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A Data-Driven Multi-Variable Adaptive Closed-Loop Control Framework for Energy Efficiency Optimization

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Abstract – *The increasing energy consumption and urbanization of the built environment necessitates better energy management solutions to combat climate change. Despite the optimal energy savings offered by modern approaches such as Reinforcement Learning (RL) and Model Predictive Control (MPC), their real-world implementation is often limited by high computational costs, complex thermal modeling, and the requirement of extensive training data. To bridge this gap, this paper proposes a data-driven, multi-variable adaptive closed-loop control architecture for real-time energy efficiency optimization in smart buildings. The system dynamically adjusts power consumption by leveraging occupancy proxies and external climatic parameters, particularly wind speed and dew point, to account for air infiltration and latent heat loads, using a lightweight decision logic. The system's operational constraints are strictly tuned to ASHRAE 55 standards to guaranty accurate thermal comfort. By numerical simulations with UCI Appliances Energy Prediction dataset, the proposed adaptive system achieves a significant 28.01% reduction in overall energy consumption, and a 26.85% reduction in peak demand compared to baseline operations. This efficiency is estimated to have reduced the system's carbon footprint by 28.01%. These findings demonstrate that the integration of multi-variable climatic data within an easily deployable, heuristic adaptive control logic represents a highly responsive and sustainable alternative to computationally intensive predictive systems, greatly improving modern building management with no compromise to occupant well-being.*

Keywords: *Smart Building; Energy Efficiency; Adaptive Control; Closed-Loop System; Internet of Things*

I. INTRODUCTION

Climate change and the increase of global energy consumption are the two most urgent challenges of modern society. Economic growth and technological progress have led to a dramatic increase in energy consumption that in turn accelerated global climate change through the increase of greenhouse gas emissions (Pimenow et al., 2024). The built environment is playing a very significant role in this context, as it accounts for almost 40% of the world's total energy use and more than 30% of carbon dioxide emissions. Indeed, the building sector is responsible for 39% of process-related greenhouse gas emissions worldwide. This scenario emphasizes the importance of designing clean or near-zero energy buildings for the race to reach global climate neutrality goals (Bera & Nag, 2025; Ürge-Vorsatz et al., 2020).

Urbanization is occurring at an ever-increasing rate in the world and the rapid growth of population is putting more pressure on cities (Rodriguez-Nikl, 2022) According to UN data, the proportion of people living in urban areas has gone up from 30% in 1950 to 55% in 2018 and is projected to rise to 68% by 2050. Moreover, the world's population is expected to increase by 2.1 billion between 2018 and 2050 to reach 9.8 billion by 2050 (Farid et al., 2021). These demographic trends directly lead to an increase in the demand for HVAC (heating, ventilation and air conditioning) systems, which are a critical part of the modern building infrastructure known as the "breathing system." Given the vital role of the system in the potential dissemination of microbial contamination and a large share of the world energy consumption (Asim et al., 2022), the improvement of the sustainability of HVAC systems is now a task for researchers, industry players, and politicians alike. The severity of the situation is that the energy consumption of air conditioning systems is expected to more than triple by 2050 if substantial

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efficiency improvements are not made (Khosravi et al., 2023).

The building system is still undergoing development, but the operation efficiency is still an important challenge as most of the energy of the building is wasted due to lack of energy management. It has been shown in the studies that energy management systems have great potential to reduce the waste of energy in buildings which is 20 % due to poor management (Hossain et al., 2023; Vinothine et al., 2022). Such mismanagement is directly contributing to global climate change, as the building sector is responsible for a large part of CO2 emissions. So besides having enough energy, it is a big problem in energy management to have effective and efficient energy management.

The Internet of Things (IoT) technology has been a useful tool to enhance the energy efficiency of smart buildings, which has led to a significant reduction in energy consumption and operating costs (Jia et al., 2024; Pathare & Sethi, 2024). IoT enables integration of sensors, actuators, and communication devices in a single system for real time energy monitoring and control. Such systems can also enhance the integration of renewable power systems by increasing efficiency, operational reliability and sustainability by the use of state-of-the-art IoT devices and remote monitoring interfaces.

Existing research has explored the benefits of using IoT for improving building energy efficiency with different architectures and methodologies. For example, a template has been developed for a cloud-based management system integrating all technical systems, to enable automated remote control and storage of data on energy performance to support building certification (Metallidou et al., 2020). In a more complex scenario, Pathare and Sethi use the coalition game theory for optimization of energy distribution between the smart buildings in a smart city based on fog computing and Wi-Fi communication (Saeed et al., 2023). Mahmoud also suggested a real-time energy management system using the K-Nearest Neighbour (KNN) algorithm to predict power consumption, and a facial-recognition features for an eco-friendly building security system (Mahmoud et al., 2022).

Active energy savings have been widely obtained through several control strategies. While setpoint optimization techniques are efficient in guaranteeing thermal comfort (Li et al., 2023; Z. Wang et al., n.d.), they often rely on static criteria that are difficult to adjust to quickly changing occupancy and weather (Kidari & Tilioua, 2026; Talami et al., 2024). This is achieved through Model Predictive Control (MPC) that optimizes the future actions based on the predictions (Chen et al., 2023; Plewe et al., 2020; Taheri et al., 2024; Talib & Joe, 2025). However, the adoption of MPC is severely hampered by the need for high order thermal models and the significant computational cost of repetitive online optimization (Cole et al., 2013; Goyal & Barooah, 2012; Schweiger et al., 2020; Stoffel et al., 2023; Zheng et al., 2024). Reinforcement Learning (RL), in this way, does not explicitly model but learns from the interactions with the environment (Saleh et al., 2026; Solinas et al., 2024; Stippel et al., 2024; M. Wang & Lin, 2023). In practice, however, this approach is hard to implement due to the need for large amounts of training data, violation of safety constraints during exploration, and the difficulty of generalizing to changing seasonal patterns.

There exists a gap between the state-of-the-art model-based or data-driven control algorithms and the practical need for responsive control strategies. To address these drawbacks, this paper presents an adaptive IoT-based energy management framework with a real-time closed-loop control strategy for enhancing energy efficiency in smart buildings. The proposed system is based on the use of dynamic thresholds and correction factors which adapt themselves continuously to multidimensional environmental variables, such as indoor conditions, occupancy indicators and outdoor weather, instead of resorting to computationally expensive predictive models or large training datasets. The system transforms from a simple monitoring tool to an active controller, which adapts energy consumption to real needs. This is achieved by embedding ASHRAE standard based comfort constraints in a lightweight decision-making logic. Thus, it provides a very practical solution that can be applied without a large burden of computational resources, unlike the advanced predictive control systems that are generally used.

II. METHODS

2.1. Problem Formulation

The main approach to creating a framework to minimize total energy consumption is to (E_{total}) in the smart building environment without compromising indoor environmental *quality*. The measurements carried out in this case use 2 main standards: thermal comfort standards for room boundaries according to ASHRAE Standard 55 [25], and indoor air quality (IAQ) standards. The mathematical model for this automation problem is expressed in Equation 1.

$$\min \sum_{t=1}^{n} E_{total}(t) = E_{HVAC}(t) + E_{lighting}(t) + E_{appliances}(t) \quad (1)$$

With the following constraints:

$$T_{set_min} \leq T_{in}(t) \leq T_{set_max} \quad (2)$$

$$E_{total}(t) = f(T_{out}, W_{speed}, D_{point}, O_{occ}) \quad (3)$$

Where:

- $T_{in}(t)$ indicates the indoor temperature at time *t*.
- T_{set_min} and T_{set_max} is an adaptively defined temperature threshold based on the comfort zone in ASHRAE 55.
- Function f represents energy consumption behavior driven by data-driven inputs, including outside temperature (T_{out}), wind Speed (W_{speed}), dew point (D_{point}), and occupation status (O_{acc}).

2.2. Propose Framework Architecture

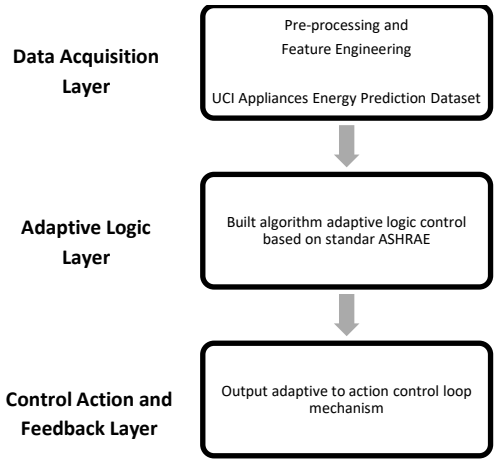


Figure 1. Proposed Framework

In Figure 1, you can see an overview of the overall framework architecture, which consists of several layers to optimize energy.

2.2.1. Data Acquisition Layer

In this part, it plays a role in pre-processing and feature engineering for multivariable data from the UCI Appliances Energy Prediction dataset (Candanedo, 2017), one of the standard datasets in building energy management research. The data used are environmental conditions and energy use in a smart home over a period of 4.5 months. This dataset has the advantage of very high time granularity, with data every 10 minutes. This dataset also shows significant seasonal variations, with energy use fluctuating in extreme weather conditions, such as changes in wind speed and dew point.

2.2.2. Adaptive Logic Layer

This layer serves as the system's decision-making hub, utilizing sensor data evaluated against ASHRAE 55 comfort standards. Meteorological variables are correlated with their adaptive control algorithms. This system calculates the energy correction factors to bring building operations to the highest level, unlike traditional systems that only utilize static thresholds.

2.2.3. Control Action and Feedback Layer

To run the closed-loop mechanism, the output from the adaptive logic is converted into a signal and is sent to the actuator. In this mechanism, signaling includes a setpoint parameter, which is automatically adjusted to reduce power consumption during periods of low load or unfavorable environmental conditions. This information is then fed back to the acquisition layer.

2.3. Dataset and Experimental Setup

This study employs a numerical method based on historical data to validate the adaptive control framework.

2.3.1. Dataset Characteristics

In this experiment, we use the UCI Appliances Energy Prediction dataset, which contains a number of variables derived from measurements taken by Internet of Things devices. The variables in this dataset are the main inputs in a multivariate design framework. **Table 1** shows the two types of variables; meteorological factors and internal conditions.

Table 1. Variable Dataset Specifications

Category	Symbol	Variable Description	Units
Internal	T_{in}	Temperature in the kitchen area (thermal load representation)	°C
	RH_{in}	Humidity in the kitchen area	%
	E_{base}	Equipment energy consumption (baseline)	Wh
	L	Energy use of light	Wh
External	T_{out}	Outdoor air temperature	°C
	W_{speed}	Wind speed	m/s
	T_{dew}	Dew point	°C

2.3.2. Adaptive Control Algorithm

This framework is based on an adaptive closed-loop control algorithm that continuously monitors sensor data and dynamically adjusts energy usage in real time. The following is the systematic pseudocode for the adaptive control process:

1. Initialize System and Load Dataset *D*;
2. For each time step *t* in *D* do:
3. Read internal sensor data: $T_{in}(t)$, $E_{base}(t)$, $L(t)$;
4. Read external meteorological data: $T_{out}(t)$, $W_{speed}(t)$, $T_{dew}(t)$;
5. Step 1: Occupancy Inference
6. Calculate f_{occ} based on Working Hours and $L(t)$ status;

7. Step 2: Environmental Factor Calculation
8. If $W_{speed}(t)$>5.0 AND $T_{out}(t) < T_{in}(t)$ then f_{wind} = 1.15; Else f_{wind} = 1.0;
9. If $T_{dew}(t)$> 15.0 then f_{dew}= 1.1; Else f_{dew}= 1.0;
10. Step 3: Adaptive Power Calculation
11. Calculate Base Power (P_{base}) based on thermal gap;
12. $P_{target}(t) = E_{base}(t) * f_{occ} * f_{wind} * f_{dew} * P_{base}$;
13. Step 4: Constraint Validation (ASHRAE Safety Check)
14. If $T_{in}(t) < T_{min}$ OR $T_{in}(t) > T_{max}$ then:
15. Adjust $P_{target}(t)$ to prioritize Thermal Comfort;
16. End If
17. Step 5: Control Action & Feedback
18. Update $P_{optimized}(t) \leftarrow P_{target}(t)$;
19. Calculate Instantaneous Saving: $\Delta E(t) = E_{base}(t) - P_{optimized}(t)$;
20. Feedback new $T_{in}(t+1)$ for next cycle;
21. End For
22. Return $P_{optimized}$ and Total Efficiency Metrics;

In addition, active dehumidification is assumed with a 10% load increase (an energy load factor of 1.1) at the 15.0°C dew point threshold. For room unoccupancy periods, a multiplier of 0.3 is applied to represent an aggressive maximum energy saving condition of 70% assuming standby operation is required. Although deterministic in this simulation, these parameters serve as reliable baseline proxies for dynamic system response.

IV. RESULTS AND DISCUSSION

4.1. Comparative Performance Analysis: Baseline vs. Adaptive

This experiment was performed by processing the first 1,000 data intervals, which correspond to one week of operation, to observe the system's response to changes in the environment. The baseline energy consumption data was obtained from the Appliances column of the UCI dataset. The behavior of the adaptive system was decided using a dynamic optimization factor.

The simulation results (Fig. 2) demonstrate that the proposed framework is capable of maintaining the energy usage continuously below the baseline level, while not exceeding the thermal comfort threshold of 21.0°C. By utilizing real-time sensor data, the adaptive system's load-factor clamping mechanism is able to considerably decrease the peak load, with a reduction of up to 0.7.

4.2. Impact of Multi-Variable Environmental Factors

This framework differs from traditional control algorithms in that it uses external factors to modify building system loads.

- Wind Infiltration Mechanism If the outdoor temperature is less than the indoor temperature, and the wind speed is greater than 5.0 m/s, the system logic applies to a correction factor of 1.15. This accounts for heat loss from air entering the structure through the building envelope.
- Latent Load Compensation (Dew Point) If the Dew Point > 15.0 °C, the system will automatically increase the operating load by 10% (1.1) to manage the dehumidification process. This combination allows for occupant comfort in high humidity conditions.
- Occupancy-Based Optimization: The system created occupancy proxies (based on working hours 08:00–18:00 and light sensors) to deliver aggressive savings of up to 70% during times when buildings were empty.

4.3. Quantitative Energy Saving Assessment

Table 2 below provides a summary of the system's quantitative performance data:

Table 2. Total Energy Consumption Comparison

	Total Energy (Wh)	Average Power (Wh)	Peak Demand (Wh)
Baseline	114460.0	114.46	1080.00
Adaptive	82399.7	82.4	790.0
Reduction	32060.30	32.06	290.0
Efficiency	28.01%	28.01%	26.85%

The 28.01% saving is considered significant. These results suggest that a data-driven method that considers humidity and wind is potentially superior to building management systems that rely on a single temperature sensor or a fixed schedule.

4.4. Environmental Impact and Carbon Footprint Reduction

In addition to the operational cost effectiveness, the proposed adaptive control framework significantly reduces the negative environmental impacts of the building's energy consumption. To quantify this sustainability metric, the energy consumption values were translated to estimated carbon emissions by applying a standard conversion factor of 0.87 kg CO2 per kWh (equivalent to 0.00087 kg/Wh).

The baseline system generated approximately 99.58 kg of CO2 over the simulated period, as shown in Table 3. By applying multi-variable adaptive logic, the carbon footprint was reduced to 71.69 kg. For the duration of one week of operation, this results in a reduction of 28.01% of environmental impact, or the equivalent of avoiding 27.89 kg of

CO2 emissions. These results demonstrate the dual potential of the framework to both provide significant contributions to the achievement of global climate neutrality objectives and improve energy demand optimization.

Table 3. Environmental Impact Assessment

Environmental Metric	Baseline	Adaptive
Carbon Emissions (kg CO2)	99.8	71.69
Carbon Reduction (%)	-	28.01%

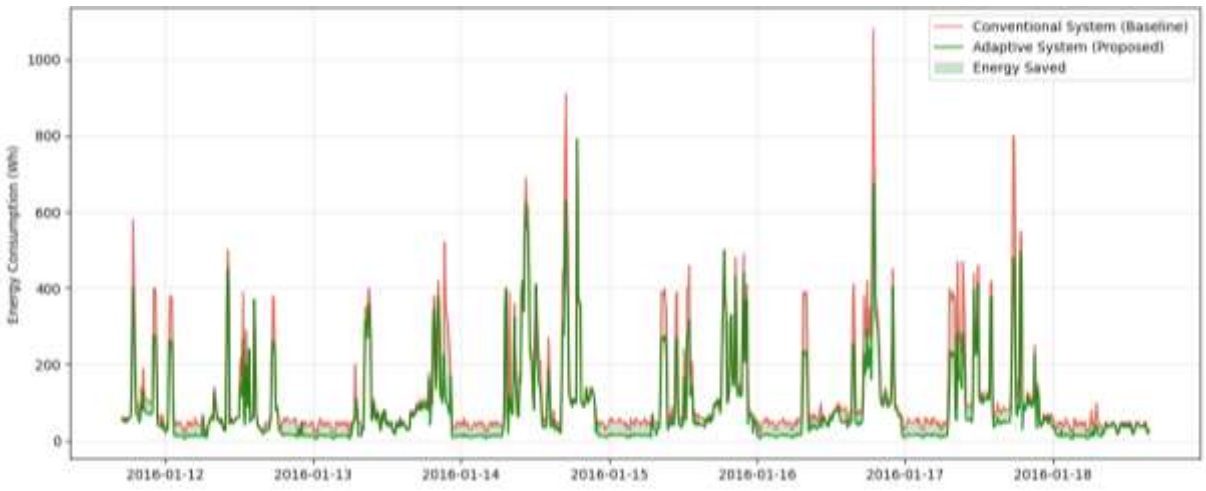


Figure 2. Comparison Baseline vs Adaptive Control

V. CONCLUSION

The closed-loop, data-driven adaptive control system presented in this paper actively integrates occupancy proxies and external meteorological factors (wind speed, dew point) to maximise the energy efficiency of smart buildings. This framework demonstrates how multivariable adaptive control logic can make building management smarter, more responsive, and more sustainable, maintaining high sensitivity to weather changes while reducing peak operational loads by 28.01% using data from the UCI Appliances Energy dataset.

However, these findings do not capture all aspects of real-world sensor latency and actuator response, as the study relied on data-driven numerical simulations rather than practical implementation. Third, the system used deterministic control parameters and heuristic occupancy proxies, instead of direct presence sensors. Future research should apply this framework to a physical testbed for empirical validation, incorporate reinforcement learning algorithms to automatically calibrate optimization thresholds, and include indoor air quality (IAQ) sensors to verify CO2 limits in real-time.

AUTHOR'S CONTRIBUTION

Conceptualisation, data curation, formal analysis, methodology, validation, visualisation, writing, and editing by **Anang Prasetyo, Kumara Pinastika Dharaka,** & **Prabowo Wahyu Sudarsono**.

AVAILABILITY DATA AND MATERIALS

The dataset used can be accessed via the link *https://archive.ics.uci.edu/dataset/374/appliances+energy+prediction*

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