

AI for Climate: Quantifying the Energy & Carbon Impact of Building Optimization

White Paper 521

by Efrie Escott and Will Alpine

Executive summary

Buildings must significantly improve energy efficiency to remain aligned with climate targets. This paper evaluates whether AI-enabled HVAC optimization can help close that gap and whether the resulting emissions reductions outweigh the environmental impacts associated with operating the AI systems themselves.

The study compares models of edge-based and cloud-hosted AI architectures deployed on top of IoT-enabled building management systems (BMS) in mid-sized offices deployed in Australia, the US, and India. These HVAC optimization systems rely on lightweight machine-learning inference workloads within the AI layer.

Relative to a baseline BMS system, AI-enabled HVAC optimization delivered energy-demand and emissions reductions of 9 - 21%, helping close the gap toward 2030 building-efficiency targets. Across the scenarios evaluated, first-order impacts associated with operating the AI solutions represented less than 1% of the emissions reductions from improved HVAC performance, indicating that the climate value of AI in this application is driven primarily by the building-performance improvements it delivers.

Key takeaways

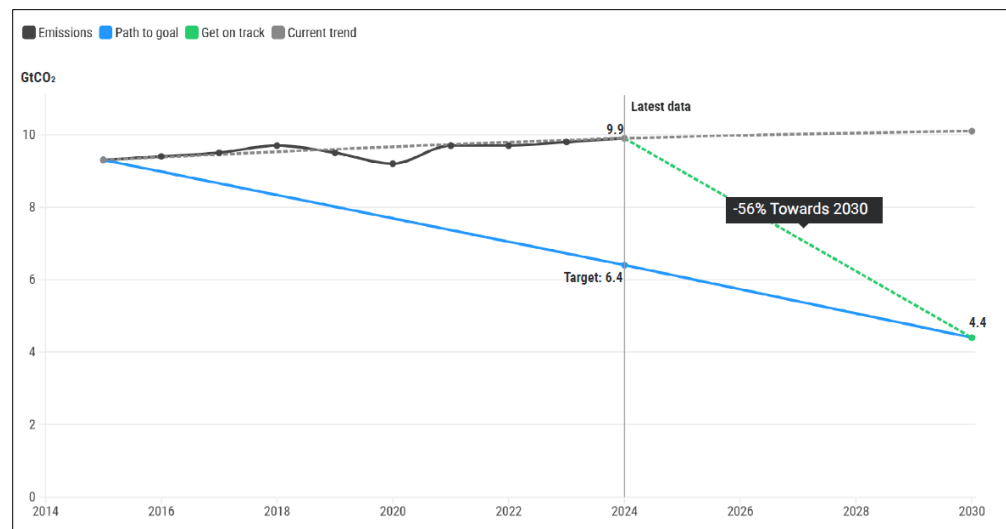
1. **AI can improve performance beyond established building management best practices.** Adding an efficient AI layer on top of existing Building Management Systems (BMS) technology best-practices more than doubled the energy savings and reduced carbon impacts by up to 21% compared to a BMS configured using established energy-efficiency practices in the modeled pilot scenarios. By integrating data from more systems and automating optimization, AI delivered energy reductions approaching those needed to meet 2030 building-efficiency targets.
2. **Emissions avoided through AI-enabled Heating, Ventilation, and Air Conditioning (HVAC) controls substantially exceeded the emissions from operating the AI system.** The emissions associated with operating the AI solution, including allocated data-center energy use, represented less than 1% of the resulting emissions reductions achieved through energy savings in the modeled building.
3. **Cloud and edge deployments can both satisfy the conditions for environmentally frugal AI, but not every AI architecture is equally appropriate for every building.** While cloud deployments generally achieved greater average energy savings, edge deployments delivered meaningful climate benefits in buildings with less complex operational requirements. Architecture selection should consider the building and application requirements beyond energy savings, including performance, latency, reliability, cost, and operational complexity.
4. **AI technologies should be designed to use only the minimum computational power required to solve the problem.** Meaningful climate benefits can often be achieved by matching lighter-weight AI approaches to the operational problem being solved rather than assuming the most computationally intensive solution is always the optimal choice.
5. **Future research can extend the analysis to broader system-level effects.** This study focused on first-order impacts associated with operating AI systems and second-order impacts enabled through improved building performance. Future research should examine higher-order effects, including changes in occupant behavior, building utilization patterns, organizational decision-making, market dynamics, and rebound or induction effects that may emerge as AI-enabled building optimization is deployed at scale.

Introduction / Problem

The building sector accounts for roughly 37% of global CO₂ emissions and 26% of energy-related greenhouse gas (carbon) emissions¹; achieving international climate targets will require substantial reductions in building operational energy demand. The sector has made progress, with building energy intensity improving by approximately 6% since 2015. However, this rate of improvement remains well below the pace required to align with the International Energy Agency's Net Zero Emissions scenario, which estimates that average building energy intensity must improve by roughly an additional 20% by 2030² and building emissions must be reduced by 40% by 2050,³ underscoring the gap between current progress and required climate pathways. While long-term decarbonization will rely on building electrification and equipment retrofits, meaningful near-term emissions reductions will also depend on improving the operational efficiency of existing buildings.

Figure 1

Buildings operational emissions from 2015-2024, with projected performance in business-as-usual scenario compared to climate targets.



Source: United Nations Environment Programme (2026) "Global Status Report for Buildings and Construction: Building Fast, Falling Short." <https://www.unep.org/resources/report/global-status-report-buildings-and-construction-2025-2026>

A significant share of this opportunity lies in the heating, ventilation, and air conditioning (HVAC) systems of buildings, which account for nearly 40% of total building energy use⁴. Many net-zero pathways call for an approximately 20% reduction in energy by 2030 by removing wasted energy in space and water heating, with further targets to achieve a 70% overall energy reduction by 2050.⁵

Many HVAC systems consume more energy than necessary because building conditions, occupancy patterns, equipment performance, and operating requirements change over time, while control strategies often remain relatively static.

¹ International Energy Agency (2023) "Tracking buildings. Energy consumption." <https://www.iea.org/energy-system/buildings>

² International Energy Agency. (2023). "Breakthrough Agenda Report 2023 - Buildings." <https://www.iea.org/reports/breakthrough-agenda-report-2023/buildings>

³ International Energy Agency (2021). "Net Zero by 2050: A Roadmap for the Global Energy Sector," https://iea.blob.core.windows.net/assets/deebef5d-0c34-4539-9d0c-10b13d840027/NetZeroBy2050-ARoadmapfortheGlobalEnergySector_CORR.pdf.

⁴ Schneider Electric. (2024). *Global optimization: Decarbonize the office* (White Paper). https://www.se.com/us/en/download/document/WP_Global-Optimization/

⁵ International Energy Agency (2022) "The Value of Urgent Action on Energy Efficiency," <https://www.iea.org/reports/the-value-of-urgent-action-on-energy-efficiency/highlights>

Conventional building controls contribute to this challenge because buildings have historically operated largely as passive energy consumers, often resulting in avoidable energy waste, limited responsiveness to changing conditions, and suboptimal indoor environments⁶.

As buildings become increasingly electrified, connected, and software-defined, these inefficiencies represent a significant opportunity for improvement. Smart building technologies have significantly expanded the sensing, data, and control capabilities available to building operators. Enabled by Internet of Things (IoT) technologies, modern building management systems can now incorporate networks of sensors, communications infrastructure, and digital controls that are easier to deploy, configure, and reconfigure as building needs evolve.

Previous Schneider Electric⁷ studies quantified the energy efficiency improvements possible from upgrading traditional building controls to digitized smart BMS. In the designs evaluated, daylight and building occupancy sensors communicated with the BMS to reduce HVAC and lighting demand in unoccupied spaces and in spaces with adequate daylight. These improvements achieved energy reductions of 10.5-12.7%. However, these improvements alone remain insufficient to fully close the gap to meet the targeted 20% energy reduction.

While these systems improve visibility and control, translating growing volumes of operational data into effective operational decisions remains an ongoing challenge. In many cases, building operators struggle to translate expanding volumes of operational data into building-scale optimization decisions. Data is often fragmented across HVAC zones and building systems, limiting visibility into interactions occurring across the building as a whole. As a result, extracting actionable information from the data frequently requires additional analysis tools, in-depth audits, or specialized expertise⁸.

Control limitations in small and mid-sized buildings

These challenges are particularly acute in small and mid-sized buildings, where building automation capabilities often lack the sensing, data, and control capabilities needed to continuously optimize HVAC performance. In retail stores, schools, smaller offices, and outpatient clinics, simplified control systems such as wall-mounted thermostats cannot simultaneously account for real-time occupancy, weather conditions, equipment performance, and the complex thermodynamic interactions occurring across a building.

Historically, overcoming these limitations required expensive building automation systems and specialized expertise that were often difficult to justify in smaller facilities. Currently, the effectiveness of many existing systems often depends on facility managers' ability to operationalize signals and recommendations from increasingly digitalized building infrastructure, including HVAC equipment, sensors, communications gateways, and building energy management platforms.

Adding Intelligence to Smart Building Data

⁶ International Energy Agency. (2025). Energy and AI report. <https://iea.blob.core.windows.net/assets/de9dea13-b07d-42c5-a398-d1b3ae17d866/EnergyandAI.pdf>

⁷ For more details on these improvements or other solutions for improving office building performance beyond the building controls system, see Schneider Electric's Decarbonize the Office series.

⁸ D. Minoli, K. Sohraby and B. Occhiogrosso, "IoT Considerations, Requirements, and Architectures for Smart Buildings—Energy Optimization and Next-Generation Building Management Systems," in *IEEE Internet of Things Journal*, vol. 4, no. 1, pp. 269-283, Feb. 2017, doi: 10.1109/JIOT.2017.2647881.

Recent advances in artificial intelligence (AI), however, have the potential to expand sophisticated optimization capabilities to a much broader range of buildings. AI-enabled HVAC control builds on, rather than replaces, connected building infrastructure, enabling an evolved building energy management system to process and contextualize data from a much broader range of sources than conventional controls, continuously adapting to changing occupancy, weather, equipment performance, and other operating conditions. This creates opportunities for integration of data streams that previously were not integrated. Rather than simply generating data, AI can recommend or automate optimization decisions, making efficiency gains a continuous process.

AI applications in buildings span design and construction, operational optimization, predictive maintenance, and demand flexibility services³. Given the significant role of heating and cooling in overall building energy demand, HVAC optimization represents one of the most significant near-term opportunities for building energy and emissions reductions.

Compared with traditional control systems that rely primarily on predefined schedules and rules, AI-enabled controls can learn patterns in building behavior over time and adjust HVAC operation using both internal building data and external inputs such as weather forecasts, utility tariffs, and grid conditions³. Depending on the application, AI can also be combined with traditional physics-based and mathematical models to create hybrid solutions predicting building performance under changing operating conditions. In addition to reducing energy demand, AI-enabled controls can support demand flexibility by shifting electricity use in response to real-time grid conditions. AI may also provide value through predictive maintenance and fault detection, improving equipment performance and reducing operational inefficiencies over time.

At scale, the potential impact could be substantial. The IEA estimates that, based on current digitalization trends, widespread use of AI-led building controls could reduce global electricity demand by more than 300 TWh by 2035, equivalent to approximately 5% of the total electricity consumption for heating and cooling³.

Assessing AI's Net Impacts

While these benefits are compelling, the climate impact of an AI application cannot be evaluated solely by the energy savings it enables. A complete assessment must account for the emissions attributable to developing, deploying, and operating the solution, the net impacts enabled through its application, and broader system-level effects that may emerge over time. AI's environmental effects can be understood through three categories⁹, as shown in **Figure 2** and defined below:

- **First-order impacts** capture the direct environmental consequences of developing, deploying, and operating AI systems, including electricity consumption, associated emissions, water use, and other resource requirements.
- **Second-order impacts** capture the indirect effects enabled through the application of AI, which may have positive or negative environmental effects. In building operations, these positive impacts may include reduced energy consumption, improved demand flexibility, predictive maintenance,

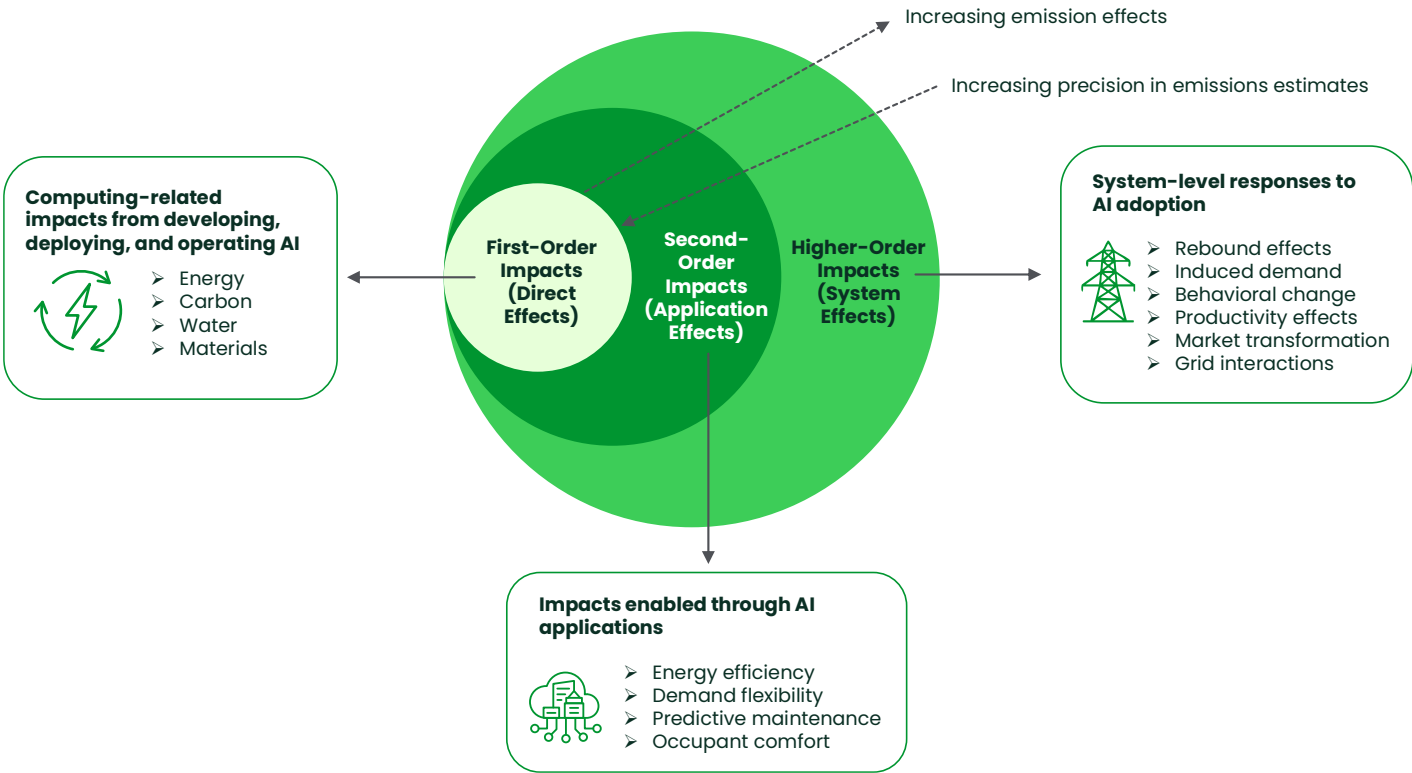
⁹ European Green Digital Coalition. (2024). Net carbon impact assessment methodology for ICT solutions. European Green Digital Coalition. <https://www.greendigitalcoalition.eu/assets/uploads/2024/04/EGDC-Net-Carbon-Impact-Assessment-Methodology-for-ICT-Solutions.pdf>

equipment optimization, and enhanced occupant comfort.

- **Higher-order impacts** capture broader system-level responses that emerge over time as a result of AI deployment, including behavioral changes, organizational responses, market dynamics, grid interactions, productivity effects, and rebound or induction effects that may amplify or reduce realized emissions reductions.

Figure 2

This paper investigates the relationship between the first-order (direct) effects of AI optimization algorithms for HVAC efficiency with the second-order effects at the building scale.



Although this framework can encompass energy, water, emissions, materials, and other environmental effects, this study applies it specifically to greenhouse gas (carbon) emissions. Because many second-order and higher-order effects are highly context-dependent and difficult to quantify reliably, this analysis focuses on second-order emissions reductions from improved building performance and the minimal first-order impacts of operating the AI solution.

Testing and results

This paper evaluates the potential for AI-enabled HVAC controls in mid-sized commercial buildings using modeled building performance. It uses energy modeling to compare edge-based and cloud-hosted architectures and quantifies their energy, added embodied emissions, and operational emissions relative to an IoT-enabled BMS system and a baseline BMS system without IoT capabilities.

Using the Frugal AI criteria,¹⁰ we compare the first-order impacts and second-order emissions reductions associated with each system architecture, whether the net of

¹⁰ Lala Bouali, Yassamine and Ben Ahmed, Olfa and Bradai, Abbas and Mazouzi, Smaine (2024) "Frugal AI: The New Era of Sustainable Deep Learning." <http://dx.doi.org/10.2139/ssrn.5334656>

these produces a positive benefit, and examine how architecture selection influences that outcome.

To quantify the second-order impacts of each solution on building operational performance, this study compares energy models of a typical office building with three high-performance BMS scenarios, as shown in Table 1: (1) a digitized, IoT-enabled BMS, referred to as a “smart” BMS; (2) the smart BMS with edge-based AI control, and (3) the smart BMS with a cloud-hosted AI layer. Together with the traditional BMS baseline without IoT capabilities, four building configurations are evaluated.

Table 1
Scenarios compared a traditional schedule-based BMS with a Smart BMS, edge-based AI controls, and cloud-based AI controls

	Traditional	Smart	AI on the Edge	AI in the Cloud
1 # of HVAC zones	15 (5 per floor)	(34 – 11 per floor with an extra on ground level near entrance)	34 (match “smart”)	34 (match “smart”)
2 Installed Hardware	Thermostats	Thermostats and some sensors in perimeter zones, 1 flex server	TRC in each room and wires	Flex server on each floor, around 30 sensors, wiring
3 Location of energy use	Site	Site	Site	Site + Data Center

The four configurations were evaluated in three locations with similar climate zones: Brisbane (Australia), Miami (United States), and Mumbai (India). Holding the climate zone constant highlights the sensitivity of the results to interactions between site, grid emissions intensity, and data center location while reducing the impact of variation of heating and cooling degree days (see Appendices A, B, and C for more details on the study configuration, prototype building, and grid emissions intensity factors).

Modeling of the AI layer performance in both cases relied on a combination of application of the algorithm rules within the energy model and iteratively tuning the results to match early pilot deployment of the respective AI controls. Further details on these deployments are given in **Appendices B and C**.

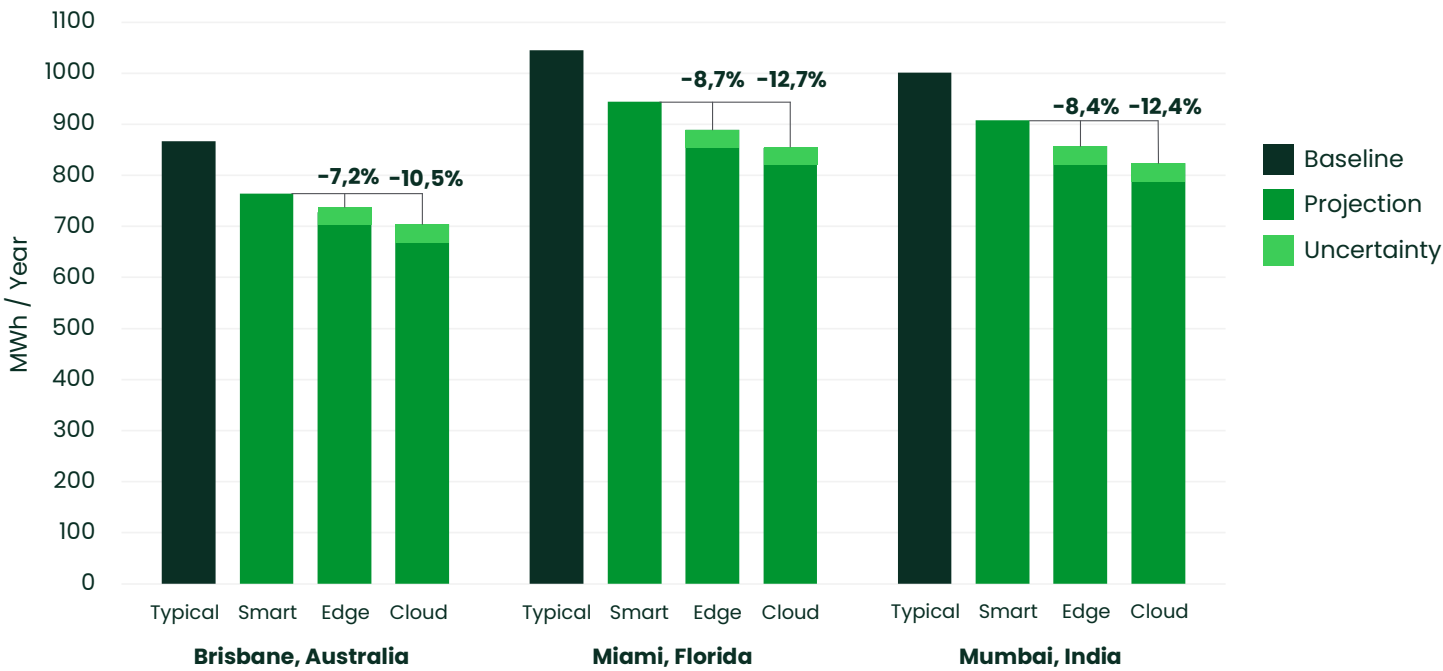
Can AI Close the Efficiency Gap?

The modeled results suggest that AI can unlock additional efficiency gains beyond the savings achieved by the smart BMS. The cloud-hosted AI configuration produced the greatest savings in each location, reducing annual whole building energy use by 21.7 – 22.4% relative to the traditional BMS baseline. This is a significant improvement from the smart BMS savings of approximately 9.3 – 11.8%. This is also a level of savings that closes the majority of the gap toward 2030 building-efficiency targets, with improvements of the AI-enabled controls to the smart controls called out in **Figure 4**.¹¹

¹¹ Additional actions should be taken to meet the targets for 2050. The [Impact Building Calculator](#) explores BMS and additional alternative energy and carbon conservation measures across climate zones and building types.

Figure 4

Energy demand reduction comparing whole building energy demand in each scenario to the baseline case



The modeled energy savings also reduced operational emissions and electricity costs. Table 2 presents the annual energy, emissions, and electricity cost savings for each AI-enabled configuration relative to the smart BMS and traditional BMS baseline.

Table 2

Carbon emissions associated with the solutions in terms of whole building savings of site energy, utility cost, and on-site emissions compared to a traditional BMS system, and total net emissions compared to a Smart BMS

Location	Solution	Site Energy Reduction (MWh)	Utility Savings	Modeled Site Emissions Reduction (t CO ₂ e)	Net CO ₂ e Savings Compared to Smart BMS (%)	Net CO ₂ e Savings Compared to Baseline (%)
Miami, FL, US	Edge	182.90	\$21,948	65.8	3 – 9%	10 – 15%
	Cloud	221.09	\$26,531	79.58	6 – 13%	15 – 21%
Brisbane, AUS	Edge	156.86	\$42,352	105.1	2 – 7%	12 – 16%
	Cloud	182.50	\$49,274	122.3	6 – 11%	16 – 21%
Mumbai, IND	Edge	169.49	\$13,559	120.3	3 – 8%	9 – 14%
	Cloud	205.27	\$16,422	145.7	6 – 12%	15 – 21%
Average	n/a	186.35	\$28,347	106.5	7.15%	17%

The AI solutions significantly increase energy efficiency when compared to the smart BMS. While there is some overlap between the performance of the two solutions, largely associated with variability in the building layout and HVAC zone deployment, the cloud-hosted AI solution tends to outperform the edge AI solution. On average, the cloud solution saves 203 MWh per year compared the edge solution's 169 MWh per year. Because the solutions evaluated in this study were developed independently and were not designed as a controlled comparison of optimization approaches, the analysis does not attempt to attribute the performance differences to specific technical factors. Future research should examine the extent to which differences in deployment architectures, algorithms, available data, and control strategies contribute to observed performance outcomes.

It is important to note that these results are modeled from the first year of real-world pilot deployments. Both solutions are expected to improve their performance in subsequent years as the algorithm continues to optimize; this improvement is not captured in this study. The two solutions can also be layered into a single controls system architecture, but insufficient data is available to predict the nonlinear interactions likely to emerge in a typical deployment of a combined solution. Therefore, this third "combined" solution, while commercially available, is considered out of scope for this study.

Assessing AI's first-order emissions

To estimate the first-order emissions associated with AI-enabled HVAC control, we conducted a screening assessment with the Software Carbon Intensity (SCI) specification¹². The SCI method provides a holistic estimate of the environmental impacts associated with the AI solution, because it accounts for both operational emissions associated with software execution and embodied emissions attributable to supporting hardware infrastructure.

Across all scenarios evaluated, the operational and allocated embodied emissions of the AI solution was less than 1% of the second-order impacts associated with the HVAC performance improvements, even when using methodologically conservative SCI-based estimates (See **Appendix D**). Because these first-order impacts were not material relative to the resulting second-order emissions reductions, the carbon-savings figures presented throughout this paper are reported as gross second-order emissions reductions; their inclusion would not change the overall conclusions or reported results.

The AI operational emissions were small because the HVAC control application primarily relies on lightweight machine learning (ML) inference workloads executed periodically on standard CPUs or low-power edge devices, rather than computationally intensive generative AI workloads. Based on the processing frequency, execution time, and computing equipment assumed in the analysis, the resulting energy was very small relative to the energy consumed by the HVAC equipment itself. Viewing this from whole-system operational perspective, a CPU (~150W) can control an entire building's energy consumption profile (~750 MWh annually). Embodied emissions associated with sensors, gateways, communications equipment, and computing hardware were estimated using a ten-year amortization period (See **Appendices C and D**).

¹² Green Software Foundation. (n.d.). Software Carbon Intensity (SCI) specification. Green Software Foundation. <https://sci.greensoftware.foundation/>

Holistically accessing trade-offs

The optimal architecture depends on the specific requirements and operating conditions of each building and should be considered holistically. While cloud deployments generally achieved greater average energy savings in this study, both architectures delivered climate benefits that substantially exceeded their associated first-order impacts. The choice between cloud and edge AI is driven by the specific tradeoffs each architecture presents across performance, cost, reliability, operational visibility, latency, and site-specific requirements. Examples include:

- **Cost Efficiency.** Edge AI reduces the need for extensive cloud storage and compute power, lowering operational costs, while Cloud AI reduces the need for extensive hardware installation on-site, leading to reduced installation costs. However, the difference in operational energy savings may offset the Cloud AI computation costs.
- **Reliability.** Edge AI data can be operated and optimized independently of internet connectivity, making it a better solution in areas with poor or no connectivity or in building types where cloud-hosted data is undesirable.
- **Visibility.** Where facilities are not necessarily managed by an on-site expert, the Cloud AI solution is monitored remotely, giving greater visibility across a portfolio from a centralized location. Edge AI can be configured to report to a centralized cloud location, but requires an additional software layer to enable this feature.
- **Speed of processing.** Edge AI is processed locally, making decisions with latency measured in seconds. Cloud AI requires data to be sent through the network, which can introduce latency of up to a few minutes when the network is congested. In sensitive building types where conditions change quickly, the Edge AI condition may be preferred.

Conclusions

Implications of AI-enabled HVAC control

The modeled results demonstrate that AI-enabled HVAC control improves building energy performance beyond the savings achieved by a smart BMS alone. Across the scenarios evaluated in this study, AI-enabled HVAC control substantially improved building performance, with energy reductions approaching or exceeding the improvements associated with 2030 building-efficiency targets. These findings are particularly relevant for small and mid-sized buildings, where advanced controls and specialized building operations expertise can be difficult to deploy and maintain.

Across all scenarios, the calculated first-order emissions of the AI solution represented less than 1% of the second-order emissions reductions enabled through improved building HVAC performance. These findings suggest that, for HVAC optimization applications, the climate impact from deploying AI are far less than the benefits from the persistent reductions in building energy demand that it delivers.

More broadly, these findings highlight that not all AI applications have the same environmental profile. The AI control systems evaluated in this study rely primarily on lightweight machine-learning inference workloads, requiring modest computational resources while delivering substantial reductions in building energy demand. These findings suggest that, through a Frugal AI lens, meaningful climate benefits can

often be achieved by matching the right AI approach to the operational problem being solved.

Future research needs

This study quantified select first-order emissions and second-order emissions reductions for one mid-sized office prototype across three warm, cooling-dominated locations with validation against a minimal number of deployments of the technology in actual buildings. Future research should extend this analysis across a broader range of climate zones, building typologies, and operational conditions. It should also explore hybrid edge-cloud deployments, which may deliver benefits beyond those achieved by either architecture independently. Finally, it should examine the higher-order effects that may emerge as AI-enabled building control is deployed at scale.

Better understanding of these whole-system effects will be essential for assessing the long-term role of AI in building-sector decarbonization.



About the authors

Efrie Escott is the Research Leader for the Software and Services Division at Schneider Electric. As a Fellow of the American Institute of Architects and a LEED Fellow, Efrie leverages her expertise to accelerate the transition to a regenerative built environment. She served as a member of the USGBC Materials + Resources and the ILFI Energy + Carbon Technical Advisory Groups, founder of Philadelphia's Dynamo User Group, the AIA Committee on Climate Action and Design Excellence and Co-Chair for AIA Philadelphia Women in Architecture. She currently participates on the ASHRAE/ICC Standard 240p Committee, ILFI's Board of Directors, and the CIBSE Sustainability Task Force. Previously, as Principal of Environmental Research at architecture firm Kieran-Timberlake, Efrie co-developed *Tally*, the first BIM-integrated Life Cycle Assessment software. Efrie has a BA from Yale College, MArch from the University of Michigan, and MEM from the Yale School of the Environment.

Will Alpine is a Sustainable Software Design Leader at Schneider Electric with expertise spanning AI, sustainability, and technology innovation. Prior to joining Schneider Electric, he spent four years at Microsoft, where he worked as a Technical Product Manager supporting AI platform capabilities, Responsible AI initiatives, and Microsoft's Green AI strategy. He also co-authored Microsoft's 'Accelerating Sustainability with AI' playbook. Will co-founded the Green Software Foundation's Carbon Aware SDK and contributed to the development of the Software Carbon Intensity (SCI) specification. Previously, he worked as a mechanical engineer in the solar industry and earned four patents at SolarCity/Tesla Energy. Will holds an M.S. in Technology Innovation with a specialization in Connected Devices from the University of Washington's Global Innovation Exchange and a B.S. in Mechanical Engineering from Virginia Commonwealth University.

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Resources



[Using AI to Optimize HVAC Systems in Buildings: A Real-world Example](#)
White Paper 508



[AI Fundamentals for Buildings](#)
White Paper 502



[Three Essential Elements of Next Generation Building Management Systems \(BMS\)](#)
White Paper 500



[Power Digitalization: Understand and Achieve Active Energy Management in Buildings](#)
White Paper 503



[Integrating Smart Building Control Systems to Enable Grid-Interactive Buildings \(GIB\)](#)
White Paper 509



[AI-Driven Data Centers: Revolutionizing Decarbonization Strategies](#)
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APPENDIX A: Study Design

Study design

Three building-control scenarios were evaluated relative to a traditional building-controls baseline¹³:

1. Smart building (digitized IoT-enabled BMS without AI)
2. AI-enabled edge controls
3. Cloud-hosted AI controls

To isolate differences related to deployment architecture, the analysis was conducted using comparable building configurations in three locations: Brisbane (Australia), Miami (United States), and Mumbai (India). Cooling-dominated locations were selected to reduce variability associated with heating demand and allow a more consistent comparison of HVAC optimization performance across scenarios. At the same time, differences in grid emissions intensity and cloud-region location enabled assessment of how local conditions influence the results.

The analysis quantifies:

- **Second-order impacts:** reductions in building energy demand and associated carbon emissions resulting from improved HVAC performance.
- **First-order impacts:** operational and embodied emissions associated with deploying and operating the AI solution.

The assessment includes:

- Edge computing hardware
- Cloud computing resources
- Room controllers
- Sensors
- Communications equipment
- Power and cooling of the supporting server infrastructure

The assessment excludes:

- Embodied emissions associated with the building structure and HVAC equipment (held constant across all scenarios)
- Maintenance and renovation activities
- System decommissioning
- Higher-order impacts such as rebound effects, behavioral changes, market transformation, and other system-level responses

¹³ The edge and cloud solutions were evaluated independently; potential interactions between the two approaches operating simultaneously within the same building were not assessed.

APPENDIX B: Building and control details

The analysis is based on a representative mid-sized commercial office building derived from the Pacific Northwest National Laboratory (PNNL) Medium Office prototype. The three-story building has an approximate gross floor area of 5,000 m², a window-to-wall ratio of 33%, and was modeled in OpenStudio using 2023 Actual Meteorological Year (AMY) weather files downloaded from the NASA P.O.W.E.R. database¹⁴. The office is assumed to operate on a typical weekday schedule, with normal office plug loads, appropriate lighting conditions for office work, and occupied-zone temperatures maintained within a thermal comfort range of 21-23°C.

The reference building was based on the 2004 Pacific Northwest National Laboratory (PNNL) Medium Office prototype,¹⁵ and deployed in Brisbane, Miami, and Mumbai. Construction assemblies and HVAC systems were adapted to reflect regional building practices while maintaining comparable building functionality¹⁶. The following building conditions were analyzed:

- **Traditional Building:** In the baseline ("traditional") scenario, the building operates using static schedule-based controls without daylight-responsive controls. Each floor is divided into five HVAC zones (Core, North, East, West, and South), resulting in fifteen total control zones.
- **Smart Building¹⁷:** The smart building scenario incorporates IoT-enabled building management controls, occupancy sensing, and daylight-responsive lighting controls. To better represent real-world building operation, occupancy schedules were generated using the Lawrence Berkeley National Laboratory Occupancy Simulator¹⁸ rather than deterministic schedules. Previous Schneider Electric research demonstrated that these smart-building capabilities can deliver meaningful energy savings relative to traditional controls.
- **Edge AI-Enabled Building:** The edge AI-enabled scenario builds upon the smart-building foundation by introducing room-level HVAC zoning and AI-driven optimization with on-site hardware and software. Energy-savings found in the modeled results are validated against field data from pilot deployments for the Room Controllers documented in [Leveraging AI-Optimization at the Edge for Optimal Comfort and Energy Efficiency](#).
- **Cloud AI-Enabled Controls:** The cloud AI-enabled scenario builds upon the smart-building foundation by introducing room-level HVAC zoning and AI-driven optimization within the BMS DHO algorithm. Energy savings in this study were calculated using the expectation of the DHO optimization sequence as a post-processing measure to the HVAC energy demand, with validation against field data from pilot deployments for Schneider Electric's EcoStruxure Activate Cloud software. Full details from this field trial and the performance of the AI system are expected to be published in both peer-reviewed journals and a Schneider Electric white paper later in 2026 and early

¹⁴ [NASA P.O.W.E.R. database](#)

¹⁵ https://www.pnnl.gov/main/publications/external/technical_reports/PNNL-32815.pdf

¹⁶ In Brisbane and Miami, the reference building assumes steel-frame construction with code-compliant insulation and a precision air conditioning unit (PACU) coupled with a multizone variable-air-volume (VAV) gas furnace. In Mumbai, the reference building assumes uninsulated CMU mass-wall construction and a representative all-electric HVAC system consistent with typical local practice.

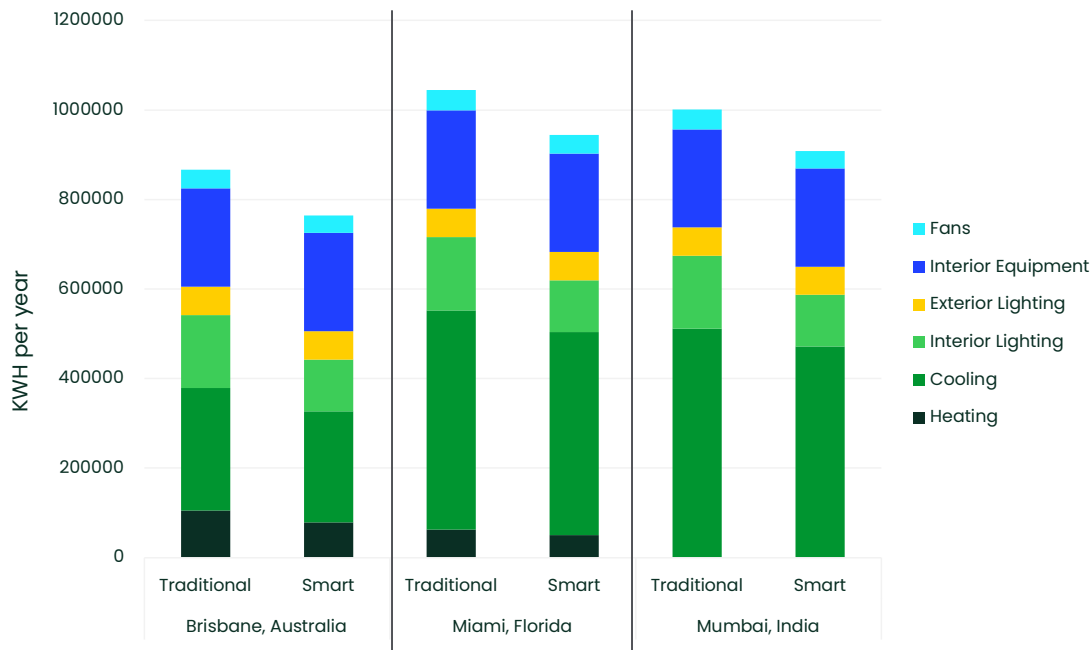
¹⁷ For the "smart" and AI prototypes, HVAC zones are subdivided to the room level. Instead of using schedule-based controls, use occupancy simulation to turn off systems and lighting. Full assumptions in this data set tied to occupancy-based temperature and lighting controls, daylighting-based lighting controls, duct pressure-sensor VAV controls, outdoor air-based temperature resets, and power improvements associated with submetering in the "smart" building condition are detailed in the [methodology for the Impact Building Calculator](#).

¹⁸ <https://occupancysimulator.lbl.gov/>

2027.

Because HVAC zoning design can materially affect achievable energy savings, AI results are presented as performance ranges rather than single-point estimates for both controls systems using AI¹⁹.

For reference, a comparison of energy demand reductions between a traditional and smart BMS system are identified by end use in Figure 3.



Sources of Uncertainty

Building-scale energy performance is influenced by factors beyond HVAC optimization, including plug-load density, occupancy patterns, and office layout. These sources of variability were not explicitly modeled in this study.

Similarly, higher-order impacts resulting from changes in occupant behavior, operational practices, building utilization, or other responses to improved comfort and building performance were considered outside the study scope; this represents a substantial agenda for future research.

¹⁹ Deployment of IoT and AI hardware is strongly influenced by office layout, including the number of open and enclosed spaces, which influences the achievable HVAC zoning configuration. Variations in zoning design can have a significant impact on energy performance and contribute to the range of results reported in this study.

Appendix C: Embodied Carbon

Table C1

Embodied carbon calculations for the “AI at the Edge” solution

Embodied Carbon

The representative system architecture described in **Table C1** represents the full scope of hardware required for the “AI at the Edge” solution. Adding together the sums in the Embodied Carbon column creates the full embodied carbon footprint associated with the solution.

Reference Product	Quantity	Embodied Carbon (kg CO ₂ e)	Data Source
Touchscreen Room Controller	34	914.6	Product Environmental Profile
22-24 AWG strand twisted pair wire	10	5	https://climatecost.org/wiki/cables-accessories/
Total		919.6 kg CO ₂ e	

Table C2 shows the sample on-premises system architecture used for the “AI in the Cloud” solution, while **Table C3** lists the server hardware required at the data center. Combining the embodied carbon figures from **Tables C2 and C3** creates the embodied carbon footprint for the “AI in the Cloud” solution.

Table C2

Embodied carbon calculations for the on-premise hardware in the “AI in the Cloud” solution

Reference Product	Quantity	Embodied Carbon (kg CO ₂ e)	Data Source
Flex server	3	92.1	Product Environmental Profile
RP-C-16B-F-230V	3	0.023921	Product Environmental Profile
CO2+TRH sensor	15	44.5	Product Environmental Profile
Daylight + Motion Sensor	15	3.2	Product Environmental Profile
PAS 600	3	174	Product Environmental Profile
SE8000	0	18.1	Reuse existing (in baseline)
AS-B	0	32.2	Reuse existing (in baseline)
AS-P	0	87.4	Reuse existing (in baseline)
Energy Meter iEM3000	0	34.5	Reuse existing (in baseline)
Added 22-24 AWG stranded twisted pair wire	1	0.5	https://climatecost.org/wiki/cables-accessories/
Total		982.1 kg CO ₂ e	

Table C3

Embodied carbon calculations for server hardware located at the data center and used by the “AI in the Cloud” solution

Reference Product	Quantity	Embodied Carbon (kg CO ₂ e)	Data Source
1 vCPU, 4GB	1	19.228	Hubble Database
AMMS	1	13.2	Boavizta Database
Total		32.43 kg CO ₂ e	

Appendix D:
First-order
impact
assessment

First-order impacts were estimated using the Software Carbon Intensity (SCI) methodology developed by the Green Software Foundation. SCI calculations include both operational emissions associated with electricity consumption during AI operation and embodied emissions allocated to computing, sensing, networking, and control hardware.

Operational emissions were calculated using location-specific electricity carbon intensity factors for both building sites and cloud-hosting locations. Embodied emissions were estimated using product-specific environmental product declarations and other recognized industry-average sources where necessary as shown in Table C3 and were amortized over a ten-year expected service life.

To avoid understating first-order impacts, deployments were modeled using a conservative allocation of server capacity substantially larger than the measured compute demand of the HVAC optimization workload. Consequently, the results presented here should be interpreted as approximate upper-bound estimates rather than expected impacts in a shared-production environment.

Table D1

First-order impacts of edge and cloud ai (upper-bound estimate)

Metric	Edge AI	Cloud AI
AI Operational emissions (kgCO ₂ e/year)	85-167	61-143
AI operational share of building energy consumption ²⁰	0.03%	0.03%
Embodied emissions, amortized (kgCO ₂ e)	92	102
Total first-order impacts (SCI) (kgCO ₂ e/year)	177-259	163-245
Annual emissions reductions enabled (kgCO ₂ e/year)	19,640-59,869	19,640-59,869*
First-order (SCI) impacts as % of second-order emissions reductions	<1%	<1%

**Note: SCI estimates include both operational and embodied emissions as defined by the Software Carbon Intensity specification. Functional unit (SCI's 'R') is per-building, annually. Operational emissions were calculated using location-specific grid emission factors as defined below; deployments were modeled using conservative server-capacity allocation assumptions that substantially exceeded the measured compute demand of the HVAC optimization workload (measured demand was on the order of only a few watts). Embodied emissions were amortized over a ten-year service life. Building energy baseline was 750MW.*

²⁰ For insights on reducing the environmental impacts of data centers, please see white papers [240](#), [169](#), [180](#), and [106](#) by the Schneider Electric Data Center Science Center.

Table D2

Energy grid carbon emissions intensity at building site and associated data center locations

Location	Local grid intensity (kg CO ₂ e/kWh)	Server location	Server grid intensity (kg CO ₂ e/kWh)
Miami, FL, USA	0.36	Virginia, USA	0.30
Brisbane, AUS	0.67	Sydney, AUS	0.64
Mumbai, India	0.71	Mumbai, India	0.71