Experimental Evaluation of Control Strategies for an IoT-Enabled Solar Thermal System

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***Abstract*— The operational performance of a flat-plate solar thermal collector (STC) depends strongly on the effectiveness of circulation pump control, which regulates the transfer of heat between the collector and the storage tank. Conventional on–off controllers with hysteresis remain dominant due to their simplicity, yet their limited adaptability often results in temperature fluctuations, inefficient use of available solar energy, and increased mechanical stress on components. This paper presents an experimental validation of a fuzzy logic controller (FLC) in a domestic scale IoT-enabled STC system equipped with a load-side heat exchanger that simulates domestic hot water consumption. Comparative experiments under variable weather conditions demonstrate that the FLC achieves smoother and more stable temperature regulation, improves overall thermal efficiency, increases the useful thermal power delivered to the storage tank, adapts more effectively to environmental variations, and reduces wear on the circulation pump, compared with conventional on–off control. Furthermore, the study develops and implements a framework that integrates simulation-based design, industrial hardware implementation, real-world experimentation, and IoT-enabled monitoring. This framework provides hands-on learning experiences that extend beyond theoretical design and simulation, equipping researchers with practical skills in system dynamics, controller programming, experimental data analysis, and digital transformation for sustainable energy management.**

Keywords—Experimental Evaluation, Fuzzy Logic Control, IoT-Based Control and Monitoring, Solar Thermal Systems

I. INTRODUCTION

A. Background and Motivation

The growing global demand for sustainable energy has positioned renewable thermal systems as a cornerstone of modern energy infrastructure. Among these technologies, solar thermal collectors (STCs) play a crucial role in domestic hot water production and in reducing reliance on fossil fuels [1], [2]. While significant progress has been achieved in collector design and thermal storage technologies, the overall efficiency, reliability, and longevity of STC systems are strongly influenced by their control strategies, particularly those regulating the circulation pump responsible for transferring heat from the collector to the storage tank [3], [4]. In domestic-scale applications, circulation pump control has traditionally been implemented using simple, low-cost on–off controllers with hysteresis [5]. These controllers activate the pump when the temperature difference between the collector and the storage tank exceeds a predefined threshold and deactivate it otherwise. Despite their simplicity and robustness, such controllers exhibit limited adaptability to changing environmental and load conditions. This often leads to frequent pump cycling, temperature oscillations within the storage tank, increased mechanical wear, and suboptimal utilization of available solar energy [6].

To overcome these limitations, continuous control strategies, most notably Proportional–Integral–Derivative (PID) controllers have been investigated [7]. By modulating the pump flow rate rather than operating in a binary manner, PID control can enhance temperature stability and reduce mechanical stress. However, the performance of PID controllers is highly dependent on accurate parameter tuning, which is challenging in solar thermal systems characterized by nonlinear dynamics, time-varying behavior, and strong sensitivity to meteorological conditions. More advanced control techniques, such as Model Predictive Control (MPC), have been proposed to further improve system performance [8]. MPC employs dynamic models to predict future system behavior and optimize control actions over a finite horizon, enabling improved thermal efficiency and reduced unnecessary pump operation [9]. Despite these advantages, MPC requires accurate system modeling, substantial computational resources, and sophisticated implementation, which limits its practicality for small-scale, cost-sensitive residential systems.

These challenges motivate the exploration of control strategies that can cope with the nonlinear, time-varying, and uncertain nature of solar thermal systems without demanding precise mathematical models or excessive computational resources. Fuzzy logic control offers an attractive compromise between simplicity and adaptability, as it can encode expert knowledge and respond smoothly to environmental variations [10]. Although previous studies have indicated the potential advantages of fuzzy logic controllers for solar thermal applications, many of these investigations are limited to simulation-based analyses or controlled laboratory environments [11], [12]. Consequently, there remains insufficient experimental evidence demonstrating their practical benefits under realistic operating conditions.

At the same time, the increasing adoption of Internet of Things (IoT) technologies in energy systems creates new opportunities for implementing and evaluating advanced control strategies in real-world settings [13]. IoT-enabled platforms allow continuous monitoring, high-resolution data acquisition, and systematic performance comparison, yet they have rarely been leveraged for experimental validation of control methods in domestic-scale solar thermal systems with representative load dynamics.

Motivated by these gaps, this study aims to provide an experimental evaluation of fuzzy logic–based pump control in an IoT-enabled domestic solar thermal system and to benchmark its performance against conventional on–off control under variable weather conditions. By bridging the gap between simulation, hardware implementation, and real-world experimentation, the work seeks to deliver practical insights into control effectiveness, system efficiency, and operational robustness, thereby supporting the development of more intelligent, reliable, and sustainable solar thermal energy systems.

B. *Organisation of This Paper*

The remainder of this paper is organized as follows. Section II presents the methodology adopted in this study, including the control design for the experimental flat-plate solar thermal collector system, simulation procedures, hardware implementation, and experimental validation. Section III describes the control strategies under investigation, encompassing both the conventional on–off controller and intelligent approaches such as the fuzzy logic controller. Section IV provides a comparative analysis of the control systems based on experimental results obtained under variable operating conditions. Finally, Section V concludes the paper and outlines future perspectives for further research and development.

II. Methodology: Control Design, Simulation, Implementation and Validation

The proposed methodology is designed to ensure rigorous technical validation of control strategies for solar thermal systems. As illustrated in Fig. 1, the approach follows a structured workflow that integrates theoretical design and simulation, industrial control deployment, real-world experimentation via IoT-based monitoring, and comparative performance evaluation. Each stage builds upon the preceding one, enabling a coherent transition from conceptual design to experimental implementation.

By integrating simulation and field experimentation within a unified framework, the methodology supports systematic performance assessment and reliable comparison of control strategies. This approach strengthens the validity of the experimental outcomes and provides a scalable and repeatable process for the development, deployment, and evaluation of intelligent control solutions in renewable thermal energy systems.

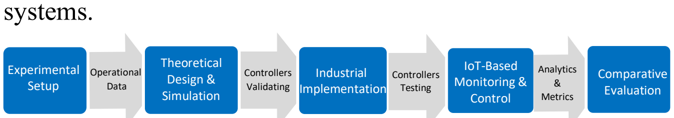

Fig. 1. Integrated methodological framework for control design, simulation, implementation, and validation.

A. *Experimental Setup*

The experimental installation, schematically shown in Fig. 2, consists of a flat-plate solar thermal collector, a 150-liter insulated storage tank, and a load-side heat exchanger with adjustable cooling demand to simulate domestic hot water consumption. The presence of load-side dynamics provides a realistic environment to observe how fluctuations in demand influence temperature stability and overall system performance.

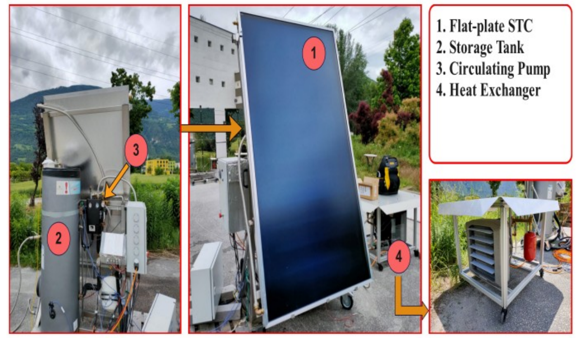

Fig. 2. Experimental solar thermal installation in Granges, Switzerland.

B. *Theoretical Design And Simulation*

The second stage is carried out in MATLAB/Simulink, where detailed models of the complete solar thermal system are developed. Within this environment, the different control strategies are simulated. For example, for the fuzzy logic controller, the fuzzy inference system is designed and tuned by defining membership functions, rule bases, and controller parameters, enabling systematic analysis of parameter sensitivity and control behavior. This simulation stage provides a flexible and risk-free platform for rapid testing, debugging, and refinement of control strategies prior to hardware deployment, thereby supporting robust controller validation and informed design decisions.

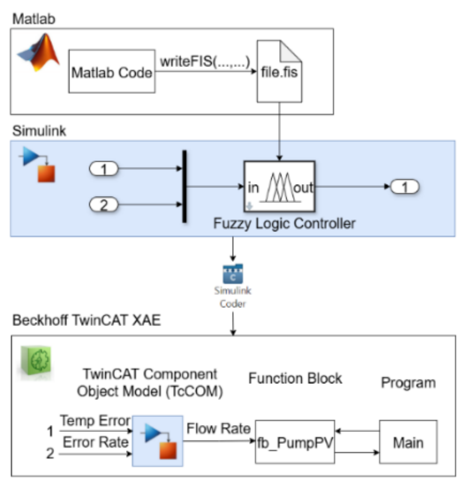

Fig. 3. Three-tier framework for the fuzzy logic controller.

C. *Industrial Implementation*

The industrial implementation stage follows a systematic three-tier development approach, illustrated in Fig. 3, designed to ensure both advanced control design and reliable real-world deployment. In the first tier, the controllers are conceptually designed and tuned within MATLAB/Simulink, enabling parameter definition, performance analysis, and validation in a controlled environment. For example, when implementing a fuzzy logic controller, MATLAB's Fuzzy Logic Toolbox is used to define membership functions, establish rule bases, and optimize controller parameters. This stage allows rapid prototyping and performance analysis without hardware constraints. The second tier employs Simulink to integrate the designed controller within a simulated dynamic model of the system, enabling validation under realistic operating conditions and fine-tuning prior to hardware implementation. The third tier involves transferring the validated controller to a Beckhoff Programmable Logic Controller (PLC) via the TwinCAT environment, where it is executed as a real-time function block through the TwinCAT Component Object Model (TcCOM).

D. *IoT-Based Monitoring And Control*

A dedicated IoT framework, illustrated in Fig. 4, enables real-time data acquisition, cloud connectivity, and interactive dashboard visualization. At its core, a Beckhoff Programmable Logic Controller (PLC) performs high-frequency data collection, supervisory control, and actuator management. The PLC interfaces with I/O modules to acquire different measurements from temperature, flow, and irradiance sensors, while executing real-time control of the circulation pump according to the selected strategy. Connected via Ethernet to HOOC Gateways, the system ensures secure remote communication with cloud services. Data streams are processed through Node-RED and stored in an InfluxDB time-series database hosted on Microsoft Azure, enabling scalable and reliable data management. Visualization is provided by Grafana, offering an intuitive web-based dashboard for real-time monitoring, historical analysis, and system performance evaluation. The collected data can be exported to MATLAB/Simulink for advanced analysis, including machine-learning-based modeling and controller optimization.

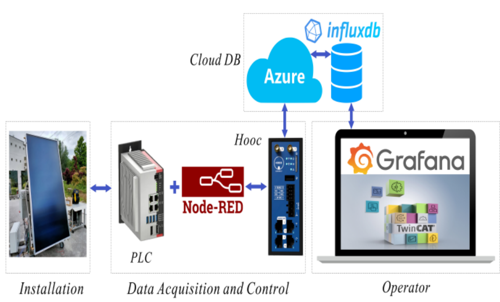

Fig. 4. IoT-based monitoring and control system architecture for the experimental solar thermal installation.

In addition, a Human-Machine Interface (HMI) interface, shown in Fig. 5, provides a user-friendly environment for system supervision, anomaly detection, and performance optimization.

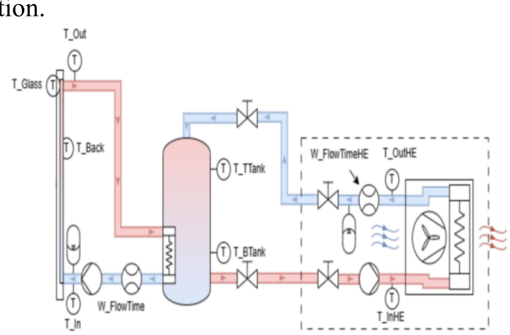

Fig. 5. The HMI interface for real-time monitoring of the solar thermal installation.

E. *Comparative Evaluation*

The performance of the developed control strategies is assessed through a comprehensive comparative evaluation using a set of quantitative and qualitative metrics. Key indicators include the system's overall thermal efficiency, the stability and responsiveness of tank temperature regulation, the cycling frequency and operational durability of the circulation pump, as well as the reliability and continuity of hot water delivery under variable and dynamic load conditions.

III. THE CONTROL STRATEGIES

A. *Conventionnal On-Off Controller*

The conventional on–off control strategy is the most common control approach employed in solar thermal collector systems due to its simplicity and ease of implementation. This method relies on two temperature sensors: one placed at the collector outlet, T_{out} , and another at the bottom of the storage tank, T_{tank} as seen in HMI interface in Fig. 5.

The circulation pump is activated when the collector outlet temperature exceeds the tank inlet temperature by a specified threshold ΔT_{on}, and it is deactivated when the temperature difference falls below a lower threshold ΔT_{off} [14]. To ensure stable operation and avoid rapid cycling of the pump, the turn-off threshold ΔT_{off} must satisfy the following inequality:

$$\Delta T_{\text{off}} \leq \frac{A_c F_R U_L}{\dot{m} C_p} \Delta T_{\text{on}} \tag{1}$$

Where $\dot{m}$ is the mass flow rate of the working fluid, A_c is the collector aperture area, F_R is the heat removal factor and U_L is the overall heat loss coefficient.

The relationship between the on- and off-thresholds, ensuring that useful energy is always delivered when the pump operates and preventing instability due to premature pump switching. This on–off controller maintains the storage tank temperature within a hysteresis band of approximately 3–4 °C. While this control strategy is robust and computationally simple, it remains sensitive to fluctuations in solar radiation and load dynamics, which can lead to frequent pump cycling and temperature oscillations in the storage tank.

The overall thermal output power generated by the solar thermal system is calculated using the following equation:

$$P_{th}(t) = \dot{m} C_p (T_{out}(t) - T_{in}(t)) \tag{2}$$

Where C_p is its specific heat capacity, and T_{in} and T_{out} are the inlet and outlet temperatures of the solar thermal panel.

B. *Fuzzy Logic Controller*

Fuzzy Logic Controller (FLC) has emerged as an attractive alternative to conventional rule-based strategies for solar thermal applications due to its ability to handle nonlinearities, uncertainties, and imprecise measurements without requiring an explicit mathematical model of the system. Unlike PID controllers that rely on exact numerical relationships, fuzzy controllers are based on linguistic rules that mimic human reasoning and decision-making. The fuzzy logic controller can be designed as a Mamdani-type inference system with two inputs and one output, specifically targeting the maintenance of tank temperature within a specified range. The input variables of the FLC can be expressed as:

$$e(t) = T_{setpoint} - T_{tank}(t) \tag{3}$$

$$\dot{e}(\mathrm{t}) = \frac{de(t)}{dt} \tag{4}$$

Where e(t) represents the temperature error and $\dot{e}(t)$ denotes the rate of change of the error signal.

The first input variable, temperature error e(t), is defined with an operational range of [-13, 4]°C, based on comprehensive analysis of experimental data. The second input variable, error rate $\dot{e}(t)$ which reflects the system's temporal dynamics spans a range of [-1.3, 1.3]°C/min.

The membership functions for temperature error are designed using trapezoidal and triangular shapes to provide appropriate linguistic interpretation. Fig. 6(a) illustrates the five membership functions implemented for temperature error: Negative Big (NB), Negative Small (NS), Zero (ZE), Positive Small (PS), and Positive Big (PB). The asymmetric distribution provides higher resolution in the negative error region, reflecting the predominant operational scenario where tank temperatures tend to exceed the setpoint during periods of high solar irradiance. For erreor rate, Fig. 6(b) illustrates three membership functions utilized with deliberately wide zero bands to provide noise immunity and accommodate the inherently slow thermal dynamics characteristic of solar thermal systems. The membership functions for error rate include Negative (N), Zero (Z), and Positive (P).

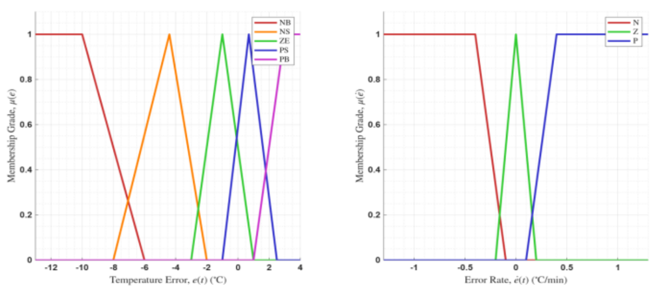

Fig. 6. Input membership functions for the fuzzy logic controller: (a) Temperature error membership functions and (b) Error rate membership functions.

The output variable represents the pump flow rate setpoint spanning the range [0, 6.74] L/min based on system capacity constraints. Seven triangular membership functions provide fine-grained control resolution, as illustrated in Fig. 7. These functions include Very Low (VL), Low (L), Medium Low (ML), Medium (M), Medium High (MH), High (H), and Very High (VH). This fine-grained resolution is selected to provide smooth control transitions and eliminate potential bimodal behavior that could result in abrupt changes in pump operation.

A comprehensive rule base consisting of 15 linguistic rules is developed following expert knowledge and system understanding as seen in Table I. The rules implement an inverse control relationship where negative temperature errors (indicating tank temperature above setpoint) generate higher flow rates to enhance heat extraction and promote cooling, while positive errors (tank temperature below setpoint) produce lower flow rates to facilitate heating through reduced circulation.

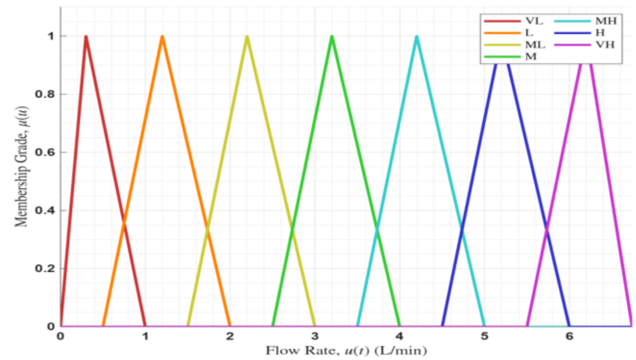

Fig. 7. Output flow rate membership functions.

TABLE I. FUZZY LOGIC CONTROLLER RULE BASE

Rule	Temperature Error	Error Rate	Flow Rate
R_1	NB	N	VH
R_2	NB	Z	VH
R_3	NB	P	H
R_4	NS	N	H
R_5	NS	Z	MH
R_6	NS	P	M
R_7	ZE	N	MH
R_8	ZE	Z	M
R_9	ZE	P	ML
R_{10}	PS	N	M
R_{11}	PS	Z	ML
R_{12}	PS	P	L
R_{13}	PB	N	ML
R_{14}	PB	Z	L
R_{15}	PB	P	VL

The fuzzy inference system employs the Mamdani method with minimum t-norm for implication and maximum t-conorm for aggregation. The firing strength of each rule R_i is calculated:

$$\alpha_i = \min\left(\mu_{A_i}(e), \mu_{B_i}(\dot{e})\right) \tag{5}$$

The aggregated output membership function is obtained through:

$$\mu_{output}(u) = \max_{i=1}^{15}\left(\alpha_i \cdot \mu_{C_i}(u)\right) \tag{6}$$

Centroid defuzzification converts the fuzzy output to a crisp control signal:

$$u^* = \frac{\int u \cdot \mu_{output}(u)\, du}{\int \mu_{output}(u)\ du} \tag{7}$$

The complete input-output mapping of the fuzzy controller is visualized in Fig. 8, which presents a three-dimensional control surface showing the nonlinear relationship between temperature error, error rate, and the resulting flow rate output. The surface demonstrates the smooth transitions between different operating regions and the nonlinear control characteristics inherent in the fuzzy logic approach. The contour lines provide clear delineation of iso-flow rate regions, illustrating how the controller responds to different combinations of error and error rate inputs.

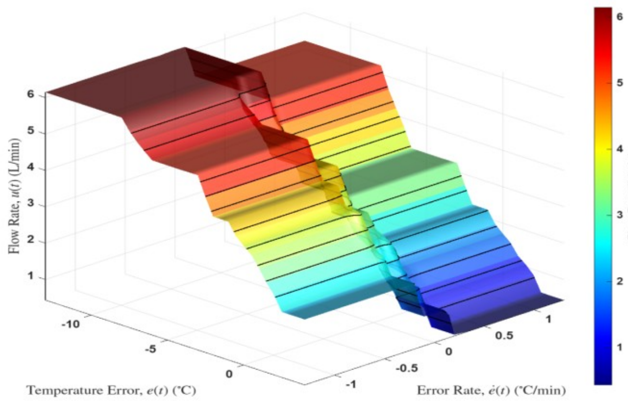

Fig. 8. Three-dimensional control surface of the fuzzy logic controller showing the nonlinear mapping between temperature error, error rate, and flow rate output.

IV. COMPARATIVE ANALYSIS OF CONTROL SYSEMS

The on–off and FLC control strategies were experimentally tested over three-day periods in June 20–22 and August 29–31, 2025, respectively, to evaluate their effectiveness in maintaining stable tank temperatures under varying environmental conditions. The comparative analysis of the controllers covers heating cycle dynamics and environmental correlation, temperature control accuracy, thermal efficiency, and system performance metrics. Extended results and discussion can be found in [15].

1) Heating Cycle Dynamics and Environmental Adaptation: The comprehensive heating cycle analysis for the FLC across all experimental days reveals substantially different behavior compared to conventional on-off control. Each heating cycle reveals a distinctively smooth and continuous temperature rise, resulting from the fuzzy logic controller's adaptive modulation of the flow rate, markedly contrasting with the stepped temperature profiles characteristic of conventional on-off control systems. The environmental correlation analysis reveals significant improvements in the FLC's adaptive capabilities.

A positive correlation between heating rate and solar irradiance as seen in Fig. 9(a), indicates that the FLC effectively utilizes available solar energy to optimize heating performance. Heating rates range with higher irradiance levels consistently produce faster heating rates through intelligent flow rate adaptation. Conversely, a negative correlation between heating time and irradiance as seen in Fig. 9(b), confirms that the FLC achieves faster heating cycles under favorable solar conditions. This inverse relationship demonstrates the controller's ability to dynamically adjust its response based on available energy input.

2) Temperature Control Performance and Precision: The overall temperature control behavior of the FLC exhibits smooth and continuous profiles that distinguish fuzzy logic control from conventional strategies. The temperature transitions are gradual and controlled, eliminating the abrupt changes typical of binary control systems. Experimental results show that the FLC reduces the average control error by 67.4% while achieving a 12.8% improvement in time-in-range accuracy. This precision enhancement ensures improved user comfort, system reliability, and operational predictability under varying environmental conditions.

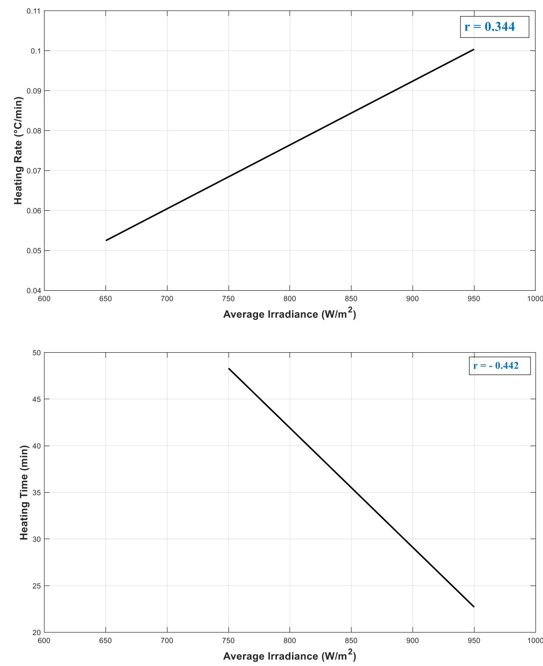

Fig. 9. Relationship between (a) solar irradiance and heating rate and (b) solar irradiance and heating time for FLC.

3) Thermal efficiency: Average thermal efficiency μ, defined by equation 8, has been used as metric for thermal efficiency comparison.

$$\mu = \frac{P_{out}}{G.A_c} \tag{8}$$

With P_{out} the average thermal output power, G the average solar irradiance over the experimental period and A_c collector absorber area.

Normalized performance metrics are calculated to facilitate a comparative analysis of the two control strategies. Thermal efficiency and power output were normalized by expressing each value as a percentage of the maximum value observed for the respective metric across all experimental conditions. This normalization allows direct comparison between variables with different measurement scales. The results indicate that the FLC demonstrates superior performance in key areas, achieving higher normalized thermal efficiency (0.74 vs. 0.26 for the on–off controller) and power output (0.56 vs. 0.24 for the on–off controller). This consistent advantage highlights the overall effectiveness and holistic benefits of implementing fuzzy logic control.

4) Performance Radar Chart Analysis: Fig. 10 presents a detailed visualization of the multidimensional performance comparison using radar chart analysis, encompassing all the experimental days of the study. The FLC demonstrates superior performance across the four evaluated dimensions, with the area enclosed by the FLC polygon significantly exceeding that

of the on-off controller. Thermal efficiency comparison demonstrates the most significant performance gap, with the FLC achieving 0.74 compared to 0.26 for the on-off controller, visualizing the 184.6% efficiency improvement. Power output analysis shows the FLC reaching 0.56 compared to 0.24 for the on-off controller, representing the 133.3% enhancement in thermal energy delivery. The consistency analysis reveals more complex characteristics, with the on-off controller achieving 0.92 compared to 0.95 for the FLC, indicating comparable day-to-day stability despite the FLC's superior absolute performance levels. Environmental adaptation assessment shows the FLC's moderate advantage (0.40 vs. 0.25), reflecting the stronger correlations between performance metrics and environmental conditions.

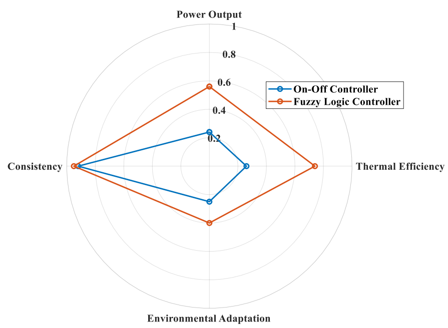

Fig. 10. Comparative performance radar chart.

V. Conclusion and Future Perspectives

This study experimentally validates the effectiveness of fuzzy logic control (FLC) for pump regulation in a flat-plate solar thermal collector system equipped with a load-side heat exchanger. Compared with conventional on–off control, the FLC demonstrates significant improvements in temperature stability, thermal efficiency, power output, environmental adaptability, and overall operational robustness under real-world conditions. The enhanced performance arises from FLC's ability to continuously adjust pump operation in response to dynamic solar irradiance and load variations, minimizing thermal losses and optimizing energy capture. These results confirm that fuzzy logic control provides a reliable, efficient, and adaptive solution for domestic-scale solar thermal systems, with performance gains that justify the additional design and implementation complexity.

Future work will focus on extending the proposed approach through integration of advanced AI-based control techniques, such as neural networks and reinforcement learning, to further enhance adaptability, predictive optimization, and fault tolerance. Additional developments include expansion toward hybrid renewable energy systems combining solar thermal, photovoltaic, and energy storage technologies, as well as long-term monitoring campaigns across seasonal variations to enable comprehensive performance evaluation and controller benchmarking. These research directions aim to advance the scalability, intelligence, and resilience of next-generation renewable thermal energy systems while enabling more efficient, environmentally sustainable domestic energy solutions.

Acknowledgment

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