SvedbergOpen
DISSEMINATION OF KNOWLEDGE

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

AI-Driven Predictive Energy Management for Sustainable Smart Buildings: A Machine Learning Framework for Optimizing Building Performance in Hot-Arid Climates

Paulson Geo Philip

Master of Business Administration (MBA) in Project Management, Jaipur National University, India. Email: paulsongeophilip@gmail.com, ORCID ID: 0009-0008-1676-0190

Abstract

Buildings in hot-arid regions have one of the highest demands for cooling due to high temperatures, solar gains, large temperature variations, and prolonged air-conditioning operating hours. Most of the time, conventional building management systems are not able to proactively manage the indoor built environment due to the inability to predict the peak load cooling demands in advance. An AI-based predictive energy management system for smart buildings in hot-arid regions is proposed and evaluated in this research. An 8,400 m^2 office building was taken as an example for smart building energy performance assessment. The study prepared a two-year hourly physics-informed operational data set for model training and testing, which included outdoor air temperature, relative humidity, solar radiation, building occupancy, past electricity consumption data, indoor temperature, and HVAC electricity consumption. Five machine learning algorithms were trained and evaluated to predict the hourly electricity consumption for one-hour-ahead forecasting. Extra Trees regressor showed the best performance with R^2, RMSE, MAE, and MAPE equal to 0.975, 14.11, 10.85, and 7.23. A forecast-driven supervisory energy management system for smart buildings was designed to manage the building energy performance by considering occupancy-related HVAC operation scheduling, start-up, pre-cooling, re-set points, and demand response. Compared to conventional approaches, the proposed method decreased the whole-building electricity consumption by 14.26% (from 1.515 to 1.299 GWh) and reduced the HVAC electricity consumption by 21.09%. The peak demand was lowered by 19.59% for the same test year. The energy use intensity was reduced from 180.37 to 154.65 kWh/m^2 per year or 14.26% for the same building. Meanwhile, the occupant comfort was provided for 98.94% of occupied hours. The research shows that demand-side energy management in smart buildings can transform traditional building management from reactive to proactive mode. The proposed method can be applied in various aspects of sustainable construction, buildings commissioning, facilities management, project delivery, and digital handover in hot-arid regions with a fast-growing construction industry.

Keywords: artificial intelligence; machine learning; smart buildings; predictive energy management; sustainable construction; HVAC optimization; building performance; hot-arid climate; energy efficiency; construction management

Introduction

Buildings increasingly dominate global energy-efficiency initiatives as the operational needs of this sector comprise an appreciable percentage of total global consumption. According to the International Energy Agency, buildings account for almost 30% of overall energy consumption, with residences being the largest contributor. Increasing urbanization, a growing emphasis on indoor comfort, the rise of mechanically assisted cooling, and a rise in extreme temperatures due to climate change, will only exacerbate the burden of energy related to buildings [1].

The challenge is especially acute in hot-arid regions. Cities throughout Saudi Arabia, the Gulf region, North Africa and other desert locales are accustomed to long stretches of torrid temperatures punctuated by searing sunlight. Cooling is not an enhancement, it is a requirement for the efficient operation of buildings in the heat. Riyadh offers a suitable climate for studying these challenges. ANSI/ASHRAE Standard 169 identifies Riyadh King Khaled International Airport within Climate Zone 1B, representing a very hot and dry climate [2].

The energy-performance challenge in these climates also has implications for construction and the management of the built environment. Decisions about the building envelope, glazing, HVAC capacity and control, building management systems, commissioning procedures, sensors, and digital infrastructure are typically made during design and construction, but have ramifications beyond construction and into the building's operations.

Sustainable construction is therefore a transition away from thinking about energy efficiency as a design requirement towards managing the building as a process.

Artificial intelligence and machine learning may contribute positively to this transition, as recent studies have shown that nonlinear learning algorithms are able to predict building energy consumption based on climatic, geometrical, operational, and occupancy-related variables. Wefki et al. implemented artificial-intelligence techniques to building energy estimation in semi-arid and arid desert climates, and showed the influence of such variables as building geometry, solar heat gain and indoor temperature requirements [3]. Golafshani et al. demonstrated similarly the potential of ensemble machine-learning algorithms for predicting operational energy consumption in office buildings in different climate conditions [4].

However, mere prediction is not sufficient; the critical factor is the exploitation of these predictions. Machine-learning based forecasting can be employed to improve building performance by providing information about potential energy needs, and thus enabling control decisions to take place before peaks, such as thermal or electrical, have been reached. These control actions might include pre-cooling or dynamic set-point adjustment, optimal operation considering occupancy and adaptation, start-up and shut-down scheduling, demand shifting, and smart management of renewable energy or storage facilities.

The latest studies tend to focus on the connection between predictive analytics and sophisticated HVAC control. For example, Almazam et al. designed a novel building control system based on a radial basis function neural network and model predictive control to optimize the energy consumption of air conditioning in Najran, Saudi Arabia [7]. Sha et al. proposed an online-learning-based data-driven predictive-control scheme, which takes into account both HVAC consumption and indoor environment including thermal comfort and indoor air quality [6]. Moreover, recently, some researchers have introduced reinforcement-learning-based methods into sustainable building energy management [5] and proved that it is promising to schedule and optimize the operation process by combining prediction and decision-making.

Nevertheless, there are still some practical limitations. First, most of the articles focus on prediction accuracy rather than control algorithms that can be easily implemented in existing building-management systems. Second, the use of computationally expensive reinforcement learning or unnecessarily complex control schemes in many articles creates a barrier for commercialization in existing buildings. Finally, there are fewer studies that relate the operation of buildings with artificial intelligence to construction projects, commissioning, BIM, and lifecycle management.

The present study therefore explores a pragmatic middle ground: multiple high-accuracy machine learning algorithms are developed and evaluated, alongside a transparent forecast-informed supervisory control strategy that can modify HVAC operating schedules and setpoints using data typically available in a modern building-management system.

Research Aim

The main purpose of this research is to propose an artificial intelligence-based prediction platform and study its energy-saving potential in terms of electricity consumption and demand reduction in commercial smart buildings in hot-arid climates through optimal indoor thermal comfort control.

Research Objectives

- To develop a representative hourly operational dataset for a commercial smart building operating under very hot and dry climatic conditions.
- To compare multiple machine-learning algorithms for one-hour-ahead building electricity-demand prediction.
- To identify the operational and climatic parameters having the strongest influence on short-term building energy consumption.
- To develop a forecast-informed HVAC supervisory control strategy integrating occupancy scheduling, optimal start, adaptive temperature setpoints, pre-cooling, and peak-load management.
- To evaluate the implications of predictive building operation for sustainable construction, commissioning, facility management, and lifecycle building-performance management.

Research Hypotheses

H1: The nonlinear ensemble-based machine-learning models can provide much better prediction accuracy than the traditional linear regression approach for short-term building energy forecasting in hot-arid regions.

H2: Using machine-learning predictions with predictive supervisory HVAC control can reduce annual building electricity and cooling-energy use compared to using a fixed-schedule HVAC control
H3: The value of predictive control for saving energy is greatest when cooling loads and solar heat gains are largest, that is, on the hottest days of the year.

Research Contribution and Novelty

The major contribution of the present work relies on the developed Hot-Arid Predictive Energy Management framework which integrates built environment operation control and life cycle performance management through machine-learning-based energy prediction.

Unlike purely predictive energy models, HAPEM uses the forecast as an operational decision variable. The algorithm predicts future demand and chooses from four possible modes of operation of the HVAC system: normal occupied operation, unoccupied setback, predictive pre-cooling, and peak-load relief. These options provide a transparent control strategy that can be embedded in a standard building-management system; a separate self-learning controller is not required.

A second contribution is an explicit focus on hot-arid operating conditions, where outdoor temperature and solar radiation impose highly nonlinear cooling requirements that are more suited to machine-learning-based energy forecasts.

The third contribution is in connecting operational AI with construction and asset-management practice. We view the framework not as an HVAC control problem but rather as a lifecycle building-performance system where the effectiveness depends on sensors' specifications, building automation design, commissioning, information handover, data quality, and facilities-management capabilities realized during project delivery.

Materials and Methods

Research Design

The study utilized an experimental computational research design that consisted of four sequential stages, including the development of the hot-arid smart-building operational data set, preprocessing and feature engineering, machine-learning model training, testing, and selection, and the integration of the selected predictive model with the HAPEM supervisory energy-management strategy. Therefore, the research is an original simulation-based investigation rather than a review of previous studies.

Prototype Building

A medium-size five-story commercial office building was taken as the reference case. It was a contemporary reinforced-concrete office development typical of commercial buildings in many Gulf cities that are undergoing rapid urbanization.

Table 1. Prototype building and simulation characteristics

Parameter	Study Assumption
Building use	Commercial office
Gross floor area	8,400 m^2
Number of floors	5
Climatic context	Riyadh, Saudi Arabia
ASHRAE climate classification	Very hot–dry, Zone 1B
Typical occupied period	08:00–18:00, Sunday–Thursday equivalent weekday schedule
Primary controllable load	HVAC cooling
Building-management capability	Smart meters, temperature sensors, occupancy information and HVAC supervisory control
Data resolution	Hourly
Study duration	Two years
Total raw observations	17,520
Prediction horizon	One hour ahead
Baseline control	Fixed operating schedule and conventional thermostat
Proposed control	Forecast-informed HAPEM supervisory strategy

The climatic context is consistent with the very hot and dry classification assigned to Riyadh under ASHRAE Standard 169 [2].

Data Generation

Because of the lack of field measurements from a particular completed building for the present study, a physics-informed operational dataset was created for controlled experimentation. The data set is explicitly treated as building operational simulation data and not measurement utility or BMS data.

Hourly observations were generated for two consecutive operating years. Outdoor dry-bulb temperature was characterized by seasonal and diurnal components with stochastic variability. The climatic profile was constructed to mimic a hot-arid environment characterized by high summer temperatures, large day-night temperature differences, low-to-moderate relative humidity, and high solar irradiation during the day.

Cooling demand was generated as a non-linear function of the outdoor temperature above the cooling balance point, solar gains, occupancy-related internal gains, humidity, and short-term thermal inertia. This approach was used because non-linear interactions are widely known as an essential part of AI-based building-energy prediction, particularly in hot climates [3].

The resulting baseline annual electricity use during the test year was found to be approximately 1.515 GWh which translates to an Energy Use Intensity (EUI) of approximately 180.37 kWh/m^2/year. HVAC operation was found to constitute approximately 67.61% of a building's total simulated electricity use, confirming that cooling was the dominant controllable building load in the computational case.

The operational data set included:

- outdoor air temperature;
- relative humidity;
- global horizontal solar radiation;
- occupancy level;
- hour and day indicators;
- one-hour, two-hour, three-hour, and 24-hour lagged electricity demand;
- lagged outdoor temperature;
- HVAC electricity consumption; and
- indoor temperature.

Data Preparation and Feature Engineering

Missing values resulting from the lag generation were removed prior to model development. Calendar variables were generated by applying sine and cosine functions to retain their natural cyclical behavior. For instance, it is expected that hour 23:00 and hour 00:00 would be close to each other because calendar variables retain their natural cyclical behavior.

The predictor vector at time can be expressed as:

$$X_t = [T_{out,t}, RH_t, GHI_t, Occ_t, H_t, D_t, E_{t-1}, E_{t-2}, E_{t-3}, E_{t-24}, T_{out,t-1}, T_{out,t-3}]$$

where T_{out} = outdoor temperature; RH = relative humidity; GHI = global horizontal solar radiation; Occ = occupancy; H = cyclical hour variables; D = cyclical day variables; and E = total building electricity consumption.

The target variable was the electricity requirement one hour ahead:

$$\hat{E}_{t+1} = f(X_t)$$

The chronological nature of the data has been maintained by selecting the first operating year as a basis for building the model and the second year for testing against it. Such an approach reduced any possibility of future observations falling into the sample.

Machine-Learning Models

- Linear Regression (LR): conventional baseline model for comparison.
- Support Vector Regression (SVR): kernel-based learning method, effective for nonlinear energy relationship modeling, especially with moderate predictor count.
- Random Forest Regression (RF): ensemble approach demonstrating resilience to nonlinear predictors and flexible functional forms.
- Gradient Boosting Regression (GBR): ensemble technique using decision trees to sequentially correct prediction errors, with demonstrated accuracy in building-energy prediction.
- Extra Trees Regression (ETR): ensemble of randomized decision trees with enhanced variance reduction through additional randomness, maintaining nonlinear relationship modeling capabilities.

Ensemble machine-learning methods have demonstrated strong performance for operational energy prediction in previous building research [4].

Model Evaluation

The model's performance was evaluated using four widely used indicators, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination R^2.

$$MAE = (1/n)\ \Sigma\ |y_i - \hat{y}_i|$$
$$RMSE = \sqrt{[(1/n)\ \Sigma\ (y_i - \hat{y}_i)^2]}$$
$$MAPE = (100/n)\ \Sigma\ |(y_i - \hat{y}_i)\ /\ y_i|$$
$$R^2 = 1 - [\Sigma(y_i - \hat{y}_i)^2\ /\ \Sigma(y_i - \bar{y})^2]$$

The preferred forecasting model was identified by simultaneously considering high R^2 and low MAE, RMSE, and MAPE values.

Hot-Arid Predictive Energy Management Framework

Framework Architecture

The proposed HAPEM architecture comprises four interconnected layers. The first layer is the data acquisition layer that gathers the weather, indoor environment, occupancy, and electricity information. The second layer is the prediction layer that utilizes the current and past data to predict the building's hourly electricity consumption using the trained machine-learning algorithm. The third layer is the decision layer that evaluates the predicted electricity demand against historical demand percentiles, occupancies, and time of day. The fourth layer is the building-control layer that makes the decisions to update the heating, ventilating, and air conditioning (HVAC) schedules and temperatures via the supervisory building-management system.

The control loop is thus: Building and weather data → ML load forecast → operating-state classification → HVAC control action → updated performance of the building → new data.

Supervisory Operating Modes

- Mode 1: Occupancy with Moderate Demand for Cooling: The set point was close to 24 C for the same period instead of a lower baseline during the heating ventilation and air conditioning (HVAC) system operation period with moderate predicted cooling demand.
- Mode 2: Unoccupied Setback. During unoccupied periods, unnecessary cooling was cut back by allowing the indoor temperature set point to rise while maintaining a minimum level of conditioning during very hot outdoor weather.
- Mode 3: Predictive pre-cooling. By anticipating peaks in afternoon demand, limited pre-cooling was performed before the period of high demand. Cooling was shifted to an earlier hour by taking advantage of the building's thermal mass as a means of temporarily storing coolth.
- Mode 4: Peak-Load Relief. During periods of exceptionally high predicted cooling demand, the occupied setpoint was temporarily increased within the acceptable comfort band in order to reduce compressor loading and avoid simultaneous maximum cooling demand.

The method differs from standard thermostat-based approaches in that it takes into account predicted future states as well as present indoor temperature when determining the control actions of the system.

Results

Machine-Learning Prediction Performance

The testing results are presented in Table 2.

Table 2. One-hour-ahead electricity prediction performance

Model	MAE (kWh)	RMSE (kWh)	MAPE (%)	R^2
Linear Regression	16.84	21.84	11.84	0.941
Support Vector Regression	11.15	14.51	7.39	0.974
Random Forest	11.38	14.93	7.57	0.972
Gradient Boosting	11.61	15.32	7.73	0.971
Extra Trees Regression	10.85	14.11	7.23	0.975

The Extra Trees model provided the best general forecasting results. The R2 of the model reaches 0.975 which implies that 97.5% of variance in one-hour ahead electricity demand is explained by the model. The prediction errors were relatively low even for cases with a significant difference between winter and extreme summer temperatures.

The comparison of performance of Linear Regression and the ensemble models supports Hypothesis H1. While Linear Regression provided a respectable R^2 of 0.941, its MAPE was as high as 11.84% as compared to 7.23% of Extra Trees. It can be concluded that the interplay between external temperature, solar exposure, occupancy, thermal inertia, and historical demand cannot be captured by a linear approximation adequately.

This result is in line with the recent building-energy research which has shown that ensemble and other nonlinear AI models perform best when building energy use is governed by complex climate- and operational-related interactions [4].

Influence of Predictive Variables
Feature-importance analysis of the selected Extra Trees model is presented in Table 3.

Table 3. Principal predictors of short-term electricity consumption

Variable	Relative Importance (%)
Electricity demand 24 hours previously	33.04
Outdoor temperature	16.95
Electricity demand 1 hour previously	16.80
Global horizontal solar radiation	8.46
Hour-of-day cosine component	6.19
Outdoor temperature 1 hour previously	5.70
Occupancy	4.21
Electricity demand 2 hours previously	3.47
Hour-of-day sine component	1.87
Outdoor temperature 3 hours previously	1.03

The most significant predictor was the electricity load at the same time of the previous day. It suggests that commercial buildings have a large component of operating equipment with similar daily cyclical patterns.
The most significant direct weather factor was the outdoor temperature. Together with the lagged outdoor temperature and solar radiation, weather factors dominantly contributed to the prediction model.
Solar radiation was found to be an important climate predictor with a significant influence on the one-hour-ahead prediction. It could be explained by increased façade and roof thermal gains in hot-arid climates that raise the indoor temperature regardless of the outside air temperature. Consequently, the study highlighted the importance of smart-building energy management systems that take into account weather forecasts.
While being less influential compared to temperature and previous day electricity load, occupancy had an essential impact on the model. It specifies the contribution of internally induced heating and gives the control system an opportunity to perform when unoccupied.

Baseline Building Energy Performance
The traditional scenario consumed a huge amount of energy, which totaled 1515090 kWh per year and equal to 180.37 kWh/m^2 per year.
HVACs consumed approximately 1024393 kWh per year, accounting for 67.61% of the total electricity consumption of the building, indicating that energy-saving potential is significant in the areas of cooling-control. Especially in such a scorching and dry climate, it is meaningful to do this.
The monthly consumption increased dramatically from spring and peaked at June-August when the simulated outside temperature and solar radiation were at the highest.

Energy Performance of the Proposed HAPEM Framework
After integration of the machine-learning forecast with supervisory HVAC control, annual building electricity consumption decreased to approximately 1,299,095 kWh.

Table 4. Annual performance comparison

Performance Indicator	Baseline Operation	HAPEM Operation	Improvement
Annual electricity consumption	1,515,090 kWh	1,299,095 kWh	14.26% reduction
Annual EUI	180.37 kWh/m^2	154.65 kWh/m^2	25.71 kWh/m^2 reduction
HVAC electricity consumption	1,024,393 kWh	808,398 kWh	21.09% reduction
Annual electricity avoided	—	215,995 kWh	—
Peak-period maximum demand	449.52 kWh/h	361.46 kWh/h	19.59% reduction

Occupied-hour comfort compliance	100% baseline simulation	98.94%	Maintained at high level

The results presented above confirm Hypothesis H2 since the whole building's electricity consumption was decreased by approximately 14.26%, and the HVAC electricity consumption was reduced by around 21.09%. The difference between these figures can be explained by the fact that lighting, equipment, lifts, ICT infrastructure, and other electrical appliances were not formally controlled by the proposed framework designed for the HVAC system.

The reduction in consumption during peak demand periods was especially noticeable since the highest electricity demand was registered during the afternoon. The peak demand was decreased by around 19.59%. Basically, predictive pre-cooling shifted a small amount of the electricity load from the afternoon peak to the morning period, while peak-load relief decreased the simultaneous compressors' electricity demand during the hottest hours of the day.

Seasonal Energy-Saving Pattern

Table 5. Monthly whole-building energy savings

Month	Baseline Energy (kWh)	HAPEM Energy (kWh)	Reduction (%)
January	79,277	72,387	8.7
February	74,775	67,724	9.4
March	95,148	83,995	11.7
April	118,520	101,704	14.2
May	155,276	130,500	16.0
June	177,637	148,279	16.5
July	194,819	163,120	16.3
August	181,325	151,110	16.7
September	148,386	124,775	15.9
October	120,082	103,383	13.9
November	90,393	79,845	11.7
December	79,455	72,274	9.0

It can be seen that savings grew as the intensity of the cooling season increased. In winter, savings were consistently below 10%, whereas, for several months, they turned out to be over 16% in summer. The biggest saving was achieved in August and amounted to roughly 16.7%. Thus, Hypothesis H3 was supported, and it was found that the value of predictive energy management increases in case of higher climatic stress.

Thermal Comfort

Energy reduction must not be confused with good performance of the building if it causes unacceptable indoor environment conditions. Controlled indoor-temperature profile was therefore assessed during occupied hours using a practical temperature acceptance band.

Approximately 98.94% of occupied operating hours were within selected acceptable temperature range. Temporary deviations occurred mainly during a limited number of extreme external-temperature events.

This result demonstrates that a significant amount of the decreased energy was achieved by improved timing and avoidance of unnecessary cooling, rather than by significant deterioration of indoor conditions.

Discussion

Predictive Versus Reactive Building Operation

Traditional HVAC control is essentially reactionary. A thermostat senses that the temperature has moved away from a setpoint and instructs the system to either cool or heat the space. The example in this paper provides anticipatory control: if the electricity demand is likely to be high in the next hour, the system will change its operation to reduce demand.

This is particularly valuable in buildings with large thermal masses such as concrete slab, walls, partitions and internal surfaces. These can be used to store cold energy. Pre-cooling can exploit this to move demand from a period of peak demand to an earlier period when demand is lower. There is no need to add extra storage to exploit this effect: the building itself provides the necessary thermal capacity.

Importance of Hot-Arid Climate Conditions

The results illustrate why hot-arid climates necessitate specialized building-control strategies. Cooling load is jointly influenced by ambient temperature, accumulated thermal gains, solar, occupancy, and prior operating conditions.

Recent AI work in the context of hot and semi-arid building-environments has also demonstrated the importance of summer indoor temperature requirements and solar related attributes to predict energy demand [3]. Research focusing on the specific topic of hot-arid passive design have also demonstrated the ability of nonlinear machine-learning models to uncover key interactions between geometry, envelope properties, glazing and cooling demand [8]. The present work extrapolates this reasoning from design prediction towards operational control.

Why Extra Trees Performed Well

The Extra Trees model was superior to the linear baseline and slightly better than the other nonlinear algorithms. The process of building energy-consumption for the facility was characterized by repetitive and irregular behavior. The daily occupancy schedule produced characteristic patterns in consumption while the excursions of outdoor temperature, solar, and internal loads introduced variations. Tree ensembles are best at such tasks which require partitioning of the input space into several operating regimes instead of modeling the entire relationship with a set of mathematical expressions.

The randomized nature of Extra Trees allows reducing the variance of the algorithm and avoids a single predictor dominating the process. A further notable finding is the relatively small difference in predictive performance among Extra Trees, SVR, Random Forest, and Gradient Boosting. When selecting the most appropriate algorithm for implementing a smart-building project, one should consider that the best choice may not be the most sophisticated one. Model selection should balance predictive accuracy with other practical factors, including cost, explainability, retraining requirements, computational resources, cybersecurity, and personnel expertise

Relationship with Existing Smart-Building Research

The approximate 14% whole-building saving achieved in the present computational experiment falls within the general range reported in recent studies, which combine AI forecasting plus intelligent HVAC control.

For instance, Almazam et al. reported an approximate 15% energy reduction using an RBFNN-MPC framework for Saudi Arabian building applications [7]. Sha et al. showed that energy reductions can be achieved through online-learning-enhanced predictive HVAC control while simultaneously considering both thermal comfort and air quality [6]. Reinforcement-learning research also demonstrated the potential for AI to coordinate building energy decisions with storage and renewable-energy utilization [5].

The main difference of the present framework is its operational simplicity. HAPEM does not require continuous autonomous exploration by a reinforcement-learning agent. Rather, machine learning makes forecasts, while a transparent supervisory policy determines building control actions based on these predictions. Such transparency may facilitate its uptake by consultants, commissioning agents, building owners, and/or facilities managers.

Implications for Sustainable Construction and Construction Project Management

Energy Performance Should Be Designed as an Operational System

Sustainable construction projects often emphasize design-stage factors, e.g., insulation, glazing, equipment, renewable energy, and certification. Although these are all relevant, efficient elements do not guarantee efficient operations.

The results imply that future initiatives need to develop an operating energy-management strategy, specifying therefore sensor sites, energy meters, occupancy detection, building management system (BMS) interaction, data-storage design, and control permissions during design rather than after project completion.

Commissioning Requirements

Predictive energy management increases the stakes for commissioning. An AI model trained by incorrectly calibrated sensors or badly commissioned HVAC equipment would predict non-optimal behavior accurately, but it will not be optimal. Thus, construction project managers should tie digital-energy systems to commissioning processes, such as sensors calibration, functional performance testing, HVAC balancing, BMS point verification, equipment-control testing, energy-meter validation, seasonal commissioning, etc. The completion of construction should be when performance verification for energy management truly begins.

Digital Handover

The typical handover of a project includes drawings, manuals, warranties, and inventory lists. Sustainable buildings benefit from additional digital information. Building handover documentation should include sensor metadata, BMS point lists, equipment control sequences, energy-meter hierarchies, naming conventions, data-retention policies, commissioning records, and baseline performance information. This type of information enables the development and continuous retraining of predictive-energy models.

Performance-Based Contracts

Predictive analytics can also be used for performance based procurement and for energy-performance contracts. By focusing on outcomes, not just equipment efficiency, owners can specify targets, including annual EUI, HVAC energy intensity, peak power, percent time within temperature range, and energy-performance degradation. Monitoring that uses machine learning can recognize when these targets are not being met and can provide a defensible audit trail for verifying the cause.

Lifecycle Asset Management

The benefits of the proposed framework go well beyond energy saving. Persistent deviations between predicted and actual energy performance may indicate equipment degradation, control malfunctions, fouled filters, faulty dampers, sensor drift, or changes in occupancy patterns. The forecasting model can thus be used as a part of a wider predictive-maintenance and an asset-management platform. It enhances the linkages among the sustainable construction, facilities management, energy management, and digital asset management realms.

Practical Implementation Framework

For practical implementation in the building, the proposed system can be organized into five interconnected components Firstly, smart meters and BMS sensors can collect the information on the outdoor temperature, solar radiation, presence of people, as well as the data on indoor environment, HVAC equipment, and consumption of electricity. Secondly, the forecasting model, which was previously trained, will provide an hourly or 15-minute ahead forecast. Thirdly, the supervisory decision-making system will analyze the information and decide whether the building needs to be operated under normal conditions, a setback or pre-cooling strategy should be initiated, or if it is appropriate to provide peak-load relief.

Fourthly, the model's commands will enter the building's supervisory control system, which will adjust HVAC setpoints and schedules. Lastly, the actual results of the performed calculations will be saved and utilized to update the prediction model.

The implementation of an AI should be staged, starting perhaps with a simple advisory function in which the model simply recommends suggested courses of action, but does not enact them. This allows operators to be comfortable with the system's predictions before any actual equipment control is delegated to it. This would reduce risk and increase acceptance.

Sensitivity and Sustainability Implications

A reduction of 215,995 kWh/year was achieved in the prototype building. For a ten-building portfolio of similar size and usage, the same percentage reduction would result in 2,160,000 kWh or 2.16 GWh of reduced electricity consumption per year.

For example, at an assumed electricity-related emission intensity of 0.55 kg CO_2-equivalent per kWh, the saving of a single building would amount to approx. 119 tonnes of CO_2-equivalent saved per year. This value serves merely as an example since actual benefits depend on a site's electricity generation mix and should therefore be determined on the basis of the respective local grid factor.

The more important finding is that operational optimisation can generate sustainability benefits without requiring major physical reconstruction. Hence, AI-enabled controls complement rather than replace passive design, efficient envelopes, high-performance glazing, efficient HVAC equipment, and responsible occupant behaviours.

Limitations

- First, it must be noted that the operating data set used in this study was not obtained from a monitored and occupied building. The data set is physics-informed and computationally generated. Although the comparison between the considered algorithms and strategies is insightful, such a model should be validated against actual building management system and smart-meter data before attempting to extrapolate the results to a portfolio of commercial buildings.

- Second, the prototype in this work is an office-building archetype, and different results are expected for hospitals, universities, hotels, shopping centers, residences, and mixed-use buildings, due to large differences in occupancy schedules and internal loads.

- Third, the analysis was performed using indoor temperature as the sole thermal-comfort metric. In practice, other variables such as relative humidity, indoor air quality, ventilation needs, occupancy feedback, and possibly predictions of PMV/PPD might be needed.

- Fourth, the work was focused on heating, ventilating, and air-conditioning systems. Future work should include other building loads such as lighting, photovoltaic power, battery storage, plug loads, transportation, thermal storage, and demand response.

- Fifth, the equipment failures and degradations were not modeled. They can adversely impact the accuracy of the forecasts in real buildings, which would decrease the value of the approaches proposed in this work. These points are not intended to eliminate the contributions of this work but to provide the context and directions for future research.

Future Research

The next step of this research should be to test the model on high-resolution BMS data from commercial buildings in Saudi Arabia or another hot-arid region. A practical experiment would require comparing the energy performance of traditional and AI-modified systems during the same time frame but considering outside air temperature and occupancy rates.

Other areas of future research include 15-min forecasts, multi-zone physics based models, digital twins, XAI, probabilistic load forecasts, photovoltaics, batteries, dynamic electricity pricing, and reinforcement learning.

Another promising avenue of research concerns operational-energy information integration with Building Information Modelling (BIM). Whereas the BIM contains geometric, envelope, equipment, and asset information related to construction, IoT operational analytics can provide real-time performance data. By binding the two informational constructs in a lifecycle digital-twin framework it is possible to perform simulations and analyses across the design-construction-commissioning stages as well as the operations and maintenance.

Research questions for further analysis include the following: organizational issues related to adoption (i.e. procurement strategy, allocation of data ownership in contracts, cybersecurity, facility-management staffing, lifecycle cost, and return on investment).

Conclusion

This study presents an innovative AI-driven predictive energy-management framework for smart commercial buildings located in hot-arid climates. Five machine-learning approaches were applied for the purposes of one-hour-ahead building electricity forecasting, with Extra Trees Regression demonstrating the highest performance in terms of the R^2 (0.975), RMSE (14.11 kWh), MAE (10.85 kWh), and MAPE (7.23%) metrics.

The results highlighted the historical daily demand, outdoor temperature, electricity consumption history, and solar irradiance as key predictors of a building's near-term electricity consumption. When applied together with the occupancy-based start, adaptive setpoints, and predictive pre-cooling plus peak-cutting demand response, the selected machine-learning approach reduced building electricity consumption by around 14.26%, with a 21.09% decrease in the HVAC consumption and an almost 19.59% reduction in the critical peak power. It is also worth noting that the annual EUI was improved from around 180.37 to 154.65 kWh/m^2 with a 98.94% fraction of the occupied hours maintained at a desirable indoor-temperature state.

The results of the research provide an additional illustration of the value of artificial intelligence for energy-related purposes beyond improved forecasting capabilities. More specifically, the integration of predictive analytics into practical building-control-oriented strategies can enable the transition from the conventional thermostat-centric approach to truly predictive building-performance management.

The implications of the study for construction and built-environment professionals provide valuable insights for considering smart-building performance during project planning, building management system design, sensor specification and installation, commissioning, digital handover, facilities-management preparation, and long-term performance verification. Therefore, predictive energy management should be regarded as an integral element of sustainable construction and an essential aspect of building asset management in hot-arid climates.

References

1. International Energy Agency. (2025). Energy Efficiency 2025: Buildings. IEA, Paris. https://www.iea.org/reports/energy-efficiency-2025/buildings
2. ASHRAE. (2020). ANSI/ASHRAE Standard 169-2020: Climatic Data for Building Design Standards, Addendum a. American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta.
3. Wefki, H., Khallaf, R., & Ebid, A. M. (2024). Estimating the energy consumption for residential buildings in semiarid and arid desert climate using artificial intelligence. Scientific Reports, 14, 13648. https://doi.org/10.1038/s41598-024-63843-w
4. Golafshani, E., Chiniforush, A. A., Zandifaez, P., & Ngo, T. (2024). An artificial intelligence framework for predicting operational energy consumption in office buildings. Energy and Buildings, 317, 114409. https://doi.org/10.1016/j.enbuild.2024.114409
5. Li, D., Zhao, Y., & Xi, H. (2024). A novel two-stage reinforcement learning framework for sustainable building energy management systems. Journal of Building Engineering, 98, 111475. https://doi.org/10.1016/j.jobe.2024.111475
6. Sha, X., Ma, Z., Sethuvenkatraman, S., & Li, W. (2025). Online learning-enhanced data-driven model predictive control for optimizing HVAC energy consumption, indoor air quality and thermal comfort. Applied Energy, 383, 125341. https://doi.org/10.1016/j.apenergy.2025.125341
7. Almazam, K., Humaidan, O., Shannan, N. M., Bashir, F. M., Gammoudi, T., & Dodo, Y. A. (2025). Innovative energy efficiency in HVAC systems with an integrated machine learning and model predictive control technique: A prospective toward sustainable buildings. Sustainability, 17(7), 2916. https://doi.org/10.3390/su17072916
8. Abdeyazdan, H., Safaeianpour, A., & Amini, M. A. (2025). Explainable machine learning for passive design: Early-stage building energy reduction in hot-arid climates. Sustainable Energy Technologies and Assessments, 83, 104589. https://doi.org/10.1016/j.seta.2025.104589
9. Li, Y., Arellano-Espitia, F., Aler, R., Igualada, L., & Corchero, C. (2025). Data-driven methods and their applications to building HVAC energy consumption prediction: A review. Journal of Building Engineering, 116, 114612. https://doi.org/10.1016/j.jobe.2025.114612
10. U.S. Department of Energy. EnergyPlus Engineering Reference: Climate, Sky and Solar/Shading Calculations. Building Technologies Office / National Renewable Energy Laboratory.