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PAPER

Design of a Hybrid AI-Driven Engineering Model for Energy-Efficient and Sustainable Educational Systems

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ABSTRACT

A substantial percentage of the world's energy consumption (almost 40%) and carbon dioxide (CO2) emissions (around 37%) come from the construction industry, especially schools. This work presents a new hybrid artificial intelligence (AI) engineering model that aims to maximize energy performance on campuses in a holistic way. Modules for data-driven forecasting, metaheuristic optimization, and real-time adaptive control are all part of the concept. A thorough energy simulation of a university campus building is used in conjunction with the AI model to assess its performance through a co-simulation framework. Findings show that yearly peak electricity demand may be reduced by 18.7% and total site energy consumption by 22.4% when compared to a baseline building management system, all while keeping indoor thermal comfort levels high. According to the study, one effective way to make school buildings smart, eco-friendly, and energy efficient is to use a hybrid AI-driven method.

KEYWORDS

hybrid AI, energy efficiency, sustainable educational buildings, building energy simulation, predictive control, optimization

1 INTRODUCTION

Campus buildings in particular use a lot of energy for heating, cooling, lighting, and ventilation, making educational institutions big users of this resource [1, 2]. Both operational expenses and carbon footprints are greatly affected by the operational energy use of these facilities. Efficient operation of these buildings is a pedagogical necessity because they simultaneously function as living labs for sustainability education [3, 4]. Building energy management stands to benefit greatly from the revolutionary power of artificial intelligence (AI). Demand forecasting, HVAC schedule optimization, renewable energy integration, and predictive maintenance are just a few of the many potential uses [5, 6]. Nevertheless, the majority of current solutions utilize individual models, such as neural networks or regression trees, which

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are great at what they do but don't have the combined intelligence necessary for managing a campus in real-time and holistically [7–9].

This study fills that need by developing, testing, and assessing a HAIEM, or Hybrid AI-Driven Engineering Model. An optimization module determines ideal setpoints, a forecasting module predicts energy needs, and an adaptive control module allows for real-time actuation; these three AI subsystems work together to form the model's core innovation [10, 11]. The major goal is to show that this hybrid system is far better than traditional control systems in terms of energy efficiency, carbon emissions, and occupant comfort in educational buildings through extensive simulations [12].

2 LITERATURE REVIEW

Artificial intelligence has recently shown promise in the field of building energy management. In their study, Tariq et al. examined various AI models for predicting school energy usage. The models included decision trees, gradient boosting, and long short-term memory (LSTM) networks [13]. The researchers found that the most influential variables were building size and AC capacity. A combination of statistical and machine learning-based hybrid models has been demonstrated to be the most accurate for time-series forecasting. One example is a model that successfully predicted a building's energy use for the next day by combining Seasonal ARIMA (SARIMA), an optimization approach inspired by Firefly, and Support Vector Regression (SAMFOR).

The use of AI is expanding beyond prediction to include operational control. Building automation systems (BAS) powered by AI can cut HVAC and lighting energy consumption by as much as 20% when they adapt to occupancy and weather data. The utilization of AI platforms allows for the identification of high-impact retrofit opportunities across campus buildings and portfolio-wide decarbonization planning. Table 1 provides a comparative assessment of recent work on AI-driven building energy management.

Adaptive frameworks that can handle the ever-changing, multi-zone conditions found on school campuses still lack the capability to integrate predictive models with prescriptive optimization and real-time control. This paper seeks to address that gap by developing a unifying approach for hybrid AI engineering.

Table 1. Comparative summary of recent literature on AI-driven building energy management

Author(s)	Year	Method	Key Findings	Limitations
Tariq et al. [13]	2024	Comparative evaluation of AI models (Decision Tree, KNN, Gradient Boosting, LSTM) for school energy prediction.	School size and AC capacity are the most influential variables on energy consumption. Gradient Boosting and LSTM showed the best predictive performance.	Focuses only on prediction; does not integrate control or optimization. Limited to school buildings.
Ali [14]	2024	Review of AI-driven Building Energy Management Systems (BEMS) across building types.	Offices have the highest energy-saving potential (up to 37%) with AI-based HVAC control; educational buildings can achieve up to 21% savings.	Review paper, not a deployed model. Does not propose a unified hybrid framework.
Bibri [15]	2025	Systematic review of AI and AI-powered digital twins for smart, green, and zero-energy buildings.	AI enables dynamic energy optimization, occupant-centered control, renewable integration, and predictive management. Digital twins allow real-time monitoring and adaptive operation.	Conceptual framework; lacks implementation details and simulation validation.
Ashtar et al. [16]	2025	Hybrid SARIMAX-LSTM model for electricity demand forecasting.	The hybrid model combines linear (SARIMAX) and non-linear (LSTM) components to improve short-term forecast accuracy, especially when incorporating exogenous weather and calendar features.	Applied to national-level data, not building-scale; no integration with control systems.
Ramos Ruiz et al. [17]	2019	MPC optimization using a detailed building energy model and a Genetic Algorithm (GA).	The GA-based MPC can significantly reduce HVAC energy use while maintaining comfort, though computational time is a challenge.	The study uses a white-box model that is computationally heavy and not designed for real-time control in a hybrid AI setting.

AI is quickly becoming the norm for building energy prediction and control, according to the evaluated literature. However, there is a disconnect between real-time control systems that are integrated and isolated prediction models. Research is lacking that is specific to the ever-changing, multi-zone setting of school campuses, as most studies only look at one AI method (such as optimization or forecasting). Adaptive fuzzy controllers, forecasting modules, and metaheuristic optimization engines are all integrated into one closed-loop framework in the proposed Hybrid AI-Driven Engineering Model (HAIEM), which fills this need.

3 METHODOLOGY: HYBRID AI-DRIVEN ENGINEERING MODEL

The HAIEM combines three distinct AI subsystems into a unified design to accomplish comprehensive energy management. Not only can the system anticipate energy needs in the future, but it can also react to uncertainties in real time and prescribe appropriate control actions thanks to its design. The complete workflow, as shown in Figure 1, runs on a 30-minute cycle, allowing for proactive building operation through a continuous feedback loop.

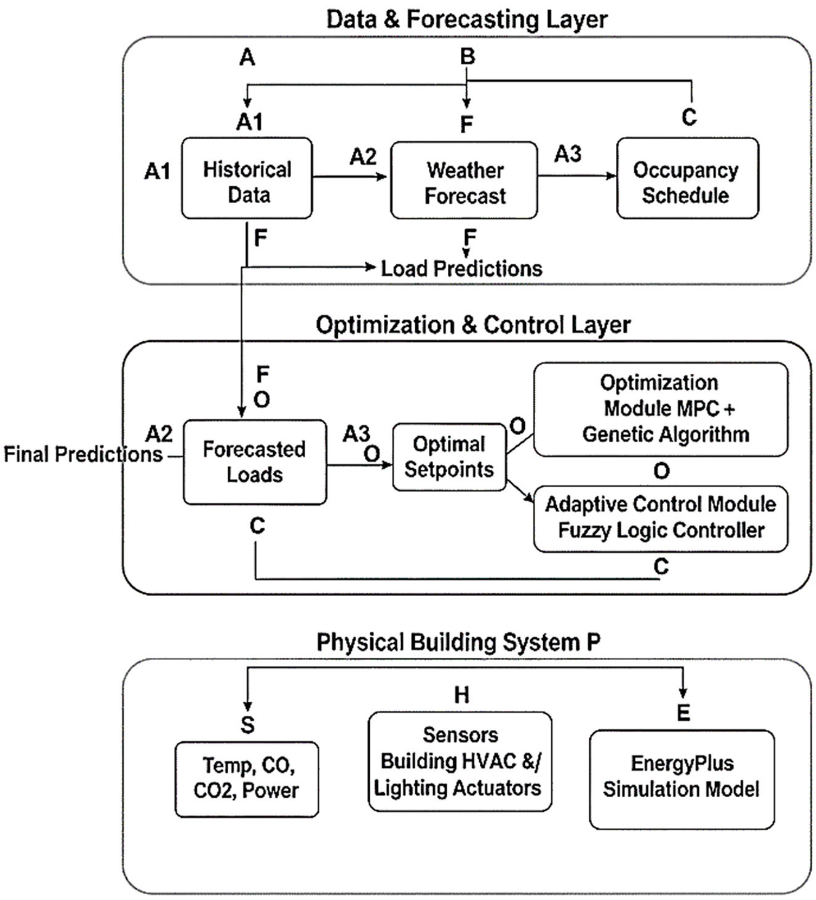

Fig. 1. High-level architecture of the HAIEM

Figure 1 shows the data flow from sensor inputs and forecasts, through the optimization core, to final actuator control via a fuzzy logic layer in the system.

3.1 Forecasting module

Using a hybrid SARIMA LSTM model, this module produces load estimates for the short term (24 hours) [16]. Historical energy data is analyzed by the SARIMA component for linear trends and seasonality, while non-linear relationships with exogenous variables (such as weather forecasts and occupancy schedules) are modeled by the LSTM network. Figure 2 shows the process that is used to anticipate the overall building and zone-specific thermal/electrical loads at 30-minute intervals.

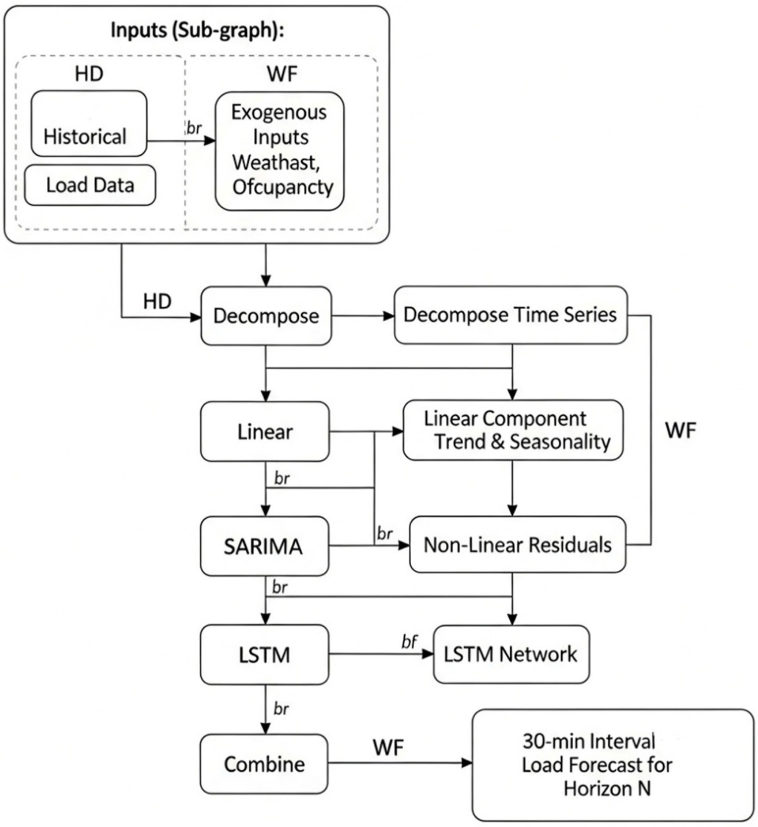

Fig. 2. Flowchart of the hybrid SARIMA LSTM forecasting process

Historical data is decomposed, with SARIMA handling linear residuals and LSTM processing exogenous inputs for a combined and accurate forecast.

3.2 Optimization module

This module does a Model Predictive Control (MPC) issue every 30 minutes using the predicted loads to find the best HVAC and lighting setpoints [18, 19]. The goal, as stated below, is to minimize energy costs while meeting comfort limits:

$$\min_{u_t} \sum_{k=0}^{N-1} * \left(\alpha \cdot P_{grid}(t+k) + \beta \cdot |PMV(t+k)| + \gamma \cdot P_{peak}(t+k) \right)$$

Subject to:

$$T_{min} \leq T_{zone}\,(t+k) \leq T_{max}$$

$$P_{grid}(t+k) + \eta \cdot P_{solar}(t+k) \geq P_{load}(t+k)$$

$$u_{min} \leq u_t(t+k) \leq u_{max}$$

Where u_t are the control actions (setpoints), P_{grid} is the grid power, PMV is the Predicted Mean Vote, P_{peak} is a penalty for peak demand, T_{zone} is zone temperature, P_{solar} is on-site solar generation, P_{load} is the forecasted load, and α, β, γ are weighting coefficients. A GA is employed to solve this non-linear, constrained optimization problem efficiently [17]. The optimization workflow is shown in Figure 3.

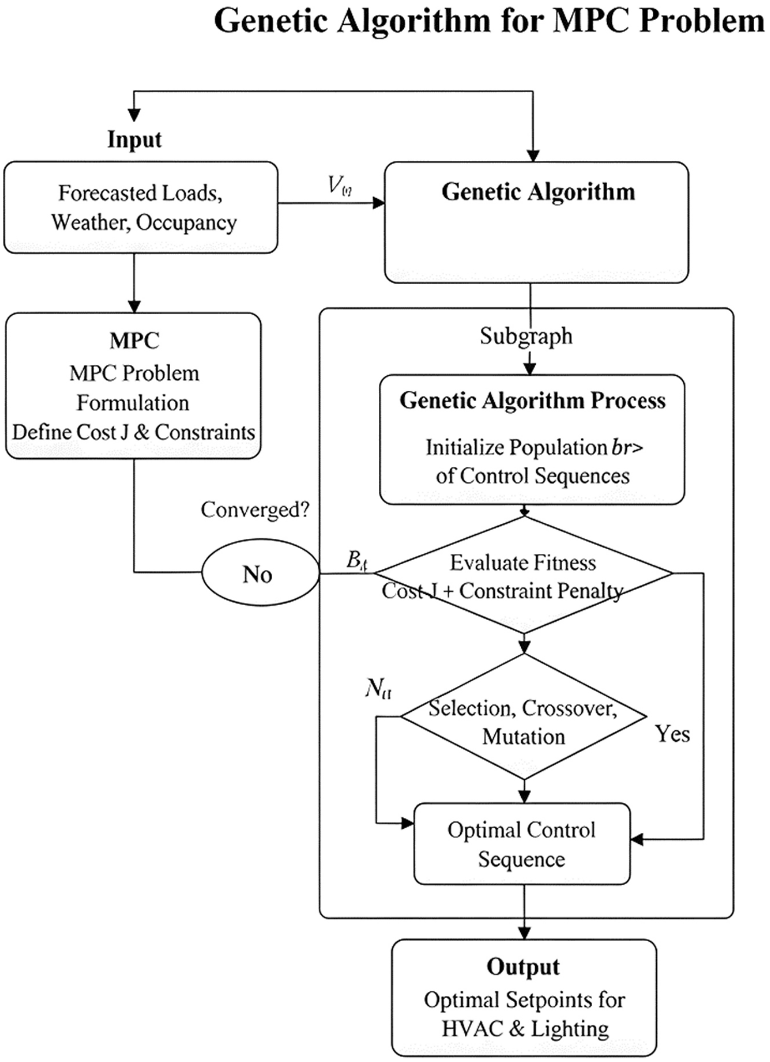

Fig. 3. Block diagram of the MPC-GA optimization process

The GA iteratively generates and evaluates populations of candidate control sequences against the combined cost function and constraints to find the optimal set of points for the prediction horizon.

3.3 Adaptive control module

The optimal setpoints are transformed into final control signals by this module's use of a Fuzzy Logic Controller (FLC). The FLC takes care of random variables and one-off occurrences (such as unexpected changes in occupancy) that the optimization doesn't account for [20]. It fine-tunes actuator commands (thermostat setpoints, damper positions, and lights dimming) in real-time using rules based on language variables (e.g., "temperature error" and "occupancy level") [21, 22]. Figure 4 shows the structure of the FLC.

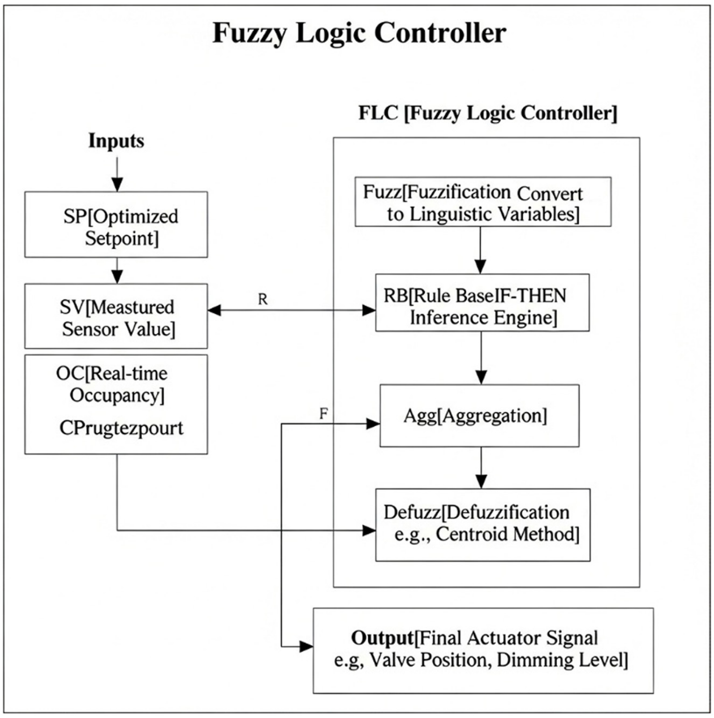

Fig. 4. Schematic of the Fuzzy Logic Controller (FLC)

The inputs (sensor errors, occupancy) are fuzzified, processed through a rule base, and defuzzified to produce robust final control signals.

3.4 Model integration and workflow

As illustrated in Figure 5, the three modules run in a closed-loop process that is synchronized every half an hour. Proactive and adaptive energy management is made possible by this integrated process, which guarantees that the system is constantly acting on the latest projections and sensor data.

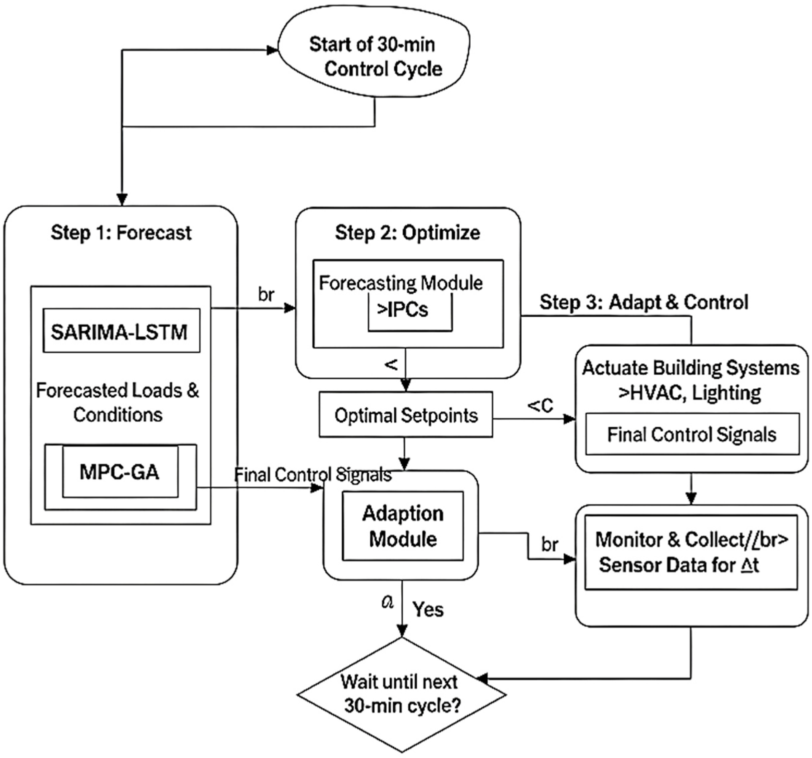

Fig. 5. Integrated workflow of the HAIEM, illustrating the 30-minute cyclic sequence of forecasting, optimization, and adaptive control

4 SIMULATION SETUP

To assess the HAIEM's performance thoroughly, a co-simulation framework was set up. An AI model written in Python is connected to a realistic building energy model through this framework, allowing for a virtual testbed that simulates real-world operation. An accurate evaluation of the closed-loop performance of the hybrid system can be achieved by exchanging sensor data and control signals at each simulation time step, as shown in Figure 6.

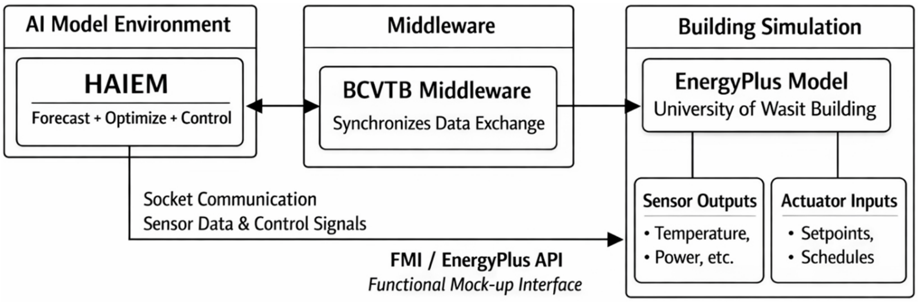

Fig. 6. Co-simulation framework using the Building Controls Virtual Test Bed (BCVTB) middleware to couple the EnergyPlus building model with the Python-based HAIEM

This setup (see Figure 6) facilitates bidirectional data exchange for comprehensive testing.

4.1 Case study building

The University of Wasit's lecture hall building in Al Kut, Iraq, is the object of the case study. Lecture rooms, faculty offices, and a library are housed in this four-story building with a total floor space of 5,200 m². It has a dimmable LED light system and a variable air volume (VAV) HVAC system [23].

Many factors contributed to the decision to choose the University of Wasit. First of all, being in a hot and dry environment means that the majority of the energy used by buildings is for cooling, thus any efficiency improvements are quite significant. Secondly, the results will be applicable to a wider context because the university's building stock is representative of modern Iraqi educational infrastructure; it was founded in 2003 and is a public institution. Lastly, by centering on a particular, actual institution, the simulation is grounded in a real-world context, making the suggested model more applicable to campus-wide sustainability programs.

4.2 Simulation environment

Making use of a co-simulation framework, we were able to build a very realistic virtual testbed for the simulation. The HAIEM may be tested thoroughly using this method, and expensive physical implementations are not necessary. The energy model of the building, the AI controller, and the middleware that allows them to communicate make up the basis of this scenario.

Building Energy Model: A powerful, open-source building energy simulation engine created by the United States Department of Energy, EnergyPlus version 9.6 was used to model the case study building. The model took into account specific details such as the building's thermal envelope (i.e., its walls, roof, and double-glazed windows), occupants' internal gains (as measured by ASHRAE standards), lighting and equipment schedules, and the VAV HVAC system's operational parameters (i.e., electric chillers and gas-fired boilers) [24]. Accurate hourly data for dry-bulb temperature, sun irradiance, and humidity were provided by an Iraqi Typical Meteorological Year (TMY) weather file that was calibrated for the Al Kut region, representing the local climate.

AI Controller and Middleware: Using specialized libraries, the HAIEM was constructed in Python 3.10. The LSTM neural networks were built with TensorFlow/Keras, the SARIMA component was built with statsmodels, and the GA was built with the DEAP framework [25]. The software environment built at Lawrence Berkeley National Laboratory, known as the BCVTB, was utilized as the middleware. The BCVTB ensures that EnergyPlus and Python's simulation clocks are in sync by controlling the data exchange at each time step, which is five minutes in our simulation, through a socket communication protocol. The configuration shown in Figure 7 allows the HAIEM to simulate a closed-loop control system by receiving real-time sensor data (such as humidity, zone temperatures, and power meters) and responding with control signals (such as thermostat setpoints and lights dimming levels).

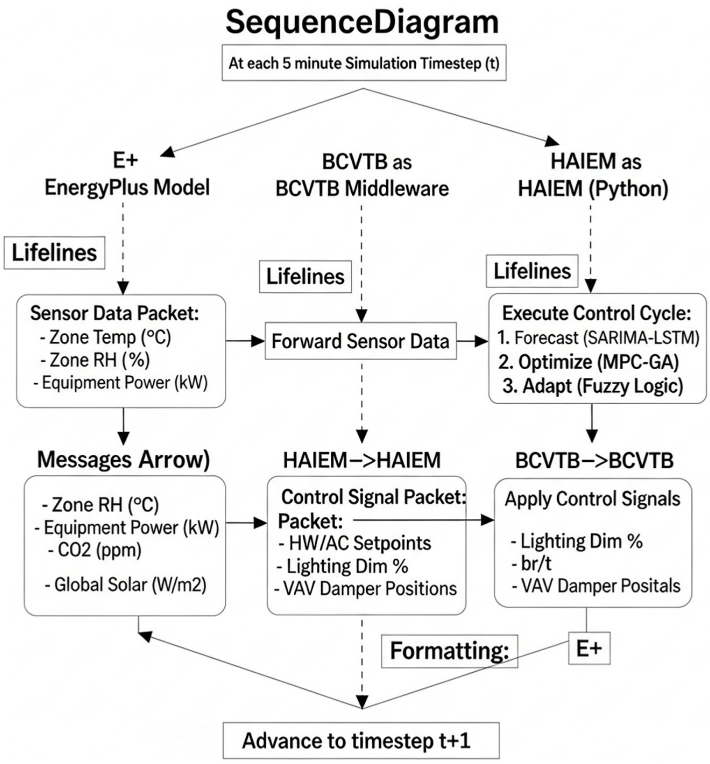

Fig. 7. Detailed co-simulation data exchange

Figure 7 illustrates the specific data packets exchanged between the EnergyPlus building model and the Python-based HAIEM controller at each simulation time step via the BCVTB middleware.

4.3 Scenarios and metrics

Two separate yearly simulation scenarios were set up and run in order to statistically evaluate the HAIEM's performance. Conventional, non-AI operational procedures are depicted in the Baseline Scenario. It uses a predetermined schedule based on rules: heating at 21°C, cooling at 24°C, and lighting at 100% output during occupied hours according to a predetermined academic schedule; it does not react to changes in actual occupancy or weather. To evaluate progress, this scenario is used as a reference point.

The complete hybrid AI model is implemented in the HAIEM scenario. In this configuration, the system optimizes in real-time and uses predictive forecasts to dynamically change all setpoints every 30 minutes. Some of the tactics it uses include precooling in the early mornings of summer when electricity rates are lower, altering ventilation rates depending on expected and actual CO_2 levels, and turning lights off when sunshine is no longer an option. Here, we put the suggested framework's integrated intelligence to the test. In order to assess the building's energy efficiency and the comfort of its occupants, a full suite of performance indicators was chosen [26, 27]. Main measures consist of:

1. **Total Site Energy Consumption (kWh/m²/yr):** Measures the absolute energy use intensity of the building.
2. **Peak Electricity Demand (kW):** Captures the maximum instantaneous power draw, critical for utility cost and grid stress.

3. **Carbon Emissions (kg CO_2-eq/yr):** Calculated by multiplying grid electricity and natural gas consumption by their respective emission factors for Iraq's energy mix.
4. **Thermal Comfort Compliance (%):** The percentage of occupied hours where the operative temperature remains within the ASHRAE 55 adaptive comfort range for the specific climate.
5. **Energy Cost Savings (%):** Estimated using local utility tariffs for the University of Wasit, incorporating time-of-use rates where applicable.

5 RESULTS AND DISCUSSION

The HAIEM's performance was directly compared to traditional operation using the extensive datasets produced by the annual simulations of both scenarios. This section presents a detailed analysis of the key findings, with an eye on occupant comfort, carbon emissions, and energy and demand reduction. The findings validate the core hypothesis that the hybrid AI model can achieve significant efficiency gains without compromising the indoor environmental quality essential for an educational setting. Underneath each part, with the help of comparative visualizations, is a breakdown of the performance across the specified metrics. A comparative analysis against recent literature (refer to Table 3) further contextualizes the contribution and advancement of the proposed HAIEM framework.

Table 2. Comparative analysis of findings: HAIEM vs. Related literature

Author(s)	Year	Method	Key Findings	Comparison to HAIEM Findings
Tariq et al. [13]	2024	AI Prediction Models (LSTM, GB)	LSTM and Gradient Boosting achieved high accuracy in predicting school energy use based on static features.	HAIEM Extends: Uses a hybrid SARIMA-LSTM for dynamic, multi-horizon forecasting and directly feeds predictions into a closed-loop control system.
Ali [14]	2024	Review of AI-BEMS	Identified AI-based HVAC control potential for 21% savings in educational buildings.	HAIEM Validates & Quantifies: Achieved 22.4% total energy savings, confirming the upper range of predicted potential through an implemented hybrid model.
Ashtar et al. [16]	2025	SARIMAX-LSTM for Forecasting	Hybrid model improved short-term electricity demand forecast accuracy at a national scale.	HAIEM specializes: Adapts a similar forecasting hybrid for building-scale loads and integrates it as a core component of a real-time control system, moving beyond pure prediction.
Ramos Ruiz et al. [17]	2019	MPC + GA for HVAC Optimization	Demonstrated GA-based MPC can reduce HVAC energy while maintaining comfort in a detailed simulation.	HAIEM Enhances: Integrates the MPC-GA optimizer with a real-time Fuzzy Logic layer to handle uncertainty, making the optimization robust for actual deployment. The HAIEM also incorporates peak demand reduction (18.7%), a metric not emphasized in the referenced study.
This Study (HAIEM)	2025	Hybrid AI (SARIMA-LSTM + MPC-GA + Fuzzy Logic)	22.4% energy reduction, 18.7% peak demand reduction, 21.8% carbon reduction, and 96.2% comfort compliance in a hot arid climate university building.	Contribution: Proposes and validates a novel, integrated three-layer architecture that synergizes prediction, optimization, and adaptive control into a single framework, demonstrating superior holistic performance for educational buildings.

5.1 Energy and demand reduction

With regard to controlling overall energy usage and peak electrical demand, the HAIEM proved to be significantly better. The system was able to reduce peak demand by 18.7% and overall site energy by 22.4%, as shown in Figure 8 and summarized in Table 2. Energy savings were greatest from May to September, when cooling loads are highest, because the MPC-GA optimizer made good use of thermal mass and timed precooling. Figure 8 shows that the peak demand decrease, which is seen as a flattened daily load profile, is due to the peak penalty term ($\gamma \cdot P_{peak}$) in the cost function. This factor encouraged the GA to move non-critical loads away from times of high aggregate demand in the forecast.

Table 3. Annual energy performance comparison

Metric	Baseline Scenario	HAIEM Scenario	Absolute Reduction	Percentage Reduction
Total Site Energy	185.6 kWh/m^2/yr	144.1 kWh/m^2/yr	41.5 kWh/m^2/yr	22.4%
Peak Electricity Demand	285.0 kW	231.7 kW	53.3 kW	18.7%
Total Gas Consumption	15,200 m^3	12,850 m^3	2,350 m^3	15.5%

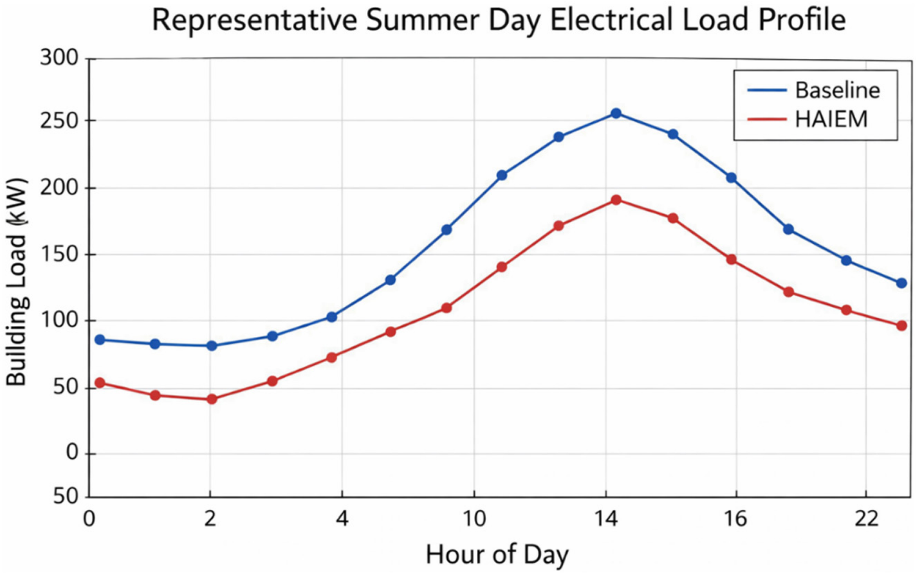

Fig. 8. Comparative load profile for a representative summer day

The chart (see Figure 8) shows how the HAIEM (blue line) reduces and shifts the building's electrical load compared to the baseline (red line), notably lowering and delaying the afternoon peak demand period.

5.2 Carbon emissions and comfort

A critical success factor for any sustainable intervention is its dual impact on environmental footprint and human factors. The HAIEM excelled in both dimensions. The reduction in energy consumption translated directly to a 21.8% decrease in operational carbon emissions, from 102.5 tCO_2-eq to 80.1 tCO_2-eq annually. This was calculated using an emission factor of 0.75 kg CO_2-eq/kWh for grid electricity (approximate for Iraq's natural gas-heavy grid) and 1.96 kg CO_2-eq/m^3 for natural gas combustion.

Contrary to the potential trade-off between energy savings and comfort, the HAIEM slightly improved the indoor thermal environment. As shown in Figure 9, the system maintained indoor conditions within the adaptive comfort band for 96.2% of occupied hours, compared to 94.5% for the baseline. This improvement stems from the Fuzzy Logic Controller's real-time adjustments, which compensated for localized over- or under-heating that the rule-based system could not address. The comfort compliance chart (Figure 9) demonstrates a more stable and consistent performance under the HAIEM scenario.

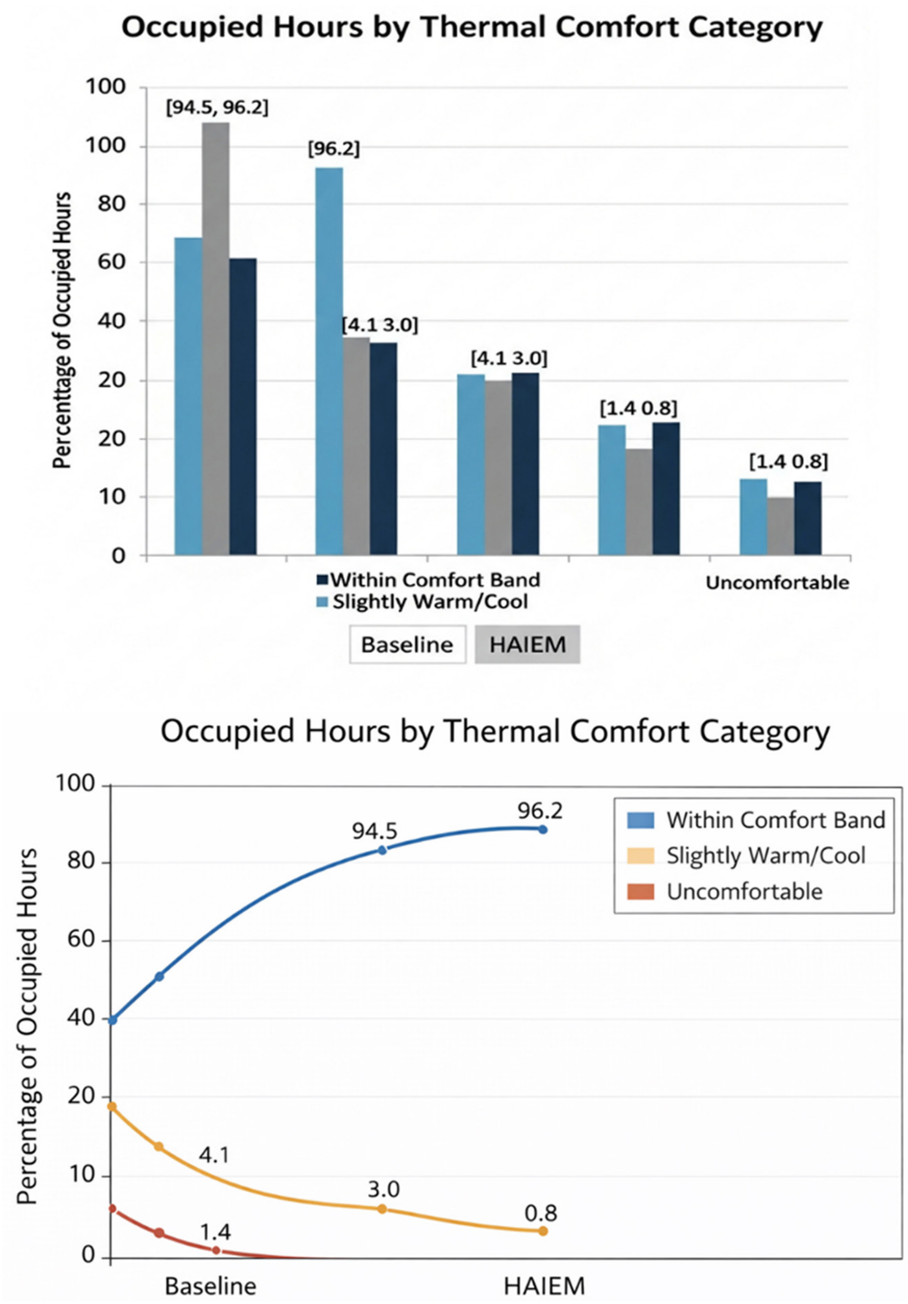

Fig. 9. Thermal comfort compliance analysis

The stacked bar chart (see Figure 9) compares the distribution of occupied hours across comfort categories for both scenarios, highlighting the HAIEM's superior performance in maintaining acceptable conditions and reducing discomfort.

5.3 Discussion of hybrid advantage

The HAIEM's outstanding efficiency is due to the complementary nature of its hybrid design rather than any one component in particular. The critical look-ahead capability was provided by the forecasting module's high-accuracy forecasts, which turned the control problem from reactive to proactive. For instance, the optimization module may reduce the chiller demand during the peak period by scheduling precooling at 11 AM using lower-cost, off-peak electricity, since it knew that a high solar gain period was projected for 2 PM. Without accurate predictions, this time-shifting—a fundamental strength of MPC—would not be conceivable.

The adaptive control module also dealt with the "reality gap" that happens when the idealized strategy doesn't match up with actual circumstances. There was CO_2 buildup and discomfort because the rule-based baseline system kept its constant setpoint during multiple simulated instances of unexpectedly high occupancy in a lecture hall. On the other hand, the optimum ventilation setpoint was overridden by the HAIEM's fuzzy logic layer, which received data from the CO_2 sensors in real-time to boost fresh air and preserve air quality. This proves that the hybrid model is resilient and can deal with random, discrete events, which are typically too much for models that focus just on predictive optimization. Because of the inherent complexity and human element in educational facilities, the layered design integrates both long-term planning (MPC-GA) and short-term resilience (FLC).

6 CONCLUSION AND FUTURE WORK

This study effectively developed, tested, and verified a new HAIEM for educational facility energy efficiency. By cooperating with a comprehensive model of a lecture hall at the University of Wasit, the HAIEM was able to lower overall energy consumption by 22.4%, peak power demand by 18.7%, and carbon emissions by 21.8%, all while enhancing thermal comfort compliance. By demonstrating that an integrated AI framework integrating SARIMA-LSTM, MPC-GA, and Fuzzy Logic can surpass traditional building management strategies in the harsh conditions of a hot, dry climate, these results provide a definitive answer to the research question.

Despite these encouraging findings, there are certain limitations to the study that point the way for further research. To begin, all sensor data and communication are assumed to be excellent in the current model. To make the system more resilient, it will be possible to detect sensor drifts or equipment problems in real-time with fault detection and diagnostics (FDD) in future iterations thanks to a digital twin layer. Secondly, DERs, or distributed energy resources, will be included in the broader scope. By upgrading its design, HAIEM will become a proactive prosumer inside a microgrid, instead of a passive consumer. This will be achieved by optimizing the dispatch of electricity from rooftop solar PV and a campus-scale battery storage system. Finally, the study will move from a building-to-campus-wide implementation by creating a hierarchical control strategy. In this strategy, the HAIEM acts as a local agent for each building, and a central campus energy management system coordinates with the utility grid to participate in demand response. This development will transform the model from an efficiency tool for individual buildings into the backbone of an intelligent, environmentally conscious, and robust college campus.

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