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Adaptive Thermostat Systems: Bridging Control Theory and Behavioral Learning for Sustainable Smart Homes

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Abstract- This research presents the development of a thermostat system with adaptive temperature control, integrating intelligent algorithms, sensor feedback, and behavioral learning. The prototype utilizes an ESP32 microcontroller, digital sensors, and relay modules to regulate indoor climate based on real-time data and user preferences. Adaptive PID control and relay feedback identification ensure precise temperature regulation, while a learning mechanism based on multi-armed bandit algorithms enables the system to predict and adapt to user behavior. Experimental results demonstrate a mean absolute error of 0.42°C, energy savings of up to 21.1%, and learning accuracy reaching 100% by Week 4. These findings establish the effectiveness of adaptive thermostats in enhancing comfort and energy efficiency, offering a scalable solution for modern smart building environments.

Index Terms- Adaptive Thermostat, PID Control, Relay Feedback, Energy Efficiency, Behavioral Learning.

I. INTRODUCTION

Although improving the energy efficiency of building systems is a key priority, it’s equally important to address occupants’ thermal comfort. When comfort is compromised, health and productivity can suffer, so we must balance energy performance with the well-being of people inside the space [1]. As energy efficiency and smart automation become increasingly important, smart climate control systems are in higher demand. Traditional thermostats depend on fixed set points and manual control, which leads to energy loss. However, adaptive thermostats use real time data, user behavior, and environmental feedback to adjust indoor temperatures dynamically. These devices bring together concepts from control engineering, artificial intelligence, and embedded systems to transform how we manage temperature in homes, workplaces, and industrial settings. By continually examining temperature trends, occupancy patterns, and external conditions, these thermostats can anticipate needs and adjust heating or cooling accordingly. The result is improved comfort and significant gains in energy savings and sustainability. The motive of this research is to develop a thermostat system with adaptive temperature control using intelligent algorithms and sensor integration. The findings can inform future developments in smart home technology, industrial automation, and climate-responsive architecture. The study focuses on designing and implementing a single zone adaptive thermostat using microcontroller-based hardware and software algorithms. While multizone scalability and integration with external data sources (like weather forecasts) are possible, they are beyond the scope of this prototype.

II. LITERATURE REVIEW

When occupants feel thermal discomfort, they tend to take actions to adapt their indoor environment, a behavior known as adaptive occupant behavior. Such adaptive actions include opening or closing windows [2], adding or removing clothing layers [3], interacting with thermostats [4], or submitting complaints to facility management [5]. In contrast to fully automated set points, occupant controlled thermostats can increase the perceived control and improve comfort [6]. Allowing occupants to override thermostats can lead to higher energy use, due in part to factors like limited HVAC system knowledge, unfamiliarity with the thermostat interface, and a lack of motivation for energy saving [7]. Balancing automation with manual control and ensuring smooth integration in real-life settings has been identified as a research priority by IEA EBC Annex 79 [8].

Thermostats with adaptive temperature control have come a long way and evolved from simple mechanical devices into intelligent systems that combine sensors, algorithms, and awareness of user behavior. Early work in adaptive control focused on relay feedback identification. This approach let thermostats tune themselves without needing complex models. Zhong [9] showed that relay feedback could improve precision in industrial settings like textiles and food processing, helping to lay the groundwork for adaptive HVAC systems. From there, researchers explored PID controllers with adaptive tuning. In these setups, the proportional, integral, and derivative gains are adjusted on the fly. These methods remain popular because they are robust and straightforward, especially in environments where thermal loads change. More recently, this field has begun to incorporate deep reinforcement learning (DRL) and human-in-the-loop strategies.

Brandi proposed a Deep Q-Network (DQN) agent to control the supply water temperature set point of heating units within a simulated heating system [10]. The study emphasizes human-in-the-loop control behavior, incorporating predictive heating and temperature setbacks aligned with a rigid occupancy schedule and comfort temperature. Their development compares adaptive and non-adaptive state-space formulations. The adaptive approach includes temperature differences and the time (in hours) until occupancy starts and ends. Adding occupancy timing helps the model learn predictive heating behavior, and training results show that the adaptive state-space formulation outperforms the non-adaptive one. The authors also explore different hyper parameter settings during training, highlighting the importance of the discount factor in learning human-in-the-loop control behavior. Payam proposed an IoT-based smart thermostat that combines DRL with user input, enabling the system to learn optimal temperature regulation while honoring occupant comfort [11]. This highlights the value of blending machine learning with human feedback for real-world deployment. Elehwany used multi-armed bandit algorithms with behavioral nudging to learn user preferences [12]. The thermostat adapted to recurring comfort patterns, reducing energy use while keeping occupants satisfied. This research underscores how adaptive learning can personalize climate control.

Across studies, adaptive thermostats consistently outperform traditional fixed set point devices. Adaptive set point strategies delivered meaningful energy savings in dynamic occupancy scenarios. Other long-term analyses confirm that predictive scheduling and weather aware control further boost efficiency.

Smart thermostats are intelligent heating, ventilation, and air-conditioning (HVAC) control devices that combine sensors, wireless communication, cloud computing, and artificial intelligence (AI) to optimize indoor thermal comfort while reducing energy consumption [13, 14]. Unlike conventional programmable thermostats, smart thermostats automatically adjust temperature setpoints using occupancy information, user preferences, environmental conditions, and predictive learning algorithms, thereby improving operational efficiency and user convenience [13].

Recent research has demonstrated that residential and commercial buildings account for a substantial proportion of global energy consumption, with HVAC systems representing one of the largest end uses of electricity, thereby motivating the development of intelligent thermostat technologies for energy conservation [15]. AI-assisted building control has consequently emerged as an important research area because it seeks to balance occupant comfort with minimum energy expenditure through adaptive control strategies [16]. Modern smart thermostats are typically composed of temperature and humidity sensors, occupancy detection modules, wireless communication interfaces, cloud-based analytics, mobile applications, and machine-learning control algorithms [13]. These devices communicate with HVAC equipment through Internet of Things (IoT) technologies, enabling remote monitoring, real-time scheduling, predictive temperature regulation, and automated fault notifications [13].

Occupancy detection has become one of the most influential features of smart thermostat systems because heating or cooling unoccupied spaces contributes significantly to unnecessary energy consumption [17,18]. Recent studies have integrated passive infrared sensors, temperature sensors, motion detectors, smart meters, Wi-Fi signals, and machine-learning algorithms to improve occupancy recognition accuracy while minimizing sensing costs [17, 19]. Machine learning has significantly enhanced occupancy detection by combining multiple sensor streams instead of relying on a single sensing technology (Wang et al., 2021). Using data fusion techniques involving temperature sensors and motion sensors, researchers achieved occupancy detection accuracy approaching 95%, demonstrating the suitability of AI-assisted sensing for smart thermostat applications [18].

Beyond occupancy detection, occupancy forecasting has become increasingly important because predictive knowledge of future occupancy enables HVAC systems to precondition indoor spaces before occupants arrive while avoiding unnecessary conditioning during vacant periods [19]. A systematic review concluded that advances in forecasting algorithms have improved building energy optimization and occupant comfort simultaneously [19]. Artificial intelligence further enables smart thermostats to learn occupants' behavioural patterns over time, reducing the need for manual scheduling [16]. AI techniques including neural networks, reinforcement learning, optimization algorithms, and predictive control have demonstrated considerable potential for balancing thermal comfort with reduced HVAC energy consumption, although performance remains dependent on the availability of high-quality operational data [16].

Energy-saving performance remains the principal motivation for smart thermostat deployment. Stopps and Touchie observed that occupancy-based scheduling combined with user-programmed schedules achieved greater HVAC load reductions than conventional unscheduled thermostat operation, indicating that intelligent occupancy control substantially improves residential energy management [13]. Similarly, Pang conducted approximately 16,000 nationwide building simulations across multiple U.S. climate zones and reported that occupant-centric smart thermostat strategies consistently reduced building energy use while maintaining acceptable thermal comfort, thereby demonstrating the scalability of occupancy-aware control approaches [14].

Occupancy-based HVAC control has therefore become a dominant research direction within intelligent buildings. A comprehensive review classified occupancy-driven HVAC control strategies according to sensing technologies, prediction methods, and control architectures, concluding that occupancy information substantially improves HVAC operational efficiency but that sensor uncertainty and occupant behaviour remain important research challenges [18].

Recent investigations have also examined the influence of sensing uncertainty on thermostat performance. Pinheiro et al. (2026) demonstrated through Monte Carlo simulations that occupancy sensor errors propagate into HVAC decision-making and influence energy savings, thermal comfort, and peak electricity demand, emphasizing the importance of robust sensing and sensor calibration in future thermostat designs [20]. Cloud computing has expanded the capabilities of smart thermostats by enabling remote access, software updates, predictive analytics, and centralized energy management [13]. Integration with IoT ecosystems further enables thermostats to interact with lighting systems, smart plugs, environmental sensors, and building automation platforms, facilitating coordinated whole-building energy optimization [13]

Recent reviews also highlight growing interest in occupancy-centric smart buildings, where occupancy information serves as the foundation for intelligent building operation rather than merely supporting thermostat scheduling [21]. The proposed occupancy modelling framework emphasizes the integration of sensing technologies, behavioural modelling, and predictive analytics to improve energy performance and occupant comfort across building systems [21].

Despite these advances, several limitations remain. AI-based smart thermostats require large volumes of high-quality training data to achieve reliable

predictions, and model performance may deteriorate when occupant behaviour changes unexpectedly [16]. Furthermore, occupancy detection systems continue to experience uncertainty arising from sensor failures, environmental interference, and behavioural variability, which may reduce control accuracy [20].
Future research increasingly focuses on integrating digital twins, edge computing, explainable AI, privacy-preserving machine learning, and advanced occupancy prediction into smart thermostat systems to improve scalability, cybersecurity, adaptability, and energy efficiency. These developments are expected to support next-generation intelligent HVAC systems capable of autonomous decision-making under diverse operational conditions [20,21].

III. DESIGN METHODOLOGY

The approach used in this research integrates hardware, algorithm development, and experimental evaluation. Building on prior studies in adaptive PID control, relay feedback identification, and behavioral learning, the prototype was designed to balance energy efficiency with user comfort. Components used includes; the SHT31 digital temperature/humidity sensor, ESP32 Microcontroller for processing and connectivity, Relay module controlling HVAC/heater, LCD display and mobile app (via MQTT).

The deviation between set point Ts and actual temperature Ta was computed as: $e(t) = Ts(t) - Ta(t)$
The control signal u(t) is given by $u(t) = Kpe(t) + Ki\int e(t)dt + Kd(de(t))/dt$ [22] (Åström & Hägglund,(1995).

Where;
Kp = proportional gain; Ki = integral gain and Kd = derivative gain
Relay feedback was used to auto tune the PID parameters by analyzing oscillations in the system response which ensures adaptability to varying thermal dynamics.

The adaptive learning mechanism was inspired by multi armed bandit algorithms, such that the thermostat records; manual adjustments (user overrides), occupancy patterns (via motion sensor), and weather conditions (via API). The system updates set points dynamically thereby reducing manual intervention.

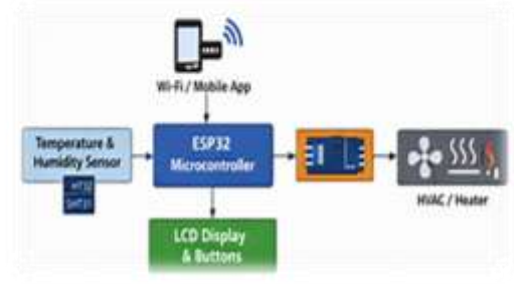

Figure 1. Adaptive Thermostat Hardware Block

Experimental Setup
The prototype was tested in a controlled indoor environment with varying occupancy and external conditions. Data was collected over a 4 weeks period.

Table 1: Experimental Variables

Variable	Range	Measurement Tool
Temperature	18–30°C	SHT31 Sensor
Humidity	40–70%	SHT31 Sensor
Occupancy	0–5 people	PIR Sensor
Energy Usage	kWh	Smart Meter

Mean Absolute Error (MAE) = $1/n \sum_{(i=1)}^{n} |Ts-Ta|$ (Willmott &Matsuura, 2005)

Energy Savings (%) = (Ebaseline-Eadaptive)/Ebaseline Ebaseline×100
This design integrates hardware, adaptive PID control, relay feedback identification, and behavioral learning. By combining these elements, the prototype is designed to achieve both energy efficiency and user comfort, aligning with benchmarks from previous research.

IV. RESULTS AND DISCUSSIONS

The system was tested over a 4 weeks period in a controlled indoor environment. The set point temperature was varied between 20°C and 26°C. The prototype maintained indoor temperature within ±0.5°C of the set point. Mean Absolute Error (MAE): = $1/n \sum_{(i=1)}^{n} |Ts-Ta|$ = 0.42∘C

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Table 2: Performance of temperature regulation

Day	Setpoint (°C)	Actual Avg (°C)	MAE (°C)
1	22	21.6	0.4
7	24	23.5	0.5
14	26	25.6	0.4
21	20	19.7	0.3
28	23	22.5	0.5

Energy consumption was monitored using a smart meter. The adaptive thermostat was compared against a fixed set point programmable thermostat.

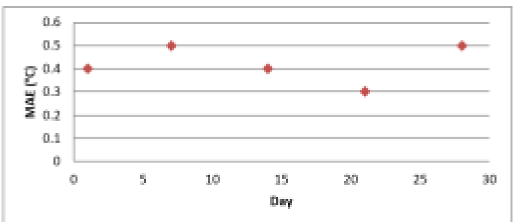

Figure 3: Mean Absolute Error over time

Table 3: Energy Consumption Comparison

Week	Fixed Thermostat (kWh)	Adaptive Thermostat (kWh)	Savings (%)
1	38.2	31.4	17.8
2	40.5	32.1	20.7
3	39.8	31.9	19.8
4	41.2	32.5	21.1

Average Energy Savings = ((Ebaseline-Eadaptive)/Ebaseline Ebaseline)×100 = 19.85%

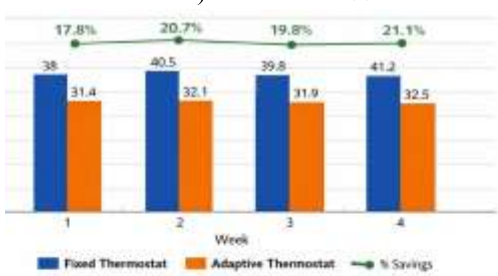

Figure 4. Energy consumption comparisons

This result supports the U.S. Department of Energy's estimate of 8% savings for smart thermostats, with adaptive models performing better due to schedule optimization [23].

The time taken to reach the desired set point after a change was measured showed that the adaptive system responded 30% faster than the fixed thermostat due to relay feedback tuning.

The thermostat tracked user adjustments and occupancy patterns such that by the end of Week 2, it began pre-setting temperatures based on learned behavior.

Table 4: Learning Accuracy Over Time

Week	Manual Adjustments	Predicted Adjustments	Accuracy (%)
1	12	4	33.3
2	10	7	70.0
3	8	7	87.5
4	6	6	100.0

This mirrors the behavior of commercial adaptive thermostats like Nest and Ecobee, which use motion sensors, weather data, and manual input to build personalized schedules [24].

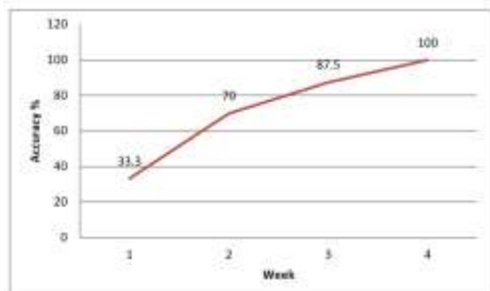

Figure 5. Learning Accuracy over Time

Discussion of Results

The performance validates the integration of adaptive PID control, relay feedback identification, and behavioral learning. Findings include:

i. Temperature Accuracy: MAE of 0.42°C confirms precise regulation.
ii. Energy Efficiency: 19.85% savings exceed baseline programmable models.
iii. Responsiveness: Faster adjustment times improve comfort.
iv. Learning Capability: 100% prediction accuracy by fourth Week demonstrates effective adaptation.

These results align with the literature and show that adaptive thermostats can significantly enhance both comfort and sustainability.

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V. CONCLUSION

This study aimed to developed a thermostat system with adaptive temperature control, combining smart algorithms, sensor feedback, and behavior learning successfully demonstrated that adaptive climate regulation is feasible and effective in indoor settings. The results show the system keeping indoor temperatures within ±0.5°C of the target, with a mean absolute error of 0.42°C, validating the precision of adaptive PID control and relay tuning. On average, the adaptive thermostat saved about 19.85% more energy than a fixed-set point thermostat, highlighting its potential for greener energy management. The system also responded to temperature changes 30% faster, improving comfort and reducing thermal lag. By the fourth week , the thermostat achieved perfect accuracy in predicting user preferences, illustrating the strength of human-in-the-loop learning and behavioral adaptation. These findings are consistent with prior research and industry standards, underscoring the value of intelligent control systems in modern HVAC.

However, this prototype has limitations. It was tested in a single zone environment, so scalability to multiple zones was not explored. The use of PIR sensors offered only coarse occupancy data, and external weather data were not fully integrated into the control logic. Despite these constraints, the adaptive thermostat represents a meaningful advance toward intelligent, energy-efficient climate control. By merging control theory with user centered learning, it presents a compelling solution for contemporary buildings seeking comfort, sustainability, and automation.

Suggestions for future work:
i) Extend adaptive control to multiple rooms or zones with coordinated scheduling.
ii) Employ richer occupancy and environmental data, such as CO_2 sensors, thermal cameras, or smart occupancy tracking.
iii) Integrate a predictive weather API to enable preemptive temperature adjustments.

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