Physics-Infused Retrofit Isolation Measurement and Verification for AI-driven Energy Application

Amir Behjat, Gulai Shen, Gurpreet Singh, Gerald Toge, Ali Mehmani[1],
Research and Development, Nantum AI

ABSTRACT

Tracking energy efficiency improvements, meeting environmental targets, and promoting sustainability practices are possible through accurate measurement and verification. In this paper, we offer a retrofit isolation measure and verification technology founded on the IPMVP standard of measuring the impact of different AI-driven ECMs, anomaly detection, and notification services. This technology uses physics-infused machine-learning models that are constructed using static and dynamic data. The key attributes of this scalable and open-source technology lie not only in its ability to provide accurate measurements and validations of the target ECMs, but also in its robustness to common non-routine adjustments such as changes in occupancy, alterations in facility size (e.g., added square footage), variations in space type or usage, increase in energy demand(e.g., new IT centers, additional plug loads, and new data centers), as well as adjustments in zone temperature set points.

Introduction

Measurement and Verification (M&V) is a fundamental process in energy management that is essential for verifying the efficiency and effectiveness of energy conservation measures (ECMs) (Abrol et al. 2018, Shen et al. 2021, Wang et al. 2024). The International Performance Measurement and Verification Protocol (IPMVP) (IPMVP Committee 2002) and ASHRAE Guideline 14 (ASHRAE 2014) are standards that assure M&V provides a rigorous approach to quantifying energy savings. This process is not only important for verifying the performance of energy-saving initiatives but also crucial for ensuring the validity of performance-based contracts, particularly for Energy Service Companies (ESCOs) (Haberl & Culp 2020, Aggarwal 2020). These companies require precise M&V practices to validate their economic significance. The role of M&V extends beyond economic benefits, facilitating sustainable energy management through:

- **Credibility and Transparency:** Demonstrating the effectiveness of ECMs through transparent and verifiable data, thereby building stakeholder confidence.
- **Performance Optimization:** Identifying areas for improvement and ensuring sustainability of energy savings.

[1] Corresponding Author: amehmani@prescriptivedata.io

- **Policy and Program Support:** Supporting the development of energy efficiency and renewable energy policies based on robust data.

Advancements in Retrofit Isolation with Physics-Infused Machine Learning

The IPMVP standards provide different options for measuring energy savings in building retrofit projects. Option A focuses on Retrofit Isolation and specifically on measuring key parameters that impact energy use and demand (IPMVP Committee 2002). This approach ensures accurate quantification of energy savings resulting from energy conservation measures (ECMs). This method integrates both short-term and continuous field measurements tailored to the variability of parameters and the length of the reporting period. This paper investigates the incorporation of physics-infused machine learning to estimate non-measured parameters. This represents a significant advancement by utilizing historical data and manufacturer specifications to enhance estimation accuracy, thereby reinforcing the robustness and reliability of the M&V process.

The paper is structured as follows: Section 2 discusses the development of the innovative Measurement and Verification technology (M&V). Data collected from various ECMs deployed in commercial buildings is discussed in Section 3. Results and analysis of M&V are provided in Section 4. Section 5 concludes with some final thoughts and suggests future research directions.

Technology

The traditional scope of M&V, as delineated in foundational documents like the IPMVP, focuses on establishing a rigorous, standardized framework for quantifying energy savings (IPMVP Committee 2002). These practices are crucial for validating the efficiency of ECMs and underpinning the financial models of Energy Service Companies (ESCOs) (Cagno et al., 2022). With the advent of AI and ML, the landscape of M&V is undergoing a transformative shift. AI-driven ECMs focus on building schedules, and efficiency and comfort optimization with continuous monitoring, anomaly detection, control, and notification which are redefining the efficiency and precision of energy management strategies (Mehta et al. 2023, Trueheart et al. 2024, Merabet et al. 2021). In this context, the application of physics-infused ML represents a significant innovation, offering a method that combines the rigor of physical models with the adaptability and predictive power of ML algorithms (Iqbal et al. 2022, Behjat et al. 2020, Gokhale et al. 2022). This technology not only enhances the capability to manage and verify energy savings in complex scenarios but also fortifies the M&V process against common non-routine adjustments like changes in occupancy, facility modifications, and variations in space usage (Balali et al. 2023).

The proposed technology presents a two-component system design: First, it features an ECM detection algorithm that employs machine learning to identify the impact periods of target ECMs within both aggregated and disaggregated energy consumption data. Second, the framework focuses on modeling the impact of these ECMs, accurately predicting energy consumption behavior in scenarios without the ECM implementation. This innovative approach allows for energy savings estimation independent of variations in occupancy levels and types of weather conditions. Such a methodology aligns with the dynamic advancements in Measurement and Verification (M&V) driven by AI and ML technologies. It secures the reliability and accuracy of energy savings predictions, facilitating more informed decision-making in energy management.

ECM Detection

To ensure the effective monitoring and verification of ECMs, it is essential to design a technology that is formulated based on accessible data sources. Electricity data at the building level is often readily available for this purpose. It is important to note that equipment-level demand data could greatly facilitate the execution of IPMVP Option A processes. However, this requires the installation of submetering devices for every piece of equipment. The initial version of the proposed M&V Option A technology is designed based on electrical demand data, recorded at five-minute intervals, representing the energy usage patterns of a building.

An optimization-based method has been formulated to identify the impact periods of targeted ECMs. This approach processes interval demand data to create a piecewise linear approximation that represents the building's energy consumption over a day. The mathematical model within this function utilized a series of parameters ($A_X, A_Y, B_X, B_Y, C_X, C_Y, D_X, D_Y, E_X, E_Y, F_X, F_Y, G_X, G_Y, H_X, H_Y, I_X, I_Y, J_X, J_Y$) to define breakpoints and slopes of the fitted curve. Figure 1 shows these points in a typical one-day commercial building's electricity consumption.

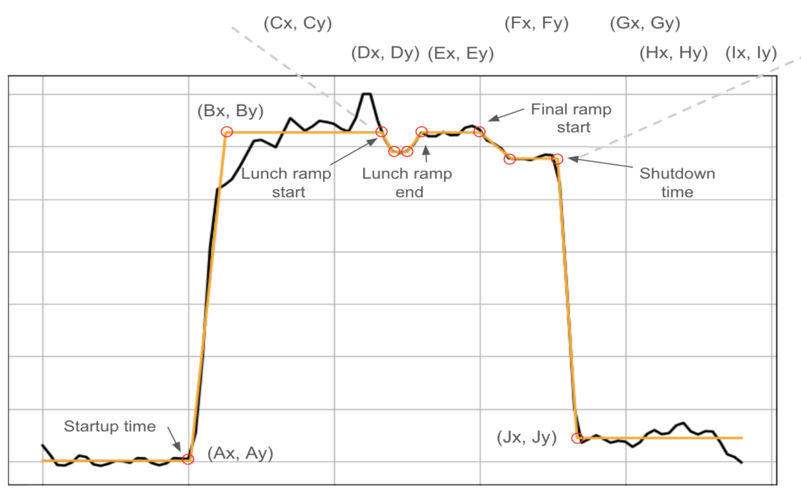

Figure 1. Building operation schedule detection through total electricity demand data

These parameters were adjusted to ensure a smooth transition between different segments, capturing the differences in the building's energy use pattern. The model was specifically designed to take into account the building's characteristic operational schedules and energy consumption behaviors. The overall procedure can be modeled as solving this multivariate optimization:

$$\int_{t=0}^{24hr} (D(t) - \widehat{D}(t))^2 \, dt$$

where:

$$\widehat{D}(t) = \{A_Y \ \ if \ \ t \ \in [0, A_X]; \ A_Y + (t - A_X)\,(B_Y - A_Y)/(B_x - A_x) \ if \ t \ \in (A_X, B_X); \ ...$$

$$s.t.\{\ A_X < B_X < C_X < D_X < E_X < F_X < G_X < H_X < I_X < J_X;$$
$$A_Y < B_Y;\ B_Y = C_Y;\ C_Y > D_Y;\ D_Y = E_Y;\ E_Y < F_Y;\ F_Y = G_Y;\ G_Y > H_Y;\ H_Y = I_Y;\ I_Y > J_Y;$$

The optimization is solved using the Levenberg-Marquardt Algorithm (LMA) for each day and the solution is used as the ECM schedule outcome. Another helpful aspect of the optimization is its application as an implicit low-pass filter, which is essential since the electricity demand data may be very noisy.

Upon applying the optimization to the data, the energy usage pattern of the building was characterized by several distinct phases corresponding to different operational activities. The first breakpoint in the curve was interpreted as the startup time, marking the initiation of the building's chiller, pumps, and fans. Following this, the building's temperature was regulated to meet a specific threshold within a set Service Level Agreement (SLA) time. A notable feature in the daily pattern was identified around midday, termed the 'lunch-time ramp', where a reduction in fan speed was observed for approximately one to two hours. This was followed by a return to the initial fan speed. As the day progressed towards closure, another phase, known as the 'end day ramp', was evident, characterized by a decrease in fan speed, leading up to the shutdown phase.

The final phase, labeled as the shutdown, was marked by the last breakpoint in the curve. This phase represented a period, typically lasting half an hour to an hour, where the building maintained a reduced temperature and fan speed before completely shutting down the chiller, pumps, and fans. This phase marked the end of the daily operational cycle. The analysis of these phases provided valuable insights into the building's energy efficiency and operational dynamics. By understanding these patterns, strategies can be developed to optimize energy usage, reduce costs, and improve the overall sustainability of the building's operations. This methodology demonstrates the potential of applying advanced mathematical modeling techniques to practical energy management problems, offering a framework for similar analyses in other buildings.

ECM Modeling

To accurately model the impact of different ECMs, a physics-infused machine learning model is constructed using historical building data and based on the thermal specification of a typical building. In this study, four different ECMs were considered. Each ECM has its unique models that are used for energy savings:

Startup ECM

An AI-driven optimal startup ECM automates or recommends building startup procedures based on refined predictions of outdoor weather, indoor temperature, relative humidity, and energy demand. The system ensures that environmental conditions inside the building achieve optimal comfort levels during occupancy times, which are determined by occupancy prediction algorithms or set according to lease agreements.

To calculate the savings associated with this ECM, the startup time needs to be shifted back to before the ECM was installed. Figure 2 illustrates how changing the startup time can affect electricity consumption and demand. Depending on the timing, consumption and demand may either increase or decrease. In these figures, we can see that an earlier startup time leads to more energy, but a slightly lower peak in demand.

Using these models, we can calculate the energy savings associated with Start-Up ECM by

$$S_{startup} = \int_{t=0}^{t_{SLA}} (D_{NO\ ECM}(t) - D(t))\, dt$$

In this equation, D represents the current electrical demand (kW) and $D_{NO\ ECM}$ is used to model no-ECM demand. The time service legal agreement, SLA, is shown by t_{SLA} and $S_{startup}$ is used for total daily savings due to startup ECM. It can be positive or negative based on the shift in demand, as illustrated in Fig. 2.

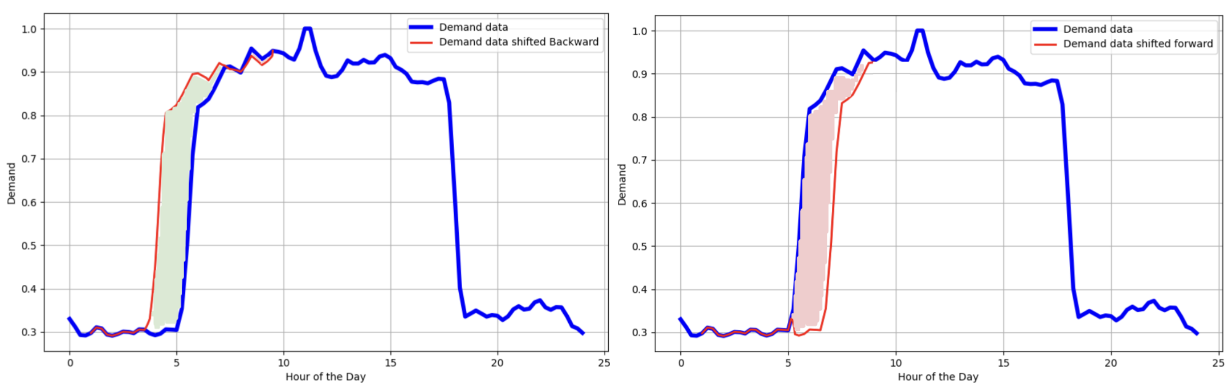

Figure 2. The illustration of Startup ECM and its positive or negative effect; Left: Positive saving, Right Negative saving

ShutDown ECM

The procedure for the building shutdown is determined by the prediction of occupancy levels using the occupancy prediction algorithm. This approach involves maintaining a reduced temperature and fan speed before the chillers, pumps, and fans shut down.

The process of calculating energy saving associated with ShutDown ECM is quite similar to that of StartUp. Essentially, the ShutDown ECM saves energy by utilizing the existing heat/cooling in the building instead of turning off the HVAC system only after all the occupants have left the building. Figure 3 provides an illustration of how the ShutDown ECM impacts the typical commercial day's demand for electricity. Shutdown energy saving can be formulated as

$$S_{shutdown} = \int_{t=t_{final\ Ramp}}^{24hr} (D_{NO\ ECM}(t) - D(t))\, dt$$

In this equation $S_{shutdown}$ is used for total daily savings due to Shutdown ECM. It can be positive or negative based on the shift in demand as illustrated in Fig. 3.

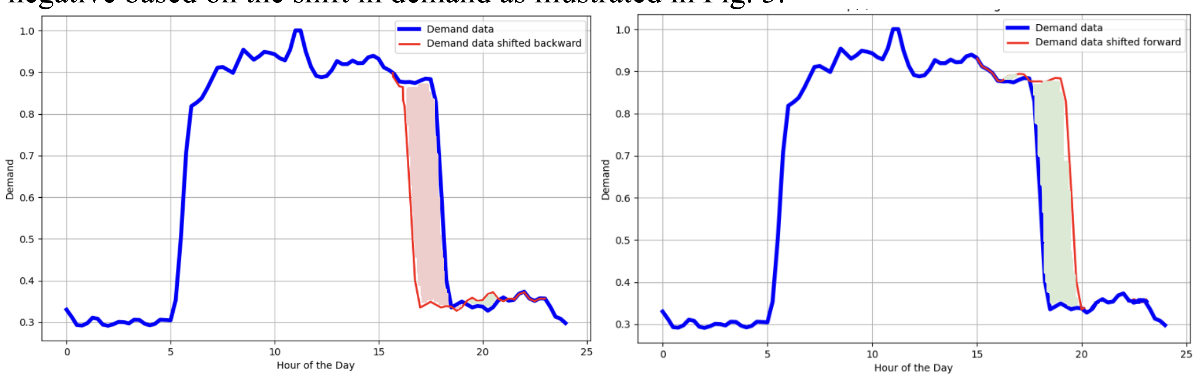

Figure 3. Illustration of Shutdown ECM: Left: Negative saving, Right Positive saving

Ramp ECM

The energy savings achieved with RAMP ECM can be calculated by modeling the demand using before and after the RAMP ECM detection period. The impact of the ECM can be measured without requiring any modeling if the fan specifications and demand readings are available. Figure 4 shows how buildings behave with and without RAMP ECMs for lunch and final ramps. The savings associated with Ramp ECM can be calculated by

$$S_{lunch\ ramp} = \int_{t=t_{Lunch\ ramp\ start}}^{t_{Lunch\ ramp\ end}} (D_{NO\ ECM}(t) - D(t))\, dt$$

$$S_{final\ ramp} = \int_{t=t_{Lunch\ ramp\ start}}^{t_{Shutdown}} (D_{NO\ ECM}(t) - D(t))\, dt$$

If the fan specification is available, the savings can be calculated by

$$S_{lunch\,ramp} = \int_{t=t_{Lunch\,ramp\,start}}^{t_{Lunch\,ramp\,end}} \left(hp(N_{fan,NO\,ECM}(t)) - hp(N_{fan}(t))\right) dt$$

$$S_{final\,ramp} = \int_{t=t_{Lunch\,ramp\,start}}^{t_{Shutdown}} \left(hp(N_{fan,NO\,ECM}(t)) - hp(N_{fan}(t))\right) dt$$

where $S_{lunch\,ramp}$ and $S_{final\,ramp}$ are lunch and final ramp saving respectively and N is the fan speed (rpm). The *hp* function specifies the fan electric demand as a function of fan speed.

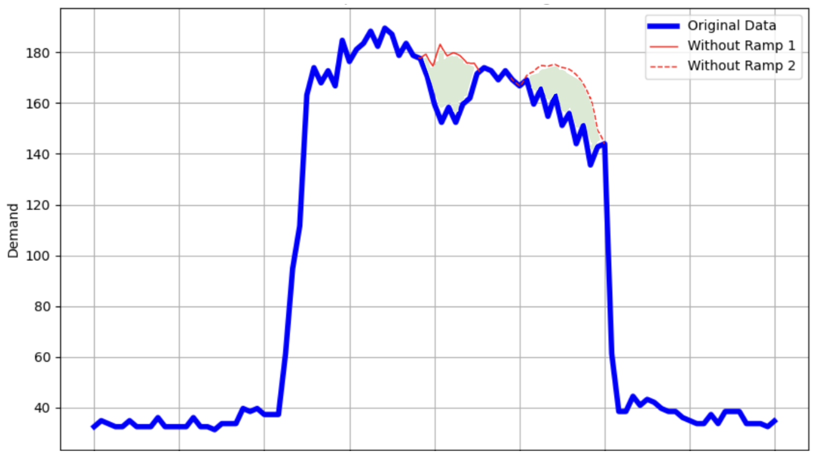

Figure 4. The illustration of Lunch Ramp (Ramp 1) and Final Ramp (Ramp 2) on savings.

Data

To investigate the effectiveness of a proposed M&V Option A technology, a case study on a commercial building in San Francisco, California is used. This building has an approximate area of 135,000 square feet and is equipped with a Variable Frequency Drive system. The building operates from 8 AM to 6 PM on weekdays and remains closed on weekends and national holidays. We excluded these days from our savings calculations.

Result

Table 1 represents the energy savings from different ECMs using the proposed technology in the commercial building case study. We estimated an average electrical cost of $0.22/kWh (Parkhill, 2020) and used 0.205 kg CO_2 / kWh as the emission factor for greenhouse gases generated for the location (California State average (GHGAPI 2024)).

Table 1. Yearly savings using the ECMs

ECM	Energy saving (kWh)	Saving [%]	CO2 Reduction [kg]	Cost Saving [$]
Startup	22,392	4.3	4,590	4,892
Lunch Ramp	3,755	0.7	770	820
Final Ramp	7,134	1.4	1,463	1,559
Shutdown	8,777	1.7	1,799	1,917
Total	42,058	8.0	8,622	9,188

Based on the size of the building, the cost savings is approximately 7 cents per square foot. It's important to note that this calculation does not include the potential reduction in human labor costs or other benefits such as improved situational awareness (Munir et al. 2023). Most importantly, these cost savings are achieved without sacrificing the comfort and well-being of the tenants.

The data displayed in Figure 5 illustrates the impact of ECMs on start-up and shut-down times. The ramp was not implemented prior to the installation of ECMs, therefore its impact cannot be shown in this figure.

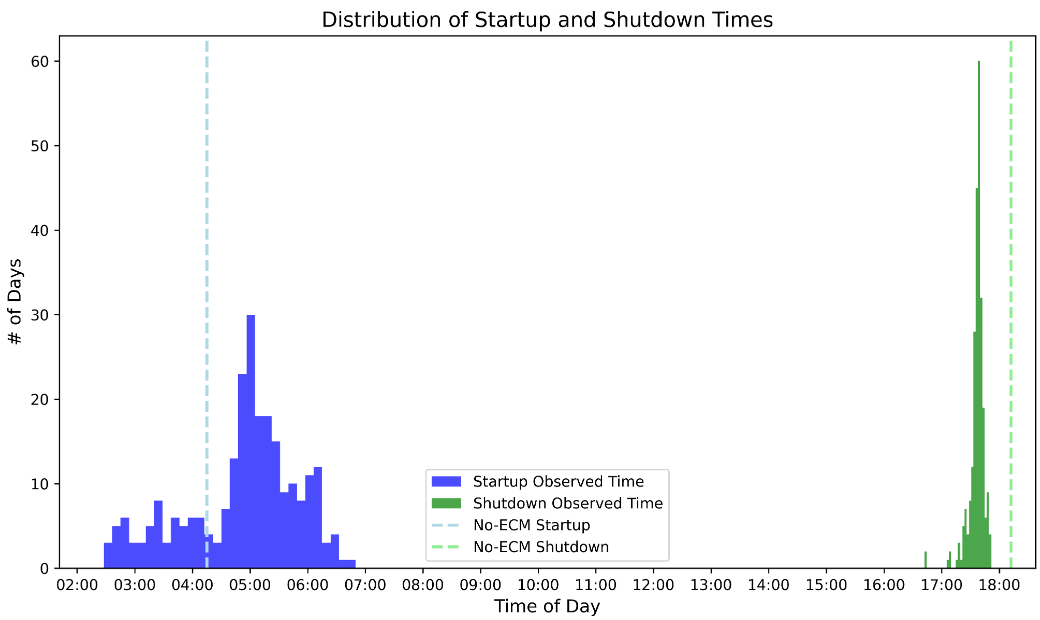

Figure 5. Distribution of startup and shutdown generated by ECMs compared to the no-ECM startup and shutdown times

Figure 6 shows the savings for each ECM based on the calendar date. As the figure illustrates, the savings are not equal in all months. Although overlay seasons with warm weather have more savings, this is not equal between all months.

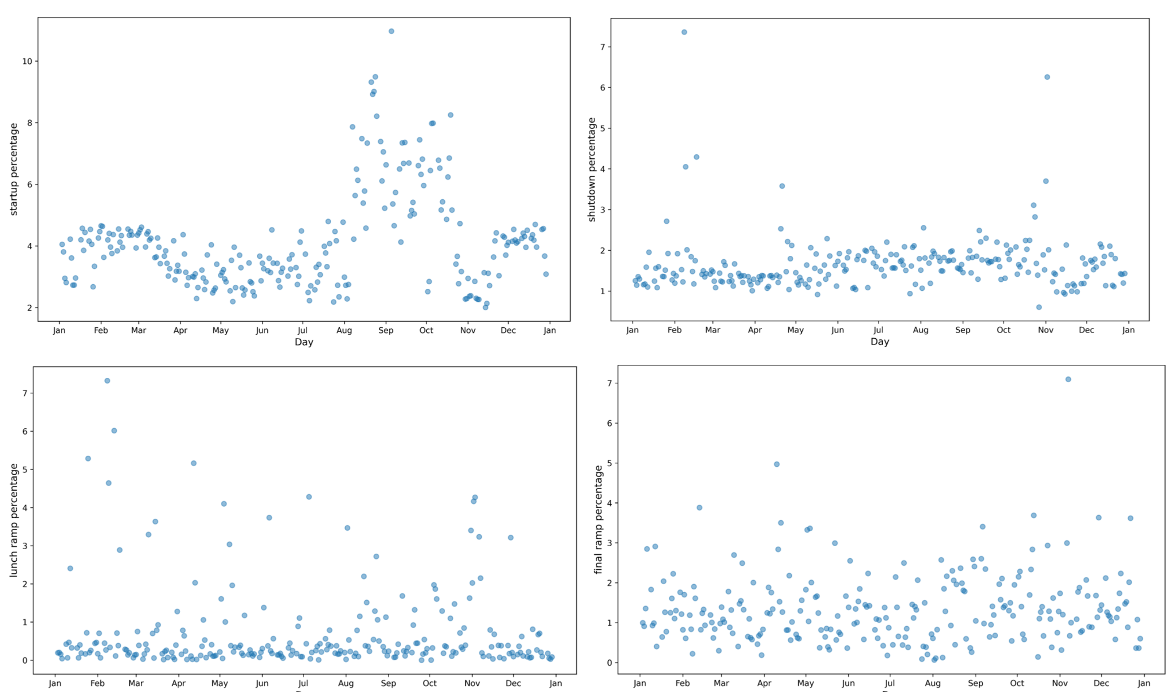

Figure 6. Energy savings per day. Top-left Startup saving, Top-Right Shutdown saving, Bottom-Left Lunch Ramp, Bottom-Right Final Ramp

Although using the date is helpful since many buildings show relatively fixed schedules, another more sophisticated approach is analyzing the savings for different outdoor conditions, as illustrated in Figure 7. A more pronounced relationship exists between weather and savings; savings increase with higher wet bulb temperatures. Due to the climate and moisture in the case study area, cooling is a major concern.

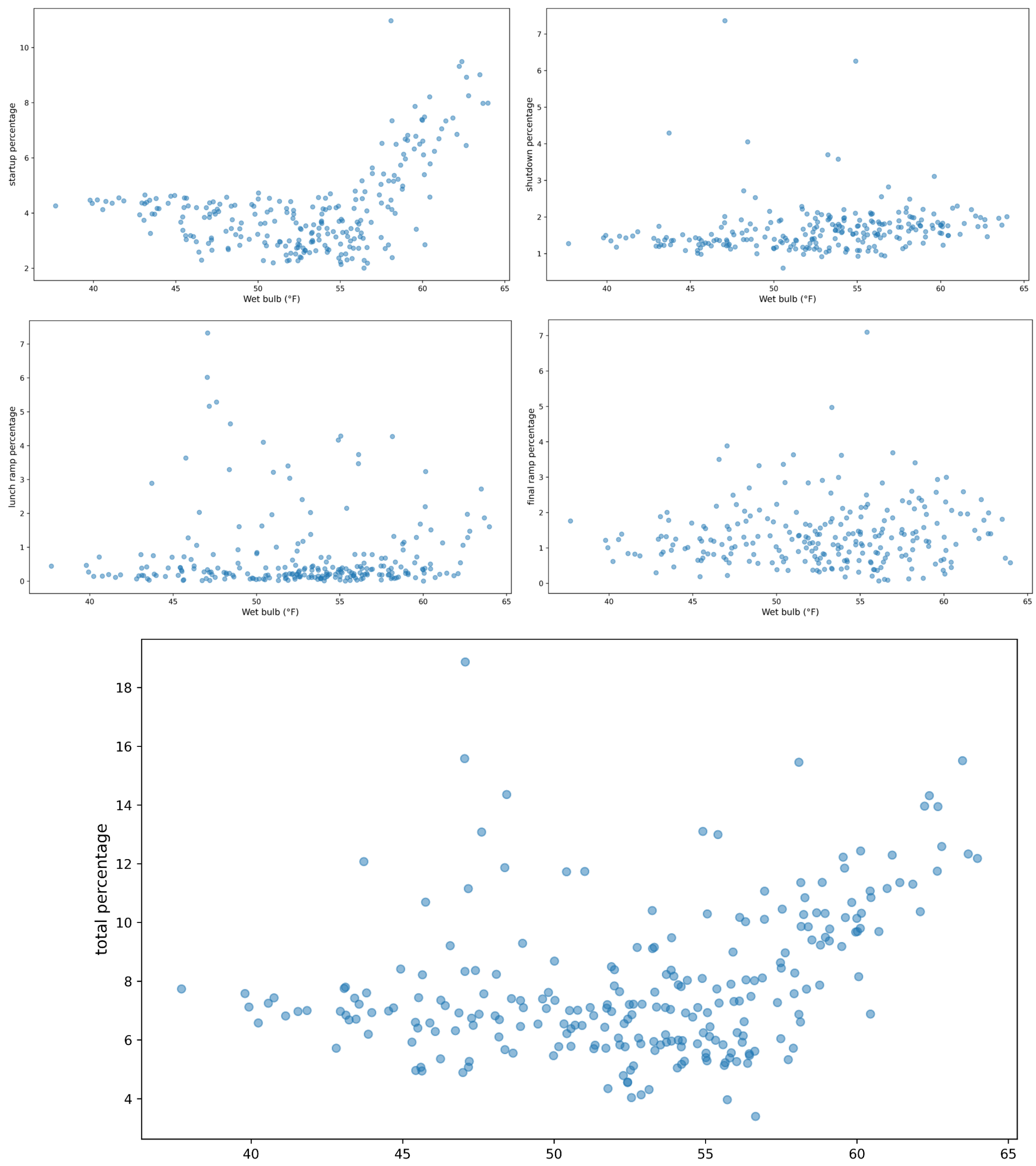

Figure 7. Variation of Energy savings with outdoor wet-bulb temperature. Top-left Startup saving, Top-Right Shutdown saving, Middle-Left Lunch Ramp, Middle-Right Final Ramp, Bottom Total savings.

Conclusion

This paper presents a novel paradigm in the area of energy conservation and building retrofits. With its foundation in the International Performance Measurement and Verification Protocol (IPMVP) guidelines, this research specifies a refined approach to M&V, optimized explicitly for retrofit isolation measures in building energy management. The method adeptly handles non-routine adjustments encountered in building energy scenarios, such as changes in occupancy, facility size, and usage patterns. Traditional methods of M&V frequently fail in these areas due to their limited adaptability to dynamic building environments.

The application of physics-infused machine learning enhances the accuracy and credibility of the M&V process. This advancement is pivotal, particularly for Energy Service Companies that rely on the reliability of M&V to confirm the economic and ecological efficacy of their projects. This methodology simplifies the assessment of different energy conservation measures (ECMs), it also opens doors for future explorations in the field. The study concludes by urging broader adoption of advanced measurement and verification (M&V) techniques in energy management. The study emphasizes that M&V techniques play an essential role in validating and optimizing ECMs, and contribute significantly to achieving sustainable energy practices and efficient resource utilization in building infrastructures.

Appendix A: M&V for Demand Management Application

Demand management applications aim to optimize building energy demand to enhance efficiency and reduce costs. Continuous (Recommended or Automated) Demand Management (DM) employs advanced prediction and uncertainty modeling to set adaptive demand limits, automatically activating demand reduction measures to prevent excessive peaks. This application can significantly lower peak demand while maintaining occupant comfort. These systems exemplify how intelligent energy management can yield economic and operational benefits, providing substantial cost savings and improving grid reliability.

To accurately measure the impact of DM during event periods, our proposed M&V application isolates the ADM savings from other ECMs. As ADM is not a continuous factor and only affects the building periodically, the event period refers to times in the billing cycle when DM is activated. The algorithm compares kW reading data during DM event periods with and without activated stages, without altering the controlled environment. By collecting reading data for both scenarios, the verification method adheres to IPMVP (International Performance Measurement and Verification Protocol) Option B. In recommended demand management, Nantum M&V estimates kW reduction by comparing expected and observed kW results from provided recommendations, using an approximation model that aligns with IPMVP Option A.

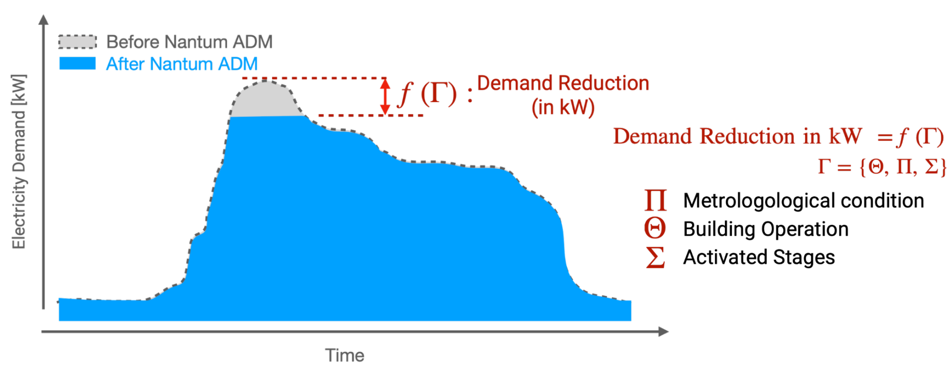

Figure 8. Quantifying Demand Reduction through Nantum ADM Implementation

Appendix B: Static Pressure Optimization

Static pressure optimization is designed to minimize the energy consumption of Air Handling Units (AHUs) while maintaining indoor comfort. The air-side optimization system dynamically adjusts the static pressure setpoint based on real-time data from the Building Management System (BMS), which includes static pressure, fan speed, and Variable Air Volume (VAV) damper positions. The process begins by identifying critical zones, which are zones with significant HVAC impact, such as those with active temperature control or prone to hot/cold calls. These critical zones' cooling or heating load is estimated using inputs like damper positions, space temperature readings, and airflow measurements. A Model Predictive Control (MPC) algorithm optimizes the static pressure setpoint. Combining physics-based and data-driven models, this hybrid algorithm adjusts the setpoint in real time to balance energy savings and comfort.

To accurately measure the energy savings achieved through static pressure optimization, the following methodologies are used:

- Baseline Comparison: Establish a baseline for energy consumption and comfort levels before implementation
- Energy Consumption Tracking: Monitor AHU energy usage before and after optimization to identify reductions.
- Comfort Metrics Monitoring: Track indoor temperature, humidity, and occupant feedback to maintain or improve comfort levels.
- Savings Calculation: Compare energy consumption data before and after optimization to calculate percentage savings.

References

Abrol, S., Mehmani, A., Kerman, M., Meinrenken, C., and Culligan, P. "Data-enabled building energy savings (DE BES)." Proceedings of the IEEE 106, no. 4 (2018): 661-679.

Aggarwal, R. 2020. "Financial Model of an Energy Savings Project for Energy Services Company (ESCO)." Doctoral dissertation.

ASHRAE. 2014. Measurement of Energy, Demand, & Water Savings. ASHRAE G. 14, 1-150.

Balali, Y., Chong, A., Busch, A., & O'Keefe, S. "Energy modelling and control of building heating and cooling systems with data-driven and hybrid models—A review." Renewable and Sustainable Energy Reviews 183 (2023): 113496.

Behjat, A., Zeng, C., Rai, R., Matei, I., Doermann, D., & Chowdhury, S. "A physics-aware learning architecture with input transfer networks for predictive modeling." Applied Soft Computing 96 (2020): 106665.

Cagno, E., Franzò, S., Storoni, E., & Trianni, A. "A characterisation framework of energy services offered by energy service companies." Applied Energy 324 (2022): 119674.

GHGAPI. 2024. "Sustainability Data Platform GHG API for Real-Time Carbon Intensity Factors." Accessed [date]. https://www.ghgapi.io/.

Gokhale, G., Claessens, B., & Develder, C. "Physics informed neural networks for control oriented thermal modeling of buildings." Applied Energy 314 (2022): 118852.

Haberl, J S., and Charles C. C. "Measurement and verification of energy savings." In Energy Management Handbook, pp. 733-795. River Publishers, 2020.

International Performance Measurement & Verification Protocol Committee. 2002. International Performance Measurement & Verification Protocol: Concepts and Options for Determining Energy and Water Savings, Volume I. U.S. Department of Energy. https://www.nrel.gov/docs/fy02osti/31505.pdf.

Iqbal, R., Behjat, A., Adlakha, R., Callanan, J., Nouh, M., & Chowdhury, S. "Efficient training of transfer mapping in physics-infused machine learning models of uav acoustic field." In AIAA SCITECH 2022 Forum, p. 0384. 2022.

Mehta, Yukta, Rui Xu, Benjamin Lim, Jane Wu, and Jerry Gao. "A Review for Green Energy Machine Learning and AI Services." Energies 16, no. 15 (2023): 5718.

Merabet, G. H., Essaaidi, M., Haddou, M. B., Qolomany, B., Qadir, J., Anan, M., Al-Fuqaha, A., Abid, M. and Benhaddou D.. "Intelligent building control systems for thermal comfort and energy-efficiency: A systematic review of artificial intelligence-assisted techniques." Renewable and Sustainable Energy Reviews 144 (2021): 110969.

Munir, A., Aved, A., & Blasch, E. "Situational awareness: techniques, challenges, and prospects." AI 3, no. 1 (2022): 55-77.

Parkhill,. REopt Lite Tutorial: Utility Rate Analysis. No. NREL/FS-7A40-77140. National Renewable Energy Lab.(NREL), Golden, CO (United States), 2020.

Shen, G., Lee Z., Amadeh, A., and Zhang, K. "A data-driven electric water heater scheduling and control system." Energy and Buildings 242 (2021): 110924.

Trueheart, L., Koritala, C., & Stopkoski, C. "Applying Artificial Intelligence to Optimize Engine Power Demand." In SPE/IADC Drilling Conference and Exhibition, p. D012S001R005. SPE, 2024.

Wang, Y., Shen, G., and Mehmani, A. "Indoor environmental wellness index (IEW-Index): Towards intelligent building systems automation and optimization." Building and Environment 247 (2024): 111039.