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Implementation of predictive modelling-empowered HVAC-driven PV self-consumption Enhancement Strategies in a Warehouse

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Abstract. The current work proposes a machine learning (ML)-based HVAC management strategy that shifts heating load to periods of high photovoltaic (PV) output, using demand and generation forecasts, aiming to maximize self-consumption. In this context, the case study of a conditioned warehouse with installed onsite PV panels and dedicated office and storage areas is considered. EnergyPlus is used to simulate building baseline behavior under varying conditions, generating data to train physics-informed ML models that would predict the hour-ahead load of the building. Additionally, PV generation forecasts are obtained from an open-access dataset. The strategy agent receives real-time and short-term forecasts for both building load and PV generation, continuously monitoring their balance. Based on this information, the agent applies slight heating setpoint adjustments, relaxing the setpoints or preheating the indoor environment by one degree, to shift the heating load away from grid reliance and toward periods of high PV availability. The results show that implementing the proposed interventions increases the building's self-consumption rate by 9% during the targeted intervention periods and by 7.47% over the entire heating season. Likewise, the self-sufficiency rate improves, indicating that a larger share of the building's energy demand is met by the PV system.

1. Introduction

Variable renewable energy sources, particularly solar photovoltaic (PV) systems, are expected to supply more than 50% of global electricity by 2050, signaling a major shift toward decentralized and low-carbon energy. This trend is especially evident in Europe, where supportive policies and favorable climate conditions have made distributed PV a key pillar of the energy transition [1]. Warehouses are essential to logistics and have expanded rapidly with the rise of e-commerce. Warehousing activities contribute roughly 11% of the total GHG emissions generated by the logistics sector across the world [2], roughly 2% to 3% of total global greenhouse gas emissions[3]. Their large roof surfaces make them well-suited for energy innovations such as PV installations, an effective strategy to reduce grid dependence and lower carbon emissions. However, aligning solar generation with actual energy demand remains challenging. PV output peaks at midday, which may not match energy-intensive activities like early-morning heating or overnight equipment charging. As a result, surplus energy may be exported to the grid or



curtailed, reducing self-consumption and limiting the overall impact of on-site solar generation [4]. Warehouses can implement strategies to boost PV self-consumption, the portion of solar energy used directly on-site, thus lowering dependence on the grid, energy costs, and emissions [5].

During periods of high solar irradiance, the HVAC operation can be strategically adjusted to precool or preheat the building beyond typical setpoints, effectively storing thermal energy in the building's structure (charging the building's thermal mass). These HVAC-driven adjustments would require predictive and intelligent energy management systems for real-time coordination of building loads and on-site generation [6]. Leducq et al. [7] demonstrated that using the thermal mass of a refrigerated warehouse to shift cooling loads to off-peak periods achieved approximately 10% energy savings. Additionally, thermostat-based control strategies—such as adjusting zone temperature setpoints and implementing precooling or preheating—have been demonstrated to effectively lower peak electricity demand in large office buildings, thereby improving overall load flexibility [8]. Despite advancements in individual technologies, the implementation of integrated energy management systems in warehouses remains limited. Most efforts focus on standalone upgrades, such as PV or LED lighting, without forming a cohesive strategy. Existing management systems typically rely on static rules that fail to respond to variations in renewable generation [9]. Accordingly, a methodology can be proposed to shift HVAC energy consumption from periods of low PV generation to times of high solar availability. Implementing this approach would require accurate predictions of both baseline energy demand and PV generation to enable effective scheduling and control. Campodonico Avendano et al. [10] compared machine learning models for hour-ahead load forecasting and found that the Extra trees algorithm with a 5-week sliding window outperformed offline training, highlighting the benefit of regularly updating models with recent data. To address the challenge of increasing PV self-consumption in warehouse buildings, this study proposes a methodology applied to a simulated case in Bologna, Italy, during the heating season. The building's baseline energy behavior is first simulated, followed by the development of ML-based pipelines for hour-ahead load prediction. A dynamic HVAC setpoint management agent is then implemented, adjusting temperatures in office and storage zones based on real-time and forecasted PV and load values through a co-simulation framework linking EnergyPlus and Python.

2. Case Study

The warehouse building utilized in this study is based on the DOE Commercial Reference Building Models, which are developed in accordance with standards such as ASHRAE 90.1 and the International Energy Conservation Code (IECC) [11] and is located in Bologna (Italy) and has been revised to reflect local construction practices and standards in Italy. In particular, the building's materials and structural layers were defined based on previous studies of warehouses in similar climatic zones and in accordance with Italian regulatory frameworks [12]. The warehouse is modeled to represent the winter heating season of 2023 in Bologna, Italy, covering the months from November to December and January through April. Simulations are carried out using EnergyPlus Version 9.4 [13], integrated with its Python API [14], enabling a detailed representation of the building's HVAC system, occupancy schedules, internal loads, and operational setpoints. The HVAC system is modeled in EnergyPlus as an air-to-air heat pump with unitary components, including an on/off fan, heating and cooling coils, and auxiliary electric resistance heating. Component connections follow schematics from the EnergyPlus documentation [15]. The baseline HVAC setpoints are set to 21°C for the office and 19°C for the storage zone, with building operation scheduled from 7:00 a.m. to 7:00 p.m., Monday through Saturday. Rooftop PV panels, modeled using specifications from the SAM database [16] and compatible with the Sandia PV model [17], are arranged in 60 parallel strings of 25 modules each taking in to account system specifications such as panel efficiency, installation tilt

angle, shading effects, and inverter performance. In this study, weather data for simulations are sourced from Open-Meteo. This open-access API provides hourly meteorological data to realistically capture external environmental conditions [18].

3. Methodology

This study proposes an ML-based agent that implements targeted adjustments to the HVAC setpoints to shift the heating load in response to forecasted demand and the PV generation, aiming to increase the self-consumption of onsite-produced PV energy in conditioned warehouse buildings. The methodology specifically targets two key periods of the day. The first occurs in the morning, aiming to temporarily reduce the building's high energy consumption just before the PV generation ramps up, when demand is still high due to the morning warm-up, but solar output is still low. The second targeted period is in the early afternoon, when PV generation is still high but not fully utilized. The methodology aims to partially shift HVAC consumption from the subsequent period of declining solar output to this interval of greater PV availability. Since the duration of the load-shifting interventions (including both the relaxation and overheating processes) is on average close to and within one hour, a one-hour horizon has been chosen as the most suitable prediction window.

The agent uses real-time values and hour-ahead predictions of building load and PV generation. In the morning, if PV output is lower than the load but a surplus is forecasted, the controller temporarily lowers the heating setpoints to allow a controlled 1°C drop in indoor temperature. When PV generation exceeds the load, the setpoints return to default, shifting part of the heating load to periods of higher PV output and improving self-consumption. Conversely, in the afternoon, when PV generation exceeds demand but is predicted to drop, the agent temporarily raises the heating setpoint to preheat using the surplus. Once PV falls below the load, the setpoint is restored to default, maintaining comfort while optimizing self-consumption. Transitions between setpoints follow defined thresholds to handle forecast uncertainty and avoid unnecessary activation. Adjustments are made incrementally, typically in 0.5°C steps per control interval, to leverage thermal inertia, prevent abrupt HVAC responses, and avoid peak demand spikes.

3.1. Prediction Pipelines

This study uses historical irradiation forecasts from Open-Meteo, which combines data from global models, satellites, weather stations, and buoys to provide accurate, high-resolution predictions. Instead, the baseline load prediction models are obtained by training regression-based machine learning algorithms on the data obtained from the simulations. The performance of the Random Forest Regressor (RFR), Extra Trees Regressor (ETR), XGBoost Regressor (XGBR), and K-Nearest Neighbors Regressor (KNNR) models in predicting the baseline load is assessed and compared. Additionally, Linear Regression (LR) is included as a reference model to benchmark the results. In this study, key input features used for training include indoor and outdoor air temperatures, time of day, day of the year, solar irradiance, energy consumption, and lagged values of these variables. The models' performance is evaluated using four key metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), the coefficient of determination (R²), and MAPE (Mean Absolute Percentage Error). To ensure adaptability to evolving conditions and to reflect a realistic implementation scenario in which data is progressively accumulated, an expanding window training approach is adopted. The models are initially trained on a two-week dataset sampled at 15-minute intervals. Thereafter, the training set is updated daily by appending newly collected data, and the models are retrained.

Lastly, improvements in two key energy performance metrics, Self-Consumption Ratio (SCR) and Self-Sufficiency Ratio (SSR), are used to assess the effectiveness of the proposed methodology. The SCR measures the proportion of PV-generated electricity that is consumed

directly by the building. The SSR instead measures the proportion of the building's total energy demand that is met directly by on-site PV generation.

4. Results and Discussions

Baseline simulations show significant variability in PV output and heating load. As expected, extreme cold days coincide with low PV generation and elevated heating demand. Under such conditions, the proposed control strategy becomes ineffective, as insufficient PV surplus prevents the setpoint management agent from intervening in the heating schedule. Similarly, on warmer days, high PV but low heating demand offers little opportunity for intervention, as there is limited HVAC load to shift or optimize. Figure. 2 initially illustrates the building's behavior on a midseason day, where midday PV generation surpasses the building's energy demand. This scenario presents optimal conditions for the setpoint management strategy to shift a portion of the heating load to coincide with peak solar availability.

Table 1 provides a comparative evaluation of the machine learning models used in this study for hour-ahead baseline load prediction of the building. The nonlinear nature of the building's energy demand is evident, as LR yields the poorest performance among the evaluated models. In contrast, the tree-based algorithms exhibit significantly better performance. Specifically, the Extra Trees Regressor shows the highest predictive accuracy, with an average error of less than 0.8 kW, effectively capturing the complex and nonlinear energy consumption patterns of the warehouse. Although RandomForest and ExtraTrees exhibit small differences in prediction accuracy, ExtraTrees is computationally more efficient and better suited for implementation in a warehouse environment using edge devices. Therefore, ETR is selected as the prediction model, consistently supplying load forecasts to the agent. Its ability to effectively capture demand fluctuations ensures reliable and accurate predictions for dynamic decision-making.

Table 1. Model performance comparison

Model	MAE [W]	R ²	RMSE	MAPE [%]
RandomForest	947.021	0.9509	2383.764	8.164
XGBoost	1024.773	0.9448	2526.417	10.076
ExtraTrees	784.891	0.9693	1884.722	7.284
KNeighbors	1264.368	0.9024	3359.793	12.396
LinearRegression	3032.363	0.8473	4203.025	38.859

Additionally, Figure 1 illustrates the differences in prediction performance among the ensemble tree-based models on a representative day.

Table 2. Monthly SCR and SSR improvement during the narrowed period

Month	SCR improvement (%)	SSR improvement (%)
January	8.967	5.441
February	9.328	8.275
November	8.648	7.690
December	8.740	5.517

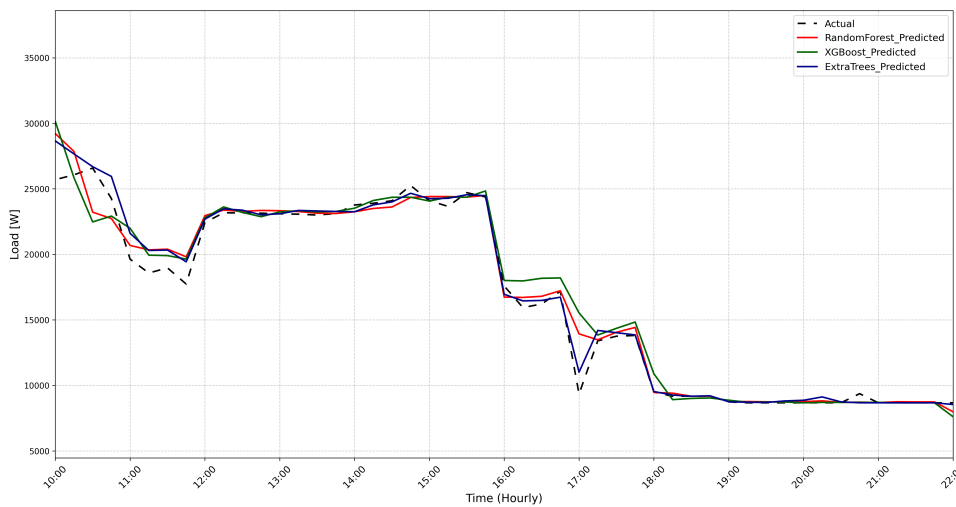


Figure 1. Comparison of Predicted vs Actual Load - March 14th

Lastly, the performance of the proposed HVAC Setpoint Management Strategy (HSMS) is evaluated comparing to the baseline scenario. Figure 2 illustrates how the HVAC setpoint management strategy effectively aligns energy demand with PV generation, shifting consumption from periods of low PV output to intervals with greater solar availability.

On certain days, the HSMS faces challenges in aligning HVAC interventions with PV generation. To identify the most effective intervention periods, a narrowed evaluation window was defined. Results suggest that excluding midseason months—October, parts of November, March, and April—improves overall performance. To evaluate the overall effectiveness of the strategy, improvements in SCR were calculated, showing an increase of 8.99% during the narrowed period compared to 7.476% over the entire heating season.

Lastly, a monthly breakdown of SCR and SSR is presented in Table 2. The results demonstrate that the proposed methodology effectively enhances both metrics, indicating improved alignment between building load and PV generation, as well as increased energy independence. These improvements indicate that the control strategy can partially address the variability in PV output, particularly during ramp-up and ramp-down periods, contributing to an enhancement in the efficiency and resilience of energy use.

5. Conclusions

This work aimed to enhance the self-consumption of on-site PV generation in conditioned warehouses through a heating setpoint modification strategy. EnergyPlus simulations were first

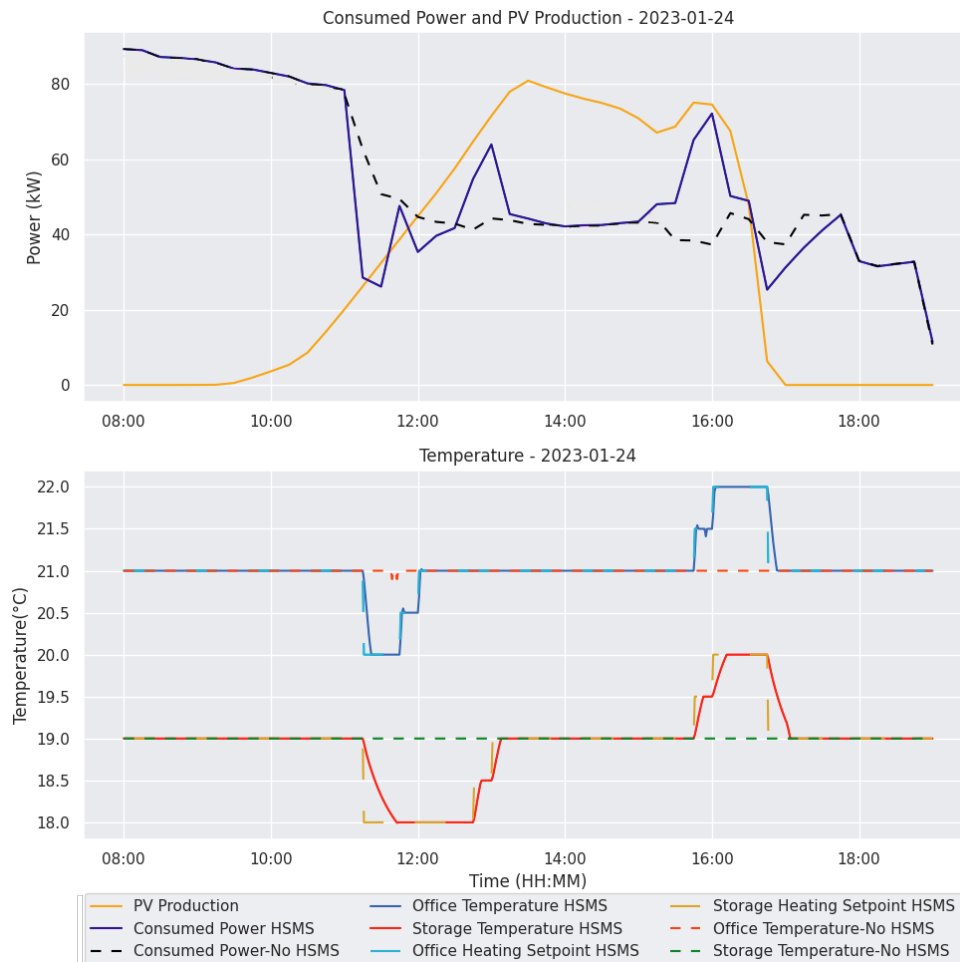


Figure 2. Implementation of the HVAC setpoint strategy on a moderately cold day in late January

conducted for a case study warehouse located in Bologna, Italy, equipped with rooftop PV panels, to capture its baseline thermal and energy performance. Significant variations in PV output and heating demand were observed, highlighting the effectiveness of the proposed strategy during midseason conditions. Various ML models were developed to predict the building’s hour-ahead baseline load, with ETR achieving the best performance, yielding an average error of less than 1 kW. Next, an agent was developed to operate in real time, receiving current and forecasted values of building load and PV generation. Based on these inputs, the agent simulated setpoint interventions (relaxation and preheating) via the Python API. The strategy led to monthly average improvements of up to 9.3% in SCR and 8.2% in SSR, confirming its effectiveness.

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