reducing overall heating energy consumption and associated costs while maintaining a consistent indoor temperature of 20°C; (2) implementing a solution capable of integration with existing building infrastructure and control systems without necessitating extensive equipment replacement; and (3) analyzing the voluminous dataset generated by the sensor network to identify optimal setpoints and facilitate real-time adjustments. These objectives formed the foundation for SISAB's exploration of AI-based solutions to enhance their building management practices.

In March 2018, SISAB selected an AI solution developed by Myrspoven, with a projected payback period of less than three years. This cloud-hosted AI service, later named SOLIDA (SISAB OnLine Intelligent Data Analysis), was designed to operate in conjunction with the existing Building Management System (BMS) rather than replacing it entirely. This solution design was jointly developed by Schneider Electric and Myrspoven, which also made re-use of existing control applications rather than having to re-program more than 50 000 applications The AI solution functions as a virtual building operator, making adjustments to setpoints temperature for HVAC systems and air flow rates for air handling units every 15 minutes, in contrast to the less frequent manual adjustments typically made by human operators. This approach allows the system to move beyond fixed schedules, instead using historical data and predicted future events to make informed decisions about equipment control and adjustment.

Exhibit 3. Example of energy performance, indoor comfort and control panel embedded in the BMS. Schneider Electric



Assessment of AI-Powered HVAC Systems (1/2)

This research adheres to established methodologies and international standards for evaluating the net environmental impact of digital solutions. The study's framework is primarily informed by the ITU-T L.1480 recommendation and the European Commission's 'Net Carbon Impact Assessment' methodology[27]. These approaches are grounded in life cycle assessment (LCA) principles, as delineated in ISO 14040:2006[28] and ISO 14044:2006[29]. By employing these recognized methodologies, the study ensures a comprehensive and standardized approach to assessing the environmental implications of AI-powered HVAC systems in buildings, facilitating comparability and reliability in the findings.

We cover four environmental issues in this study

1. Greenhouse Gas Emissions (Global Warming Potential)
This aspect is particularly pertinent due to the solution's potential to significantly reduce energy consumption in building heating, cooling, and air conditioning systems, which are substantial contributors to global emissions (IPCC, 2022)[30]. Concurrently, the study considers the emissions associated with the manufacture, use, and end-of-life management of the digital systems involved, as these can also represent a significant source of greenhouse gases (Belkhir & Elmeligi, 2018)[31].

2. Mineral Resource Depletion (Abiotic Resources Depletion)
Refers to the use and depletion of non-renewable fossil fuel resources throughout a system's life cycle. This impact category assesses the consumption of fossil fuels like coal, oil, and natural gas as energy sources. This point is key due to the often short lifespan and large-scale deployment of such devices, which can lead to accelerated resource consumption[32]. Units: kg Sb-eq.

3. Energy Consumption (Abiotic Resources Depletion, Fossils)
By assessing the depletion potential of fossil fuels, the study provides a comprehensive view of primary energy consumption throughout the systems' life cycle, including considerations of the electricity mix used[33]. Units: MJ or kWh.

4. AI Life Cycle Analysis
The environmental assessment of AI solutions necessitates a specialized methodology which incorporates both the training and inference phases of AI models, extending beyond traditional LCA techniques and requiring rigorous documentation and analysis[34]. The study by Ligozat et al. emphasizes the importance of considering the complete lifecycle of AI systems, including their development, deployment, and operational phases.

We consider two contextual factors

1. Building Renovation
While digital solutions offer optimization potential, traditional building renovation programs can also significantly improve energy performance. These programs, though more expensive and time-consuming, can be amortized over extended periods and provide long-term benefits[35].

2. Recurring Energy Optimization Interventions
The study acknowledges the possibility of manual optimization through frequent energy audits and conservation measures. However, it notes that this approach is resource-intensive, reactive in nature, and challenging to implement consistently across multiple buildings[36].

What are the core principles underlying the AI-based solution?

1. AI Learns and Adapts HVAC Schedules for Efficiency

Traditional building HVAC controls rely on fixed schedules and reactive control for energy optimization, while Myrspoven's AI solution uses historical and predictive data to determine optimal equipment controls. The AI Model Training employs a unique, physics-informed AI model that leverages symbolic regression (a technique that uses algorithms to discover mathematical equations from data) to identify the optimal mathematical equation for the given dataset. It systematically searches through a vast library of mathematical expressions and can even generate new equations when necessary, all grounded in physical principles. The derived mathematical equation (from the AI model) is used in conjunction with Model Predictive Control (MPC) to determine the optimal setpoint, considering constraints related to indoor climate and energy consumption. This ensures that the 15-minute optimization process is also physically informed. While this data-driven approach is effective most of the time, Myrspoven has hard-coded holiday and vacation schedules. This allows the AI model to learn the building's occupants' behavioral patterns during these special times, enabling adjustments to comfort requirements and increased energy savings.

2. AI Enhances HVAC Control Through BMS Integration

The AI solution is implemented in a supervisory control system which hosts field servers and devices. These are located in buildings where HVAC control equipment is connected. Through the supervisory control system, an outbound internet connection allows the AI solution to make setpoint adjustments to optimize the HVAC control in a secure manner. Those requirements are easily met when the building has a Building Management System (BMS), because it offers direct access to the equipment controls and data storage. With use of middleware the solution only requires outbound connectivity to the AI service to store data and retrieve new AI models for computing optimized setpoints which is securely written back to the BMS system. Measurements, sensor, and energy data is matched with weather data and utility rates in the cloud to reinforce the knowledge of the AI model. Then the AI solution processes the data and infers occupancy patterns, behavioral patterns and its impact to energy demand and indoor comfort. Based on this knowledge, the solution continuously and actively adjusts BMS settings for the most cost and resource effective operations while also improving indoor comfort.

How was the reference scenario constructed?

To assess the potential impact of the solution, we established a reference scenario that simulates the situation without the solution's implementation. This counterfactual scenario incorporates SISAB's existing energy efficiency initiatives, such as onsite and remote energy audits, and setpoint adjustments. While these measures would contribute to some energy savings, the complexity of building operations and potential limitations would constrain the overall impact. Due to the challenges in quantifying the specific savings from these existing initiatives, we adopted a Business-As-Usual (BAU) scenario as a baseline. This scenario assumes that SISAB would have maintained its standard operating procedures without implementing additional energy-saving measures.

Assessment of AI-Powered HVAC Systems (2/2)

How did we design the AI-powered scenario?

The AI solution was deployed to optimize building operations, including heating, cooling, and air conditioning, across 87 of the 120 properties in Stockholm, Sweden. Thirty-three properties were excluded due to insufficient energy data for 2019 and 2023 or because they were involved in various energy conservation projects that complicated the attribution of savings to the AI solution alone. The solution is trained using data from 9,901 sensors, with 5,496dedicated to indoor temperature measurement and 4,405 to indoor carbon dioxide (CO2) levels. These sensors were installed prior to the AI solution's deployment and are complemented by weather and climate data from Stockholm.

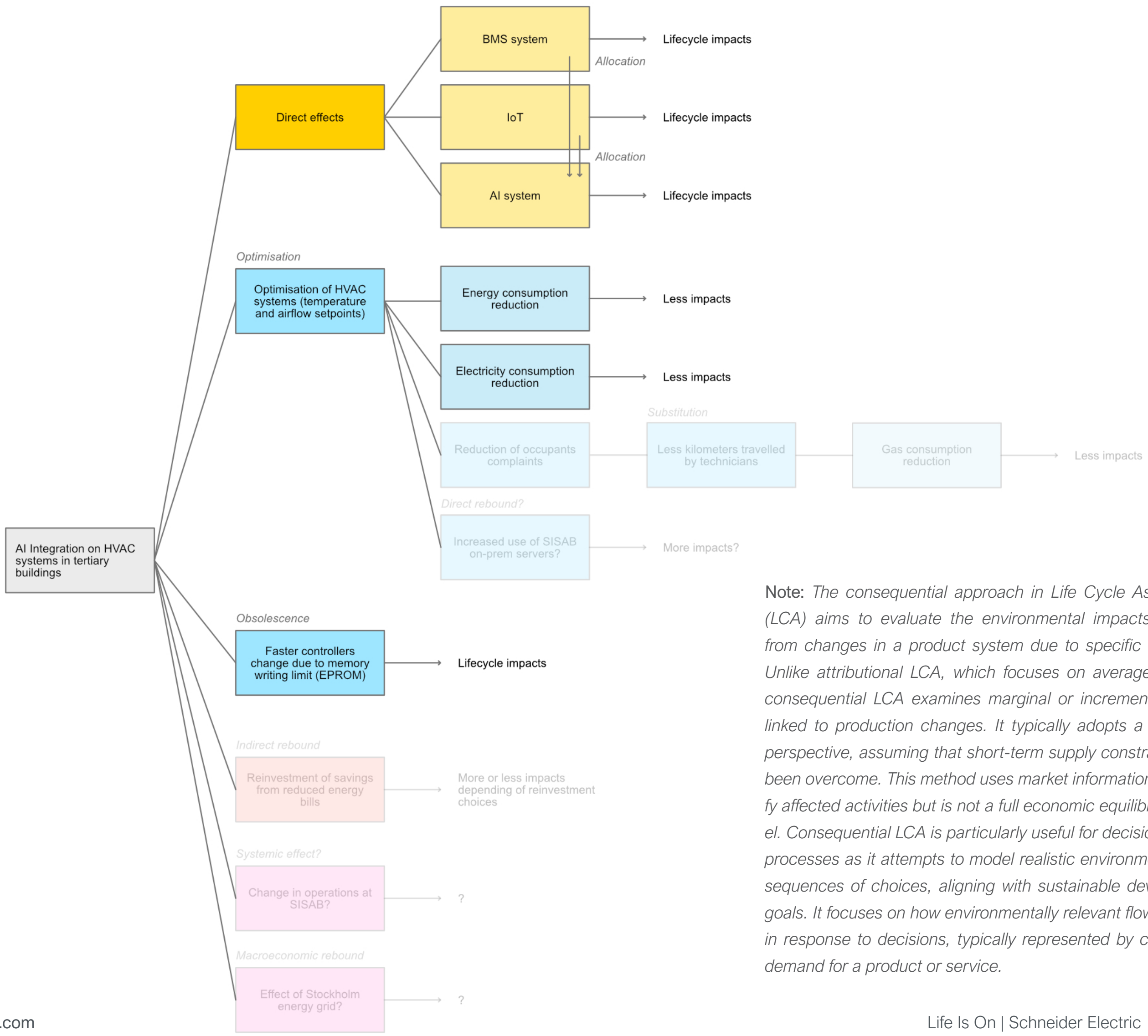
A tailored model was developed for each property and is retrained daily to adjust temperature setpoints for HVAC systems and air flow rates for air handling units every 15 minutes. This solution utilizes Microsoft Azure clusters for training and inference, located in Northern Europe, with data transmitted daily between the building management system (BMS) and the servers of SISAB and the solution provider.

The solution aims to reduce energy consumption associated with heating, cooling, and air conditioning in buildings by dynamically and precisely adjusting HVAC setpoints to achieve optimal indoor comfort with minimal energy demand, considering weather, geographical, and architectural factors. This solution has been iteratively implemented across these properties since 2019, providing four years of data to evaluate its potential and actual impacts.

We have defined the following scope of this assessment

The evaluation includes the digital systems modified and mobilized by the deployment of the AI solution. It aims to assess both the direct effects of these systems and the indirect effects on the management of properties overseen by SISAB. The analysis considers the impacts linked to the manufacture, use, and end-of-life of certain building management system (BMS) components that have been modified, as well as the IoT systems that enable the transmission of HVAC equipment data and sensor measurements. Additionally, it evaluates the resources mobilized by the AI solution, including those related to data centers and networks. While all potential indirect effects are studied, only those with quantifiable data and significant materiality are included in the modeling. See Exhibit 4 for detailled consequential tree.

Exhibit 4. Consequential Tree of the Stockholm's AI-Powered HVAC case. Schneider Electric



Note: *The consequential approach in Life Cycle Assessment (LCA) aims to evaluate the environmental impacts resulting from changes in a product system due to specific decisions. Unlike attributional LCA, which focuses on average impacts, consequential LCA examines marginal or incremental effects linked to production changes. It typically adopts a long-term perspective, assuming that short-term supply constraints have been overcome. This method uses market information to identify affected activities but is not a full economic equilibrium model. Consequential LCA is particularly useful for decision-making processes as it attempts to model realistic environmental consequences of choices, aligning with sustainable development goals. It focuses on how environmentally relevant flows change in response to decisions, typically represented by changes in demand for a product or service.*

Assessing the Direct Digital Effects (1/2)

Direct Effect #1: Assessing the BMS system

The Building Management System (BMS) typically consists of several components, including a SpaceLogic™ AS-P Automation Server, a third-party controller, HVAC equipment, mechanical components, the EcoStruxure™ Building Operation Enterprise Software, and the EcoStruxure™ Building Operation SmartConnector Software. In comparing the reference scenario to the scenario with the solution, only two elements are modified: the HVAC system, which is optimized through the AI solution, and the third-party controller, which experiences a reduced lifespan due to its limited memory capacity being strained by increased data writing from the new solution.

The optimization provided by the AI system results in lower electricity consumption for HVAC systems, including electrical radiators, which is considered an indirect effect of optimization and does not necessitate a separate environmental assessment. However, the accelerated end-of-life of the third-party controllers requires an environmental assessment to evaluate the additional environmental costs associated with their more frequent replacement.

Using data from Schneider Electric regarding the fleet of third-party controllers in operation, we calculated the average environmental impact of these controllers. Assuming a lifespan of 10 years and utilizing a Swedish electricity mix during their operational phase, we also considered that these controllers are situated in a dry, cold, clean environment within enclosed panels. The total life cycle impact has been determined as follows:

Exhibit 5. Life Cycle Impact of the BMS System

Life cycle impacts - BMS System			
	kg CO2 eq.	kg SB eq.	kWh
1 third-party controller	67.83	0.0011	314.93
1 controller per year (10-year life span)	6.78	0.0001	31.49
Total impacts for all controllers (life cycle)	51,077	0.80	237,144
Total impacts for all controllers per year	5,107.75	0.08	23,714

Direct Effect #2: Assessing the IoT system

There are 9,901 sensors deployed in the properties managed by SISAB for this AI solution. These include THS-1002-1 devices (used as temperature and CO2 sensors) and AR-0002-1 Air Receivers from EcoGuard, which collect the data sent by the sensors. On average, there are 60 sensors per property, distributed across 120 properties totaling 1 million square meters of space. This equates to approximately one sensor per 140 m² of floor space. It can be assumed that there is one Air Receiver per property. In the absence of comprehensive life cycle analyses or carbon footprint assessments for IoT devices, an alternative methodology has been employed to approximate their environmental impact. Pirson et al. introduced a novel approach that estimates the environmental consequences of both the manufacturing and end-of-life phases of these devices. This method evaluates the average impact of components integrated into a device to execute specific functions, such as connectivity.

The approach involves the following steps: identification of device functions, assessment of component impacts for each function, and input of hardware specification levels (HSLs) for individual functions. For the purpose of this analysis, sensors and receivers are presumed to have a mean operational lifespan of 15 years. This assumption allows for a standardized timeframe when considering the long-term environmental implications of these devices. Detailed information about the calculation model is provided in the appendix.

Our environmental impact assessment of the IoT system focuses on the manufacturing and End-of-Life (EoL) phases, as these represent the most significant impacts given our data constraints. While this method doesn't replace a comprehensive Life Cycle Assessment (LCA) and excludes use-phase impacts, it's the best available approach considering our limitations. We lack data on the devices' operational electricity consumption, but given that battery-powered sensors typically have very low energy needs and Sweden's electricity mix has a low carbon intensity, the use-phase impact is likely minimal. The manufacturing and EoL impacts of the IoT system are as follows:

Exhibit 6. Manufacturing and EoL impacts for the IoT system

Manufacturing and EoL impacts - IoT system			
	kg CO2 eq.	kg SB eq.	kWh
Ecoguard THS-1002-1 (1)	2.00	0.0001	8.91
per year (15 year lifespan)	0.13	0.00	0.61
for 9.901 units, per year	1323.01	0.06	6467
Ecoguard AR-0002-1 (1 unit)	10.09	0.0004	50.53
per year (15 year lifespan)	0.82	0.000004	3.49
for 103 units, per year	80.48	0.0026	370.84

In attribution-based environmental impact assessment, a portion of the Internet of Things (IoT) system's footprint must be allocated to the AI system it supports. This is because the AI system relies on data from IoT sensors for its operation.

However, this allocation is not considered in short-term consequential analysis approaches. Determining an appropriate allocation key for this footprint presents challenges. Based on our research, 9,901 out of 20,000 sensors were utilized in training the AI solution, and approximately 120 gateways were involved. If we assume the AI solution used these sensors and gateways for 5 years out of their 15-year lifespan, a simplistic approach might suggest allocating 33% of the footprint of the used equipment to the AI system. However, this equipment and its data serve multiple purposes beyond the AI system, necessitating a more nuanced allocation.

Given the complexity and lack of a definitive allocation method, we have adopted a conservative estimate of 10% attribution. This choice aims to acknowledge the AI system's reliance on the IoT infrastructure without overstating its impact. To assess the implications of this decision, we conduct a sensitivity analysis, varying this allocation percentage to understand its effect on the overall environmental impact assessment of the AI system. This approach balances the need for attribution with the recognition of the multi-purpose nature of IoT in complex systems.

Assessing the Direct Digital Effects (2/2)

Direct Effect #3: Assessing the AI system

The AI System in this study utilizes cloud computing resources for both training and inference phases. Specifically, an Azure Cluster CPU (Standard_E8ds_v4) is employed daily for model training, running 230-second sessions for each of the 100 managed properties. For setpoint optimization, an Azure Cluster GPU (Standard_NC8as_T4_v3) performs inferences every 15 minutes, with each inference lasting 100 seconds per property, totaling 1920 inferences daily. Additionally, the system stores 7.5 GB of data annually and transmits 333.8 MB daily for training and 3.62 MB for inferences.Assessing the environmental impact of an AI system is complex, requiring consideration of specific lifecycle stages. Luccioni et al. propose an approach which incorporates model training and deployment (inference) phases alongside traditional lifecycle stages. In this case study, the deployment phase corresponds to the continuous optimization of setpoints.

Exhibit 7. Luccioni et al. Life Cycle Stages for AI System

Two distinct methodologies were employed to estimate the environmental footprint of the AI system, serving to test and validate each approach:

1. The first method utilizes public data from the NegaOctet database and its associated Life Cycle Assessment (LCA) method. While not aiming to produce a standardized LCA, this approach models the Azure clusters used by the AI solution as medium-sized virtual machines: two for computing and one for storage.

2. The second approach employs Boavizta's open-source approach, derived from the 'Green Cloud Computing' study commissioned by Umweltbundesamt. This method facilitates more precise modeling of cloud infrastructure components, particularly for CPU and storage. However, due to data limitations, GPU computing is assumed equivalent to CPU computing in both approaches, potentially underestimating results. The assessment encompasses manufacturing and use phases, utilizing the EU-27 average electricity mix due to uncertain datacenter locations. While this approach has limitations, it represents the most robust option currently available for modeling AI system environmental impacts.

Detailed information on the calculation model, in appendices.

Exhibit 8. Manufacturing and Use impacts for the AI System

Manufacturing and Use impacts for AI system			
	kg CO2 eq.	kg SB eq.	kWh
AI system per year	1061.26	0.017	9256.02

The calculation method and the Boavizta data are entirely open-source, allowing for a complete audit of the process. This transparency enables the improvement of results over time for future assessments if any errors become apparent. It is important to note that these results are likely underestimated due to the fact that the cluster using a Tesla-4 GPU has not been accurately modeled in this assessment.

Direct Effect #4: Assessing the Networks

Data is transmitted daily among the servers in the Building Management System (BMS), SISAB servers, and Mysproven servers. These transmissions are included in the analysis.

Utilizing the AI solution necessitates daily data transfers, which can be incorporated into the impact assessment. The impact of data transfer is typically calculated by translating into the volume of data transferred (in GB) to electricity consumption (in Wh), as well as considering lifecycle impact factors associated with the network used (whether fixed or mobile, and including core network considerations). It is important to note that this calculation employs an attribution logic, which distributes impacts retrospectively. In a short-term consequential approach, the impact of data transfer might not be considered due to the volume of data involved. For this analysis, we have adopted an impact factor of 0.069 kWh per GB for the use phase, along with multi-criteria factors for the manufacturing and end-of-life phases. The data utilized in this assessment comes from the NegaOctet and ADEME/Arcep databases.

We estimate that the daily data transmission for training amounts to 333.8 MB, while optimization involves 3.62 MB per day, with both operations occurring daily. The impact factors for manufacturing and end-of-life are based on EU-27 data rather than Swedish data because the transmitted data is sent to servers located in Northern Europe. The electricity consumption associated with the use phase is calculated using the Swedish energy mix. This results in a total of 123 GB of annual data transfers, leading to a relatively small environmental footprint, as detailed below. Additional information on the calculation methodology can be found in the appendices.

Exhibit 9. Life Cycle impacts for the Networks

Life cycle impacts of network use			
	kg CO2 eq.	kg SB eq.	kWh
Total per year	14,38	0,00014	115.42

Exclusions. The scope of this analysis includes only the elements of the Building Management System (BMS) which are modified by the introduction of the AI solution. Specifically, this encompasses the electricity consumption of HVAC systems and the environmental footprint of third-party controllers. The AI system modeling is limited to the manufacturing and use phases, with the end-of-life phase excluded due to missing data in the Boavizta approach, which prevents comparison with the NegaOctet approach. For the IoT system, only the manufacturing and end-of-life phases are modeled.

Limitations. While the assessment presents a valuable analysis, several limitations influence its precision. The diverse range of third-party controllers necessitates the use of average environmental impact models due to the absence of specific Life Cycle Assessments. Additionally, constraints in data availability for the GPU cluster and data center locations limit the accuracy of the AI system modeling. The IoT system modeling is further constrained by the absence of usage phase data and power specifications. These limitations highlight the challenges inherent in conducting comprehensive environmental assessments of complex technological systems, especially when dealing with diverse components and uncertain operational conditions.

Assessing the Indirect Digital Effects (1/2)

Indirect Effect #1: Optimisation of HVAC setpoints

The AI solution has been specifically deployed to enable more precise and dynamic control of temperature and indoor air quality in SISAB-managed buildings, utilizing data from existing sensors. This solution incorporates weather, climate, and utility rate data to create and continuously optimize models for each building. The improved control of temperature and air flow can lead to reduced energy consumption for heating and cooling, as well as decreased electricity consumption by air handler fan motors.

Energy consumption records for heating and electricity are available from 2018 to 2023. For this analysis, we compared 2019 (pre-AI system deployment) with 2023 (post-deployment), excluding intermediate years due to atypical building usage during the Covid-19 pandemic. Energy and electricity consumption data were weather-adjusted to isolate the solution's benefits from temporary weather condition changes. In 2019, the buildings in the study consumed 76,586 MWh for heating and 39,489 MWh of electricity. By 2023, these figures decreased to 74,198 MWh for heating and 35,962 MWh for electricity, representing relative energy saving of 3.12% and 8.93%, respectively. On average, the relative energy savings per property were 2.84% for heating and 8.66% for electricity.

Assuming constant carbon intensity for the district heating network (46 kgCO2e/MWh) and electricity (42.3 gCO2e/kWh), the AI solution's optimization effect resulted in a gross reduction of 259.17 tCO2e in greenhouse gas emissions for 2023 (109.87 tCO2e from heating and 149.3 tCO2e from electricity).

While this analysis focuses on GHG emissions due to limited multi-criteria environmental data for Stockholm's heating network, it's important to note that reductions likely occur across other environmental indicators as well.

Exhibit 10. Indirect Effect #1 - Optimization Effect

Optimization effect				
	2019 (MWh)	2023 (MWh)	Relative savings (%)	Avg. relative savings per property (%)
District heating	76,586	74,198	-3.12%	-2.84%
Electricity	39,488	35,962	-8.93%	-8.66%

Indirect Effect #2: Faster change of third party controllers

The AI solution's impact on third-party controllers' obsolescence has been considered in this study. SISAB's third-party controllers utilize EPROM memory with a 100,000 write limit, where each setpoint change corresponds to one write. Historically, HVAC setpoints were adjusted monthly, resulting in approximately 12 writes per year, well within the memory's capacity. However, the AI solution's capability to change setpoints every 15 minutes significantly accelerates this process, potentially leading to premature hardware obsolescence.

In the reference scenario, 753 third-party controllers (six per property) have an average lifespan of 10 years with 12 annual writes. The AI solution scenario assumes 4 inferences per hour over 253 working days annually, resulting in 24,288 entries per year. This reduces the theoretical controller lifespan to just over 4 years, creating an obsolescence factor of 2.43 compared to the original 10-year lifespan. This accelerated replacement cycle increases the annual greenhouse gas (GHG) impact by 7.3 tCO2e per year. It's important to note that this calculation is based on a theoretical model. The actual impact may vary depending on factors such as the potential for 24-hour setpoint changes and the exact usage patterns of the buildings. SISAB maintains a stock of replacement controllers, but this issue may persist until they upgrade to a new generation of third-party controllers with improved specifications, potentially altering the environmental footprint and lifespan of this equipment. A sensitivity analysis of these assumptions will be conducted to better understand the range of potential impacts.

Exhibit 11. Indirect Effect #2 - Obsolescence Effect

Obsolescence effect			
	kg CO2 eq.	kg SB eq.	kWh
Added impacts per year due to faster replacement of 3d party controllers	7,297.95	0.11	33,883

Indirect Effect #3: Less technician's travels by reduction of occupants complaints

The potential reduction in technicians' travel due to fewer occupant complaints was investigated as a possible indirect effect of the AI solution's improved HVAC setpoint adjustments. In theory, better-regulated indoor environments could lead to fewer complaints, potentially resulting in fewer or shorter interventions by field technicians. However, according to data provided by SISAB, the average daily travel distance for technicians (approximately 40 km) has not shown significant variation. Consequently, this potential effect has been excluded from the current analysis due to the lack of observable change in technician travel patterns.

This finding highlights the complexity of assessing indirect effects in building management systems, where improvements in one area may not necessarily translate into measurable changes in related operational aspects. It also underscores the importance of comprehensive data collection and analysis in evaluating the full impact of technological interventions in building management.

Indirect Effect #4: Increased use of SISAB servers

The implementation of the AI solution has potentially led to a 5-10% increase in CPU and memory usage on the SpaceLogic™ AS-P Automation Server, as reported during interviews. However, due to the lack of precise data, it was not feasible to accurately model this effect in the current analysis. The environmental impact of this increased server usage is likely to be minimal for two primary reasons: the AS-P Automation Servers have relatively low electricity consumption, and Sweden's power sector has an exceptionally low carbon intensity, estimated at approximately 42.3 grams equivalent of CO2 per kilowatt-hour in 2023. Sweden's electricity generation is predominantly derived from low-carbon sources, with 95.88% of its electricity coming from a mix of hydropower (41.93%), nuclear energy (30.84%), wind energy (21.99%), and solar power (1.12%).

Assessing the Indirect Digital Effects (2/2)

Given these factors, the marginal increase in server usage is expected to have a negligible impact on overall emissions. Consequently, this effect has been excluded from the current environmental assessment. However, as Sweden continues to electrify other sectors and increase its demand for low-carbon electricity, future assessments may need to reconsider the impact of increased server usage, especially if it becomes more significant or if more precise data becomes available.

Indirect Effect #5: Reinvestment of savings due to reduced energy consumption

The implementation of the AI solution for optimizing HVAC systems in SISAB-managed buildings has led to significant energy savings, resulting in substantial financial benefits. SISAB's annual energy budget of 340 million SEK (approximately €29.4 million as of November 15, 2024) and energy consumption of 250 GWh has seen a notable reduction due to decreased energy consumption. While a portion of these savings is reinvested in the AI solution itself, the allocation of the remaining funds presents both opportunities and challenges from an environmental perspective.

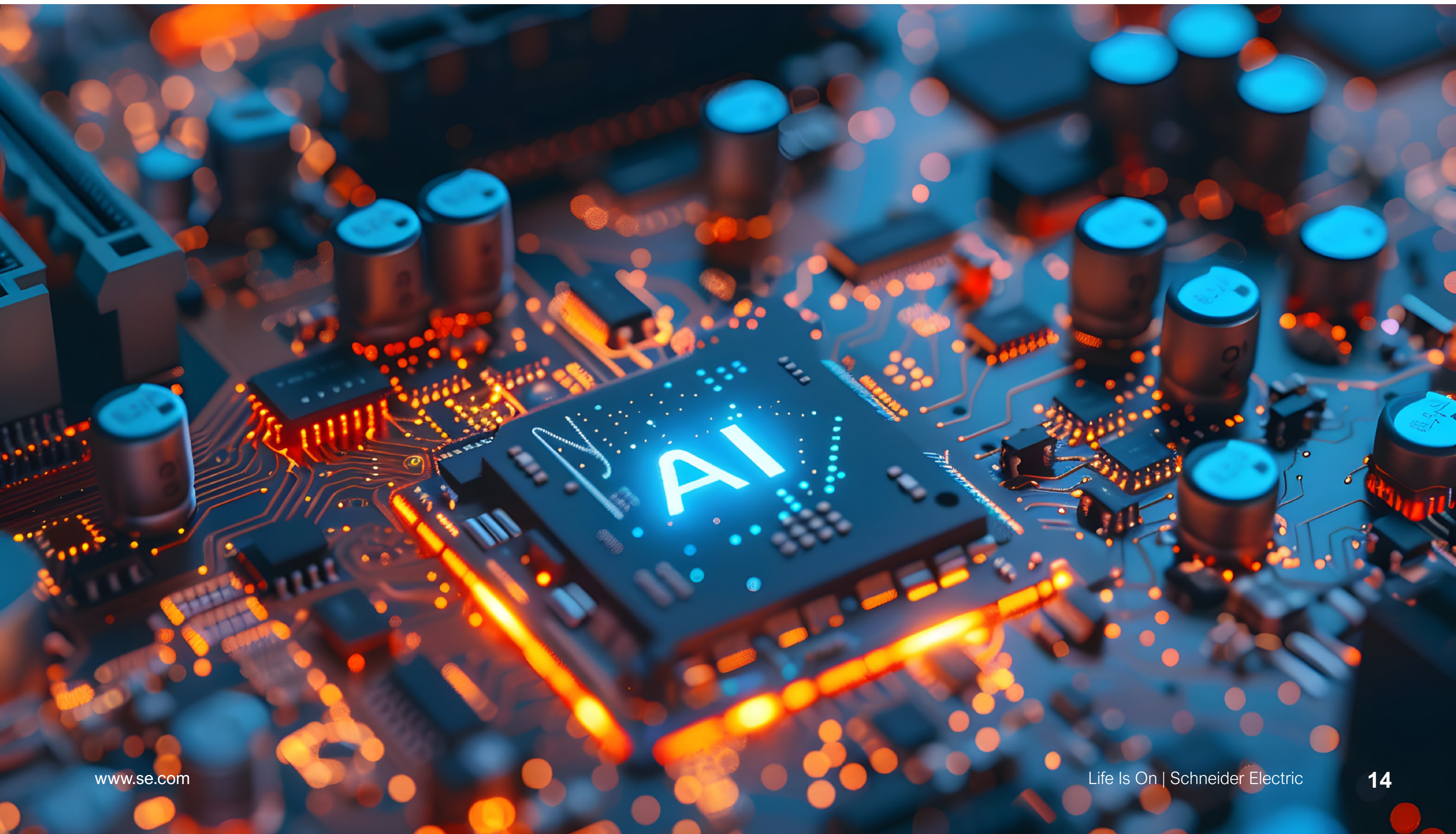
The potential uses for these savings include building renovations, retrofitting projects, or other operational improvements, which could further enhance energy efficiency and reduce environmental impact. Conversely, these funds could be invested in financial assets with varying environmental implications. The environmental impact of these reinvestment decisions is complex and can be either positive or negative, depending on the specific allocation choices. The ITU-T L.Supplement 54 provides a framework for calculating the indirect rebound effect of such reinvestments using a monetary factor approach (expressed in kgCO2eq./€).

However, due to the lack of precise data on the reinvested amount and the contractual details of the AI solution, this effect has not been quantified in the current study. The potential environmental impact of these reinvestment decisions remains an important consideration for future assessments, as it could significantly influence the overall environmental footprint of the energy-saving initiative.

Indirect Effect #6: Change on Stockholm energy grid

The implementation of AI-driven energy optimization in SISAB's buildings has potential implications for Stockholm's energy grid, particularly during peak demand periods. By reducing energy consumption in these buildings, especially during high-demand times, the AI solution contributes to a decrease in overall energy demand on the city's grid. This reduction could potentially lower the carbon intensity of the marginal electricity mix by reducing the need for higher-emission power sources typically used to meet peak demand.

However, quantifying this effect accurately requires a comprehensive analysis of Stockholm's electricity mix, including detailed data on power sources, demand patterns, and grid management strategies. Such an analysis would constitute a significant study in its own right, requiring extensive data collection and complex modeling. Due to the challenges in accessing the necessary data and the time constraints of the current study, this potential effect on the broader energy grid has not been included in the present analysis. Future research could explore this aspect to provide a more comprehensive understanding of the AI solution's impact on urban energy systems and carbon emissions.



Quantifying the Net Digital Impact

Results

The AI-powered building management solution demonstrates significant potential for reducing environmental impact, particularly in areas directly amenable to optimization. Comprehensive modeling of all considered effects reveals a substantial positive net environmental impact, with an annual reduction of 64.8 tCO2e. This corresponds to a favorable carbon cost-benefit ratio exceeding 1:60, indicating that for every unit of carbon cost invested, 60 units of carbon benefit per year are realized.

Energy savings and electricity consumption reductions are particularly noteworthy:

- District heating: Decreased from 76,586 MWh to 74,198 MWh, a total reduction of 2,388 MWh (3.12%) over four years, or 597 MWh per year.
- Electricity: Reduced from 39,489 MWh to 35,962 MWh, a significant drop of 3,527 MWh (8.93%) over four years, or 881.75 MWh per year.

These results align with industry benchmarks, as AI-powered HVAC systems have been shown to reduce energy waste in commercial buildings by up to 30%, with smart systems typically reducing electricity bills by 18% or more[39]. While SISAB's responsibility for all electricity and heating, including both HVAC energy and operational energy (appliances, lighting, and plug-loads), is a broader scope than that of a typical building owner, the achieved savings are still significant.

In terms of Global Warming Potential (GWP), direct effects from the AI system (1.06 tCO2e), IoT system (0.14 tCO2e), and networks (0.014 tCO2e) contribute minimally to emissions. The optimization of heating and electricity consumption results in a substantial reduction of 259.17 tCO2e over four years, or 64.8 tCO2e annually. However, the accelerated obsolescence of controllers adds 7.30 tCO2e, resulting in a net total reduction of 250.65 tCO2e over four years.

Regarding Abiotic Depletion Potential, the AI system and IoT devices contribute marginally to both element and fossil fuel depletion. However, accelerated obsolescence of controllers significantly increases both ADP-e and ADP-f, leading to a net increase of 0.14 kg Sb eq. and 43,938.52 kWh, respectively.

These results highlight the multifaceted nature of environmental impacts and the importance of a holistic approach to sustainability. While the AI solution demonstrates significant benefits in greenhouse gas reduction and energy savings, the increases in Future assessments incorporating multi-criteria data for the optimization effect could provide a more comprehensive evaluation, potentially revealing additional areas where benefits outweigh costs. Such holistic analyses will be crucial in guiding the development of increasingly sustainable and effective building management technologies.

Sensitivity Analysis

To assess the robustness of the study's key assumptions, we conducted a sensitivity analysis by significantly varying these parameters:

Accelerated Controller Replacement (Maximum Scenario):

We tested an extreme scenario where temperature setpoints are adjusted four times per hour, continuously, throughout the year (365 days). This maximizes the obsolescence effect, resulting in an obsolescence factor of 3.5 and an annual impact of 7.3 tCO2e on the greenhouse gas (GHG) indicator. This analysis reveals that controller obsolescence is a factor of relative importance in assessing the solution's net environmental impact.

Maximum IoT System Allocation

By attributing 100% of the annual impact from the 9,901 sensors and 120 gateways used for AI training and inference (instead of the initial 10% allocation), the impact on the Global Warming Potential (GWP) indicator increases from 0.06 to 0.63 tCO2eq. This variation has a minimal effect on the system's net impact, validating the original 10% allocation assumption as a reasonable estimate that does not significantly change the overall result.

Increased Data Traffic

The base model assumed daily data transfers of 333.8 MB for training and 3.62 MB for inference across the entire solution. We tested a scenario where these volumes apply per property, resulting in 33.38 GB for training and 0.36 GB for inference daily. This escalation adds 1.43 tCO2e, 0.61 kgSbe, and 41,552.19 MJ to the total network impacts. This analysis indicates that data traffic is a factor of relative importance in assessing the net environmental impact of the system.

These sensitivity analyses demonstrate that while certain assumptions can influence the magnitude of the environmental impact, the overall conclusion of the AI solution's positive net impact remains robust across various scenarios.

Exhibit 12. Net Digital Impact Calculation

Net Digital Impact Calculation - Difference between 2019 and 2023				
		t CO2 eq.	kg SB eq.	MWh
Direct effects	AI system	1.06	0.016	9.26
	IoT system	0.14	0,00688	0.68
	Networks	0.014	0.00013	0.12
Indirect effects	Optimization (heating and electricity consumption)	- 259.17	N/A	-5,915
	Obsolescence (faster controllers change)	7.30	0.11	33.88
Net Digital Impact		**-250.65**	**0.14**	**-5,871**

Conclusions

Key Insights On The Results

Key Insight 1: Demonstrating Significant Positive Impacts with a Favorable Carbon Cost-Benefit Ratio of 1:60 per year

Our study reveals the substantial potential of AI-Powered HVAC systems in buildings, showcasing notable energy savings and carbon emission reductions. Between 2019 and 2023, we observed a 3.12% reduction in district heating consumption and an impressive 8.93% decrease in electricity consumption. These improvements translated to significant carbon emission reductions: 109.87 tCO2e from district heating and 149.30 tCO2e from electricity, totaling 259.17 tCO2e over the four-year period. The results indicate a favorable 1:60 carbon cost-benefit ratio per year, highlighting the efficiency of the system. While these findings are encouraging, we recognize the importance of further research to validate these effects across diverse building types and geographical locations, paving the way for more widespread adoption and optimization of AI-powered HVAC systems.

Key Insight 2: Establishing a Comprehensive Meta-Study for Future Reference and Extrapolation

This study serves as a valuable meta-analysis, demonstrating the substantial environmental benefits of AI-powered HVAC systems, even in contexts with pre-existing efficient systems. The average yearly carbon saving of 64.8 tCO2e underscores the significant impact of these technologies. Notably, these results were achieved with total energy consumption reductions of 3.12% for district heating and 8.93% for electricity. These findings provide a robust reference point for estimating potential benefits in diverse settings. By offering insights that can be cautiously extrapolated, this study lays the groundwork for future research, emphasizing the importance of exploring AI's role in enhancing HVAC efficiency and sustainability across various contexts.

Key Insight 3: Unveiling the Potential for Enhanced Carbon Reductions in Diverse Contexts

Our research reveals the potential for even greater carbon reductions in environments with more demanding heating, cooling, or air conditioning requirements. The study highlights how local energy mix significantly influences achievable carbon reductions, with non-renewable energy sources offering opportunities for more substantial improvements. For instance, our comparative analysis between Stockholm and Boston revealed that implementing the same solution in Boston could yield carbon emission savings of 1,765.88 tCO2e per year, compared to 250.6 tCO2e in Stockholm. This represents an impact more than 7 times higher or 604% greater in Boston, USA compared to Stockholm, Sweden[37, 38]. This striking difference underscores the importance of considering local environmental conditions and energy sources when implementing AI-powered HVAC solutions, opening avenues for maximizing environmental benefits across diverse geographical and climatic contexts.

Key Insight 4: Advancing System-Wide Approaches for Efficient AI Integration

Our research has identified key challenges in integrating AI systems with legacy HVAC infrastructure, particularly in areas such as memory usage, computational intensity, and lifecycle limitations. These findings underscore the importance of adopting a holistic, system-wide approach when implementing AI solutions in building management. By highlighting these integration hurdles, our study paves the way for future research focused on developing innovative strategies to overcome these challenges. This insight encourages a more comprehensive and nuanced approach to AI implementation in HVAC systems, potentially leading to more efficient, sustainable, and adaptable building management solutions.

Key Insights On The Method

Key Insight 5: Enhancing Reference Scenario Definition for Robust Comparisons

Our study highlights the pivotal role of well-defined reference scenarios in accurately assessing the impact of AI-enhanced HVAC systems. While our current research provides valuable insights, we recognize the opportunity for improvement in baseline diagnostics. Future studies can build upon this foundation by incorporating comprehensive energy audits, thereby enhancing the precision and reliability of comparative analyses. This refinement will contribute significantly to the evolving field of AI-powered building management and energy efficiency.

Key Insight 6: Leveraging the Louvain Method for Efficient IoT Prototyping

The application of the Louvain method[40], utilizing the HSL model, has demonstrated promising potential for rapid prototyping of AI-powered HVAC systems. This approach offers an efficient solution for modeling IoT systems in the absence of detailed specifications. While further validation is warranted, our findings suggest that this method could accelerate the development and implementation of AI-driven building management solutions, potentially leading to more rapid advancements in energy efficiency and sustainability.

Key Insight 7: Advancing Impact Assessment through Comparative Methodologies

Our research employed a dual-method approach, combining the established Negaoctet method with the innovative Boavizta method, particularly for cloud instance calculations. This comparative strategy has yielded a more comprehensive understanding of the AI system's environmental impact. The promising results pave the way for further exploration and refinement of these methodologies. Continued research in this area has the potential to enhance the accuracy and depth of impact assessments for AI-powered HVAC systems, contributing to more informed decision-making in sustainable building management.

Future Research

High Level Conclusion And Limitations Of This Study

This study provides valuable insights into the environmental impact of AI-powered HVAC systems in educational buildings, focusing on two key indirect effects: optimization and obsolescence. While these effects are among the most significant, we acknowledge that other unmodeled effects may influence the overall results. The study demonstrates the potential for significant net positive impact through AI optimization, particularly by adjusting the frequency of setpoint changes.

However, we acknowledge several limitations and areas for future research. The context-dependent nature of our results means they may vary across different building types and geographical locations, necessitating further studies in diverse settings. The study's four-year timeframe limits our understanding of long-term system adaptability and effectiveness. While environmental benefits are clear, a comprehensive economic analysis is needed to fully assess the return on investment. Additionally, further research is required to address the complexities of integrating AI systems with legacy HVAC infrastructure. We also recognize that the study did not fully account for potential alternative energy-saving measures that SISAB might have implemented without the AI solution.

Looking forward, we propose several key areas for future research. These include conducting long-term performance and adaptability studies over 5-10 years, exploring integration with renewable energy systems and smart grids, investigating scalability across diverse building types and climatic conditions, and analyzing comprehensive economic and social impacts, which are detailed in the section on the right.

Opportunities For Future Research

Based on the content of the study and the current state of AI-powered HVAC systems, here are four key ideas for future research to extend the present study:

1. Long-Term Performance and Adaptability

Longitudinal studies spanning 5-10 years are essential to rigorously assess the long-term performance and adaptability of AI-powered HVAC systems. These studies should monitor energy savings, system performance, and the evolution of AI models in response to changing building usage patterns and climate conditions. Additionally, evaluating system resilience to major disruptions, such as renovations or occupancy changes, is crucial. This long-term perspective will provide valuable insights into the sustainability and effectiveness of AI-powered HVAC solutions throughout their lifecycle.

2. Integration with Renewables and Smart Grids

Future research should investigate the integration of AI-powered HVAC systems with renewable energy sources and smart grid technologies. This area of study would explore how these systems optimize operations in conjunction with on-site renewable energy generation, energy storage systems, and smart grids. Research should focus on balancing energy demand, maximizing renewable energy use, and contributing to grid stability. Such investigations could lead to more holistic and sustainable building energy management solutions aligned with broader clean energy initiatives.

3. Scalability Across Building Types and Climates

Further research is needed to explore the scalability and adaptability of AI-powered HVAC systems across diverse building types and climatic conditions. While this study focused on educational buildings in Stockholm, understanding system performance in different contexts is crucial. Research should examine AI-powered HVAC implementation in residential, commercial, and industrial buildings across various climatic zones. This would help identify limitations and necessary adaptations for different building types and environments, informing the development of more versatile and widely applicable AI-HVAC solutions.

4. Comprehensive Economic and Social Impact Analysis

While our study demonstrates significant positive indirect effects on efficiency and carbon emissions in this specific case, suggesting a favorable impact on overall costs, a detailed analysis of the return on investment in absolute terms has not yet been conducted. This presents an important avenue for future research. A comprehensive economic analysis would provide valuable insights into the financial viability of AI-powered HVAC systems across different contexts, examining factors such as implementation costs, operational expenses, energy cost savings, and potential revenue streams. Such research could explore how energy prices, regulations, and building characteristics affect economic outcomes, providing a balanced view of environmental and economic factors. This financial perspective would complement our environmental findings, helping stakeholders make informed decisions about adopting AI-powered HVAC technologies.

Appendices

References (1/2)

1. Bremer, C., Kamiya, G., Bergmark, P., Coroamă, V. C., Masanet, E., & Lifset, R. (2023). Assessing Energy and Climate Effects of Digitalization: Methodological Challenges and Key Recommendations. SSRN Electronic Journal. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4459526

2. Gershenfeld, N., Samouhos, S., & Nordman, B. (2010). Intelligent infrastructure for energy efficiency. Science, 327(5969), 1086-1088. https://www.science.org/doi/10.1126/science.1174082

3. Fu, G. (2018). Deep belief network based ensemble approach for cooling load forecasting of air-conditioning system. Energy, 148, 269-282. https://www.sciencedirect.com/science/article/abs/pii/S0360544218301609

4. Kazmi, H., Mehmood, F., Lodeweyckx, S., & Driesen, J. (2018). Gigawatt-hour scale savings on a budget of zero: Deep reinforcement learning based optimal control of hot water systems. Energy, 144, 159-168. https://www.sciencedirect.com/science/article/abs/pii/S0360544217320388

5. Wang, Z., Wang, Z., He, S., Gu, X., & Yan, Z. F. (2017). Fault detection and diagnosis of chillers using Bayesian network merged distance rejection and multi-source non-sensor information. Applied Energy, 188, 200-214. https://www.sciencedirect.com/science/article/abs/pii/S0306261916317615

6. Jia, F., Lei, Y., Lin, J., Zhou, X., & Lu, N. (2016). Deep neural networks: A promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data. Mechanical Systems and Signal Processing, 72, 303-315. https://www.sciencedirect.com/science/article/abs/pii/S0888327015004859

7. Park, J. Y., Dougherty, T., Fritz, H., & Nagy, Z. (2019). LightLearn: An adaptive and occupant centered controller for lighting based on reinforcement learning. Building and Environment, 147, 397-414. https://www.sciencedirect.com/science/article/abs/pii/S0360132318306747

8. Rashidi, P., & Cook, D. J. (2009). Keeping the resident in the loop: Adapting the smart home to the user. IEEE Transactions on Systems, Man, and Cybernetics, Part A, 39(5), 949-959. https://ieeexplore.ieee.org/document/5167267

9. D'Oca, S., & Hong, T. (2015). Occupancy schedules learning process through a data mining framework. Energy and Buildings, 88, 395-408. https://www.sciencedirect.com/science/article/pii/S037877881400993X

10. Zhao, J., Lasternas, B., Lam, K. P., Yun, R., & Loftness, V. (2014). Occupant behavior and schedule modeling for building energy simulation through office appliance power consumption data mining. Energy and Buildings, 82, 341-355. https://www.sciencedirect.com/science/article/abs/pii/S0378778814005453

11. Zou, H., Zhou, Y., Yang, J., & Spanos, C. J. (2018). Towards occupant activity driven smart buildings via WiFi-enabled IoT devices and deep learning. Energy and Buildings, 177, 12-22. https://www.sciencedirect.com/science/article/abs/pii/S037877881831329X

12.Paccou, R. (2024). Digital with impact. https://www.se.com/ww/en/insights/sustainability/sustainability-research-institute/digital-with-impact.jsp

13. Paccou, R. (2024). AI for Impact: A method for guiding AI applications at scale. https://www.se.com/ww/en/insights/sustainability/sustainability-research-institute/AI-for-impact-a-method-for-guiding-AI-energy-applications-at-scale/

14.https://gauthierroussilhe.com/en

15. https://boavizta.org/en

16. Naturvårdsverket. (2023). Sweden's Climate Act and Climate Policy Framework. Swedish Environmental Protection Agency. https://www.naturvardsverket.se/en/international/swedish-environmental-work/swedens-climate-act-and-climate-policy-framework/

17. City of Stockholm. (2020). Climate Action Plan 2020-2023: For a fossil-free and climate-positive Stockholm by 2040. https://start.stockholm/globalassets/start/om-stockholms-stad/sa-arbetar-staden/miljo-och-klimat/climate-action-plan-2020-2023.pdf

18. ebm-papst. (2024). Efficient heat supply in Stockholm. https://www.ebmpapst.com/de/en/newsroom/news/2024/stockholmexergi.html

19. European Commission. (2023). Stockholm, Sweden: Heat recovery from data centres. EU Covenant of Mayors for Climate & Energy. https://eu-mayors.ec.europa.eu/en/Stockholm-Heat-recovery-from-data-centres

20. Myrspoven. (n.d.). Turning your building into a solution to the energy crisis. Retrieved November 13, 2024, from https://myrspoven.com

21. Silicon Canals. (2023, October 26). Sweden's Myrspoven bags €5.4M to make buildings consume less energy using AI. https://siliconcanals.com/myrspoven-bags-5-4m/

22. Zhu, Y., Jin, X., Du, Z., & Fang, X. (2021). Artificial Intelligence-Assisted Heating Ventilation and Air Conditioning Control and the Unmet Challenges: A Review. Applied Sciences, 11(6), 2778. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6427582/

23. BSEE. (2023). Study highlights AI's potential in building energy efficiency. Building Services & Environmental Engineer. https://bsee.co.uk/study-highlights-ais-potential-in-building-energy-efficiency/

References (2/2)

24. Khanmirza, E., Esmaeilzadeh, A., & Markazi, A. H. D. (2022). Based Occupant-Centric Heating Ventilation and Air Conditioning Control System for Energy Efficiency in Buildings. Sustainability, 14(23), 16107. https://www.mdpi.com/2071-1050/14/23/16107

25.Schneider Electric. (n.d.). Using AI to optimize HVAC systems in buildings. https://www.se.com/ww/en/insights/electricity-4-0/digitalization/using-ai-to-optimize-systems-in-buildings.jsp

26. International Telecommunication Union. (2022). Recommendation ITU-T L.1480: Methodology for the assessment of the environmental impact of information and communication technology greenhouse gas and energy reduction interventions. https://www.itu.int/rec/T-REC-L.1480-202212-I/en

27. European Green Digital Coalition. (n.d.). Net Carbon Impact Assessment Methodology for ICT Solutions. https://www.greendigitalcoalition.eu/net-carbon-impact-assessment-methodology-for-ict-solutions/

28. International Organization for Standardization. (2006). ISO 14040:2006 Environmental management — Life cycle assessment — Principles and framework. https://www.iso.org/standard/37456.html

29. International Organization for Standardization. (2006). ISO 14044:2006 Environmental management — Life cycle assessment — Requirements and guidelines. https://www.iso.org/standard/38498.html

30. Intergovernmental Panel on Climate Change. (2022). Chapter 9: Buildings. In Climate Change 2022: Mitigation of Climate Change. https://www.ipcc.ch/report/ar6/wg3/chapter/chapter-9/

31. Belkhir, L., & Elmeligi, A. (2018). Assessing the carbon footprint of the ICT sector: A review of the literature and a framework for future research. Journal of Cleaner Production, 196, 1125-1137. https://doi.org/10.1016/j.jclepro.2018.06.076

32. Köhler, S., & Pizzol, M. (2019). Life Cycle Assessment of Bitcoin Mining. Environmental Science & Technology, 53(23), 13598-13606. https://doi.org/10.1021/acs.est.9b05687

33. Andrae, A. S. G., & Edler, T. (2015). On Global Electricity Usage of Communication Technology: Trends to 2030. Challenges, 6(1), 117-157. https://doi.org/10.3390/challe6010117

34. Ligozat, A. L., Lefèvre, J., Bugeau, A., & Combaz, J. (2021). Unraveling the Hidden Environmental Impacts of AI Solutions for Environment. arXiv preprint arXiv:2110.11822. https://arxiv.org/pdf/2110.11822.pdf

35. Ma, Z., Cooper, P., Daly, D., & Ledo, L. (2012). Existing building retrofits: Methodology and state-of-the-art. Energy and Buildings, 55, 889-902. https://doi.org/10.1016/j.enbuild.2012.08.018

36. Ascione, F., Bianco, N., De Masi, R. F., Mauro, G. M., & Vanoli, G. P. (2017). Energy retrofit of educational buildings: Transient energy simulations, model calibration and multi-objective optimization towards nearly zero-energy performance. Energy and Buildings, 144, 303-319. https://doi.org/10.1016/j.enbuild.2017.03.056

37. Ritchie, H., Rosado, P., & Roser, M. (2023). Carbon intensity of electricity generation. Our World in Data. https://ourworldindata.org/grapher/carbon-intensity-electricity

38. International Energy Agency. (2023). Emissions Factors 2023. IEA. https://www.iea.org/data-and-statistics/data-product/emissions-factors-2023

39. Minier V, Schneider Electric™ Sustainability Research Institute. Decarbonizing buildings: Benefit consumers & system operators. Sustainability Research Institute. Retrieved from https://www.se.com/ww/en/insights/sustainability/sustainability-research-institute/decarbonizing-buildings-benefit-consumers-system-operators/

40. Pirson, T., & Bol, D. (2021). Assessing the embodied carbon footprint of IoT edge devices with a bottom-up life-cycle approach. Journal of Cleaner Production, 322, 129009. https://www.sciencedirect.com/science/article/abs/pii/S0959652621031577

41. C40 Cities. (n.d.). Strategy for a fossil fuel-free Stockholm by 2040. C40 Knowledge Hub. Retrieved from https://www.c40knowledgehub.org/s/article/Strategy-for-a-fossil-fuel-free-Stockholm-by-2040?language=en_US

Terminology (1/2)

1. AI (Artificial Intelligence): Intelligent systems that can perform tasks typically requiring human intelligence, such as visual perception, speech recognition, decision-making, and language translation.

2. Allocation: Quantification of an organization's GHG impact as a portion of the total net carbon impact of the solution.

3. Abiotic Resources Depletion: The consumption of non-living natural resources such as minerals and fossil fuels.

4. BAU (Business-as-usual): A scenario representing the normal execution of standard operations within an organization, particularly in environmental impact assessments.

5. BMS (Building Management System): A computer-based control system installed in buildings that controls and monitors mechanical and electrical equipment.

6. Carbon Emissions: The release of carbon dioxide and other carbon compounds into the atmosphere, primarily from burning fossil fuels.

7. Component: See 'Solution component'.

8. Deep Reinforcement Learning: A machine learning technique where an agent learns to make decisions by interacting with an environment.

9. EEIO (Environmentally Extended Input-Output): An analytical method incorporating environmental impact data into economic input-output models.

10. EGDC (European Green Digital Coalition): A coalition of companies committed to supporting the green and digital transformation of the EU.

11. EGDC methodology: Term referring to the "Net Carbon Impact Assessment Methodology for ICT Solutions".

12. Embodied emissions: Greenhouse gas emissions generated during the extraction, production, transport, and manufacturing stages of a product's life, also termed as a cradle-to-gate footprint.

13. Energy Efficiency: The ratio of useful output of a process to the total energy input.

14. EU (European Union): A political and economic union of 27 member states located primarily in Europe.

15. EV (Electric Vehicle): A vehicle that uses one or more electric motors for propulsion.

16. Ex-ante assessment: A forward-looking assessment of a comparative impact expected to occur in the future.

17. Ex-post assessment: An assessment of a comparative impact that has occurred in the past.

18. First order effects: Direct emissions associated with the full life cycle of the implemented ICT solution.

19. Functional unit: The relative unit of emissions reductions selected for the assessment to describe the emissions reductions per unit of the solution.

20. GHG (Greenhouse Gas): Gases that absorb and emit infrared radiation, contributing to the greenhouse effect.

21. GHGP (Greenhouse Gas Protocol): A set of standardized frameworks for measuring and managing greenhouse gas emissions.

22. Global Warming Potential: A measure of how much heat a greenhouse gas traps in the atmosphere relative to carbon dioxide.

23. Higher order effects: Indirect impacts resulting from the deployment and use of the solution, requiring behavioral changes to have an impact.

24. HVAC (Heating, Ventilation, and Air Conditioning): Systems used to control temperature, humidity, and air quality in buildings.

25. ICT (Information and Communications Technology): Technologies used for handling telecommunications, broadcast media, intelligent building management systems, audiovisual processing and transmission systems, and network-based control and monitoring functions.

26. ICT infrastructure: ICT networks or services such as telecommunication network infrastructure, remote data storage, data processing, cloud computing, etc.

27. ICT solution: A system of ICT components encompassing ICT goods and infrastructure combined to deliver a specific service to the user.

28. ICT solution scenario: Scenario representing the implementation of the ICT solution.

29. IEA (International Energy Agency): An autonomous intergovernmental organization providing analysis, data, policy recommendations, and solutions to global energy challenges.

Terminology (2/2)

30. Implementation context: Context in which the solution is implemented, including parameters describing the context in which the reference and ICT solution scenarios operate.

31. IoT (Internet of Things): A network of interconnected devices that can collect and exchange data.

32. ITU (International Telecommunication Union): The United Nations specialized agency for information and communication technologies.

33. KPI (Key Performance Indicator): A measurable value demonstrating how effectively a company is achieving key business objectives.

34. LCA (Life Cycle Assessment): The compilation and evaluation of inputs, outputs, and potential environmental impacts of a product system throughout its life cycle.

35. Machine Learning: A subset of AI focusing on developing algorithms that can learn from and make predictions or decisions based on data.

36. MPN (Mobile Private Network): A dedicated cellular network for a specific organization or location.

37. Net Carbon Impact: Comparison between the GHG impacts of a scenario with an ICT solution and a reference scenario without the ICT solution within the same boundary.

38. Net Carbon Impact Assessment: A quantitative and qualitative assessment comparing the GHG impacts of the selected solution-ICT solution scenario and a reference scenario within the same boundary.

39. Net Digital Impact: A framework for assessing the overall environmental impact of digital solutions, considering both positive and negative effects.

40. Net environmental impact: Comparison between the environmental impacts of a scenario with an ICT solution and a reference scenario without the ICT solution within the same boundary.

41. Primary data: Data obtained directly from the ICT solution.

42. PV (Photovoltaic): A method of generating electrical power by converting solar radiation into direct current electricity using semiconductors.

43. Rebound effects: Long-term second order effects where efficiency improvements realized by the implemented solution subsequently cause an increase in system activity resulting in GHG emissions.

44. Reference activity: Activity forming the reference scenario to deliver the same service to the user as the ICT solution defined by the functional unit.

45. Reference scenario: Scenario reflecting the situation without the implementation of the ICT solution, comprised of reference activities that form the end-to-end process to deliver the same service as the ICT solution.

46. Secondary data: Data obtained from sources other than the ICT solution itself (e.g., literature review, national statistics, etc.)

47. Second order effects: The indirect emissions resulting from use of the solution or reference scenario.

48. Sector Methodologies: Set of methodologies providing further guidance on how the requirements in the EGDC methodology can be applied for specific sectors.

49. SISAB (Skolfastigheter i Stockholm AB): A municipal company responsible for operating and maintaining educational facilities in Stockholm, Sweden.

50. SOLIDA (SISAB On-Line Intelligent Data Analysis): The name given to the AI-powered HVAC optimization system implemented by SISAB.

51. Solution component: Individual elements or parts that make up the overall ICT solution.

52. tCO_2e (Tonnes of Carbon Dioxide Equivalent): A metric measure used to compare emissions from various greenhouse gases based on their global warming potential.

53. WBCSD (World Business Council on Sustainable Development): A global, CEO-led organization of over 200 leading businesses working together to accelerate the transition to a sustainable world.

Complete Results

1. Net Impacts (Average Scenario):
> Climate Change: -250.65 t CO_2 eq.
> Resource Use (Minerals and Metals): 0.14 kg SB eq.
> Fossil Resource Use: 158,177.43 MJ

2. Direct Effects:
AI System:
> Climate Change: 1.06 t CO_2 eq.
> Resource Use (Minerals and Metals): 0.016713 kg SB eq.
> Fossil Resource Use: 33,321.39 MJ
IoT System:
> Climate Change: 0.14 t CO_2 eq.
> Resource Use (Minerals and Metals): 0.006880 kg SB eq.
> Fossil Resource Use: 2,461.76 MJ
Networks:
> Climate Change: 0.01 t CO_2 eq.
> Resource Use (Minerals and Metals): 0.000137 kg SB eq.
> Fossil Resource Use: 415.52 MJ
Subtotal (Direct Effects per year):
> Climate Change: 1.22 t CO_2 eq.
> Resource Use (Minerals and Metals): 0.023730 kg SB eq.
> Fossil Resource Use: 36,198.67 MJ

3. Indirect Effects:
Optimization of HVAC Systems:
> Climate Change: -259.17 t CO_2 eq.
> Resource Use (Minerals and Metals): N/A
> Fossil Resource Use: N/A

Faster Controllers Change (Average Scenario):
> Climate Change: 7.30 t CO_2 eq.
> Resource Use (Minerals and Metals): 0.11 kg SB eq.
> Fossil Resource Use: 121,978.75 MJ

Subtotal (Indirect Effects per year):
> Climate Change: -251.87 t CO_2 eq.
> Resource Use (Minerals and Metals): 0.11 kg SB eq.
> Fossil Resource Use: 121,978.75 MJ

4. Sensitivity Analysis:
Maximum Scenario (Faster Controller Change):
> Climate Change: -12.79 t CO_2 eq.
> Resource Use (Minerals and Metals): 0.20 kg SB eq.
> Fossil Resource Use: 213,770.16 MJ

Net Impacts (Max Scenario on Controllers):
> Climate Change: 245.16 t CO_2 eq.
> Resource Use (Minerals and Metals): 0.224345 kg SB eq.
> Fossil Resource Use: 249,968.83 MJ

Higher IoT System Allocation:
> Climate Change: 0.63 t CO_2 eq.
> Resource Use (Minerals and Metals): 0.00003 kg SB eq.
> Fossil Resource Use: 11.03 MJ

Net Impacts (Max Allocation of IoT System):
> Climate Change: 250.16 t CO_2 eq.
> Resource Use (Minerals and Metals): 0.131353 kg SB eq.
>Fossil Resource Use: 155,726.70 MJ

Higher Data Traffic (333.8 MB Input Data Per Day for Training per
> Property, 3.62 MB Per Day for Inference per Property):
> Climate Change: 1.43 t CO_2 eq.
> Resource Use (Minerals and Metals): 0.01 kg SB eq.
> Fossil Resource Use: 41,552.19 MJ

Net Impacts (Higher Data Traffic):
> Climate Change: 249.24 t CO_2 eq.
> Resource Use (Minerals and Metals): 0.148066 kg SB eq.
> Fossil Resource Use: 199,314.10 MJ

Datas - Direct Effects

1. Data Center (DC) Configuration:
> PUE: 1.17
> Hardware Life Expectancy (hours): 43,800
> Hardware Life Expectancy (years): 5

2. Server Configuration (Platform):
> Name: Edsv4-Type1 Azure
> Manufacturer: Intel
> CPU Units: 2
> CPU Core Units: 52
> CPU Die Size [cm²]: 19.1
> CPU Name: Intel Xeon Platinum 8272CL
> vCPU: 64
> RAM Units: 8
> RAM Capacity [GB]: 63
> RAM Density [GB/cm²]: 8
> SSD Units: 2
> SSD Capacity [GB]: 2048
> SSD Density [GB/cm²]: 19
> PSU Count: 2
> PSU Weight [kg]: 3

3. Training VM Configuration (Instance):
> Name: standard_e8ds_v4
> vCPU: 8
> RAM [GB]: 64
> SSD [GB]: 300
> HDD [GB]: 0
> GPU: 0
> Platform: Edsv4-Type1

4. Power Consumption:
> Power Consumption for CPU [W]: 259.17
> Power Consumption for RAM [W]: 272.16
> Power Consumption for SSD [W]: 11.4
> Total Power [W]: 651.28

5. VM Training & Inference Node Per Year:
> Total for Training Node [per year]: 431.34 kg CO2 eq, 8.09E-03 kg SB eq, 13,344.15 MJ
> Total for Inference Node [per year]: 629.92 kg CO2 eq, 8.62E-03 kg SB eq, 19,977.24 MJ

6. Total AI System Per Year:
> Total for AI System [per year]: 1061.26 kg CO2 eq, 0.017 kg SB eq, 33,321.39 MJ

7. IoT System Configuration:
> Sensor Configuration (Ecoguard THS-1002-1):
> Number of Units: 9,901
> Total Climate Change Impact [kg CO2 eq.]: 1.87 per unit, 323.01 for all units per year
> Total Resource Use (Minerals & Metals) [kg SB eq.]: 9.98E-05 per unit, 0.0662 for all units per year
> Total Fossil Resource Use [MJ]: 33.08 per unit, 23,282.39 for all units per year
> Lifespan [years]: 15
> Gateway Configuration (Ecoguard AR-0002-1):
> Number of Units: 103
> Total Climate Change Impact [kg CO2 eq.]: 10.9 per unit, 80.48 for all units per year
> Total Resource Use (Minerals & Metals) [kg SB eq.]: 3.67E-04 per unit, 0.0026 for all units per year
> Total Fossil Resource Use [MJ]: 182 per unit, 1,335.22 for all units per year
> Lifespan [years]: 15

8. Networks Configuration:
> Training Transmission Per Day [GB]: 0.3338 GB
> Inference Transmission Per Day [GB]: 0.00362 GB
> Climate Change Impact for Data Transmission [kg CO2 eq.]: 14.38 per year
> Resource Use (Minerals & Metals) [kg SB eq.]: 0.00014 per year
> Fossil Resource Use for Data Transmission [MJ]: 415.52 per year

9. Allocation Factor for IoT System:
> Allocation Factor: 10% of the IoT system impacts are allocated to the AI system.

10. Total Impact for AI System (Allocated):
> Climate Change [kg CO2 eq.]: 140.35
> Resource Use (Minerals & Metals) [kg SB eq.]: 0.0069
> Fossil Resource Use [MJ]: 2,461.76

11. Total Impact for Networks:
> Climate Change [kg CO2 eq.]: 14.38
> Resource Use (Minerals & Metals) [kg SB eq.]: 0.00014
> Fossil Resource Use [MJ]: 415.52

Datas - Indirect Effects

Optimization Effect on HVAC Systems
> Unit: MWh

Total District Heating Consumption of Buildings:
> Reference Scenario [2019]: 76,586 MWh
> Scenario with Solution [2023]: 74,198 MWh
> Reduction: -3.12%

Total Electricity Consumption of Buildings:
> Reference Scenario [2019]: 39,489 MWh
> Scenario with Solution [2023]: 35,962 MWh
> Reduction: -8.93%

Carbon Intensity of District Heating:
> 61 kgCO2e/MWh (Reference Scenario)
> 46 kgCO2e/MWh (Scenario with Solution)

Carbon Intensity of Power Grid:
> 42.3 kgCO2e/MWh (both scenarios)

Saved Carbon Emissions:
From District Heating:
> 109.87 tCO2e
From Electricity:
> 149.30 tCO2e
Total Saved Carbon Emissions:
> 259.17 tCO2e

Faster Controllers Change Due to Memory Writing Limit
Controller Configuration:
> Number of Third-Party Controllers: 753
> Lifespan of Controller: 10 years

Memory Configuration:
> EPROM Writing Limit: 100,000 writes
> Life Cycle Impacts of One Third-Party Controller
> kg CO2 eq.: 67.83 kg
> kg SB eq.: 0.00 kg
> MJ: 1,133.75 MJ

Reference Scenario Configuration
> Number of Writes per Year: 12
> Theoretical Lifespan of Controller Memory (years): 8,333.33 years
> Average Lifespan of Controller: 10 years

Total Impacts for All Controllers [Life Cycle]
>kg CO2 eq.: 51,077.50 kg
> kg SB eq.: 0.80 kg
> MJ: 853,714.69 MJ

Scenario with Solution Configuration
> Number of Writes per Year:
> Scenario Max: 35,040
> Scenario Average: 24,288
> Scenario Min: 12,144

Theoretical Lifespan of Controller Memory (years):
> Scenario Max: 2.85 years
> Scenario Average: 4.12 years
> Scenario Min: 8.23 years

Obsolescence Factor:
> Scenario Max: 3.50
> Scenario Average: 2.43
> Scenario Min: 1.21

Total Impacts for All Controllers [Life Cycle]
Scenario Max:
> kg CO2 eq.: 178,975.55 kg
> kg SB eq.: 2.81 kg
> MJ: 2,991,416.26 MJ

Scenario Average:
> kg CO2 eq.: 124,057.02 kg
> kg SB eq.: 1.95 kg
> MJ: 2,073,502.23 MJ

Scenario Min:
> kg CO2 eq.: 62,028.51 kg
> kg SB eq.: 0.97 kg
> MJ: 1,036,751.11 MJ

Results for Total Added Impacts per Year
Scenario Max:
> t CO2 eq.: 12.79 t
> kg SB eq.: 0.20 kg
> MJ: 213,770.16 MJ

Scenario Average:
> t CO2 eq.: 7.30 t
> kg SB eq.: 0.11 kg
> MJ: 121,978.75 MJ

Scenario Min:
> t CO2 eq.:1.10 t
> kg SB eq.:0.02kg
> MJ:18,303.64MJ

Compliance with Existing Methodologies

Exhibit 13. Compliance with Existing Methodologies

	This study	ITU-T L.1480	Net Carbon Impact Assessment
Scope	Single solution for a given implementation context	Compatible when evaluating a single solution proposed by the method (clause 11)	Compatible with the evaluation of a solution in a specific context (non-portfolio cases)
Perspective	Company-level	Compatible	Compatible
Deployment of the solution	Stockholm (120 properties), since 2020	Compatible	Compatible
Temporal perspective	Ex-post	Compatible	Compatible
Reference scenario	Business-as-usual	Compatible but not recommended	Not compatible
Assessment depth	Identification of all indirect effects with a consequence tree and modelling of two indirect effects	Equivalent to Tier 2	Compatible
ICT solution assessment	Full life cycle	Compatible	Compatible
Indirect effects assessment	Optimisation, Induction (obsolesence effect)	Compatible	Compatible
Sensitivity analysis	Yes	Recommended	Recommended
Uncertainity analysis	No	Compatible	Compatible
Communication	Yes (Research Paper)	Compatible	Compatible
Critical review	No	Compatible	Compatible

Disclosure for the Net Impact Assessment

Exhibit 14. Disclosure for the Net Impact Assessment of the solution

	This study
Description of the solution	An AI solution integrated into a BMS allows the temperature and airflows in each building to be adjusted more frequently and more precisely.
Deployment of the solution	The solution has been deployed since 2020 in 120 properties in Stockholm managed by SISAB.
Functional unit	Heating and air conditioning the buildings at the set temperature and airflow rates for 1 year.
Reference scenario	Business-as-usual, it was not possible to determine and quantify what SISAB would have invested in reducing the energy consumption of its buildings.
Components of the solution	BMS system (third-party controllers), IoT system, AI system
Categorisation of digital technologies	A, B
Description of calculation	The AI system was analysed on the basis of the instances used for model training and inference. A share of the IoT system that provided the training data is allocated to the solution. The impact on the network has been modelled on the basis of the data flow. Optimisation was calculated on the basis of actual consumption data supplied by SISAB. The impact of the AI system on the faster renewal of controllers is modelled using data provided by Schneider and an obsolescence factor compared with the reference scenario.
Net Impact of the Solution	The net positive impact on the GWP indicator is 250.65 tCO_2e.
Assumptions	The two instances for the AI system are considered as CPU instances instead of a CPU and GPU instance. The IoT system allocation is set to 10%. The electricity mix used for modelling the AI system and the network part is the average European mix. The lifecycle footprint of a controller is defined on the basis of the average impact data for a range of controllers.
Data sources	Schneider Electric, SISAB, Boavizta, NegaOctet, Base Empreinte

Acknowledgments

We would like to warmly thank the following contributors for their valuable feedbacks and insights.

From Schneider Electric
- Karim Hussain, Product Manager, Digital Buildings
- Jacques Kluska, Principal, Responsible AI Specialist, AI Hub
- Vincent Minier, VP - Schneider Electric™ Sustainability Research Institute
- Vincent Petit, SVP - Head of the Schneider Electric™ Sustainability Research Institute
- Roselyne Thai, Green and Circular Standardization Leader, Strategy
- Axelle Weber, Lead, Data Scientist, AI Hub

From SISAB
- Erica Eriksson, Head of Energy and Sustainability
- Mats Carlqvist, Head of Operations
- Niklas Dalgrip, Director of Operations

From Myrspoven
- Anders Kallebo, Chief Executive Officer
- Carl-Johan Fredman, Chief Partner Officer
- Roberto Díaz-Pérez, Lead AI & Data Scientist

Authors

- Rémi Paccou
- Gauthier Roussilhe, Co-author

Legal Disclaimer

The contents of this publication are presented for informational purposes only. While every effort has been made to ensure accuracy, this publication is not intended as investment or strategic advice. The assumptions, models, and conclusions presented here represent one possible scenario and are inherently dependent on many factors beyond our control, including but not limited to governmental actions, climate conditions, geopolitical considerations, and technological advancements.

The scenarios and models are not projections or forecasts of the future and do not reflect Schneider Electric's strategy or business plan. The Schneider Electric logo is a trademark and service mark of Schneider Electric SE. All other marks are the property of their respective owners.

Schneider Electric™ Sustainability Research Institute

Global awareness of the need for a more inclusive and climate-positive world is at an all-time high. This includes reducing carbon emissions and preventing environmental damage and biodiversity loss.

Nation states and corporations are increasingly making climate pledges and including sustainability themes in their governance. Yet, progress is nowhere near where it should be. For global society to achieve these goals, more action and speed is needed.

How can we convert momentum into reality?

By aligning action with United Nations Sustainable Development Goals. By leveraging scientific research and technology. By gaining a better understanding of the future of energy and industry, and of the social, environmental, technological, and geopolitical shifts happening all around us. By reinforcing the legislative and financial drivers that can galvanize more action. And by being clear on what the private and public sectors can do to make all this happen.

The mission of the Schneider Electric™ Sustainability Research Institute is to examine the facts, issues, and possibilities, to analyze local contexts, and to understand what businesses, societies, and governments can and should do more of. We aim to make sense of current and future trends that affect the energy, business, and behavioral landscape to anticipate challenges and opportunities. Through this lens, we contribute differentiated and actionable insights.

We build our work on regular exchanges with institutional, academic, and research experts, collaborating with them on research projects where relevant. Our findings are publicly available online, and our experts regularly speak at forums to share their insights.

Set up in 2020, our team is part of Schneider Electric, the leader in the digital transformation of energy management and automation, whose purpose is to bridge progress and sustainability for all.

"It is better to light a candle than to curse the darkness" - Eleanor Roosevelt