Leveraging AI-Optimization at the Edge for Optimal Comfort and Energy Efficiency

White Paper

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Executive Summary

Facility managers and building owners face numerous challenges in maintaining energy efficiency and occupant comfort in diverse building environments. Traditional HVAC systems often struggle with optimizing performance due to static control strategies and lack of real-time adaptability.

This paper explores the potential of AI deployed “at the edge” to address these challenges. By leveraging AI-driven algorithms within Schneider Electric's room controllers, the aim is to enhance HVAC system control and optimization. The research involved deploying room controller units without AI to collect baseline data, followed by enabling AI to monitor and improve system performance.

The findings demonstrate that AI can significantly enhance energy efficiency and occupant comfort by providing adaptive, efficient, and user-centric solutions directly from the edge: within the device, eliminating the added expense and complexity of cloud-based processing. Quantitative analysis reveals that systems enabled with edge AI successfully maintained temperature regulation and comfort compliance over 85% of the time. Additionally, these systems achieved an average HVAC energy savings of 5% daily, with potential savings reaching up to 15% in certain scenarios. These findings highlight the benefits and effectiveness of AI in real-world applications.

Introduction

In the race for smarter and more sustainable infrastructure, the integration of advanced technologies with traditional building systems has become essential. Facility Managers and Building Owners often handle the dual challenge of maintaining energy efficiency and ensuring occupant comfort. Traditional HVAC systems, with their static control strategies, frequently fall short in adapting to dynamic conditions, leading to inefficiencies and discomfort.

Artificial intelligence (AI) emerges as a powerful tool to address these challenges. By enabling real-time optimization and adaptive control, AI offers both immediate (direct comfort for the occupants) and long-term benefits (energy saved) for HVAC systems. This white paper review in details a field trial that leverages AI-driven optimization using room controllers developed by Schneider Electric's Digital Buildings line of business.

Field trials results were extracted to encapsulate the impact of the Dynamic HVAC Optimization algorithm in its deployment environment. The goal was to assess the impact on temperature, particularly comfort, and to determine how quickly the algorithm can learn from its environment for the start and stop optimization feature. This data allows for visualization of energy behavior during the test phase and calculation of the energy savings achieved by using the AI for control at the edge.

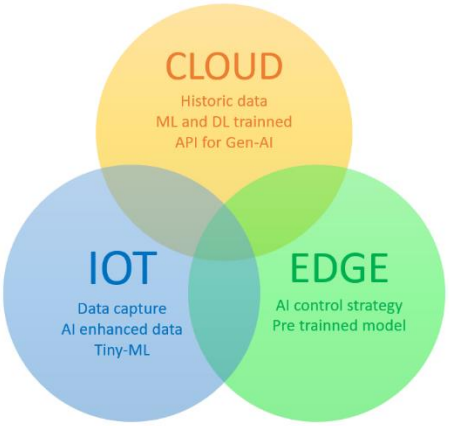
AI Applications

The advantage of a technology at the edge

AI control or analytical solutions for smart buildings can be developed at various levels, each offering unique benefits.

- **IoT/Embedded AI:** The first layer involves collecting data within buildings using sensors that monitor various parameters like occupancy, room temperature, CO2 levels, valve positions, and Wi-Fi activation. This data is used by an AI agent on the IoT layer to make decisions. Tiny-ML's advanced AI can be embedded in sensors to improve measurement precision, perform real-time calibration, identify failures, and reduce energy consumption when inactive. The IoT layer not only provides data to the AI agent but also enhances sensor data quality.

- **Edge AI:** AI within controllers can be utilized for analytics and control, such as dynamically adjusting indoor setpoints. By processing control strategies and data at the edge, real-time responses are possible without relying on extensive historical data, storage, or computational power. This presents an opportunity to design a more sustainable model that can be embedded in a dedicated product.



- **Cloud AI**: Cloud-hosted AI solutions are the most common in the smart building industry due to their access to extensive resources, enabling the execution of larger models and API calls for off-the-shelf models. These solutions can drive innovations like generative AI and deep learning for control and analytics. They provide insights for prioritizing HVAC diagnostics, focusing on energy and carbon impact, and use advanced alarm analytics for root cause analysis and priority ranking. However, the necessary storage for these options incurs associated costs.

While all three layers of AI implementation can be combined, the focus of this study is on the implementation of AI at the edge, embedded into HVAC room controllers. The goal is to evaluate both comfort and energy consumption for building occupants, leveraging the capabilities of edge-based AI to provide real-time, adaptive solutions.

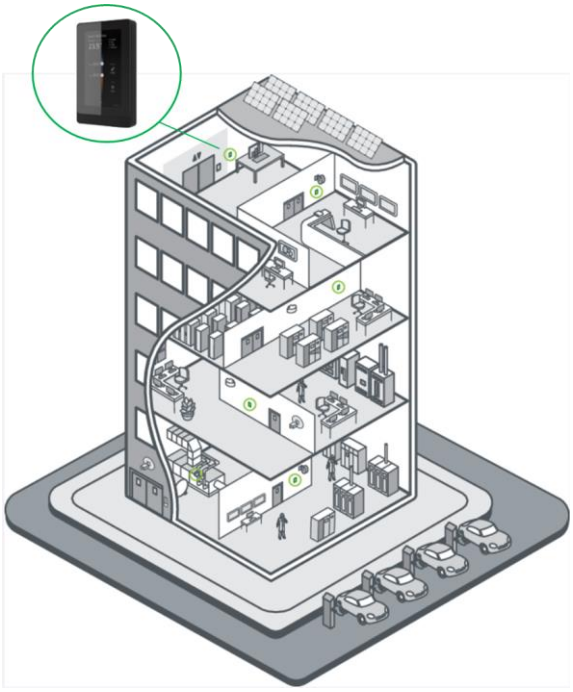


Figure 1

Smart controllers with AI optimize comfort and energy savings in each room of a building.

The room controller developed by Schneider Electric is dedicated for HVAC control with a user-friendly interface that empowers building occupants with intuitive control over their environmental comfort. This innovative device seamlessly integrates with existing HVAC systems, allowing users to adjust temperature settings, manage ventilation, and customize their comfort preferences with a simple touch. Additionally, by incorporating AI directly into the controller, without relying on cloud services or extensive data storage, the system leverages lightweight models to provide immediate and adaptive control without human interaction.

Deploying AI on an edge device like the HVAC room controller ensures that the features that are AI driven can operate efficiently and effectively, unlocking the full potential of the new control strategy without overusing compute power or requiring extensive cloud storage.

Algorithm of control – how it works

This edge-based AI processes historical temperature data, occupancy patterns, and environmental conditions in real-time, enabling dynamic adjustments that maximize energy efficiency and occupant comfort. The integration of AI transforms a simple HVAC room controller into a smart, self-regulating system that continuously learns and adapts to user preferences, delivering optimized indoor environments without the need for constant manual intervention.

Schneider Electric's proprietary and patented AI algorithm for dynamic HVAC optimization is used. For more information, refer to the patents titled "Operational Constraint Optimization Apparatuses, Methods, and Systems."

This algorithm has five phases:

- **Measure:** Gathering the data measured by the room controller temperature and humidity sensors.
- **Assess:** Assessing the conditions based on its internal weather, thermal and comfort model.
- **Predict:** Predicting the ideal temperature path based on the environmental condition of the zone.
- **Control**: Controlling the setpoints and managing the start and stop times using a comfort agent that validates that the ASHRAE 55 norms are respected by the previous steps.
- **Learn:** Learning via a feedback loop based on measurements, focusing on how to optimize the prediction and refine the internal thermal model. Which can lead to better comfort, and an optimized start and stop system.

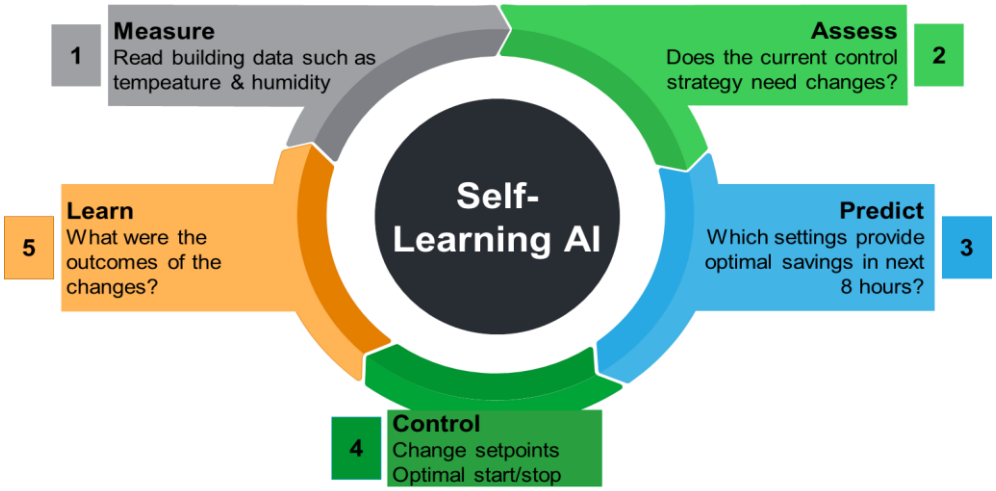


Figure 2

Logic of the Dynamic HVAC Optimization algorithm deployed in the room controller.

For more information on the Dynamic HVAC Optimization algorithm, see White Paper 508, and 500 (Using AI to Optimize HVAC Systems in Buildings: A Real-world Example, AI Fundamentals for Buildings).

Early Adopter Selection Methodology

The results presented in this document were gathered during a field trial run by Schneider Electric with the objective to test the performance of the product. The room controller embedded with the AI feature was installed across four sites, including both Schneider Electric offices and offices of an early adopter client, Ainsworth.

These installations span various office building environments, allowing for a comprehensive evaluation of the performance and benefits of AI-driven HVAC optimization in real-world scenarios. The following criteria was used to select field trial environments:

- The chosen building spaces must cover most of the surface area to ensure comprehensive control and impact on the HVAC system and energy consumption.
- Most of the selected zones within the building must have a room controller installed previously, which was replaced by a new version embedded with AI.
- Clients must be utilizing Schneider Electric's EcoStruxure™ Building Operation building management system (BMS) to facilitate data access through the BMS. *Note: This requirement is specific to the field trials.*

Table 1

Characteristics of the field trial locations.

Field Trial Location	# Room Controllers Provided	Zones Covered
SE Office 1 (Montreal, Canada)	67	2 open spaces, 2 cafeterias, 5 conference rooms, 1 storage room, 9 offices, 1 server room, 1 gym
SE Office 2 (Montreal, Canada)	7	2 open spaces, 1 cafeteria, 2 conference rooms, 1 storage room, 9 offices, 1 server room
SE Office 3 (Edmonton, Canada)	7	2 open spaces,1 cafeteria, 2 conference rooms, 1 reception, 9 offices
Ainsworth Office 1 (Ottawa, Canada)	10	6 open spaces,1 cafeteria, 4 conference rooms, 19 offices, 1 bathroom, 1 reception, 1 server room, 1 storage room

Results – Comfort and Energy Savings

Temperature compliance

The first metric reviewed is whether the comfort agent is making accurate decisions by adjusting the setpoint to maintain the client's desired comfort temperature. Temperature compliance is measured every 10 minutes, ensuring the temperature stays within the client's specified setpoint range during occupied periods each day (4 AM to 7 PM). The compliance metrics presented in Table 2 are an average of all data gathered for a site over the first 7 days following the AI installation, based on a local schedule.

Table 2

Breakdown of the impact on comfort from the AI features – first 2 weeks of deployment.

Early Adopter of the Technology	Temperature Compliance - First Week	Temperature Compliance - Second Week	Average Occupied Deadband
SE Office (Edmonton, Canada)	70.9%	82.0%	[19-22°C]
Ainsworth Office (Ottawa, Canada)	80.7%	85.0%	[21-23°C]

* To ensure a functional behavior for the Dynamic HVAC optimization algorithm a hysteresis of at least 1 °C must exist in the deadband proposed by the client. If it is not provided the flexibility part of the setpoint will be replaced by a regular control loop.

Table 2 shows that during the first week of AI optimization, the tested site achieved an average comfort compliance for the setpoints above 75%. This indicates that the comfort agent within the algorithm effectively prioritizes user comfort. During the second week of deployment, following the initial learning phase, temperature compliance increased in both Ottawa and Edmonton, reaching 82% or higher. This significant improvement in comfort was achieved within just one week, due to the deployment of the AI solution.

Table 3

Regulation compliance – occupied and unoccupied intervals.

Early Adopter of the Technology	Cool Occupied Regulation Compliance	Cool Unoccupied Regulation Compliance	Heat Occupied Regulation Compliance	Heat Unoccupied Regulation Compliance
SE Office (Edmonton, Canada)	100.0%	100.0%	80.7%	98.2%
SE Office (Montreal, Canada)	83.0%	100.0%	87.7%	100.0%
Ainsworth Office (Ottawa, Canada)	99.9%	100.0%	90.9%	99.8%
Total – All Sites	96.1%	100.0%	88.9%	99.3%

Table 3 defines regulation compliance, evaluated in cooling and heating modes, over occupied and unoccupied intervals, excluding optimal starts which are dynamic intervals. Regulation is achieved in cooling when the device temperature is 0.5 °C above the cool control temperature or lower, and in heating when the device temperature is 0.5 °C below the heat control temperature or higher. Heat regulation compliance of approximately 89% for occupied spaces and 99% for unoccupied spaces, is achieved across all zones. The system is highly effective in maintaining desired temperatures, which underscores the reliability in providing a comfortable environment.

Analysis includes data with known issues in configuration, cool or heat mode, and regulation, from all firmware releases deployed during the field trials. Weather forecast estimates were approximated by projecting the current air temperature without irradiance. More recent results show improvements relative to the reported averages, as expected considering the resolution of deployment related issues and model convergence.

Table 4

Regulation compliance – occupied and unoccupied transitions.

Early Adopter of the Technology	Cool Occupied Transition Regulation Compliance	Cool Unoccupied Transition Regulation Compliance	Heat Occupied Transition Regulation Compliance	Heat Unoccupied Transition Regulation Compliance
SE Office (Edmonton, Canada)	100.0%	60.0%	100.0%	85.0%
SE Office (Montreal, Canada)	62.5%	100.0%	61.1%	81.8%
Ainsworth Office (Ottawa, Canada)	100.0%	87.5%	88.1%	94.3%
Total – All Sites	87.5%	92.3%	75.7%	89.4%

Table 4 defines regulation compliance in cooling and heating modes, exclusively at transitions to occupied and unoccupied intervals. Regulation compliance at occupied transitions is related to the quality of optimal start guidance. Similarly, regulation compliance at unoccupied transitions is related to the quality of optimal stop guidance.

A qualitative survey was put in place to assess the comfort levels of building occupants while the HVAC system was under AI control. Participants were asked to rate their thermal comfort at various times throughout the day.

Figure 3

Individual Thermal Comfort (ITC).

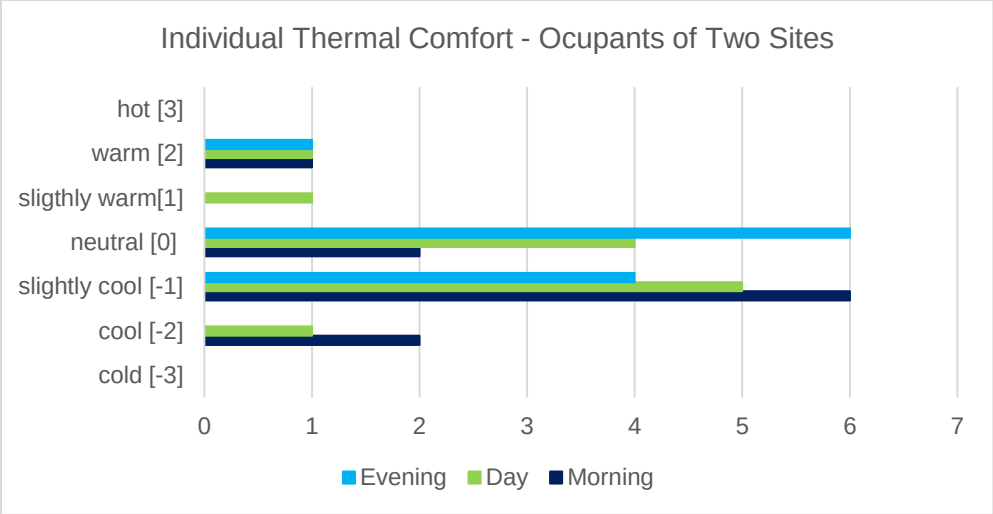


Figure 3 illustrates survey results, indicating an average Individual Thermal Comfort (ITC) score of -0.41, which falls between neutral and slightly cool. This feedback is highly encouraging, as our target is to achieve a value close to 0, representing neutral comfort. Achieving this target ensures optimal comfort for all occupants, aligning with our commitment to maintaining a comfortable indoor environment.

Start and Stop optimization

The ability to learn the optimal start and stop times for each site can be tracked by observing the evolution of the times when the algorithm activates the system. The AI solution learns the thermal inertia in the zones, which allows the area to stay compliant to the comfort setpoint. Through a feedback loop, it also learns the limits for optimizing the energy demand of the zones. This ensures that the system operates within safe and efficient boundaries, preventing overuse and reducing energy waste.

Figure 4 illustrates control temperature guidance and device observations from the Ainsworth Ottawa Panel Shop zone on 2024-12-03. Cool and heat control temperatures (red) indicate control guidance, including an optimal start (green) interval which predicts 4 hours of heating may be required to ensure that the device temperature (black) is within 0.5 °C of the control temperature at the transition to occupied (gray, upper). This zone is characterized by rapid occupied temperature transitions, typical unoccupied temperature transitions, and moderate device temperature and demand (black, lower) noise. Initial control temperature guidance assumes typical heat transfer behavior, which continuously adapts and improves.

Figure 4

Temperature control guidance and device observations – Panel Shop untrained behavior.

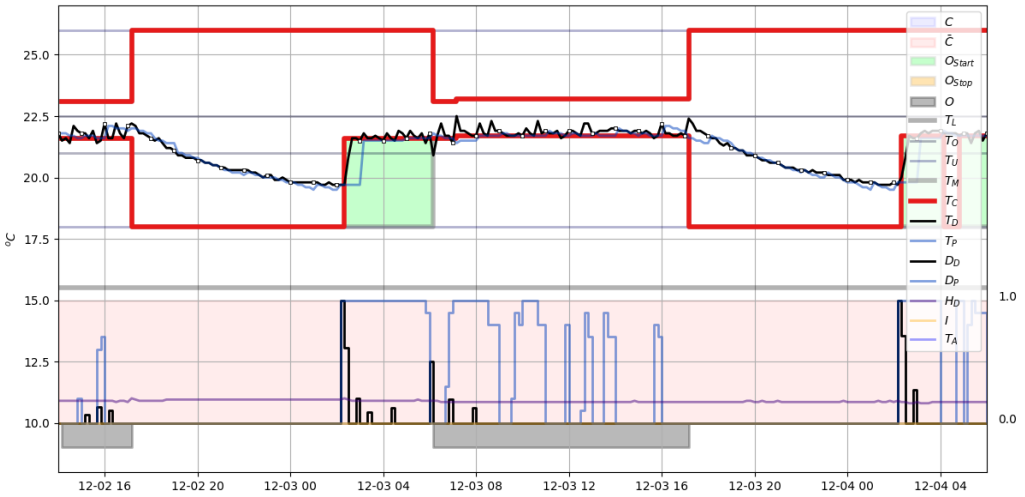


Figure 5 illustrates control temperature guidance and observations from the Ainsworth Ottawa Panel Shop zone on 2024-12-03, simulating the adaptation in control guidance behavior over 3 days of operation with identical observations, adjusting occupancy to align with the data. An optimal start (green) interval predicts 40 minutes of heating may be required to ensure that the device temperature (black) is within 0.5 °C of the control temperature at the transition to occupied (gray, upper). An optimal stop (yellow) interval predicts the device temperature will remain within 0.5 °C of the control temperature for 4 hours before of the transition to unoccupied without heating, the maximum optimal stop duration. Optimal start and optimal stop reflect improvement in control temperature guidance.

Figure 5

Temperature control guidance and device observations – Panel Shop trained behavior.

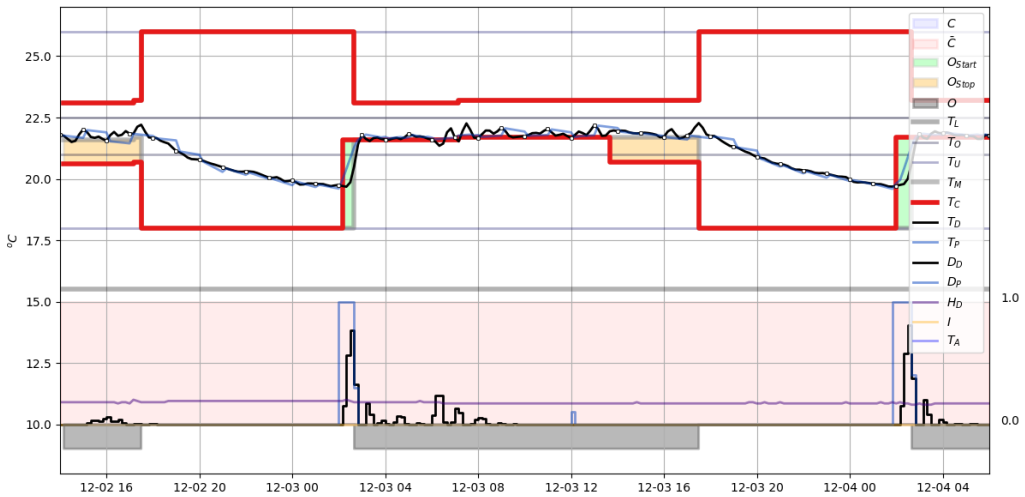


Figure 6 illustrates control temperature guidance and device observations from the Ainsworth Ottawa Sussex zone on 2024-12-03. Cool and heat control temperatures (red) indicate control guidance, including an optimal start (green) interval which predicts 4 hours of heating may be required to ensure that the device temperature (black) is within 0.5 °C of the control temperature at the transition to occupied (gray, upper). This zone is characterized by the rapid occupied and unoccupied temperature transitions and significant device temperature and demand (black, lower) noise, due to an overcapacity HVAC unit, a poorly insulated exterior wall, and thermostat placement in the path of an air return. Initial control temperature guidance assumes typical heat transfer behavior, which continuously adapts and improves.

Figure 6

Temperature control guidance and device observations – Sussex untrained behavior.

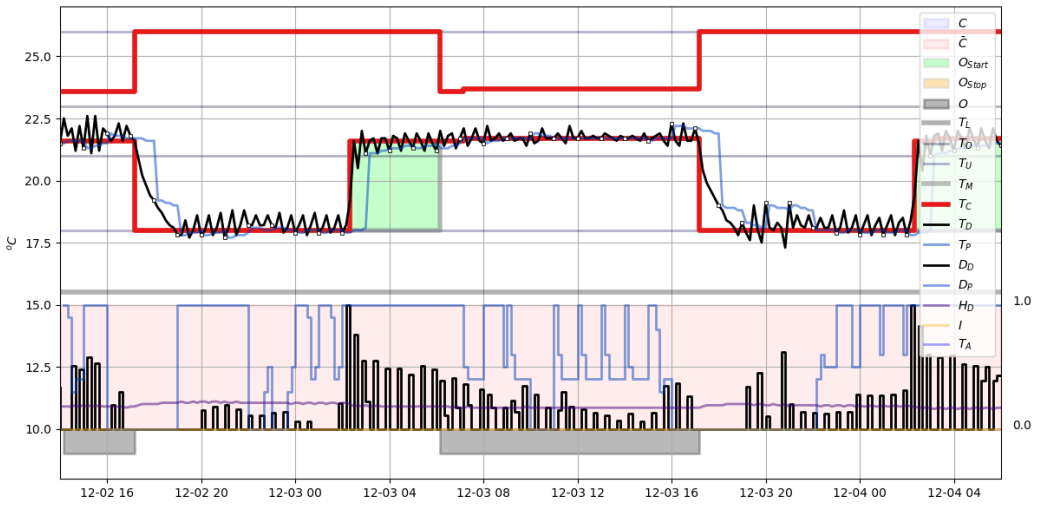
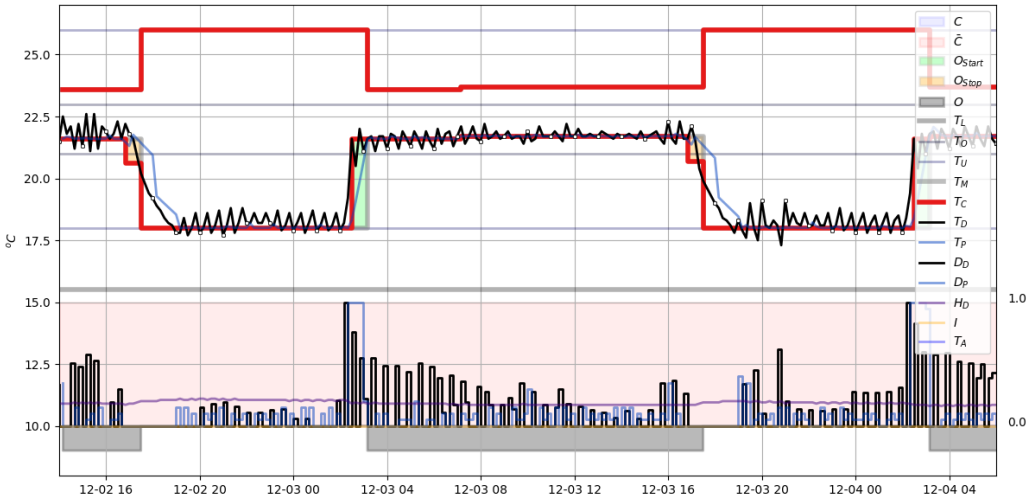


Figure 7 illustrates control temperature guidance and observations from the Ainsworth Ottawa Sussex zone on 2024-12-03, simulating the adaptation in control guidance behavior over 3 days of operation with identical observations, adjusting occupancy to align with the data. An optimal start (green) interval predicts 50 minutes of heating may be required to ensure that the device temperature (black) is within 0.5 °C of the control temperature at the transition to occupied (gray, upper). An optimal stop (yellow) interval predicts the device temperature will remain within 0.5 °C of the control temperature for 50 minutes before of the transition to unoccupied without heating. Optimal start and optimal stop reflect the improvement in control temperature guidance, which more accurately models the heat transfer behavior of this zone. Demand prediction (blue, lower) accuracy approximates demand (black, lower) well, and may be aggregated to estimate energy consumption.

Figure 7

Temperature control guidance and device observations – Sussex trained behavior.



The learning time for the stabilization of the start and stop times for each zone at the Ainsworth Ottawa site is around 7 occupied days. For the site in Edmonton, stabilization occurred around 5 occupied days, as well as at the site in Montreal. The learning time varies based on site-specific factors such as zone geometry, location, occupancy schedule, and weather. During the test period, the transition from fall 2024 to winter 2024 was occurring, as it was the end of November. Therefore, the system had to adapt to increasingly colder temperatures, requiring more pre-heating for morning comfort and a longer time than expected to stabilize. The HVAC system in Ottawa was able to learn the specific physical requirements of the zones and stabilized the start and stop system around 5:30 am and 5:15 pm after 2 days, under the conditions encountered during the test.

Energy Consumption Impact

During the field trial, only one of the sites was equipped with electrical meters precise enough to provide feedback on the energy consumed during the control time for the overall building. Those metered data were saved and gathered on the monitoring platform for energy provided by Schneider Electric (EcoStruxure Power Monitoring Expert). These values of energy from the RTU controlled by AI are used to track down the savings with a baseline without AI that span from the 1st of January 2024 to the 11th of November 2024, and an extra period for the baseline from the 4th of January 2025 to the 14th of January 2025.

The focus analysis for the energy impact is made for the system at the site located in Edmonton. The period reviewed includes the AI controls in place after stabilization of the learning phase for the winter compared with similar Heating Degree Days without the AI controls. It is noted that the system is still in constant learning and might adapt to different temperatures due to the stateless methods used in the Dynamic HVAC Optimization algorithm.

Figure 8

Energy curve in Edmonton in a day with the AI activated.

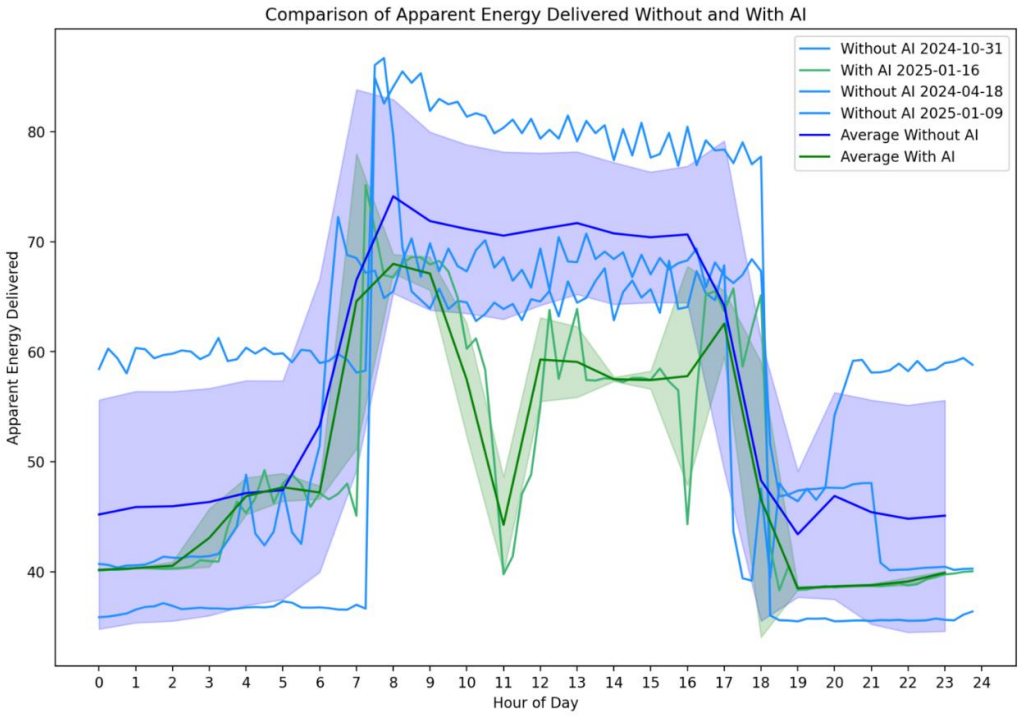


Figure 8 illustrates a day with AI control via a room controller compared to baseline days using a classical control strategy. Similar days are considered if they have a tolerance of 0.5 degrees difference in Heating Degree Days controlled by AI. The AI optimizes control to save energy by leveraging every opportunity that arises during the day, such as changes in occupancy behavior, outside weather, schedule adjustments, or environmental inertia. In this example, on January 16, 2025, the energy saved was 12% of the Roof Top Units' (RTU) electrical consumption.

Figure 9

Comparison of the electrical energy of the RTU in the Edmonton over a week with the AI activated.

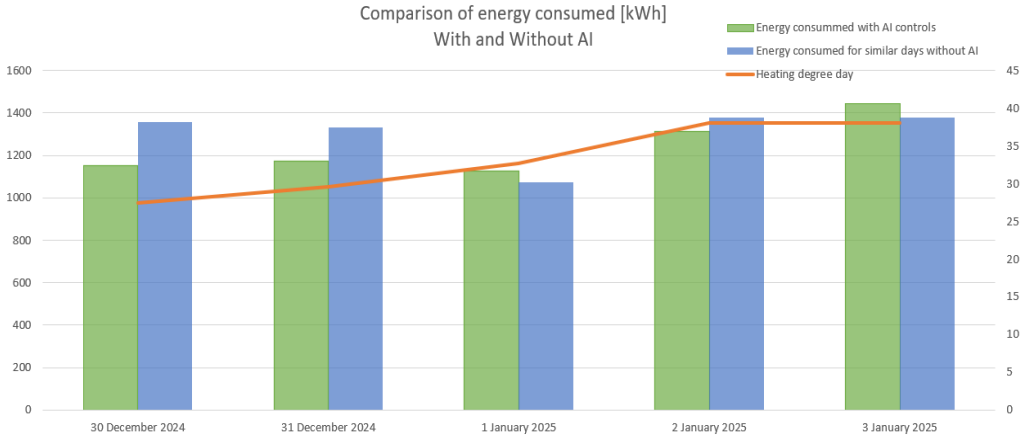


Figure 9 presents the difference in daily energy consumption with and without setpoint optimization that accounts for environmental factors to learn and adapt the setpoint. This analysis was conducted over a period of two and a half months, resulting in an average daily electricity saving of 4.85% for the RTU under AI control. The range of savings varied from a 5% increase in consumption to a 15% reduction in electricity usage for the RTU during this period, with only seven days where the AI control was outperformed by the classical control observed previously.

Figure 10

Daily percentage of electrical energy saved from the RTU in the Edmonton.

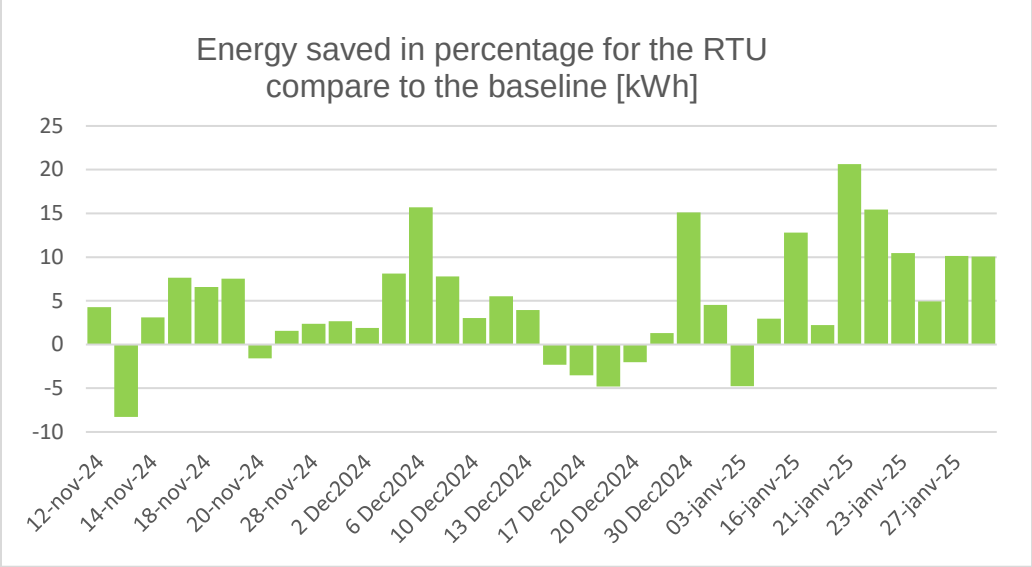


Figure 10 shows the evolution of daily savings in electrical energy from the RTU. For gas consumption, the heating stages triggered during operating times are referenced, as there are no gas meters installed for all RTUs. The heating stage have data extracted since early October 2024, providing with fewer days for baseline and savings comparison. Therefore, these savings cannot be presented as the valid baseline is only 10 days.

Insights

The field trial provided valuable insights into the implementation and impact of an AI control strategy embedded at the room controller level. The benefits of AI on edge devices can be described as follows:

- Reduced Latency: Data is processed locally, resulting in real-time decision-making with latency as low as 1-2 seconds. In contrast, a cloud-computed system requires data to be sent to the cloud for processing, which can introduce latency of a few minutes or more, depending on network conditions.
- Lower Bandwidth Usage: Only the most relevant or processed data is sent to the Building Management System, drastically reducing bandwidth usage. Only sending 10 points through BACnet dedicated to the AI control mode, which can be used for further analysis or debugging.
- Cost Efficiency: Edge AI reduces the need for extensive cloud storage and compute power, lowering operational costs.
- Reliability: The AI control optimization can operate independently of internet connectivity, ensuring continuous operation even in areas with poor or no connectivity.
- Energy efficiency: The AI-driven solution has been proven to save an average of 5% of the electrical energy used by the RTU, with savings expanding up to 15% under specific operating conditions.
- Comfort: Compliance with the setpoints requested by the user is maintained due to preventive actions taken by the AI solution, resulting in the temperature staying within the setpoint bandwidth more than 85% of the time.

Conclusion

Deploying AI on an edge device like an HVAC room controller ensures that AI-driven features operate efficiently and effectively. This approach unlocks the full potential of the new control strategy without overusing compute power or requiring extensive cloud storage. In turn, AI at the edge makes building management and operations more efficient, sustainable, and cost-effective while enhancing occupant comfort.

The Dynamic HVAC Optimization algorithm has been deployed in both test and field trial environments to ensure it adheres to the quality guidelines of Schneider Electric and performs well under real-world conditions. During the field trials, conducted for four months at various sites, the capability of the system to adapt, learn, and maintain the required level of comfort for each site was reviewed with an average of temperature compliance above 80%.

One of the priorities of the AI control optimization implemented in the room controller is to comply with the user's requested temperatures, and the performance has been excellent at all sites. The impact of the flexible setpoint during the day and optimization of the start and stop (tested only for the heating demand) are proven to have a positive impact on energy consumption with an average of saving on the electricity consumption of the HVAC controlled of 5% per day, and finally the learning phase of the algorithm only took on average seven days to stabilize per site.

In conclusion, the successful deployment and performance of the Dynamic HVAC Optimization algorithm demonstrate its potential to significantly enhance energy efficiency and user comfort. As the capabilities of this technology continue to be refined and expanded, it is expected to play a crucial role in the future of smart building management.

About the authors

Marion Blayo is an AI/ML Lead Engineer at Schneider Electric, within the Digital Buildings line of business. She leads AI and Machine Learning initiative implementation, driving innovation through advanced algorithms for HVAC and building systems. Prior to joining Schneider Electric, Marion spent nearly six years in the startup industry for HVAC and energy Innovation. Her work focused on implementing AI models for energy optimization and smart building integrations as well as developing AI algorithms for fault prediction.

Larry Turner is a Principal Data Scientist for the HVAC optimization at Schneider Electric, working within the AI Hub Customer Offers organization. His primary focus is on developing innovative AI solutions to enhance the Digital Building offers. With a strong background in artificial intelligence and machine learning, Larry has been instrumental in advancing the capabilities of HVAC systems through AI-driven optimization which leads to the submission of 9 patents dedicated to these topics.

Jeff Bowman is a Software Architect and Research Lead within Schneider Electric's Digital Buildings line of business. Specializing in system integrations and engineering efficiency, he drives innovation through advanced software solutions for HVAC and building systems. With a deep passion for modern technologies, Jeff is committed to ensuring that HVAC controls technologies are not left behind in the world of evolving technologies. In his current role, he continues to advance smart building management technologies, leveraging his expertise to push the boundaries of what's possible.

Maxime Laudren is a Global Expert Technical Support at Schneider Electric, with over seven years of experience in the field. Based in Montreal, Quebec, Maxime has held various roles at Schneider Electric, including Software Engineer and Global Expert Technical Support. His expertise spans across developing cross-platform mobile applications, creating network and software architectures, and managing internal and external teams to enhance project functionalities.

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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 500

How Integrated Room Controllers Reduce Office Energy Cost and Boost Worker Productivity
White Paper

Adaptive filter bank for modeling a thermal system
Patent US 11293812

Detecting diagnostic events in a thermal system
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Operational constraint optimization apparatuses, methods and systems
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