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Using AI to Optimize HVAC Systems in Buildings: A Real-world Example

White Paper 508

Version 1

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Executive summary

Artificial intelligence (AI) technology has the potential to significantly improve a building's energy efficiency, environmental sustainability, and occupant health, but examples have been largely theoretical. In this paper, we describe a "real-world" AI solution and its implementation in 624 school buildings. After about 5 months of operation (winter season), the solution reduced heating energy by 4%, reduced electricity usage by 15%, reduced CO_2e emissions by 205 tonnes, and reduced occupant complaints by 23%. We explain these results and provide lessons learned from the project.

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Introduction

While there has been much research in the field of AI building systems along with the complementary technologies that support them, there is far less literature on the “real-world” implementation of AI in commercial buildings and the associated results. In order to help justify AI projects, facility management and real estate leaders need examples of AI implementations that explain the challenges they address and validation that the solution really solves those challenges. They also need guidance on what to look for in an AI solution and an understanding of the steps involved with an actual AI implementation.

This paper attempts to address these points by describing an actual AI implementation across 78 properties in Stockholm, Sweden, on which there are 624 existing school buildings (see Figure 1). These buildings collectively represent 395 heating systems, all of which are district heating systems, except for one which is a geothermal heat pump. Note that the school buildings have only heating systems since they are closed during cooling season (i.e., summer).

We start by explaining the challenges that led SISAB, a municipal company responsible for operating and maintaining these school buildings, to seek an AI-based building management solution. We then describe the specific AI solution and step through the three AI implementation phases. After about 5 months of operation (winter season), the AI solution reduced heating energy by 4%, reduced electricity usage by 15%, reduced CO2e emissions by 205 tonnes, and reduced occupant complaints by 23%. The paper explains these results and closes with lessons learned and recommendations for starting an AI project.

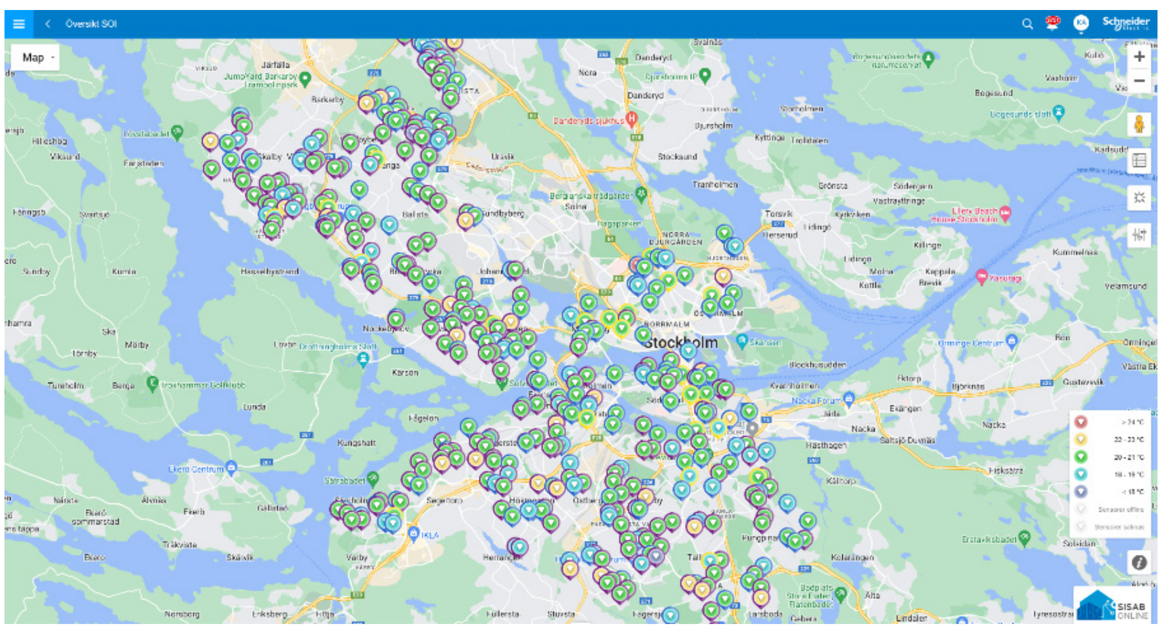

Figure 1

Map of SISAB schools as shown in Schneider building management system

It’s important to note that while AI can be used in new buildings, we focus specifically on the use of AI in existing buildings. This is an important distinction in terms of the expected savings that AI can bring. Buildings can be designed and built today with sophisticated architecture, materials, building management systems (BMS) and various smart sensors resulting in very efficient operation. AI used in existing buildings that lack modern design practices, are likely to result in greater efficiency improvements without the need to rip and replace existing systems. This is a key benefit for those managing portfolios with many older buildings.

Note, this white paper presumes the reader has a basic understanding of AI fundamentals. For more information see White Paper 502, *AI Fundamentals for Buildings*.

Building challenges

To provide context for the challenges, we first provide some background. SISAB owns, operates, and maintains over 600 preschools, primary schools, and colleges in the city of Stockholm, Sweden. With an annual energy budget of about €24.3M ($26.5), even a small efficiency improvement can result in significant savings. These savings can then be used to either reduce their budget or invest in new energy-saving technologies. These schools range in size (100-48,000 m^2) and in age (7-15 years) requiring different heating setpoints to maintain a comfortable environment year-round for the 200,000 students and staff that occupy them.

Prior to 2013, SISAB had multiple building management interfaces (provided by different vendors). After 2013, they established an operations center (like a network operations center for data centers) that operates and maintains all their buildings. This is now the only system where building control changes can be made (e.g., heating system setpoints). Even technicians in a particular school building must be given specific permission to make changes in that building. Prior to this, they had no way of knowing the history of who made what changes due to the large number of contractors who work on their buildings.

Lastly, over the years, SISAB installed temperature and CO_2 sensors inside their school buildings (currently over 20,000 sensors) so that the heating and ventilation systems could provide real-time control. This equated to roughly one million data points every day. Neither the heating & ventilation systems nor maintenance personnel were able to do this.

Given this background, SISAB realized it had three main challenges:

- Reduce their overall heating energy and the associated heating costs while maintaining a mean indoor temperature of 20°C (68°F).
- Implement a solution in the existing buildings and control system without replacing existing equipment.
- Analyze a large data set from all the sensors, identify the optimal setpoints, and then make changes in real time.

AI solution

Selection

In March 2018, SISAB selected an AI solution developed by Myrspoven. The projected payback of less than three years helped justify the investment (see Results section for actual payback). After implementation, SISAB eventually called their system SOLIDA (SISAB On-Line Intelligent Data Analysis). This solution didn't require retrofitting any of SISAB's existing components such as building controllers. The cloud-hosted AI service did not replace their conventional building controls but rather runs on top of their existing BMS. One could say that the AI solution is acting as a virtual building operator using the same control knobs a human would use. The biggest difference is that the human typically makes changes a few times a year based on occupant complaints, while this AI solution makes adjustments every 15 minutes to optimize results continuously. The AI solution expects a conventional BMS to do the basic management functions while the AI service adjusts setpoints for air temperature, air pressure (for airflow) or both (depending on the building) to get the best indoor climate and energy performance. These are key benefits for organizations with existing buildings.

Selection guidance

The core concept of Myrspoven AI is that the logic is created by data instead of a programmer. In this specific case, the school building produces the data (e.g., temperatures, valve positions, setpoints, energy readings, etc.). Also, the solution offered the option of integrating external data sources, such as weather data. Furthermore, when we discuss traditional building HVAC controls, this generally infers a building that runs on specific schedules, which can be energy optimized. For example, by turning on heating/cooling equipment at 6am and shutting down at 6pm, eliminating energy use during the holidays, operating the HVAC equipment only under the zones that are occupied, etc. However, instead of a fixed schedule, the AI solution can use past data and predicted future events to decide when to control/adjust equipment.

While other AI solutions may require custom programming to build a model from scratch, the Myrspoven software installs a generic "out-of-the-box" model with no human programming. Instead of running on schedules, the AI model is given input values and a very specific output/goal to reach, using supervised learning[1] and other AI techniques. In essence, the generic model learns by making changes to the system and observing the result, thereby transforming into a tailored model, fit for a specific building. This is illustrated in Figure 2.

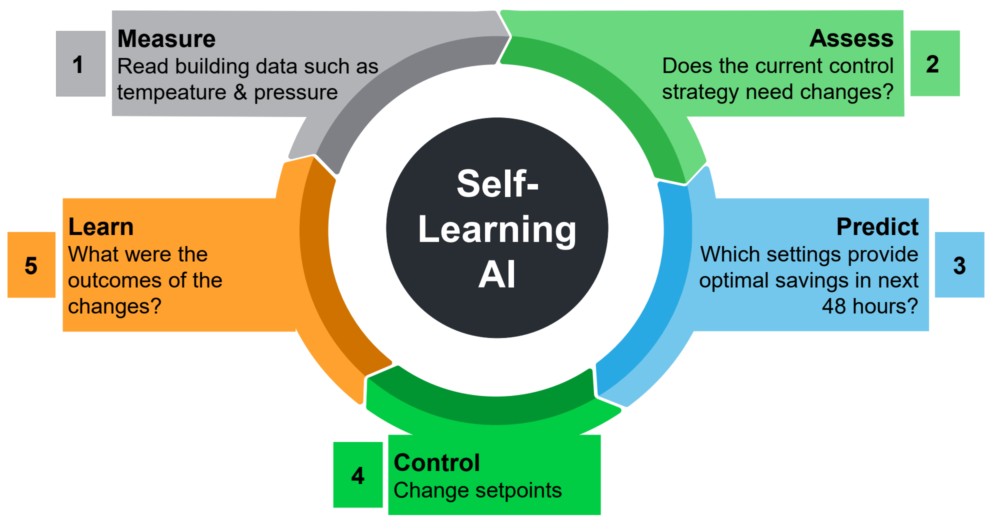

Figure 2

How a generic AI model learns over time

For facility management and real estate leaders assessing AI solutions, the following guidance may help narrow down available options. Consider solutions that:

- don't require retrofitting existing components such as building controllers
- work "out of the box", i.e., don't require custom coding, and require only changes to variables such as setpoints
- can be deployed via a private cloud hosted by a cloud provider, as a means of shifting data privacy and data security responsibility to the provider

With this background, we now discuss the details of implementing this solution.

AI solution implementation

This section breaks SISAB's AI implementation down into three main phases. However, before starting these phases, it should be noted that for any AI solution to work effectively, there are three requirements that a building must meet:

1. A means of connecting the AI solution
2. A means of collecting and storing data
3. A means of performing actions

[1] See White Paper 502, *AI Fundamentals for Buildings*, for an explanation of these terms.

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In the case of larger buildings, these requirements are relatively easy to meet. First and foremost, a building requires a BMS that controls the subsystems and core building functions in need of improvement. Buildings already contain data produced and logged by the BMS. Often, this is all the AI solution needs. In some cases, extra sensors can be installed for added benefits, for example, to get a clearer picture of indoor comfort. A rich dataset coupled with sufficient storage and computing power, is key for building AI analytics models to deliver accurate insights.

Figure 3 provides a high-level illustration of the data flows between the AI solution and the BMS.

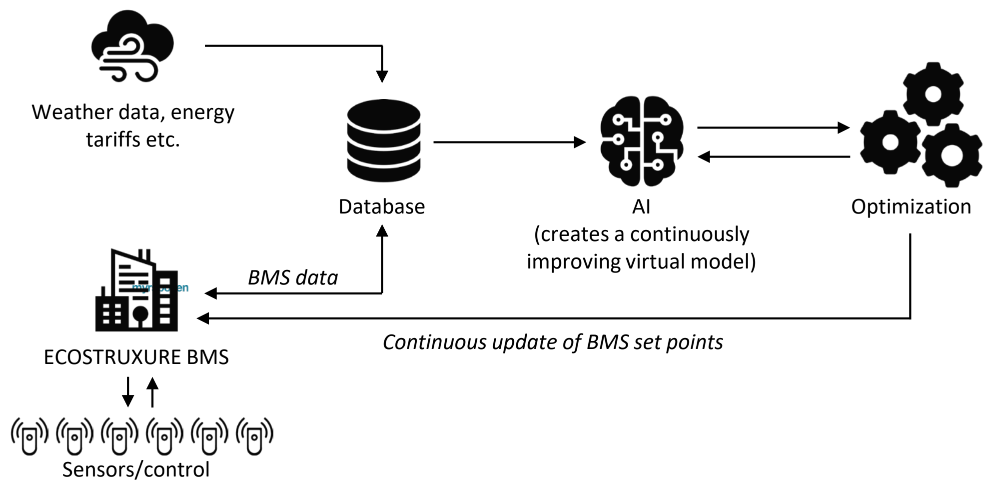

Figure 3

Illustration of data flows between the AI solution and Schneider Electric's BMS solution

We now describe each of the three AI implementation phases. While these phases apply to all 624 school buildings, we describe each phase in the context of a single school building. The three phases are:

1. Onboarding
2. AI learning
3. AI control

Phase I: Onboarding

In this phase, the AI service provider and building owner or their representative start by establishing the objective for the AI solution along with the required interactions between it and the building. There are four main steps in the onboarding phase:

1. Establish a connection with the BMS
   The communication between the cloud-based AI service and the BMS is facilitated by what is typically referred to as middleware. This is a small program running on premise that collects agreed-upon data points and also maintains and monitors communication with the cloud. In this case, the middleware is a Smart Connector[2] with a custom extension developed by Myrspoven. The middleware continuously monitors the secure uplink connection to the AI provider's cloud, which allows the solution to perform its job. Note that in this project all school buildings were running Schneider Electric's BMS solution called EcoStruxure Building Operation (EBO).

[2] This is Schneider Electric middleware software that allows communication between two different pieces of software.

2. **Collect a list of available data points**
In order to collect the building's data points, the middleware scans the BMS for all "accessible" data points in the building. Most building owners are sensitive to exposing certain data points, like those in a data center. In these cases, the sensitive data points are hidden (i.e., denied access rights), through BMS settings before data point discovery. An example of this is shown in Figure 4.

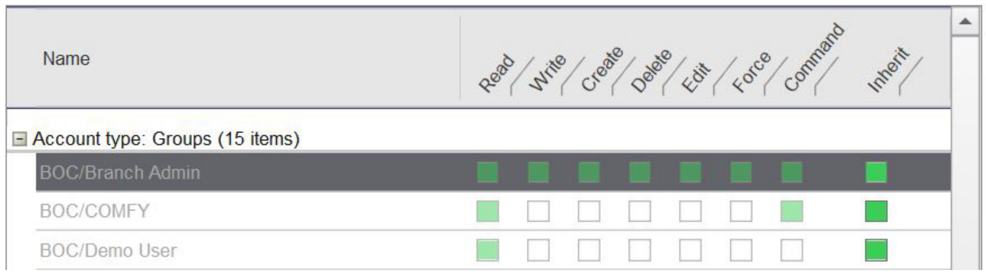

Figure 4

Example of setting BMS data point access rights

3. **Decide how to interact**
After discovering all the accessible data points, the AI provider needs to know how to interact with the building. To do this, they categorize the data as either:
    - Observable: These can be sensor readings measuring energy consumption or temperatures with an allowed range, e.g., comfortable indoor temperature. It can also be any data point that may help the AI make better choices such as external weather data. This data supports the AI in making decisions.
    - Actionable: Any data point that can be changed, usually to control a system setting such as a temperature setpoint to control supply air temperature.

Some additional information from the building is needed such as equipment types, zone classifications, etc. (information that is typically available in BMS graphics). This approach tries to minimize manual data gathering by letting the AI itself figure out how the building is connected internally. After analyzing the information, the AI provider suggests a list of actionable points, each with an allowed range within which the AI solution can act. The objective is also defined in terms of comfort measures and energy metrics. With both parties in agreement, live data can now be sent. This is discussed in the next step.

4. **Start sending live data**
This step tests and verifies the interaction between the cloud and building. For example, it verifies that a 1st floor temperature sensor isn't reporting as a 2nd floor temperature. The middleware is configured to periodically read the relevant data points from the BMS and send them to the cloud, as well as receive actions from the cloud and write them to the BMS. If the cloud service were to go offline, a problem is detected in the building, or if the building operator chooses to do so, the AI solution can be disabled for the whole building or for a particular subsystem. The BMS then automatically reverts to its default method of managing the building. As an example, Figure 5 shows the operator graphics for the supply air portion of an air handling unit. The blue text is the actual sensor reading of pressure and temperature. The grey is the setpoint by conventional control and green is the setpoint recommended by the AI service.

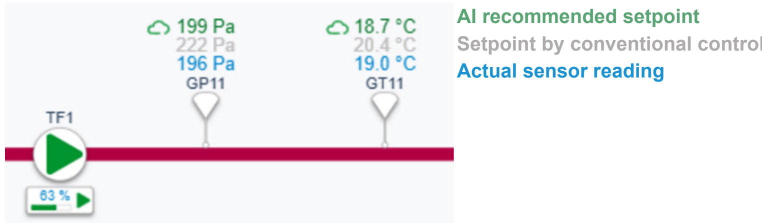

Figure 5

Example of BMS data points recommended by AI

Phase 2: AI learning

This phase involves training of the Myrspoven AI model in the cloud. Despite being in a learning phase, the AI model is capable of making small changes as we describe below. Training consists of the following three steps, carried out remotely (offsite) by the AI provider:

1. Verify collected data
The quantity, quality, and content of the datasets dictate the accuracy of any model therefore the data quality needs to be verified. If the input data is bad, the AI decisions will be bad as well. In Myrspoven's case, the models know exactly what data they need to collect for a well-functioning program. Note that this data verification is slightly different from that in step 4 of the onboarding phase. In the AI learning phase, the verification focuses on erroneous data from a correct sensor (e.g., signal noise), whereas in step 4, verification focuses on permission to read and write data, and tests the whole dataflow upstream and downstream between cloud and building, as well as automatic testing of scenarios such as broken uplink or safeguards when setpoints from the cloud are out-of-bounds.
2. Train the model
Training takes place in the cloud. The AI service learns how the building behaves given certain changes. For example, if an air flow setpoint is changed, how will indoor comfort evolve along with the associated change in energy and cost? While training is mostly based on monitoring the building, to get more interesting data, some small deviations are made to control points. For example, if two fans are usually running at the same speed, it will instruct one fan to slightly change to learn how that affects the building.
3. Test the model
With new data arriving in the cloud, the model is retrained daily, and accuracy improves. The more data, the better the model. For SISAB, after one month of data, the model was good enough to use as a basis for controlling the building (described in next phase "AI control").

Phase 3: AI control

Once the model knows the building behavior, it can be used for taking useful actions (actual control of the building). In this phase, the AI provider instructs the AI solution to begin managing the applicable building systems. The AI model and building performance continuously improves from this point.

The AI solution doesn't need to be told how to do something, only what the goal is. More precisely, it needs to know what is considered good and bad in terms of indoor comfort, energy consumption, and other factors. With the combination of the model, a performance measure, and a weather forecast, it can start turning virtual knobs to determine the best course of action in the coming hours or days. Of course, the combinations of all possible actions are too many to be tested even with the cloud's computing power. To address this challenge, the AI solution selects an initial plan and the very first control decisions are applied to the building. When new data become available, the plan is revised and is now looking a little further ahead. The main data flows are shown in **Figure 3**.

Results

The AI solution was fully implemented in 624 school buildings in November 2020 and has been running during the winter season since then. As mentioned in the introduction, the schools are in session only during the winter months. In order to assess the impact of AI, SISAB compared the energy bills between two periods:

November 1, 2019 to March 31, 2020 (No AI in any building)
November 1, 2020 to March 31, 2021 (AI implemented in 624 buildings)

In comparing the bills from each period, they found that running the AI service in conjunction with EcoStruxure Building Operation for 5 months resulted in:

- 4% heating energy savings
- 15% electricity savings
- 205 tonnes reduction in greenhouse gas (GHG) emissions
- 23% reduction in complaints from building occupants
- 2-year payback

We describe these savings below.

4% heating energy savings

All the heating systems were district heating, except for one which was a geothermal heat pump system. Heating energy savings were calculated by first normalizing the monthly district water heating bills according the degree days (weather adjusted). The normalized heating energy usage was then aggregated and compared to the same school buildings after AI was implemented. Any school building with a change of over 20% was considered an outlier and was excluded from the analysis. This same calculation was done with school buildings that were excluded from the AI project. These buildings serve as the control group to isolate the effect of the AI solution.

Overall, the AI solution reduced heating energy and heating costs by an average of 7% in the experimental group of buildings. However, the buildings in the control group saw an average savings of 3%[3] which indicates that the AI solution was responsible for 4% savings. These savings were possible through a combination of the AI model and additional heat sources: people (students and staff), lights, computers, and solar heat gain through windows. For example, the temperature would rise when students entered the classroom, or when the school room windows were exposed to the sun. By anticipating the temperature patterns, the AI model was able to proactively lower the setpoints and take advantage of these "free" heat sources. In doing so, it also prevented uncomfortable spikes in temperature. In fact, the overall mean indoor temperature increased 1°C while overall heating energy decreased.

15% electricity savings

The electricity savings was calculated based on total electricity costs before (8,000MWh) and after AI was implemented (6,800MWh) for the same time period as the heating energy comparison. These costs were not weather-adjusted and included the entire electricity bill, not just the fan motors. This means that the savings percentage would have been significantly higher if were only for the fan motors.

[3] This increase was due to the manual energy optimizations by energy engineers throughout all buildings. For example, trimming setpoints, installing VFD's, fine-tuning pumps, and improving insulation.

The 15% total electricity savings were from reduced ventilation motor energy. The ventilation system uses fan motors to supply air to the classrooms. By analyzing the CO_2 data, the AI model was able to optimize airflow through air pressure setpoints such that the CO_2 levels remained within a customer-defined range, but never below 800ppm (parts per million). More airflow decreases CO_2 levels but increases fan energy.

205 tonnes reduction in GHG emissions

Using Sweden's emissions factor for electricity (44 kg CO_2e/MWh[4]) and its average district heating emissions factor (61 kg CO_2e / MWh[5]) the buildings were able to reduce their greenhouse gas emissions by 52.8 metric tonnes and 152.5 metric tonnes respectively, for a total of 205.3 metric tonnes. These savings are equivalent to the emissions of nearly 173,000 dwellings in Sweden or 3.5% of all dwellings in Sweden[6]. Note that Sweden has a relatively low electricity emission factor due to its large proportion of renewable energy sources. Had this project taken place in a more carbon-intensive country like the United States (379 kg CO_2e/MWh[4]), the total emissions reduction from electricity savings would have been almost nine times greater.

23% reduction in complaints from building occupants

While not one of the original goals of the AI project, after evaluating the project outcomes, management discovered that by reducing the indoor temperature variation in the buildings, the AI solution was able to improve the overall occupant satisfaction in the school buildings with a 23% reduction in complaints. Occupants report deficiencies by calling SISAB customer service who pass the trouble ticket to the appropriate organization who then handles the work. This allowed SISAB to measure the complaints related to thermal comfort before and after implementing AI. This decrease in complaints also allowed SISAB's technicians to shift their efforts to other projects which improve occupant satisfaction.

2-year payback

The AI project achieved a simple payback period of 2 years based on the aggregated energy savings described above. These results were verified by comparing the school buildings before and after they were managed by AI.

Lessons learned

The stakeholders in this project learned some lessons along the way that serve as recommendations for others who embark on a similar project. We share some notable lessons below.

Define technical requirements

Clearly defining technical requirements is a must to help ensure the success of a project. This helped SISAB and Myrspoven choose the specific buildings and solution architectures most suitable for the project. Even out-of-the-box solutions have site-specific needs for a successful implementation.

Establish tight collaboration between partners

As with most new cutting-edge technologies, there tends to be a steep learning curve early on in the project and stakeholders should expect this. This was the case with implementing a new AI solution in school buildings (an uncommon AI

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[4] Our World In Data, *Carbon Intensity of Electricity*, 2021

[5] Sweden Green Building Council, *Treatment of Scandinavian District Energy Systems in LEED*, Table 8

[6] Based on 1.2 kg CO2e emissions per dwelling using 2019 electricity and district heating TWh for residential and service sector on pg. 9 of *Energy in Sweden 2021*, and Swedish dwellings in 2019,

application). This required tight collaboration between SISAB and their vendors, especially with Myrspoven and Schneider Electric. For example, early on in the implementation, there were frequent breaks in real-time data communication between the SOLIDA platform and Myrspoven's software, such as rebooting the server daily. Another challenge stemmed from the school holiday and vacation schedules, making it difficult to optimize the AI model. The team addressed this issue by hard coding the schedule, allowing the AI model to learn how the school buildings are used. The closer the collaboration between the stakeholders, the quicker issues like this are resolved.

Take an agile[7] approach to designing the solution

Start with doing the bare minimum to achieve a goal, then measure, refine, and iterate to continuously improve the outcome. Test your assumptions early and quick to make sure you are moving in the right direction. Keep a close and frequent feedback loop between developers, architects, customers, end-users, and tenants to ensure you are all aligned. Make sure that the solution is designed in a way that is open to change and customizations. Develop the initial minimum viable product (MVP) with tight collaboration between developers and end-users. This reduces risks, minimizes gaps between expected and actual outcomes, and improves the overall project experience.

Choose open BMS systems

A lack of open systems presents a big challenge to digitalizing buildings. For a long time, system vendors would lock out other vendors from their system. When systems from multiple vendors are integrated, open access to data is strongly recommended. Some stakeholders call this a "single pane of glass for information", others call it open, or non-proprietary. SISAB had firsthand experience with this challenge prior to 2013, when they had multiple building management interfaces from different vendors. See White Paper WP501, *Smart Buildings: A Framework for Assessing the "Openness" of a Building Management System (BMS)*, for more information on open systems.

Among other benefits, moving to a centralized and open system allowed them to freely share specific data between applications from different vendors. They did this initially with the AI application, but two others followed. They integrated a real-time wireless radon measurement and monitoring system. SISAB and Myrspoven have also started working with the electrical utility on programs like load sharing, dynamic energy pricing, and automated demand response, to reduce costs and further improve their environmental footprint in Sweden.

Start with a "critical mass" of buildings

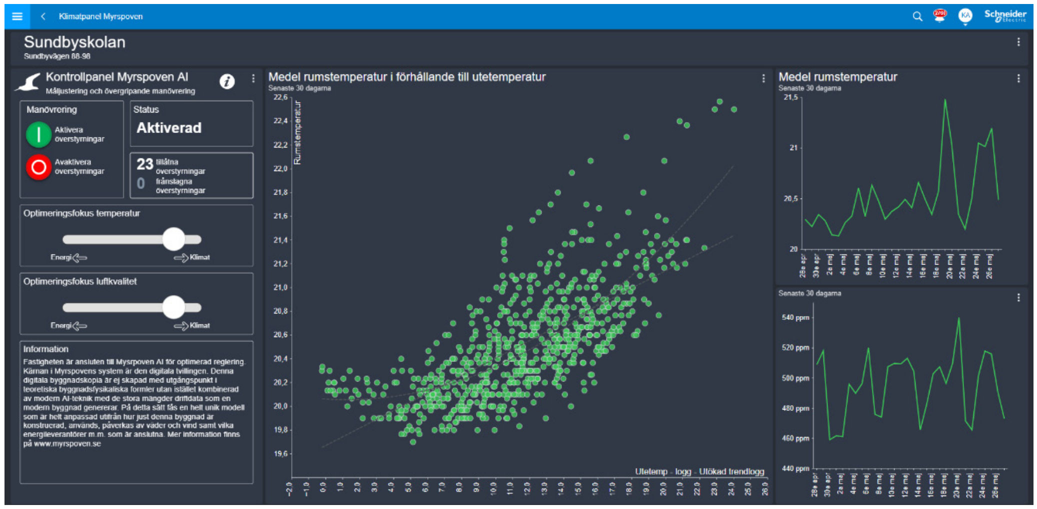
In the first winter season, the project team implemented the AI software in 624 school buildings. When the AI solution is first implemented, the model takes a longer time to learn, especially if many of the independent variables are correlated. A model needs lots of random inputs to learn quickly. If you feed the model inputs with very consistent indoor temperatures, correlated with outdoor temperatures, same amount of people every day, etc., the model predictions will be less reliable. Figure 6 shows an example of how outdoor temperatures (x-axis) are correlated with room temperature (y-axis). This meant that the team continuously adjusted the algorithm to improve the predictions. From this experience they learned that about 600 school buildings are an optimal "critical mass" or "sweet spot" to make algorithm adjustments while still managing building comfort. With too many buildings, you end up spending too much time optimizing the algorithm instead of managing

[7] "Agile is an iterative approach to project management and software development that helps teams deliver value to their customers faster and with fewer headaches. Instead of betting everything on a "big bang" launch, an agile team delivers work in small, but consumable, increments."

the buildings. Note that this critical mass may be different for different types of buildings and different AI solutions.

Figure 6

Outdoor temperatures correlated with room temperatures



Integrate AI into the BMS interface

Early in the project, contractors performing field maintenance would look at the BMS's interface and think there was a problem because they couldn't understand that AI was part of the control strategy. This prompted the team to integrate certain AI related information, including graphics elements, into the BMS interface. This also avoided having to switch between user interfaces. The team also added the capability of setting temperature boundaries (safety guardrails) for upper and lower limits to ensure that the AI control didn't deviate outside of this range. It's important to program these boundaries as close to the controller as possible to avoid issues in case of a network failure. Finally, during maintenance, contractors needed the ability to temporarily disable the external AI control. This feature was also added to the BMS interface.

Ensure AI solution is flexible

Each BMS is different in terms of communication protocols, control strategies, naming conventions, system design, etc. Flexibility allows the AI solution to scale more easily with the number of buildings. For example, can the AI solution work with the control strategies without having to retrofit or reprogram them? During the discovery phase of the project, the developers took an inventory of all the different ways to manipulate the control strategy for the different systems (e.g., HVAC units, BMS controllers, programmable logic controllers, etc.). For example, the AI solution couldn't change the BMS controller's temperature setpoint directly because the BMS controller used a separate control loop to establish the temperature. In turn, the control loop was driven by a set of indoor reference temperatures as a function of outdoor temperatures. Since these indoor reference temperatures could be changed, the AI solution learned what these inputs should be as means of establishing the intended temperature setpoint for each controller.

Avoid aggressive control overrides and bypasses

As discussed above, manipulating control systems can be beneficial but system integrators must use caution to prevent premature mechanical equipment failures. For example, making large and frequent changes to setpoints cause wear on actuators and reduce their expected "calendar" lifetime. Aggressive overrides and bypasses can also negatively impact occupant comfort if the system becomes unstable.

Conclusion

AI for buildings is a heavily researched topic but few practical real-world implementation examples are published to guide facility management and real estate leaders. The AI implementation discussed in this paper represents the integration of an active AI service with live brownfield buildings. By using artificial intelligence (AI) with data from a BMS, new analytics, optimization, and control strategies become possible. The solution reduced heating energy by 4%, reduced electricity usage by 15%, reduced CO_{2e} emissions by 205 tonnes, and reduced occupant complaints by 23%, providing an overall improvement in occupant comfort. The examples discussed in this paper focus primarily on HVAC optimization. AI for buildings, however, has a wide array of applications in facility management, resource allocation, occupancy analysis, asset tracking, access control & security, among others.

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Anubama Chinnakannan is an Application Engineer in the CTO Office of Digital Buildings at Schneider Electric. She received her bachelor's degree in Electrical and Electronics Engineering from CEG - Anna University, India and her master's degree in Energy Systems Engineering from Northeastern University, USA. She is a WELL Accredited Professional and actively works on data experimentation, thought leadership material for Artificial Intelligence in buildings, grid-interactive efficient buildings research, multi-technologies research and innovation, and evaluations of startups in the buildings domain.

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Karim Hussain is the Technical Product Manager working with Digital Services for Buildings at Schneider Electric. He is a product leader with a multi-faceted background encompassing field services, control engineering, and solution architecture. He has led, designed, and developed several solutions with high business impact and user adoption such as controlling buildings with Artificial Intelligence, and was the lead architect of the project mentioned in this paper. Karim leads the development of a suite of technical products that change the way traditional building maintenance, operations, and control are done, to create Buildings of the Future.

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Resources

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