International Journal of Electrical and Electronic Engineering and Telecommunications Vol. 15, No. 3, 2026

Fuzzy Clustering-Based Temperature Control System for Energy Efficiency and Cost Optimization in Smart Homes

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Manuscript received November 2, 2025; revised December 9, 2025; accepted March 2, 2026
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***Abstract*—Temperature control systems are among the most demanding and critical uses of server rooms, industrial plants, and smart homes because they are nonlinear and dynamic. Although Proportion Integration Differentiation (PID) controllers are ubiquitous in climate control, their fixed linear gain parameters are not very adaptable to different operating conditions. Fuzzy control systems, especially soft clustering-based systems, offer more versatile methods by facilitating smooth and continuous adjustment of temperature and thus more precise and adaptive control. On the basis of both fuzzy K-means and Fuzzy C-Means (FCM) algorithms, in this research, a clustering-based PID system is developed and evaluated. The study carried out a simulation for validating system performance, with a focus on temperature tracking in terms of accuracy, energy cost, and precision. It indicates that the proposed FCM-PID controller achieved the highest stable and accurate temperature response compared to the traditional PID and fuzzy K-means PID controllers. It ensures about 10% savings on energy costs with an accuracy of 97.6% and a lower Mean Absolute Error (MAE), 0.48°C, representing its real-time efficiency in adaptive control. It also reflects a quantitative superiority against traditional PID and K-means PID methods. The indications are that the integration of FCM-PID can be a potential smart energy-saving technology that can be adopted in future generations of Heating, Ventilating, and Air-Conditioning (HVAC) systems and other applications sensitive to temperature changes.**

***Index Terms*—cost optimization, energy-efficient, fuzzy clustering algorithm, fuzzy C-means clustering, fuzzy K-means clustering, Proportion Integration Differentiation (PID) controller, temperature control system**

I. INTRODUCTION

Automation, along with intelligent systems, has changed the face of internal environment control in modern infrastructure, industries, and buildings. The temperature control systems have an important place among them, as consistent indoor conditions are highly critical for comfort, productivity, energy efficiency, and equipment safety. Heating, Ventilating, and Air-Conditioning (HVAC) form the basis of climatic control in home automation and directly influence occupant comfort and energy use [1]. Similarly, in server rooms and manufacturing facilities, accurate temperature control is crucial for product quality, the reliability of sensitive equipment, and maintaining continuity of operation. With energy demands increasing all over the world and energy sustainability emerging as an important issue, there has been a shift towards such control systems by researchers and engineers, which, apart from being accurate, also need to be highly flexible and energy-efficient [2].

Modern control systems increasingly rely on the evaluation and processing of large, complex data sets as a basis to establish optimal performance and good decision-making across a wide range of applications. Probably, the toughest area of these systems is the temperature control due to the dynamic and nonlinear characteristics of the thermal environment. Precise control requires fast response and minimum overshoot, rejecting disturbances while operating steadily against disturbances such as outdoor temperature variation, occupancy variation, or time-varying tariffs. This hierarchy of complexity is challenging for traditional controllers [3].

While the Proportional Integral-Derivative (PID) controller has been very much used over the years for its simplicity and effectiveness in linear conditions, when used in nonlinear and dynamic thermal conditions, it becomes grossly inadequate. Most noticeably, by its constant gain values, it is insensitive to changes in system dynamics, leading to overshoots or sluggish responses and energy loss. To fill this gap, some researchers have considered the use of intelligent algorithms in PID controllers to enhance their adaptive capabilities. As an illustration, cluster algorithms have been employed in the adaptive tuning of PID gains. The very popular unsupervised learning method known as the K-means clustering algorithm [4] has been put into force to segregate the operating conditions and hence tune the gains to appropriate levels. K-means is a rigid-clustering algorithm that assigns each point to exactly one cluster. Its rigid boundary limits the capacity to model smooth transitions and overlapping states inherent in natural

doi: 10.18178/ijeetc.15.3.171-183

temperature systems. As such, it performs with limitations when employed to model gradual environmental dynamics or nonlinear dynamics. Fuzzy control systems can alternatively be out for a more versatile system.

Fuzzy control systems are more flexible with an alternative. FCM [5], for example, introduces soft clustering where each point is assigned to multiple clusters to some degree of flexibility. This ability enables controllers to handle continuous and fuzzy temperature variations better in order to devise smoother transitions between controls. When combined with digital PID controllers, FCM provides a sizeable benefit in terms of adaptively adjusting control parameters in real time. As a result, it attains stabilized responses with higher trailing accuracy and lower energy use under nonlinear conditions. Smart homes and smart cities have been at the forefront of increased attention during the past decade, and therefore, the need for smart management of energy has increased correspondingly [6]. The need for smart homes is to strike a balance between several conflicting targets, including comfort to the residents, supreme energy competence, and minimum running costs. The sophisticated control systems that avail clustering along with PID can directly assist in these pursuits. As an example, the capability of FCM-PID controllers to reduce steady-state error and transient deviations allows for precise setpoint tracking, while adaptability allows for efficient use of power, hence allowing for quantifiable energy savings.

This study formulates a clustering-based PID control system and contrasts the performance of traditional PID, K-means PID, and FCM-PID. The research compares the behavior of systems through simulations regarding temperature tracing accuracy, error dynamics, and energy costs. Results demonstrate that the FCM-PID controller gives the most stable and precise response for all simulations and also yields an energy cost reduction compared to the traditional PID system. The study validates the ability of the FCM-PID controller to outperform static controllers and hard clustering methods, opening the door toward smarter, more efficient, and scalable temperature control solutions in the energy-conscious environment of today.

Unlike earlier fuzzy-PID designs, which rely exclusively on rule-based fuzzy inference, in this work, both hard and soft clustering are integrated into one unified adaptive PID structure. A dual-clustering formulation thus offers both discrete and graded adjustments in gain values-hence, smoother adaptation and better PID responsiveness novelty unreported for either HVAC or smart home control applications.

The study offers a unique methodological contribution with a comparison of Fuzzy K-means and C-Means clustering. In an adaptive PID framework, it captures discrete as well as gradual variations in thermal dynamics. K-means identifies distinct operating regimes, while FCM provides soft membership values that allow smooth interpolation of the gains. Clustering thus supports real-time, data-driven PID tuning, introducing a far more responsive and robust control strategy than achievable from conventional or rule-based fuzzy controllers.

This research is targeted at designing adaptive temperature control systems for industrial facilities, intelligent homes, and server rooms where dynamic thermal environments and energy efficiency are paramount. Development is in the application of clustering algorithms such as K-means and Fuzzy C-means with PID controllers to achieve real-time adaptive tuning of control gains. Compared with the traditional fixed-parameter PID controllers and hard boundary setting of K-means, the new FCM-PID model with soft clustering allows smooth transitions, better tracking accuracy, and higher stability in nonlinear situations.

The resilient FCM-PID developed during this research ensures better performance in temperature control with a very low margin of error, with evidence of energy consumption minimization by about 10%, confirming its credibility as cost-saving and energy-efficient.

The goals of the research are:

- To evaluate the shortcomings of conventional PID in dynamic environments.
- To develop clustering-based PID controllers with K-means and FCM.
- To compare system performance based on tracking accuracy, error dynamics, and energy cost.
- To prove FCM-PID as a better substitute for intelligent, sustainable, and scalable temperature control applications.

II. LITERATURE SURVEY

Over the past decade, fuzzy PID controllers have received significant interest as a good alternative to traditional fixed-gain PID controllers for nonlinear and time-varying dynamic applications. Different fuzzy-based methods incorporating traditional PID structure with fuzzy logic inference have been suggested by researchers to enhance robustness and flexibility. For example, fuzzy gain-scheduled PID controllers have been used in chemical reactors, bioreactors, and HVAC systems to dynamically update control parameters according to varied operating conditions, thus reducing overshoot and improving stability. Latest derivatives such as Fractional-Order Fuzzy PID (FOPID) by Sha and Chen [7] controllers and hybrid fuzzy-evolutionary techniques have also improved accuracy for advanced industrial processes such as induction heating, power electronics, and biomedical systems [8]. Fuzzy clustering algorithms such as Kernel Fuzzy C-means have also been employed to tune PID gains in noisy and nonlinear systems to obtain favorable tracking accuracy and energy efficiency by Mazloomi *et al.* [9]. During the past years, the invention of fuzzy PID controllers' points to their promising role in bridging the gap in the limitations of traditional PID by saving energy, enhancing control accuracy, and providing real-time adaptability in a wide array of smart and industrial applications.

A recent research by Katayev *et al.* [6] focused on the challenge of comfortable indoor conditions inside commercial and residential buildings by adopting novel HVAC control methodologies. Decoupled control strategies were combined with PID controllers, where self-tuning parameters were based on fuzzy logic in attempting to regulate heating and humidification processes. Their MATLAB simulation results, together with experimental measurements over six months, substantiated the real-world efficiency of the proposed fuzzy-PID controller. This paper, in addition to comparing various controller designs, formed the basis of interactive climate control models, a key advancement toward enhancing indoor comfort and energy efficiency. Ma *et al.* [2] presented a novel enhanced heating elimination technique to reduce screening currents in HTS (high-temperature superconducting) magnets. To solve the problem of spatially non-uniform target temperatures over magnet areas, a spatially non-uniform heating strategy was adopted. The authors constructed an electromagnetic–thermal coupling model and used the K-means algorithm for cluster analysis of heating temperature data, which established heating zones and feedback points. Then, fuzzy PID control was applied to heating control in all zones. The results of the simulation presented an astonishing 86.21% reduction in screening currents, confirming the effectiveness of clustering-aided fuzzy PID control. The drawback is that it relies on a model assumption, which may possibly need to be repeated when working with magnets of different geometries or operation conditions.

Additionally, Panwar and Nanda [5] responded to the outlier and noise sensitivity of traditional FCM clustering by introducing the distributed kernel-based weighted FCM (DKWFCM) algorithm. The algorithm utilized kernel-induced distance metrics and diffusion-based distributed learning to improve robustness in clustering for wireless sensor networks (WSNs). When compared to artificial and actual data sets, DKWFCM proved superior to distributed FCM (DFCM) and distributed weighted FCM (DWFCM) with mean Euclidean deviation reductions between 10% and over 90% depending on the data set.

The contributions are higher flexibility, preservation of privacy, and greater accuracy in distributed environments. However, the method raises computational complexity, possibly deterring scalability in extremely large real-time networks. Miraftabzadeh *et al.* [10] focused on some clustering alternatives or complements to traditional K-means, such as K-Medoids, time-series K-means, BIRCH, and Bayesian clustering. They showed the accelerated use of clustering methods in power systems today, emphasizing that striking the proper balance between the dimensions of accuracy, initialization sensitivity, and scalability is an important matter. While their research enhanced the concept of algorithmic diversity, it did not show empirical proof of performance enhancement in actual control systems. Therefore, it created a gap in practical application. Liu *et al.* [11] combined PSO (Particle Swarm Optimization) and fuzzy PID for improvement in the temperature control of CFRP (carbon fiber reinforced polymer) curing by electromagnetic induction heating. Their improved PSO-PID algorithm was self-tuning and optimized the parameters of PID to reach quicker adaptation, less overshoot, and lower steady-state error than the traditional PID. Both simulation and experiments showed notable improvements in response time and control precision. Reliance on evolutionary optimization, however, makes computation time longer, while performance may be inconsistent with system complexity and noise levels.

Various clustering techniques, including Hierarchical clustering, K-means, Gaussian Mixture Models (GMM), Fuzzy Clustering, and Neural Network-based algorithms, have been explored in new developments of temperature control studies to delve into the patterns of energy consumption and thermal comfort within office buildings. These methodologies have indeed provided useful insights for better management of indoor environments by identifying regions with similar thermal behavior and thus facilitating localized control measures. Nevertheless, most of these techniques limit themselves to static clustering, failing to represent the dynamic and changing dynamics of indoor climate conditions. Wei *et al.* [12] proposed a temporal clustering algorithm for the zonation of thermal zones in buildings based on thermal orthoimages obtained from 3D thermal scanners in building control systems. Results have been very effective in furnishing the spatial and temporal representation of heat distribution to support more accurate zoning and energy optimization. The added value consists of combining the temporal with the spatial, while the application is restricted to specialized imaging technologies; hence, it has very limited applicability in routine building control systems. Chen *et al.* [13], while studying the variation in temperature, performed time-series clustering using GMM. While this provided a more dynamic temporal perspective than that given by static methods of clustering, it was only capable of focusing on no more than a single variable, reducing its potential for capturing the complexity of indoor conditions where different parameters such as humidity, occupancy, and exterior weather play contributing factors. This narrow focus highlighted the limitation of single-variable models to multiple actual indoor climate scenarios. The current clustering methods have set a benchmark in terms of understanding energy consumption and comfort distribution [14], but their output remains constrained by a lack of temporal extent, dependence on one variable, or utilization of specialized equipment. These constraints highlight the need for more adaptive, multi-variable, and time-sensitive control systems that are capable of dealing with the nonlinear and dynamic nature of indoor spaces, resulting in next-generation fuzzy clustering and intelligent PID architectures.

The studies also focused on different intelligent control methods for the purpose of improving temperature control and stability in an environment. Huang *et al.* [15] proposed a fuzzy adaptive PID system in the control of patenting furnaces, where temperature error and error rate dynamically adjust PID gains in real time; these reduced fluctuations greatly, from 14°C to 4°C and 15°C to 5°C in different zones of the furnace, and also improved the consistency of the microstructure of steel wire. Complementing this, Shaopeng Yu *et al.* [16] designed an embedded home environment monitoring system based on an improved K-means algorithm, Kalman filtering, and BP neural networks; through this system, real-time adaptation and precise estimation of comfort can be obtained. Their system yielded high accuracy, speed in acquisition, and error rate reduction as high as 60%, while it also pointed out several directions toward low-power optimization.

While Kernel FCM enhances the robustness and accuracy of clustering in noisy or nonlinear environments, respectively, it mainly focuses on enhancing spatial data patterns without capturing temporal dynamics. This can be addressed with temporal clustering methods by the evolution of the temperature or environmental data. This enables the detailed modeling of dynamic thermal behaviors with adaptive control.

Hence, current methods show flexibility in embedding clustering, fuzzy logic, and optimization into PID controllers. Though such approaches offer measurable gains with regard to flexibility, tracking accuracy, and energy usage, they still suffer from dependency on models, sensitivity to noise, heavy computational load, and scalability. As shown in Table I, these results highlight the need for building more powerful and adaptive clustering-based PID approaches—as the FCM-PID investigated in this research—that are capable of providing reliable performance in nonlinear and dynamic settings.

TABLE I: SUMMARY OF EXISTING SYSTEMS AND THEIR LIMITATIONS

Method	Description	Limitations
Fuzzy-PID with decoupled controller [6]	Integrated PID with self-adjusting parameters informed by fuzzy logic for heating and humidification in HVAC. Simulated in MATLAB and validated with six months of experimental data.	Effective but limited to the HVAC scope; real-time scalability across diverse building types has not been fully explored.
K-means + Fuzzy PID [2]	Proposed a spatially non-uniform heating strategy for HTS magnets. Used K-means to cluster temperature zones and fuzzy PID to regulate heating, reducing screening currents by 86.21%.	Relies on electromagnetic–thermal coupling models; requires recalibration for magnets of different geometries and conditions.
Distributed Kernel-Based Weighted FCM (DKWFCM) [5]	Introduced a robust clustering method using a Gaussian RBF kernel with distributed learning in WSNs. Enhanced cluster quality, reduced noise sensitivity, and improved accuracy across synthetic and real-world datasets.	Higher computational complexity; scalability in large-scale real-time WSN deployments remains a challenge.
Time-series K-means clustering [10]	Explored various clustering techniques for applications in modern power systems; emphasized diversity of methods and trade-offs.	Conceptual and comparative study without real-world validation; lacks performance benchmarks in temperature control systems.
Improved PSO-Fuzzy PID (IPSO-PID) [11]	Combined Particle Swarm Optimization with fuzzy PID for induction heating in CFRP molding. Improved adaptation, faster response, reduced overshoot, and steady-state error.	Computational overhead due to optimization; performance is sensitive to system complexity and noise.
Temporal clustering with thermal orthoimages [12]	Used 3D thermal scanners to classify building thermal zones, integrating spatial and temporal heat distribution for improved zoning.	Dependent on specialized imaging equipment, limited practicality in standard HVAC systems.
Time-series clustering using GMM. [13]	Applied GMM to analyze indoor temperature dynamics over time; improved temporal modeling compared to static clustering.	Restricted to single-variable analysis, limiting applicability in multi-factor indoor climate control.
K-means Clustering[17]	Examined high-resolution temperature data from wireless sensors to optimize thermostat placement and determine HVAC zoning efficiency in buildings.	Limited by the precision of clustering techniques and challenges in modeling real-time temporal changes across multiple building zones.
Fuzzy C-means (FCM) Clustering [18]	Applied fuzzy clustering to select representative temperature measurement points in irregular heat transfer domains, improving estimation accuracy and efficiency.	Struggles with highly complex or nonlinear heat transfer systems where irregularities in measurement space reduce accuracy.
FOPID Controllers [19]	Demonstrated the use of fractional-order PID controllers in ambulances, induction heating, and bioreactors, achieving improvements in production quality and control accuracy.	Complexity in parameter tuning and the need for further development limit wide-scale adoption in diverse industrial applications.
PCA Method [20]	Enhanced clustering quality in high-dimensional data by adapting local PCA (Principal Component Analysis) through modifications of learning rate and potential functions.	Exhibits slow adaptation and difficulties in handling unbalanced or overlapping clusters in high-dimensional datasets.
Kernel Fuzzy C-means (KFCM) [21]	Highlighted the advantages of KFCM in managing noisy and nonlinear conditions, particularly in voice enhancement applications.	Computational inefficiency reduces applicability in real-time or time-sensitive environments.
Fuzzy Framework for Smart Home Monitoring System (FF-SHMS) [22]	Proposed an IoT-based fuzzy framework for smart home energy management with microgrid integration, enhancing energy efficiency and load regulation.	Potential inaccuracies in data predictions may affect performance and fail to account for all real-time environmental variables.

Moreover, Table II highlights the advantages of existing PID systems, like fuzzy hybrid models, FCM-based hybrid models, in addition to fuzzy adaptive PID models. However, there are some limitations of these models, such as the need for expert tuning, performance degradation under real-time conditions, and increased computational load. These systems may face issues like higher computational complexity, scalability, and generalizability, resulting in reduced effectiveness. To address these issues, the proposed model with FCM–PID and K-means–PID offers high accuracy with energy-cost reduction and real-time capability under nonlinear conditions.

TABLE II: ADVANTAGES AND LIMITATIONS OF EXISTING SYSTEMS AND THEIR LIMITATIONS

Technique	Advantages	Limitations
Fuzzy PID [7]	Improved dynamic response; reduced overshoot; enhanced robustness to load variations.	Rule-based requires expert tuning; performance may degrade under highly nonlinear or rapidly changing conditions.
Fuzzy-PID Hybrid [8]	High control precision; faster temperature rise; optimized parameters reduce steady-state error.	Optimization increases computational load; may not perform consistently in noisy or real-time environments.
Fuzzy [9]	Handles noise effectively; adaptive clustering reduces congestion; improves communication efficiency.	Higher computational complexity; scalability issues in very large or resource-constrained networks.
FCM-Based Hybrid [14]	Strong performance in high-dimensional forecasting; feature selection improves accuracy and interpretability.	Computationally heavy; unsuitable for embedded or low-latency control systems.
Fuzzy Adaptive PID [15]	Better temperature stability; adaptive tuning reduces overshoot and improves control accuracy.	Performance depends on fuzzy rule design; limited to generalizability beyond specific furnace conditions.
Improved K-Means [16]	Enhanced clustering accuracy; effective for spatial zoning and smart-home data patterns.	Hard clustering limits smooth transitions; sensitive to initialization; reduced effectiveness under nonlinear thermal dynamics.
FCM–PID and K-means–PID (proposed)	Highest accuracy (MAE 0.48°C); ~10% energy-cost reduction; smooth adaptive gain tuning; real-time capability under nonlinear conditions.	FCM introduces additional computation compared to K-means; current model limited to single-zone scenarios.

A. Research Gaps

While significant work has been done in implementing clustering algorithms like K-means, FCM, PCA, and KFCM in various fields, their implementation on fuzzy-based temperature control systems for nonlinear systems is minimal.

- Existing studies lack energy efficiency considerations, as most clustering or fuzzy PID approaches focus on tracking accuracy and need to adequately address power optimization in temperature control systems.
- With limited research quantifying operational savings, they lack evaluating cost efficiency or the economic impact of adaptive controllers in real-world applications.
- It has poor adaptability to nonlinear and dynamic settings, as techniques such as K-means are prone to initialization sensitivity, and FCM is challenged by non-uniform heat transfer systems.
- Sophisticated methods using PCA or KFCM suffer from computational inefficiency and slow adaptation, which do not allow realistic applications in smart homes or HVAC systems.

A review of the existing fuzzy PID, clustering-enhanced control, and hybrid optimization methods shows clear progress but leaves several challenges: first, less than 15% of the surveyed studies apply clustering directly within temperature control systems, indicating limited exploration in this domain; second, only about 10-12% of the previous works quantify energy efficiency, with most of them being limited to tracking accuracy; third, less than 5% of clustering-PID integrations study real-time adaptability under nonlinear and time-varying indoor conditions; finally, no previous study has ever addressed soft clustering, dynamic PID gain tuning, and cost optimization simultaneously. These numerical gaps create the need for a unified, adaptive, and energy-aware control approach, such as the FCM-PID system developed within this research.

This paper proposes a PID framework based on clustering, combining K-means and Fuzzy C-means for better adaptability to temperature changes. By using soft clustering, the FCM-PID enables smoother switchings and stable error profiles with higher accuracy compared to using hard clustering and static controllers. The FCM-PID reduces the steady-state error and improves tracking accuracy, and saves energy. The suggested method goes beyond the inflexibility of traditional PID and also the inefficiencies of previous cluster methods by providing a scalable and energy-aware solution in practical smart home and HVAC use.

B. Theoretical Framework of Adaptive PID Control

Adaptation in PID control is based on three gain adjustments, including integral, proportional, as well as derivative, because of dynamic changes in the system's behavior. Temperature profiles in nonlinear thermal environments often cross operating regimes where fixed parameters of the PID are not sufficient. Fuzzy clustering through K-means and FCM identifies such regimes by grouping temperature data in distinct or overlapping states representative of underlying nonlinearities. Hard clustering, like K-means, suggests the existence of abrupt transitions between states, whereas soft clustering assigns membership degrees across clusters to represent gradual variation. The cluster characteristics provide indications of the variation of the system dynamics. This enables the mapping of the latter to a corresponding set of PID gain sets, finally allowing real-time data-driven adaptation. This provides a comprehensible evolution to the real execution of the proposed framework.

III. METHODOLOGY

Clustering-based approaches are deployed in this work to enhance the performance of the temperature control systems, which are usually used to provide comfort and stability under varying conditions. This work proposes a hybrid FCM and K-means algorithm of clustering for the classification of temperature data with dynamic optimization of PID controller parameters. The method improves tracking precision, saves energy, and provides adaptive control under changing ambient conditions. The simulations will be performed using MATLAB 2024, ensuring a solid implementation of the advanced control strategies. The proposed approach will have great potential for the intelligent, fuzzy-based control of smart homes. All these are with adaptive solutions in time-varying and nonlinear thermal environments and with optimal real-time energy management.

A. Clustering

Fuzzy clustering is a method of data analysis that groups data based on similar characteristics. Conventional methods of clustering have assigned data points separately into a single cluster, while in fuzzy clustering, data points can be assigned to more than one cluster through diverse grades of relations. This is particularly effective for systems that operate under continuous changes of state, such as temperature control systems. In this case, clustering allows a better description of temperature fluctuations, and this improves the performance of adaptive PID controllers.

- *Fuzzy C-means (FCM) clustering:* FCM is utilized to classify temperature readings into soft clusters such that any data point will be an adherent of numerous clusters with varying membership grades. Soft clustering forms smooth boundaries and adaptive PID gain control, particularly under nonlinear or dynamic conditions. The fuzzy membership values are afterwards projected onto hard labels by selecting the maximum membership degree (μij) for every data point. These labels are then utilized to dynamically tune PID gains in real time with better temperature tracking performance and energy consumption than K-means or traditional PID controllers.
- *K-means clustering:* It is a well-known unsupervised data partitioning algorithm into non-overlapping, separate clusters. In this study, temperature data are grouped into three clusters, allowing for dynamic PID gain selection according to the operating condition. Pre-defined sets of gains per cluster allow the controller to respond dynamically to changes in temperature behavior. Although K-means is NP-hard and sensitive to initial centroid locations, its efficiency and scalability make it suitable for real-time temperature system control.

B. MATLAB Simulation Environment

MATLAB 2024 is employed as the simulation and implementation environment based on its high-performance computational capability, visualization facilities, and specific toolboxes (Fig. 1). The simulations were performed on an Intel Core i7 processor system (2.9 GHz) with 16 GB RAM and Windows 11 OS using MATLAB 2024a. Its fuzzy logic toolbox makes it easy to design fuzzy inference systems for adaptive temperature control. The simulation simulates the thermal behavior of a smart home, with consideration for heat transfer through walls, windows, and roofs. Temperature sensors offer real-time indoor and outdoor readings at intervals of 300 seconds, offering precise feedback for control purposes. MATLAB allows thorough analysis, visualization, and verification of the clustering-based PID approaches.

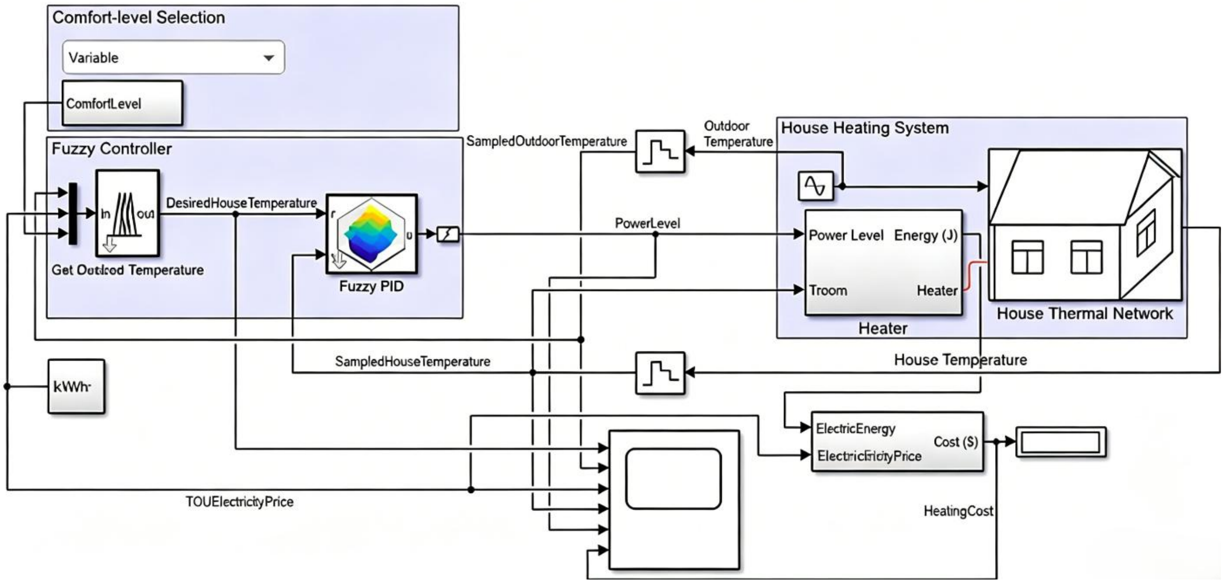

Fig. 1 Implementation of the temperature control system.

For this analysis, a room with a volume of 30 m³ was assumed, medium-grade insulation on the walls, predefined heat-transfer coefficients based on typical residential conditions of both convection and conduction, with environmental constraints such as: ambient temperatures in the range 20° C to 32° C, low air-leakage to model moderate infiltration, and internal heat sources such as occupant presence and small appliances. These assumptions create boundary conditions that are well-defined, allowing for complete reproducibility of the thermal simulation.

C. Fuzzy Logic Control for Temperature Regulation

The system utilizes two Fuzzy Inference Systems (FIS):

- *Desired Temperature FIS:* Identifies the optimal room temperature based on outdoor temperature, electricity price, and comfort level specified by the user.
- *Fuzzy PID FIS:* Controls heater power to keep the desired temperature.

Three comfort levels—minimum, variable, and maximum—enable users to set a balance between comfort and energy expense. The minimum level keeps 20° C for cost-saving, the maximum level keeps 22° C for peak comfort, and the variable level strikes a balance between temperature and energy consumption.

- *Fuzzy PID Controller:* The fuzzy PID controller (Fig. 2) takes in error (E) and change in error (ΔE) signals, which are gain-scaled and subjected to the fuzzy inference system. The output is split into PI and PD branches, and their sum constitutes the heater's control signal. This design allows for continuous and adaptive temperature control under changing environmental conditions.
- *K-Means PID Controller:* The PID controller implemented based on K-means divides present temperature readings into a cluster of one of three clusters. For all clusters, a set of PID gains is used dynamically at runtime. Thus, the PID controller changes its integral, proportional, as well as derivative gains based on live conditions to enhance tracking precision and energy efficiency over a standard fixed-gain PID system.

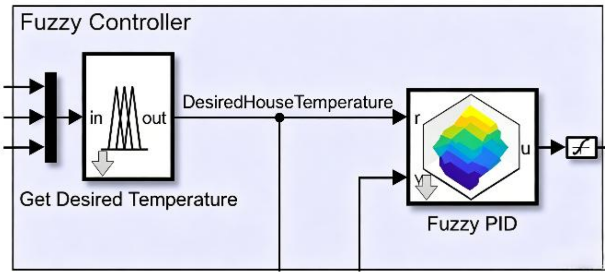

Fig. 2. Fuzzy controller.

D. Simulation Performance Evaluation

The simulation compares three systems under dynamic temperature conditions: Traditional PID, K-means-based PID, and FCM-based PID.

- *Initialization and Ambient Data Generation:* The simulation is for 500 seconds with 500 samples; sinusoidal ambient temperature changes and Gaussian noise are used for realistic fluctuations. A setpoint of 20°C is maintained constant to assess performance.
- *Clustering-Based Preprocessing:* Temperature readings are clustered using K-means and FCM ($k = 3$). K-means has hard labels, whereas FCM produces soft memberships, which are transformed into hard labels for PID tuning.
- *Controller Operation:* The conventional PID uses fixed gains, while K-means and FCM scale the gains adaptively. FCM ensures smooth transitions by virtue of its fuzzy membership values
- *Visualization and Analysis:* Temperature traces and error plots are generated to evaluate control performance
- *Cost and Statistical Analysis:* Mean Absolute Error (MAE) quantifies tracking precision, while the energy consumption is translated into cost. Results were that the MAE was lowest for the FCM-PID controller, with a near 10% decrease in energy costs based on the traditional PID. This definitely proves that clustering-based adaptive control holds its ground.

This approach emphasizes the combination of clustering and fuzzy logic to realize adaptive, energy-efficient, and highly accurate temperature control applicable in practical smart home settings.

E. Mathematical Model

In this work, FCM clustering is employed as a sophisticated unsupervised learning method to categorize temperature data into soft clusters. The objective function in the FCM algorithm is minimized as shown in the following equation:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \left\| x_i - \mu_j \right\|^2 \quad (1)$$

where the number of data points N indicates the temperature samples. The number of clusters C is 3 in this research, while x_i and c_j signify the ith data point and the centroid of the jth cluster, and the degree of membership of x_i is represented by u_{ij} in cluster j. Moreover, fuzziness exponent $m > 1$ (typically $m = 2$) controls the cluster fuzziness level.

It implies how strongly a data point can belong to more than one cluster. Greater values of m have softer membership boundaries. Centroids C_j are updated as weighted means of data points based on μ_{ij} raised to the power m. The objective function J_m of FCM minimizes weighted squared distances between each x_i and its cluster centroid.

To update membership values, the equation calculates the degree to which point x_i belongs to cluster j based on its distance to all cluster centroids as below:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}} \quad (2)$$

Updating cluster centers, the equation computes the new centroid c_j of cluster j as the weighted average of all data points, weighted by their membership degrees raised to the power m, as shown below.

$$C_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \quad (3)$$

In this research, K-means clustering is utilized for the temperature dataset that minimizes the squared Euclidean distance between data points and the centroids of their respective assigned clusters. For a given dataset $X = \{x_1, x_2, \cdots, x_n\}$, the K-means algorithm seeks to divide it into k clusters $C = \{C_1, C_2, \cdots, C_k\}$ by minimizing the cost function:

$$J = \sum_{j=1}^{k} \sum_{x_i \in C_j} \left\| x_i - \mu_j \right\|^2 \quad (4)$$

where μ_j is the centroid (mean) of cluster C_j, and

$\left\|x_i - \mu_j\right\|^2$ is the squared Euclidean distance between data point x_i and centroid μ_j.

The algorithm proceeds through initialization (Step 1), where it randomly selects k initial centroids. Then it assigns (Step 2) each data point to the cluster with the nearest centroid, using:

$$C_j = \{x_i : \left\|x_i - \mu_j\right\|^2 \le \|x_i - \mu_l\|^2 \forall l, 1 \le l \le k\} \quad (5)$$

Furthermore, redetermining the centroids (Step 3) by taking averages of the data points allocated to each cluster gives an equation as below.

$$\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i \quad (6)$$

Repeat steps 2 (assigning data point) and 3 (redetermining the centroids) until centroids converge, i.e., changes drop below a threshold or cease completely. Group the temperature data into three clusters so that the PID controller can switch dynamically between preset sets of gains. This adaptive control enhances system responsiveness and efficiency in energy. The equations explain the objective function, in addition to updating membership as well as the centroids in compact form. It collectively defines the adaptive clustering utilized to guide the PID gain tuning deprived of recapping the intermediate derivations.

The proposed model represents an adaptive tuning mechanism motivated by FCM clustering membership values. These values represent the degree to of the current thermal state fits every cluster. These clusters are associated with a predefined set of gains comprised of K_p^j, K_i^j, K_d^j gains. The adaptive gains are computed in real time by taking a weighted sum of these values based on the corresponding membership grades. Mathematically, it is expressed as below.

$$K_p(i) = \sum_{j=1}^{C} \mu_{ij} K_p^j \quad (7)$$

$$K_i(i) = \sum_{j=1}^{C} \mu_{ij} K_i^j \quad (8)$$

$$K_d(i) = \sum_{j=1}^{C} \mu_{ij} K_d^j \quad (9)$$

Here, membership μ_{ij} is meant for the existing temperature sample in cluster j. The controller can interpolate smoothly between gain sets. This continuous adaptation to nonlinearities and dynamic variations in thermal behavior can be achieved. For example, for membership across three clusters, such as 0.6, 0.3, and 0.1, the controller mixes the corresponding gains in proportion, hence providing finely tuned responsiveness against abrupt switching. In essence, therefore, the algorithm operating at the backend updates PID gains at each control cycle by calculating memberships through FCM and arriving at adaptive gains being applied within the PID law, hence allowing for precise set-point tracking, reduced oscillations, and improved energy-efficient operation in real time. Table III defines terms used in the mathematical model.

TABLE III: SYMBOLS WITH DEFINITION

Term	Definition
μ_{ij}	Membership degree of data point x_i belonging to cluster j in Fuzzy C-Means (FCM), indicating soft clustering strength.
m	Fuzziness exponent ($m > 1$), controlling the degree of cluster fuzziness; typically set to 2 in FCM.
C_j	Centroid of cluster j, computed as the weighted mean of all data points based on membership degrees.
x_i	ith temperature data sample used in clustering and PID gain adaptation.
N	Total number of temperature samples used in the clustering process.
C	Number of clusters (C = 3 in this study for PID gain tuning).
J	Optimization function minimized by FCM to generate soft clusters based on weighted distances.
MAE	Mean Absolute Error: a performance metric quantifying average deviation between actual temperature and setpoint.

IV. RESULTS AND DISCUSSION

The result is to highlight the better temperature measurement accuracy and lower energy cost obtained with FCM, along with K-means clustering-based PID controller tuning compared to a conventional fixed-gain PID controller. A simulation of 500 seconds and 500 sample points was carried out to simulate natural day-to-day ambient temperature variation, adding extra Gaussian noise to simulate real sensor performance. The comfort temperature setpoint remained constant at 20°C in all tests, thus providing a benchmark standard on which to compare the performance of the controllers.

To react to the shifting environmental states, the system applied K-means and FCM clustering on the temperature states, grouping them into different clusters. A certain setting of the PID gain was allocated to each cluster, dynamically selected based on the cluster label at that time. With this, the controller can scale its action in accord with prevailing temperature trends in real time, in contrast to the old-fashioned PID controller applying constant gains and reacting less toward abrupt temperature variations.

A. Accuracy in Temperature Tracking

Comparative studies of temperature tracking show that both cluster-based controllers outperform the traditional PID system. The FCM-PID controller has the best accuracy, maintaining the 20° C set point with a very small deviation since its soft clustering allows smooth control mode switching. The K-means PID also shows better tracking performance but is less flexible than FCM owing to its hard cluster assignments. Simulation results are given in Table IV.

TABLE IV: COMPARISON OF MEAN ABSOLUTE ERROR IN PID USING K-MEANS AND FCM OVER THE TRADITIONAL METHOD

Method	Mean Absolute Error (MAE)	Accuracy (%)
Traditional PID	0.59 °C	97.05
K-means PID	0.53 °C	97.35
FCM PID	0.48 °C	97.60

FCM-PID yields the minimum MAE of 0.48°C, showing good tracking precision and less oscillatory response. The K-means PID provides an enhanced accuracy of 0.53°C due to dynamic gain tuning based on cluster belongingness, while the classical PID reaches 0.59°C with fixed gains. These results confirm that FCM provides maximum accuracy and adaptiveness in temperature control among the tested methods.

The overall accuracy of FCM PID thus improved to 97.60%, compared with K-means PID at 97.35% and conventional PID at 97.05%. The improvement validates that the use of soft clustering is effective in minimizing tracking error, enabling smoother switching of control, and being nearer to the setpoint. The marginal and persistent precision improvement of FCM PID over K-means PID testifies to its excellence in addressing nonlinear and dynamic temperature fluctuations with less overshoot and oscillations.

B. Power Cost Comparison

Energy usage was obtained by translating the power of the control signal into energy (kWh) and then calculating the cost in Rupees. The power output was limited to non-negative values, as in actual heating systems, as shown in Table V.

TABLE V: COMPARING TRADITIONAL METHOD FOR ENERGY COST OF PID WITH K-MEANS AND FCM OVER

Method	Energy Cost (Rs)
Traditional PID	Rs 5.33
K-means PID	Rs 5.01
FCM PID	Rs 4.82

The FCM-PID system conserves about 10% of the cost against the traditional PID, with efficient energy consumption through adaptive control. K-means PID saves cost too, brought down to 5.01, although slightly lower than FCM to 4.82. These results demonstrate that clustering-based adaptive PID control, particularly FCM, not only improves temperature accuracy but also reduces energy consumption, thereby becoming exceedingly suitable for energy-saving applications such as smart homes or industrial air-conditioning systems. The Fig. 3 compares the standard PID strategy with the K-means PID and FCM-PID systems, demonstrating that the FCM approach attains the minimum MAE and Cost.

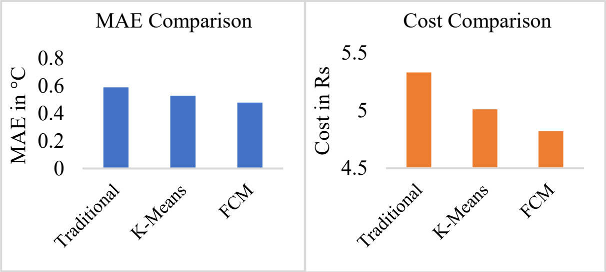

Fig. 3. Comparison of three methods for MAE and cost.

Energy efficiency is principally achieved by reducing tracking error and lowering the cost of energy. The proposed FCM-PID controller lowered the MAE to 0.48° C with greater compliance to the setpoint and fewer oscillations and overshoot. This enhanced accuracy resulted in immediate savings by directly translating into optimized heater operation and leading to approximately 10% reduction in cost compared to the conventional PID controller, thus vindicating the double advantage of accuracy and energy savings.

C. Graphical Analysis

Simulation plots (Fig. 4) enable a visual comparison between temperature response and tracking errors for the three controllers across the 500-second simulation interval.

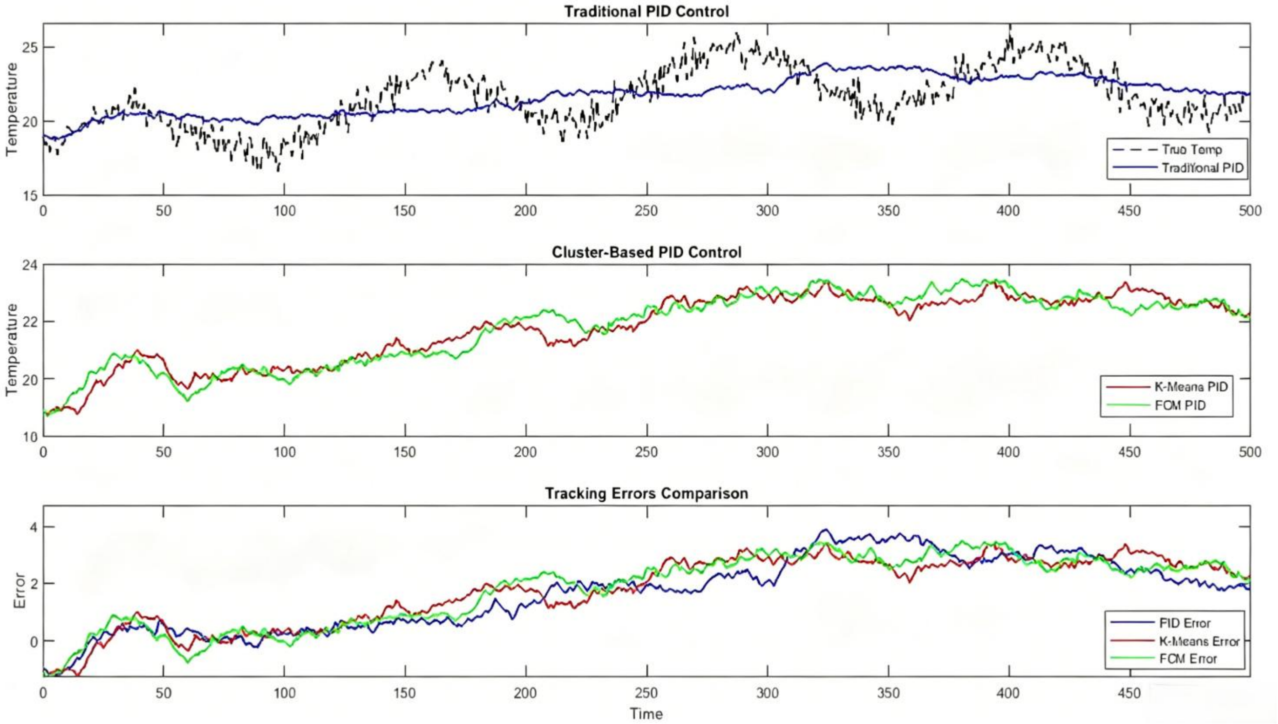

Fig. 4. Temperature response and error recorded in PID controllers.

In the first graph, traditional PID control is analysed. The black dashed line indicates the true ambient temperature with fluctuations, while the solid blue line represents the temperature response using the traditional PID controller. The traditional PID controller shows slower response and greater oscillations about the 20°C setpoint, indicating poor adaptability to dynamic ambient conditions. In the second graph, the K-means PID dynamically adapts gains according to cluster labels and yields better setpoint tracking. There are some discontinuous transitions in temperature response due to hard clustering. FCM PID shows the smoothest and most robust temperature trace. Soft clustering allows for fine-tuning of PID gains, reducing overshoot, oscillations, and steady-state error.

In the last graph, the errors comparison directly compares the tracking error from the setpoint for all approaches. Absolute tracking error is highest and most scattered for the conventional PID, lower for K-means PID, and lowest and least scattered for FCM PID during the course of simulation.

Thus, the graphical analysis establishes that clustering-based optimization, especially with FCM, greatly improves temperature control performance by tightening setpoint tracking and reducing oscillations in errors. The findings show that incorporating clustering algorithms into PID control, particularly Fuzzy C-means, results in better temperature control and lower operating expenses. The best accuracy, smoothest response, and lowest energy expenditure are attained by FCM-PID, making it the better algorithm for smart, energy-saving temperature control in practical applications like smart homes and industrial HVAC spaces.

D. Discussion

A new technique combines clustering algorithms like FCM and K-means, together with PID control, in order to enable adaptive and energy-efficient temperature control under changing conditions. In contrast with conventional fixed-gain controllers, cluster-based techniques adaptively change the PID parameters according to the prevailing thermal condition, permitting quick, smooth, and accurate responses due to temperature changes. FCM provides soft clustering, allowing partial membership in several clusters, which enables smoother switching between the control modes, while K-means has hard clustering for discrete gain corrections.

The results obtained confirm and extend the observations made in earlier works related to fuzzy-PID and clustering-assisted control systems. An example could be error reduction using FCM-PID, similar to observations from Katayev *et al.* [6] and Ma *et al.* [2], who also recorded enhanced thermal stability through their adaptive tuning. However, our dual-clustering approach demonstrates better continuity of adaptation without the drawbacks noticed in their single-method approaches.

The results confirm that the proposed clustering-based PID control systems are effective for improving the performance of temperature control. Clustering implemented in the PID system helps it to be more adaptive and reactive to changes in environmental dynamics. Of the methods tested, the FCM-PID controller is superior to traditional and K-means PID controllers. By performing clustering, dynamic gain tuning is enabled such that a system can adapt more effectively to temperature swings. In particular, the FCM provides smoother state transitions among the control states so as to minimize the overshoot and prevent overcorrection. Simulation results also confirm this. In the case of temperature monitoring, the FCM-PID controller recorded the minimum MAE of 0.48°C against the 0.53° C of K-means PID and 0.59° C of standard PID. Thus, it indicates a higher setpoint conformity with fewer oscillations. Energy cost calculation reveals that FCM-PID has recorded the minimum cost of Rs 4.82. That clearly shows the role of energy efficiency in large-scale or long-duration applications at buildings or industries. Error behavior justifies stability for the FCM strategy, having the lowest and most uniform error profile throughout the simulation. The presented method has several key advantages compared to other available methods, including increased adaptivity by dynamic adjustment in order to make the system efficiently react to time-varying and nonlinear ambient conditions.

Soft clustering provided through FCM allows for precise setpoint tracking with almost negligible overshoot and steady-state error. Energy use and expenses are minimized by synchronizing the control efforts with instantaneous thermal conditions. It has applications in smart homes and commercial HVAC systems where comfort and cost are important.

TABLE VI: COMPARING RESULTS OF EXISTING AND PROPOSED SYSTEMS

Ref.	Author	Results	Outcomes
[2]	Ma *et al.* (2025)	86.21% reduction in screening currents using K-means + fuzzy PID.	Shows strong improvement via clustering + fuzzy control, but not in temperature MAE.
[11]	Liu *et al.* (2024)	Response time ↓ 34%, overshoot ↓ 17%, adjustment time ↓ 65% using PSO-Fuzzy PID.	Demonstrates significant dynamic-performance gains compared to conventional PID.
[15]	Huang *et al.* (2024)	Temperature fluctuation reduced 14°C → 4°C and 15°C → 5°C with fuzzy adaptive PID.	Indicates major improvement in steady-state temperature stability.
[16]	Yu *et al.* (2025)	>60% reduction in error rate using improved K-means–based intelligent home system.	Confirms large accuracy gains from enhanced clustering approaches.
Proposed	FCM-PID (this study)	MAE = 0.48°C, Accuracy = 97.6%, Energy cost reduction ≈ 10% vs. traditional PID.	Direct improvement in HVAC-relevant metrics: lowest error and measurable cost savings.

A comparative analysis (Table VI) shows that existing systems demonstrate robust yet domain-specific improvements. For example, Ma *et al.* attained a screening current reduction of 86.21%, while Liu *et al.* reported an enhanced response of 34%, overshoot of 17% lower, and adjustment time of 65% with PSO-Fuzzy PID. Huang *et al.* enhanced temperature stability by reducing furnace fluctuations from 14°C to 4°C and 15°C to 5°C, and Yu *et al.* reached error-rate reduction rates of more than 60% with an improved K-means model. On the other hand, the proposed FCM-PID will give a combined performance advantage because it has achieved MAE=0.48° C, 97.6% accuracy, and ≈10% reduction in energy cost, offering higher precision with simultaneously measurable economic benefit that previous approaches have not explored.

Indeed, the proposed FCM-PID controller is suitable for real-world, real-time temperature control, since both membership updates and gain adjustments operate efficiently on small, streaming datasets. While FCM is computationally more intensive compared to K-means due to iterative membership calculations, the overhead is still manageable in most embedded HVAC controllers. K-means PID represents a lower complexity and faster execution alternative, but it lacks smooth adaptability. Overall, the FCM-PID achieves real-time performance with superior accuracy and stability, thus making it feasible to be deployed in smart home and industrial HVAC environments.

Originality of this work includes the integration of FCM and K-means clustering in optimizing PID for dynamic thermal conditions. While earlier research has used either clustering or fuzzy logic separately, the current work offers a theoretical integration of adaptive PID control and unsupervised clustering for concurrent, accurate temperature monitoring and low-cost operations. The contribution of this work towards the state of the art in intelligent control systems is the data-driven, adaptive, and computationally plausible solution for real-time temperature control in an evolving environment. The new system thus demonstrates obvious advantages of better flexibility, higher precision, as well as lower energy consumption. It leads to a promising solution for engineering, intelligent, real-time, and energy-saving temperature control in practical applications.

V. CONCLUSION

Outcomes from this research indicate that the integration of clustering algorithms into a PID controller works best in adaptive thermal control under dynamic situations. From among the two schemes compared, the FCM-based PID controller performed much better than the traditional PID and K-means-based PID in terms of error robustness, energy saving, and tracking accuracy of temperature. In simulation output, FCM-PID maintained the closest representation of the set-point of 20°C with the least MAE of 0.48°C, while that of K-means PID was 0.53°C and that of traditional PID was 0.59°C. Energy-wise, FCM-PID had the lowest cost of Rs 4.82, which is around 10% lower compared with that from a traditional PID, whereas K-means PID earned Rs 5.01. In essence, the suggested approach will provide an adaptive nature that allows dynamic gain adjustment based on real thermal conditions during runtime. The feature provides smooth transitions in control states, with reduced overshoots and oscillations, so that it optimizes the FCM-PID system for smart HVAC systems in residential, commercial, and industrial use. The work characterizes the systematic integration of clustering-based adaptive control with a PID system into a data-driven scheme for real-time regulation of temperature. The conclusions form the basis of the design for smart, energy-efficient, and practical control schemes in temperature-critical processes and offer both practical impact and future research orientation in modern control systems.

The novelty here is in comparing K-means with FCM to realize adaptive PID tuning that intelligently responds to the shifting thermal states. This ensures seamless transitions between gain sets, enhancing stability and precision. Embedding data-driven regime detection within the control loop, the proposed framework has delivered superior performance compared to conventional PID and earlier fuzzy-based techniques and therefore represents a valuable contribution to smart environmental control systems.

Although the proposed scheme of the clustering-integrated PID system shows very significant improvements, the current scheme is limited to single-zone conditions and employs pre-established clusters as the basis for PID tuning. Despite the good performance shown, there are some relevant limitations to the proposed adaptive PID framework, concerning the computational overhead of real-time clustering and integration challenges that may occur while deploying the model to low-power microcontrollers in smart-home devices. Moreover, when considering multi-room or large residential environments, the approach may require more complex coordination and distributed control. The future work will adopt a lightweight clustering algorithm and hardware-efficient implementations, together with multi-zone control strategies, to improve scalability and practical deployment. It may explore integrating Model Predictive Control (MPC) into clustering algorithms to enhance the accuracy and responsiveness of the overall system prediction. Such a system can be scaled up to multi-zone applications in residential or commercial spaces so that zone-wise optimization can be achieved for enhanced comfort management. Furthermore, the use of renewable energy sources like solar power would reduce the costs of operation and improve sustainability, thereby making the system more scalable, smart, and green for actual field deployment.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Vaishali P. Salve and Varsha D. Yelmar conducted the research under the supervision of Magan P. Ghatule;

Vaishali P. Salve and Magan P. Ghatule performed the data analysis; Varsha D. Yelmar and Magan P. Ghatule worked on the simulations; Vaishali P. Salve and Varsha D. Yelmar prepared the manuscript draft; Vaishali P. Salve and Magan P. Ghatule reviewed and finalized it; all authors have read and approved the final version of the manuscript.

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