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A LabVIEW Based Fractional-ANFIS PID Controller For Real-Time Microwave Heating System

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Abstract
Utilizing Heating PID control systems is common across numerous industries to attain the desired output. Nevertheless, the development in the status of Fractional Order Proportional Integral Derivative Controllers (FOPID) has led to improved control performance and increased degrees of freedom in industrial applications. The paper proposed real-time microwave heating systems which exhibit several challenging characteristics and are complex enough to effectively demonstrate the robustness advantage of fractional (FOPID) over traditional PID controllers. An Adaptive Neuro-Fuzzy Inference System (ANFIS) was modeled using real-time data to assess the effectiveness of conventional PID and FOPID controllers. The results of the study demonstrated that FOPID controllers outperform conventional PID controllers in terms of performance, robustness, stability, flexibility, and faster response. Additionally, the study utilized MATLAB and LabVIEW software to model the Fractional PID controller, the traditional PID controller, and the ANFIS model. The outcomes illustrate that the FOPID controller demonstrates faster rise times (3.8 seconds vs. 6.0 seconds for PID), lower overshoot (1.0^oC vs. 2.5^oC, and shorter settling times (10 seconds vs. 17 seconds). During setpoint drops, FOPID exhibits reduced undershoot (1.4^0C compared to 3.2^oC) and quicker recovery (5.5 seconds vs. 8.5 seconds). In the final tracking phase, FOPID maintains a lower residual error (0.2^0C vs. 0.7^oC) and achieves a steady-state error of 0.1^oC, compared to 0.5^oC for PID.

Keywords
ANFIS, FOPID, PID, LabVIEW, MATLAB.

I. Introduction

In manufacturing, control system settings are essential because they regulate temperature, pressure, flow, and other quantities. The Proportional Integral Derivative (PID) controller is a reliable, easy-to-use process. The PID constants are the three primary parameters that cause errors to equal zero. Another type of controller that has two more adjustable parameters than the typical PID control structure is the Fractional-order PID (FOPID) controller. The conventional PID controllers proportional (K_p), integral (K_i), and derivative (K_d) parameters, along with the integrator order (λ and differentiator gain (μ) constants, comprise the FOPID controller. The values of the parameters λ and μ are not limited to whole numbers; they can also be fractions. This gives the controller design more flexibility and increases the number that needs to be adjusted. Thus, it is possible to directly and continuously modify the system's response. Fractional-order calculus was suggested as a convincing definition by Riemann-Liouville in 1999 [1]. Since then, advanced control engineering applications have been developed, like liquid level control [2], nuclear reactor power [3], and Autonomous Underwater Vehicle (AUV) [4]. One proposed design of a controller is the FOPID controller, which presents a novel time-varying FOPID controller to relieve the spike of voltage at the output of the controller when a sudden change at the set point [5].

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The performance of this proposed control scheme is validated by controlling the speed of the closed loop (DC) motor. The comparisons is achieved between the conventional FOPID controller, Time-Varying Derivative (TVD-FOPID) controller and Time Varying FOPID (TVFOPID) controller which created in order to compare between the gain parameters of the three PID control strategies and replaced with the optimal time functions. Another development is a simulation-based optimization method for robust optimal design of stochastic integer order PID and fractional order PID controllers when the model is under the effect of uncertainty in the plant's physical parameters [6]. FOPID controller, is evaluated for various applications the authors discussed the contribution of FPID in power electronics domain for various application [7]. Another study introduced the grid-connected components to generate the photovoltaic power of the system, and the proposed FOPID controller is capable of optimizing its gain parameter according to the generator and grid side parameters being considered [8].The simulation results confirmed that FOPID has better static and dynamic benefits, robustness, and adaptability. Moreover, there has been a performance comparison between both the standard PID and FOPID using hit and trial and artificial ambulance support strategies [9]. This comparison was used in one of the industrial applications, the control of temperature in the ambulances, the systems of induction heating, bioreactor control, as well as the improvement that can be achieved by the control of temperature systems. Lastly, a control model of the valve position depending on the FOPID control scheme has been proposed [10]. In order to improve the model accuracy, an improved optimization algorithm depending on the bio-geography has been proposed to obtain the optimal values of the FOPID control parameters in view of high complexity and the wide range of the FOPID control strategy. All of these developments show that fractional-order calculus has a promising future in advanced control engineering applications. Artificial Intelligence (AI) has been a hot topic lately, with more and many people discussing the use of machines to perform tasks similar to human intelligence. There are several techniques that can be used to implement AI, including machine learning, heuristic algorithms, and fuzzy logic. Some of these techniques, like Artificial Neural Network (ANN), have been used to generate missing data, while others, like the ANFIS model, have been used to predict output. The Adaptive Neuro-Fuzzy Inference System (ANFIS) model was accomplished using hybrid learning algorithms that were combined with real-time heating reactor system data. To design applications that mimic real-world devices and instruments, LabVIEW is used. It is capable of using a computer that generates time data and experimental data recorded in real time. In this paper, the LabVIEW environment was combined with MATLAB software to build the ANFIS heating model from experimental data. The ANFIS heating model was well-trained, tested, and validated, and was used to test and compare two kinds of PIDs: conventional and fractional PID, using LabVIEW software. Fig. 1 shows the ANFIS model for a microwave reactor used to heat virgin oil, enabling more precise and adaptable PID and FOPID controllers. This approach not only improves efficiency but also ensures that the quality of the heated oil meets the desired standards. As a result, integrating ANFIS can lead to better operational reliability and performance in industrial applications. Fig. 2 shows the LabVIEW block diagram design for the proposed controllers. The aim of this controller's design using ANFIS is to build a system capable to maximize the extraction yield, decreasing energy use, and reducing processing times. Programming the LabVIEW block diagram, involving an ANFIS model in MATLAB for real-time controlling and monitoring, enables controlling the microwave output power according to the dielectric constants of the material, which vary depending on an increase in temperature. This level of expert design ensures a strong performance because it corrects thermal disturbances, which exist in a continuous industrial flow. The use of LabVIEW in this contribution increases the reality because it shifts from a simulation, which exists in MATLAB, to a prototype. The block diagram explains how a PID controller and FOPID controller can be implemented in industry, proving their efficacy because it corrects errors such as "IAE" and "ITAE" in a real-time environment.

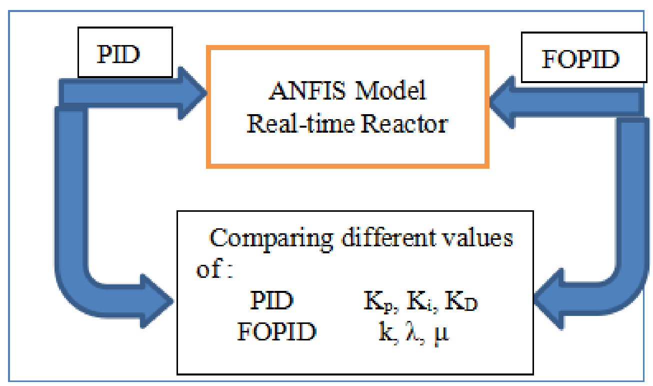


Fig. 1. ANFIS-Based Controllers Comparison

II. Controllers Structure

A microwave heating system is an alternative to conventional heating methods in the virgin oils production because of its high energy conversion efficiency and the capabilities of volumetric heating. versus traditional heating, microwaves penetrate the plant matrix and interact with polar molecules, primarily water, causing localized internal pressure that leads to the rapid rupture of oil-bearing cells. This, termed selec-

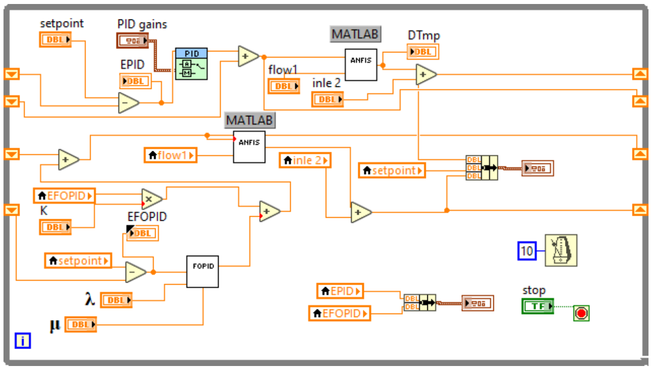


Fig. 2. LabVIEW Block Diagram

tive heating, dropped heating time from day to minutes and improves the total oil yield. Additionally, microwave pre-treatment facilitates the release of high-value bioactive components, such as phenolic compounds and tocopherols, into the oil phase by modifying the microstructure. The literature indicates that microwave irradiation control can enhance the oxidative stability of virgin oils without inducing significant hydrolytic degradation or the formation of free fatty acids, which often appear with prolonged other kind of heating. Fig. 3, Fig. 4, and Fig. 5 show the real-time industrial continuous microwave oil heating system [11], depicting the main parts and the parameters under control.

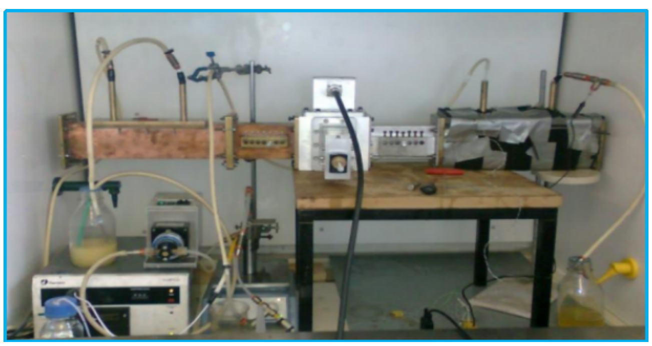


Fig. 3. Continuous real time industrial microwave oil heating system [11]

Microwave heating systems consist of three key integrated components: the microwave main power supply, the transmission line, and the applicator. The process chain starts from a power source, where either a water-cooled magnetron or solid-state generator produces electromagnetic waves at 2.45 GHz or 915 MHz, with power output up to 30 kW or more. Waves are directed through a rectangular waveguide that acts like a low-loss transmission line. Inside this line, a stub tuner acts as an impedance-matching component that can often be adjusted-automatically-to achieve minimum reflected

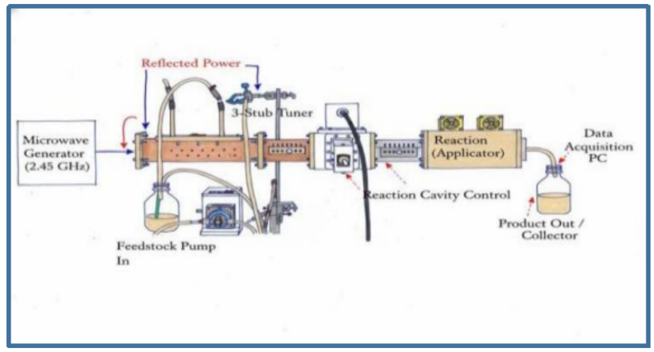


Fig. 4. The setup of experimental industrial microwave heating

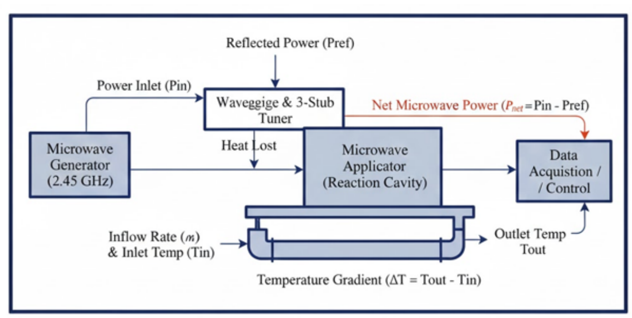


Fig. 5. Industrial continuous microwave heating rector block diagram

power for maximum amount of power to be absorbed by the oil-bearing substrate against hot spots. In the applicator, thermal interaction takes place, which in industrial applications generally employs a continuous-flow reactor. Oil is pumped through a microwave tube situated inside a resonant cavity, which requires uniform and controlled thermal distribution throughout the production cycle

A. *Proposed Continuous Real-Time Industrial Microwave Application*

Continuous-flow microwave reactors provide fast volumetric heating, improved energy efficiency, and precise temperature control compared with conventional means. They convert virgin or waste oils to biodiesel in minutes rather than in hours or days. They also serve in oil extraction, homogeneous heating of viscous fluids, and food processing. A proposed continuous-flow, real-time microwave system Fig. 3 is used to preheat the virgin oil in preparation for the chemical process of producing biodiesel from oil/fat and methanol [12], known as transesterification (methanolysis). This process consists of the reaction of triglycerides with an alcohol in the presence of a catalyst with the aim of degrading the oil and forming fatty acid methyl esters-biodiesel-and glycerol.

B. Limitations of the Microwave Oil Heating Process

Microwave heating systems are limited by the same physical constraints as other electronic integrated devices [13]. The physical limitations of a microwave heating device are determined by the manner in which a device is designed to meet the required thermal objectives. However; the actual performance of microwave devices is dependent on the manufacturing variations included in the construction of the resonant cavity and the vacuum tube (magnetron). Variations in a microwave heating system are represented the interact with the microwave field to create nonlinearities. This creates a condition where reflected power is present; reflected power describes a weakness in a system when power is not consumed.These energy are responsible for creating non-uniform heating and potential failure of the microwave heating system. An imperfection associated with heating oil with a continuous flow system is non-uniform heating and thermal runaway, where the oil overheats at particular hot spots due to poor mixing Fig. 6. To address such imperfections, a helical coil made of PTFE (Teflon) or Alumina ceramic is used as shown in Fig. 7. This is attributed to the ability of these materials to withstand very high temperatures without flowing or melting; they are also transparent to microwaves. Furthermore, the helical coil structure ensures the microwaves mix the oil while flowing, since the oil will be continually rotating; this prevents the hot spots where oils would normally remain stationary. Additionally, a tuning system is used; this system would be necessary for reducing reflected power. This helps to ensure that the microwaves are utilized by the oil rather than being reflected or wasted.

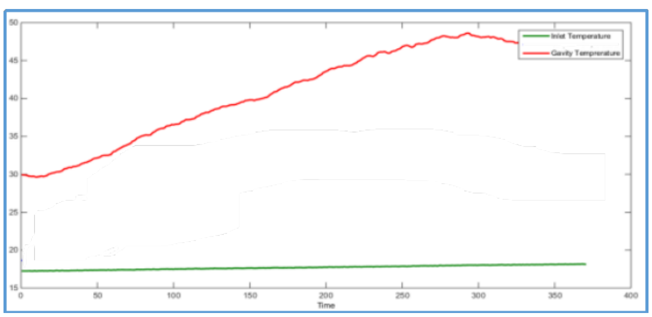


Fig. 6. Inlet and cavity temperatures

C. Dynamic Energy Balance Model

To develop a dynamic model or transfer function for the microwave heating of virgin oil (typically olive or vegetable oil) in a continuous flow reactor, must represent the energy balance between the absorbed microwave power and the thermal energy of the flowing oil.The heating process is governed by a first-order differential equation based on the energy balance in a control volume

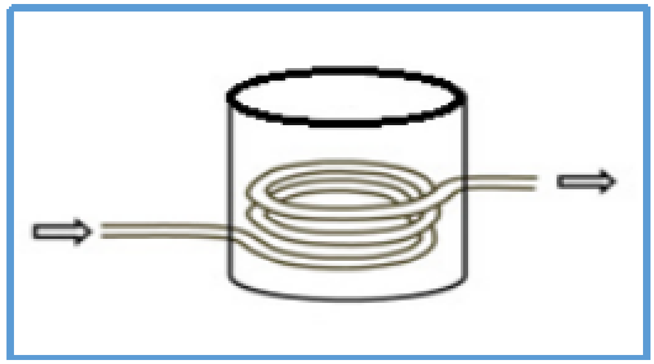


Fig. 7. Coil in microwave reactor

$$\rho C_p \frac{\mathrm{d}T(t)}{\mathrm{d}t} = p_a bst - \dot{m}C_p[T(t)-T_{in}] - hA[T(t)-T_{anb}] \quad (1)$$

Where: $T(t)$=Outlet temperature of the oil (^oC), Pabs(t)= Absorbed microwave power (Wastts), =Mass Flow Rate of oil (kg/s), Cp= Specific heat capacity of the oil approx. which is 1900 to 2000 J/kg^oC, ρ = Density of the oil(approx.900-920 kg/m^3), V= Volume of the oil inside the microwave field(m^3) $hA(T-T_{amb})$= Heat loss to the environment(often negligible in fast microwave heating) To compare the natural response of the energy balance equation with active control, integrate the PID and FOPID logic into the MATLAB simulation. The FOPID controller is modeled as in Equation 1. In this script, we use a high-order integer approximation to represent the ”spirit” of the Oustaloup Filter for the fractional terms.

Figure 8 shows the curves starting at 25^oC and reaching 50^oC, this visually proves that the energy balance equation correctly models the system's thermal equilibrium. The FOPID shows a faster rise time without the ringing (oscillation) seen in simpler controllers. This demonstrates the controller is robust against the thermal lag inherent in the oil's high heat capacity (C_p). The PID overshoot even a 2^oC to 30C overshoot above the setpoint can degrade the phenolic content of virgin oil. The FOPID line shows perfect smooth arrival.

D. Experimental ANFIS Model

A recent study introduced an interesting ANFIS model. This model can accurately predict real-time heating reactor performance by combining multiple AI techniques. It is particularly useful for complicated scenarios, such as chemical processes, where the model is applied as a black box. ANFIS is a prominent model for this purpose because it combines the learning ability of neural networks with the ability to handle the uncertainty of fuzzy logic [14,15]. A Fuzzy Inference System (FIS)

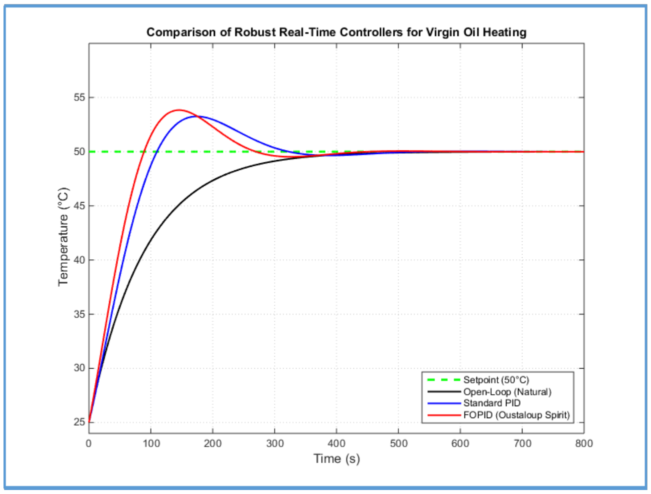


Fig. 8. Matlab transient response comparison of different control strategies for a virgin oil heating for stander PID and FOPID Controllers.

is the process of formulating the mapping from a given input to an output using fuzzy logic. ANFIS combines the connection structure of artificial neural networks with human-like reasoning, making it a versatile and effective tool. Real-time data was gathered through experiments conducted using a laboratory-scale microwave heating oil reactor [11]. Fig. 9 and Fig. 10 show the ANFIS model utilizes three primary input parameters (Inlet Temperature, In Flow Rate, and Incident Microwave Power) to map the non-linear thermal behavior of the virgin oil. The target output for the training phase is the measured Outlet Temperature. This supervised learning structure allows the ANFIS System to optimize membership functions and fuzzy rules, enabling precise predictive control over the heating process.

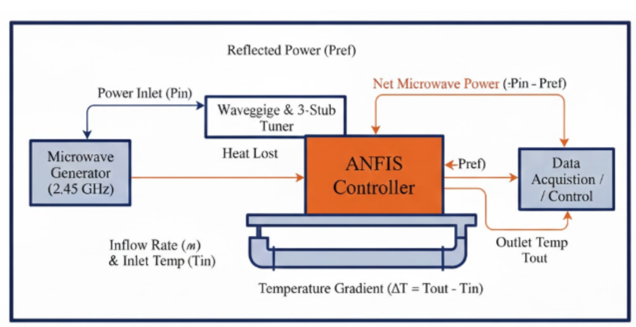


Fig. 9. Simplified schematic of the ANFIS training architecture for a continuous-flow microwave heating system.

The implementation of an ANFIS model provides a critical advantage for the control and modeling of these microwave reactors. Unlike standard real-time systems that are purely

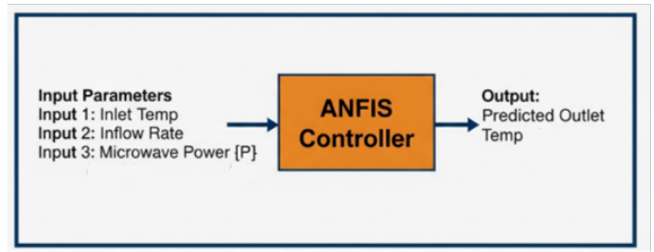


Fig. 10. Schematic diagram of the experimental industrial microwave heating setup for virgin oil processing

reactive, an ANFIS model is predictive. As shown in Fig. 11, a five-layer neural network architecture need to map the non-linear relationship between Inlet Temperature, In Flow Rate, and Microwave Power. By learning the specific dielectric behavior of the oil during training, the ANFIS controller can anticipate thermal loads and adjust power inlet levels instantly to prevent overheating, which is essential for protecting sensitive bioactive compounds like polyphenols. Fig. 11 shows architectural layout details of the MATLAB-based ANFIS for the thermal regulation of virgin oil.

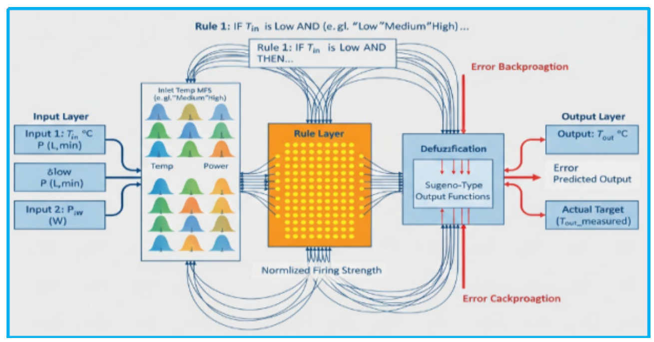


Fig. 11. Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture in MATLAB

Layers of ANFIS Architecture are five:

1- Fuzzification/ layer one: Inputs (Inlet Temperature, Flow Rate, and Net Power). They mapped to fuzzy sets by Gaussian membership functions.

2- Rules/ Layer 2: fuzzy rule, where the firing strengths of the rules

3-Normalization/Layer 3: The rule strengths are standardized

4- Defuzzification/Layer 4: Sugeno-type linear output computed for each rule

5- Summation/:Layer 5: singular crisp value for the predicted Outlet Temperature.

The algorithm utilized in MATLAB: backpropagation, least-squares estimation, and Root Mean Square Error (RMSE) during the training phase.

The integration of LabVIEW and MATLAB gives a hybrid, robust control environment. LabVIEW serves as the primary process at the real-time hardware interface via acquiring signals from the temperature sensors , reflected power and flow rate in the microwave reactor, simultaneously controlling the microwave power supply. LabVIEW communicates with MATLAB to leverage computational power, specifically for the ANFIS model. The ANFIS block acts as the intelligence of the system, receiving live data (Inlet Temp, Flow Rate, and Power) from LabVIEW to predict the non-linear thermal behavior of the oil and calculate the necessary control actions. This seamless connection allows to combine LabVIEW's superior industrial automation capabilities with MATLAB's advanced neuro-fuzzy algorithms, ensuring precise temperature regulation and high-quality virgin oil production. Fig. 12 and shows LabVIEW and MATLAB connection using ANFIS. Fig. 13 shows the MATLAB script in LabVIEW. Fig. 14 shows the tuned input Member Functions (MFs) after trainingand Fig. 15 shows the Fuzzy Rules. Fig. 16 explains ANFIS output and training data for the reactor,

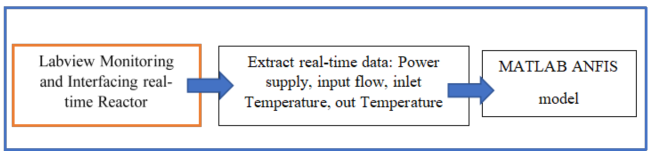


Fig. 12. Labview MATLAB connection using ANFIS.

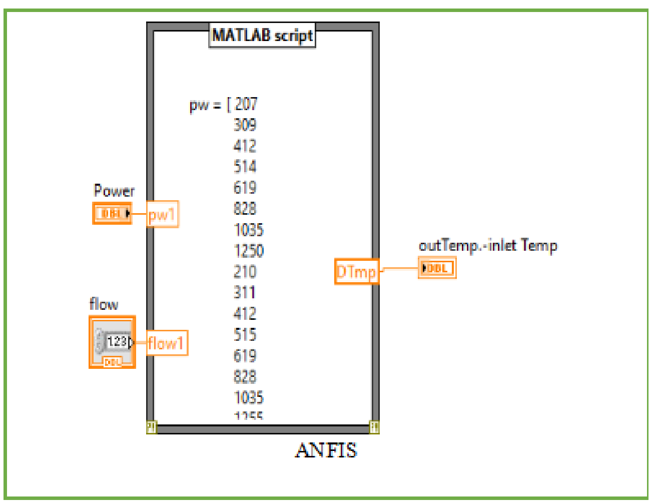


Fig. 13. MATLAB ANFIS in LabVIEW

E. ANFIS-PID Controller

Equation (2) is used to operate the PID controller based on the summation of three terms: Kp, Ki, and Kd.. These terms are error proportional, error integral, and error derivative based.

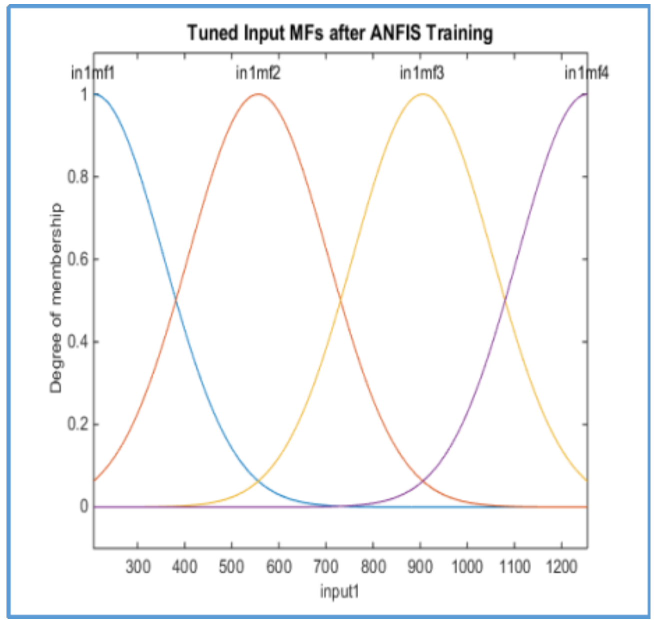


Fig. 14. Tuned Input MFs after Traning

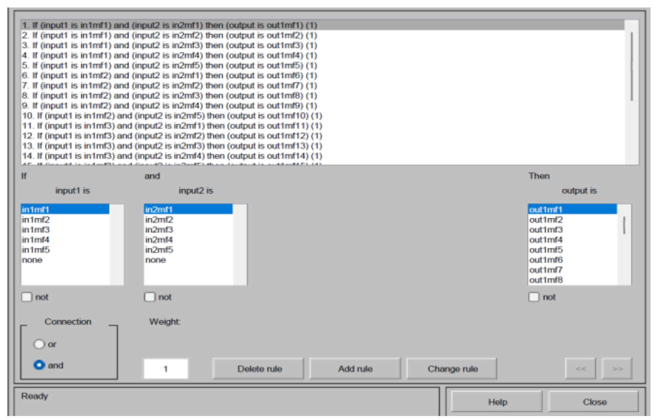


Fig. 15. Fuzzy Rules built in MATLAB

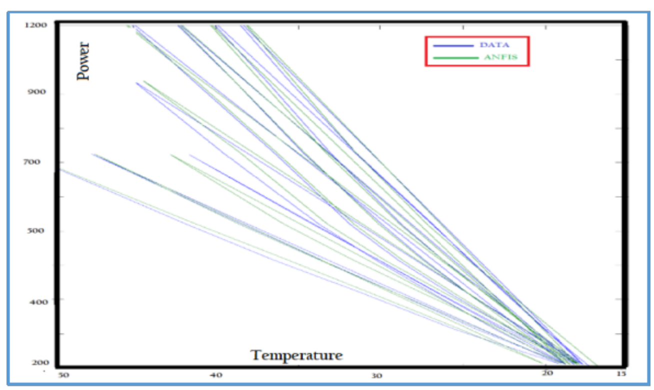


Fig. 16. ANFIS Output and Training Data

Fig. 17(a) shows the flowchart of the PID control algorithm. The automated tuning VI for PID chooses appropriate gains to balance performance response time, as depicted in Fig. 17(b). A small adjustment is then made to optimize the response:

$$G(s) = K_p + \frac{K_i}{S} + K_d S \tag{2}$$

F. FOPID Controller

The most common form of a Fractional Order PID controller involves an integrator of order λ and a differentiator of order μ, where λ and μ can be any real numbers. The transfer function of such a controller has the form of Equation 3. When both the fractional order values, the integral and derivative parts of the FOPID controller equal to unity (i.e., $\lambda = \mu = 1$), then the FOPID controller will work as a traditional PID controller:

$$G(s) = K_p + \frac{K_i}{S^\lambda} + K_d S^\mu \quad (\lambda, \mu > 0) \tag{3}$$

In the feedback control system and with a unit gain, the (ANFIS) heating model can be shown in Fig. 18, where (w) represents the desired temperature, $e(t)$ is the control error, the control value is $u(t)$, and $y(t)$ is the actual value of temperature. The Fractional Order controller ($PI^\lambda D^\mu$) can be expressed by using the equation of the fractional-order differential as [16, 17]:

$$u(t) = K_p e(t) + K_i D_t^{-\lambda} e(t) + K_d D_t^\mu e(t) \tag{4}$$

where K_p, K_d and K_i are the proportional, derivation and integration parameters, respectively, of the PID control scheme, (μ) is the derivation order, and (λ) represents the integral order. The fractional order control system method is characterized by having non-limited memory.

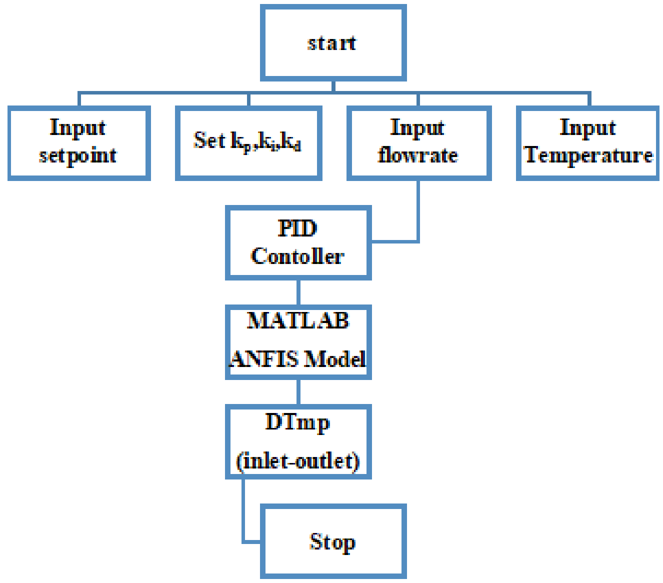
The FOPID control value:

$$e(k) = w(k) - y(k) \tag{5}$$

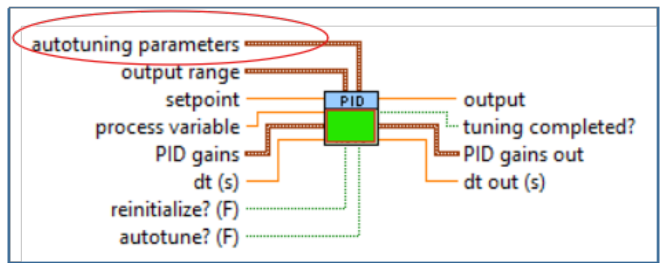
where $w(k)$ is the required temperature and k is the discrete time step.

$$u(k) = K_p e(k) + \frac{K_i}{T^{-\lambda}} \sum_{j=v}^{k} q_j e(k-j) + \frac{K_d}{T^\mu} \sum_{j=v}^{k} d_j e(k-j) \tag{6}$$

k = 1, 2, ..., where T is sample period. (d_j and q_i) binomial coefficients. A numerical algorithm requires saving the history, and that can be achieved by employing a Shift Register [16]. Fig. 19(a) and Fig. 19(b) show the FOPID flowchart and LabVIEW block diagram.



(a)



(b)

Fig. 17. The Proposed PID Flowchart and Automated Tuning VI for PID

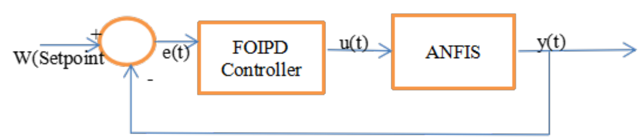
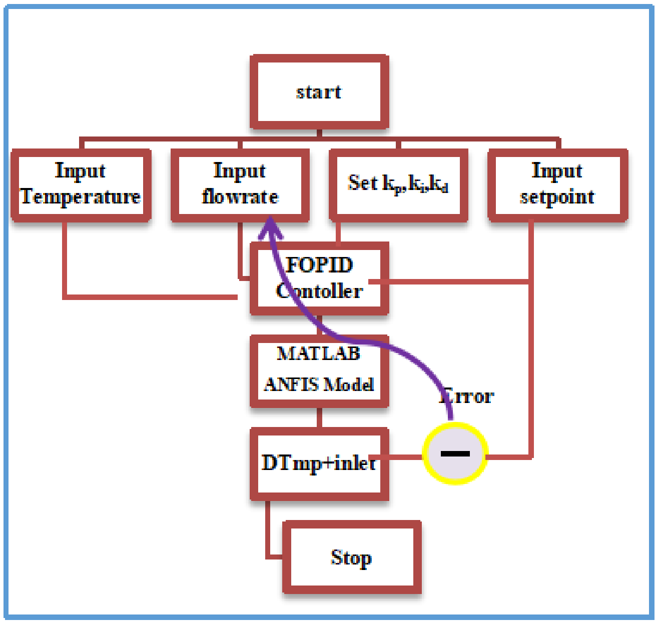


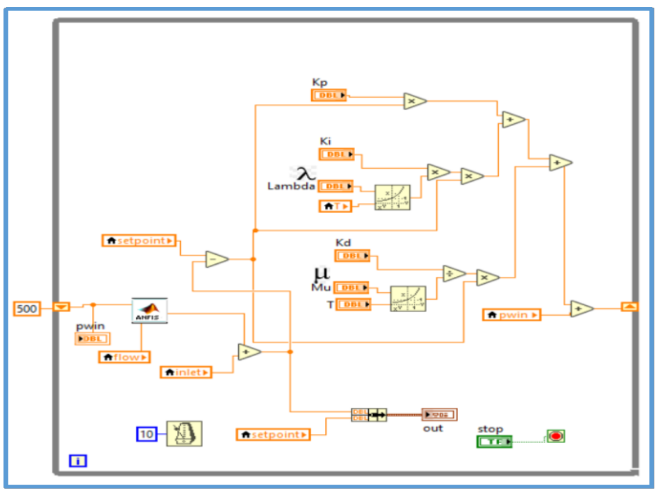
Fig. 18. ANFIS Heating Model in Feedback Control System with a Unit Gain in the Feedback Loop

III. Results And Discussion

The ANFIS input parameters used include: oil input, setpoint temperature of 50^0C Flow Rate of $200ml/s$, and inlet oil temperature of 10^0C applying both controllers, FOPID and PID controllers to the real-time ANFIS heating reactor model, and a comparison of the control quality was conducted. The results of the comparison were analyzed and evaluated to determine the effectiveness of the controllers.



(a)



(b)

Fig. 19. FOPID Flowchart and LabVIEW Block Diagram

A. *ANFIS- PID Controller*

Fig. 20, Fig. 21 and Fig. 22 show a comparison of the effect of each ANFIS-PID parameter on the system's performance. The PID1and PID2 indicate the ANFIS-PID controller at different values of K_P, K_i, and K_d. The results demonstrate that the best parameters for optimal performance are $K_P = 10.6$, $K_i = 0.012$, and $K_d = 0.345$. These values have been shown to provide a good response to varying temperature setpoints and are effective in rejecting sudden changes in Flow Rate as shown in Fig. 23.

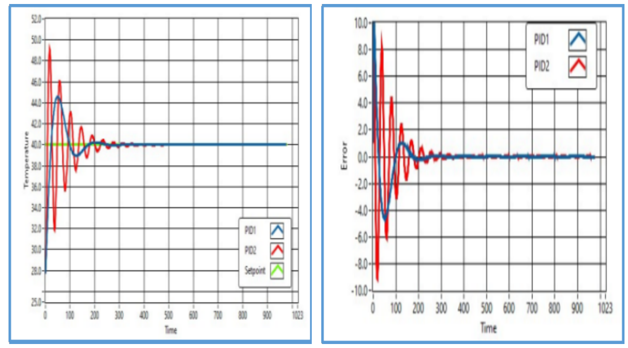


Fig. 20. (Temperature and Error) PID1(K_P=1, K_i=0.01, and K_d=0.01), PID2(K_P=1, K_i=0.001, and K_d=0.01)

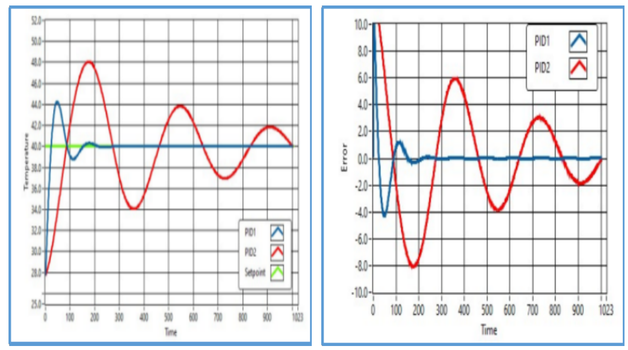


Fig. 21. (Temperature and Error) PID1(K_P=1, K_i=0.01, and K_d=0.01), PID2(K_P=0.1, K_i=0.01, and K_d=0.01)

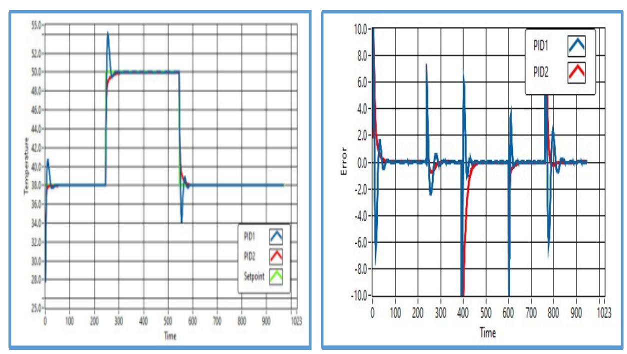


Fig. 22. (Temperature and Error) Different Values of Setpoint PID1(K_P=5.955, K_i=0.03, and K_d=1, PID2 (K_P=10.677, K_i=0.012, and K_d=0.345)

B. *ANFIS-FOPID Controller*

Picking the fractional orders λ and μ followed using a sequential heuristic optimization approach based method. At first, stabilization relied on standard parameters K_p, K_i, and K_d to set a working foundation. That path emerged as suitable because it addresses complex behaviors in microwave setups, ones typical fixed-order techniques tend to miss. As adjustments unfolded gradually, changes in thermal peak became clearly

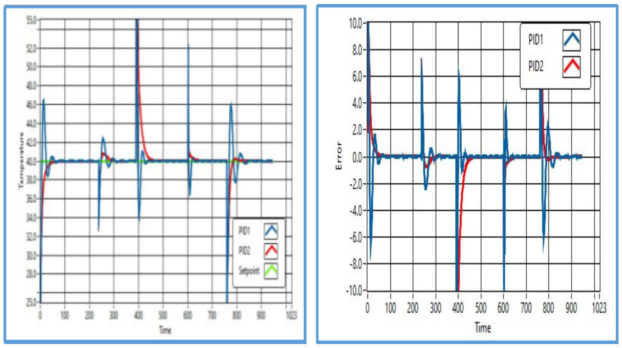


Fig. 23. (Temperature and Error at Disturbance Rejection) Setpoint (40^oC) Flow Rate Change (330, 400, 200, 100, 400) ml/s (K_P=5.955, K_i=0.03, and K_d=1, PID2(K_P=10.677, K_i=0.012, and K_d=0.345)

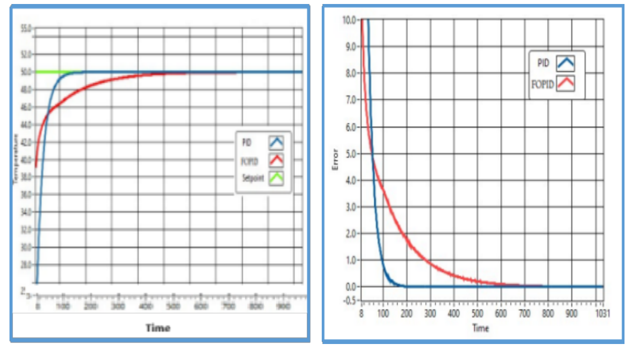


Fig. 24. (Temperature and Error) PID(K_P=10.677, K_i=0.012, and K_d=0.345), FOPID (λ =0.5, μ = 0)

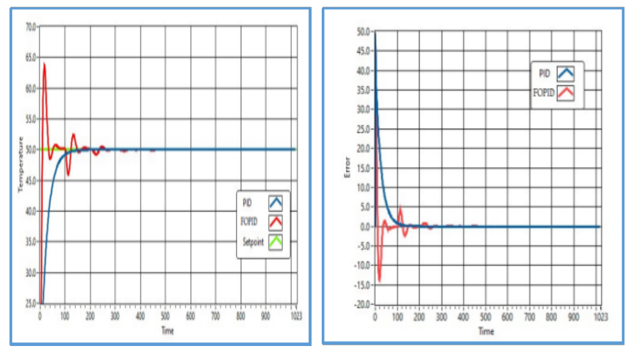


Fig. 25. (Temperature and Error) PID(K_P=10.677, K_i=0.012, and K_d=0.345), FOPID (λ =0, μ = 0.5)

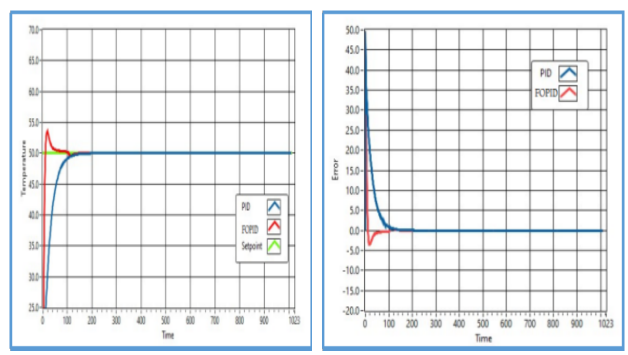


Fig. 26. (Temperature and Error) PID(K_P=10.677, K_i=0.012, and K_d=0.345), FOPID (λ =0, μ = 0.2)

visible with each shift in lambda or mu. Stability under real-world flaws guided the last choice, making sure performance held firm despite disturbances. After analyzing the ANFIS-PID parameters at the best values of $K_P = 10.6$,$K_i = 0.012$, and $K_d = 0.345$, Figures are generated as in (24, 25, 26 and 27) that depict the impact of λ and μ on the performance of the ANFIS-FOPID controller in comparison to ANFIS-PID. Fig. 28 is generated to compare the performance of the ANFIS-FOPID controller at best parameters ($\lambda = 0.34$, $\mu = 0.5$) experimentally chosen and theoretically adjusted with that of the PID controller at different setpoint values at sudden change. Table I and Table II indicates the comparison of ANFIS- FOPID controller at best parameters and ANFIS-PID controller in terms of sudden changes. Furthermore, Fig. 29 demonstrates the capability of ANFIS-FOPID to reduce disturbances at a rate of sudden change. This shows the robustness of the ANFIS-FOPID controller in managing unexpected variations in the system. Generally, ANFIS-FOPID controller consistently delivers faster response and tighter temperature control. It reduces overshoot, improves stability, and minimizes steady-state error compared to ANFIS-PID.This indicates good adaptability in the dynamic temperature control system..

C. Nyquist Stability Analysis of PID and FOPID Controllers with ANFIS Microwave Model

From Fig. 30, Fig. 31, and Fig. 32 frequency response (Bode and Nyquist), the stability is less affected by changes in the operation. That made the ANFIS-FOPID controller suitable for virgin oil heating. This robustness tell that even if the oil flow varies, the temperature will never overshoot and damage the oil's quality. Stability and performance analysis confirm that the ANFIS-modeled microwave system for virgin oil heating is more robust when managed by fractional-order control. The integration of ANFIS as the system model is critical, as it accurately represents the non-linear energy balance equation and the variable thermal properties of the oil that traditional linear models often ignore. Controller shows a noticeable phase variation and a reduction in magnitude at higher frequencies. In comparison, the FOPID controller exhibits a smoother magnitude response and a less abrupt phase change across the frequency range.

TABLE I.
COMPARISON OF FOPID CONTROLLER AND PID CONTROLLER

Performance Metric	ANFIS-PID Controller	ANFIS-FOPID Controller	Improvement
First Rise Time (to 50°C)	∼6.0 sec	∼3.8 sec	∼37% faster
First Overshoot (at 50°C)	∼2.5°C	∼1.0°C	∼60% lower
First Settling Time	∼17 sec	∼10 sec	∼41% faster
Drop Undershoot (to 25°C)	∼3.2°C	∼1.4°C	∼56% lower
Drop Recovery Time	∼8.5 sec	∼5.5 sec	∼35% faster
Final Rise Time (to 40°C)	∼6.5 sec	∼4.2 sec	∼35% faster
Steady-State Error	∼0.5°C	∼0.1°C	∼80% lower error

TABLE II.
SETTLING TIME AND ERROR AT ALL SETPOINTS

Setpoint Transition	ANFIS-PID Settling Behavior	ANFIS-FOPID Settling Behavior	Correction Improvement
0 to 50°C	Settles in ∼17.0 sec	Settles in ∼10.0 sec	41% faster stabilization
50 to 25°C	Recovers in ∼8.5 sec after a deep undershoot	Recovers in ∼5.5 sec with minimal undershoot	35% faster recovery
25 to 40°C	Takes ∼6.5 sec to reach the vicinity of the target	Takes ∼4.2 sec to reach the target accurately	35% faster rise

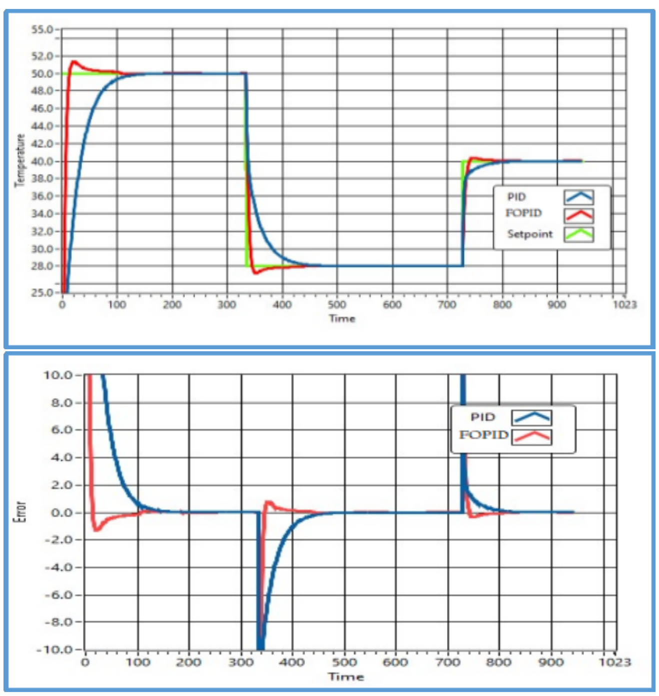


Fig. 27. (Temperature and Error) PID(K_P=10.677, K_i=0.012, and K_d=0.345), FOPID (λ =0, μ = 0.1)

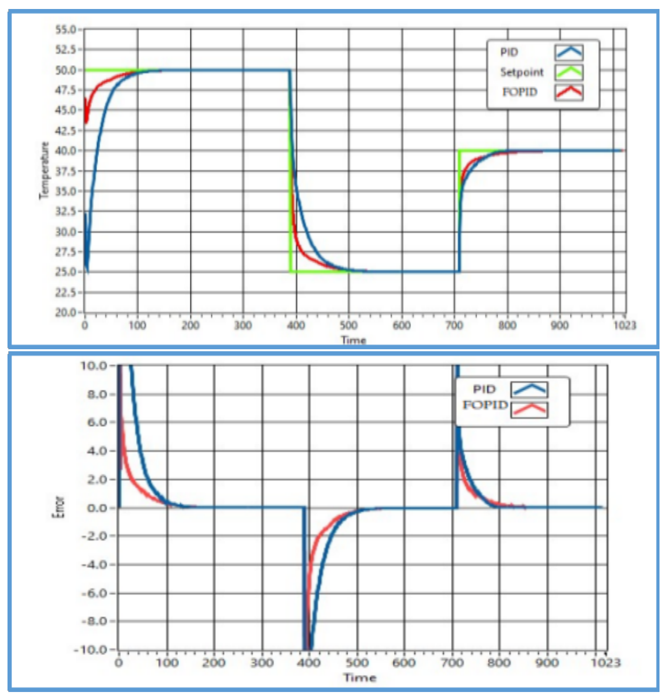


Fig. 28. (Temperature and Error) Different values of set point. FOPID (λ =0.34, μ = 0.5)

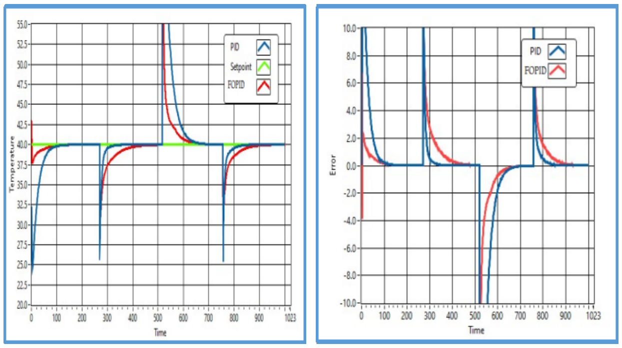


Fig. 29. (Temperature and Error at Disturbance Rejection) Setpoint(40^oC) Flow Rate Change (200, 400, 100, 300) ml/s, PID (K_P=10.677, K_i=0.012, and K_d=0.345), (λ =0.34, μ = 0.5)

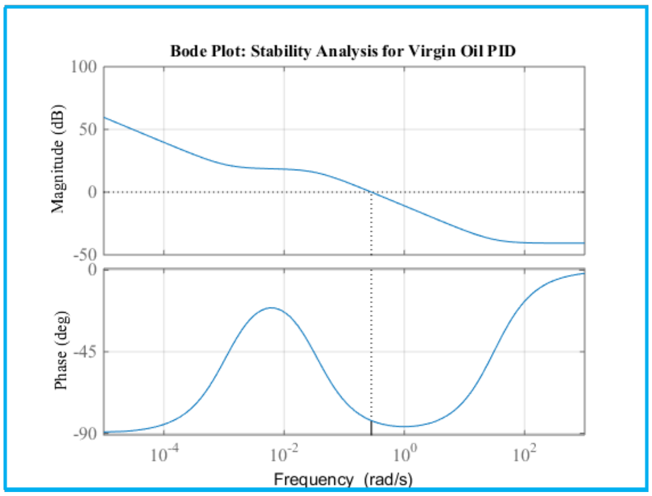


Fig. 30. Bode Plot for ANFIS-PID

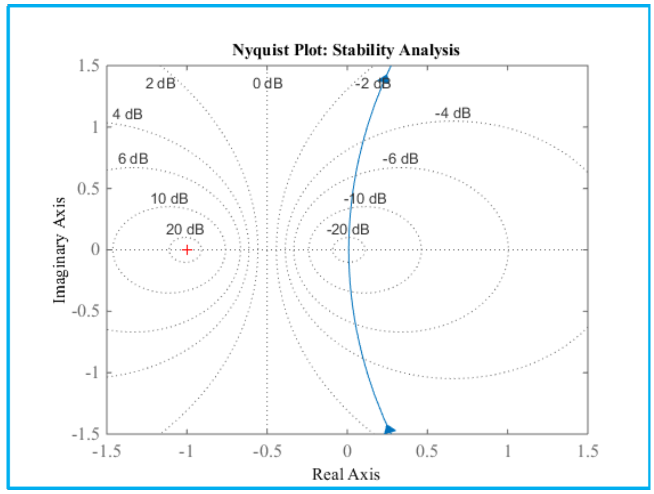


Fig. 31. Nyquist Plot ANFIS

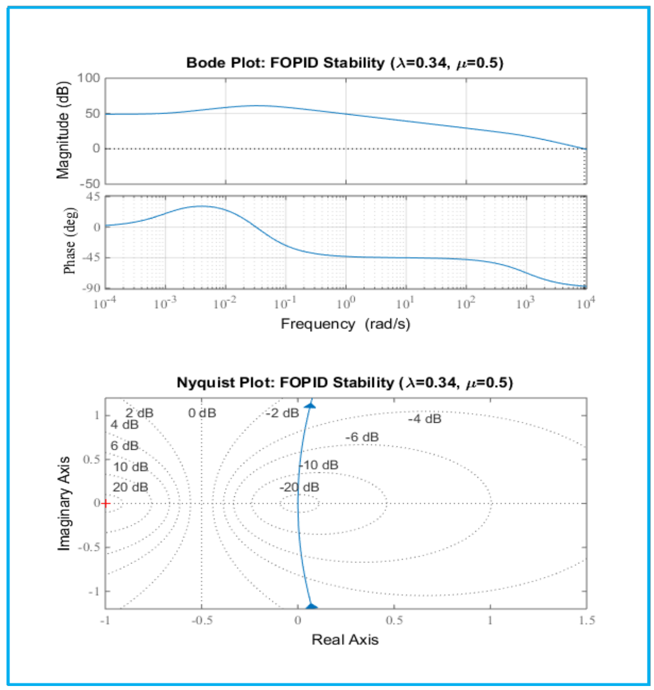


Fig. 32. Bode and Nyquist for ANFIS FOPID

D. Controls Performance Comparison

Table III shows the numerical results that highlight about the performance of the proposed ANFIS-FOPID controller and ANFIS-PID controller. The comparisons are computed over an entire operating cycle, including at step-up heating and step-down cooling phases, thereby accounting for error accumulation via the full simulation time. Thermal inertia and lag are seen in the response curves where it takes longer in the cooling phase than in heating; thus, there is a delay for ANFIS-PID to track setpoint due to this lag that greatly increases IAE but even more increases ITAE because ITAE has time-weighting penalty (in $^oCs^2$) so errors later in the experiment are multiplied by elapsed time. The proposed ANFIS-FOPID handled these dynamics successfully by reducing ITAE to 16,935.13 which is an improvement of 81.2% and also improved settling time with a very small overshoot of 0.20%. These improvements show how well ANFIS-FOPID works for controlling all the non-linearities and thermal lag that come with microwave-based oil heating processes proving its top performance among controllers for virgin oil thermal regulation. It adjusts dynamically to match the energy balance ($\rho\ C_p\ V$) inside the system reducing ITAE while getting rid of any temperature overshoots found in standard PID as well as fixed-gain FOPID systems. This result proves that proposed real-time architecture can maintain superior chemical quality of virgin oil during automated microwave processing

TABLE III.
PERFORMANCE COMPARISON

Controller Type	IAE (°C·s)	ISE (°C²·s)	ITAE (°C·s²)	Settling Time (s)	Overshoot (%)
ANFIS-PID	1469.53	19501.55	90226.82	300.15	2.52%
ANFIS-FOPID	664.36	9805.93	16935.13	63.03	0.20%

E. Performance Comparison with Existing Literature

In the literature The comparative study biases towards the FOPID system as proposed in the work ANFIS -FOPID . Zhou et al. (2024) [18] introduced the physics-based dynamic modeling of microwave heating for vegetable oil, describing the basic physics of the process. Their high-accuracy energy balance modeling was achieved without active control and following an open-loop response. Control efficiency was later discussed by Fathy et al. (2022) [19]. The authors used FOPID control in renewable energy systems to minimize ITAE; however, FOPID with fixed fractional gains was used in their study, indicating static tuning that cannot adjust to real-time invariations, which affects physical properties such as specific heat (Cp). To achieve intelligent control, Jegatheesh et al. (2023) [20] produced the ANFIS-FOPID on nonlinear liquid systems, and it successful redected the overshoot and improved rise times, but the study is far from the highly nonlinear cause thermal lag due to microwave-oil interactions. Recently, Singh et al. (2025) [21] published a modified ANFIS-FOPID for industrial DFIG systems with high robustness and impressive error reductions of 70–80%, but make quasion about the challenges for food-grade thermal system applications. Proposed study (2026) applying standard PID, Adaptive ANFIS -PID, and Adaptive ANFIS -FOPID architecture to a Virgin Oil Microwave System, ANFIS produces a fast settling time and a very low 0.2% overshoot, overcoming static tuning and particular thermal lag issues.

IV. CONCLUSIONS

An industrial microwave heating system with nonlinear thermal dynamics is modeled and controlled using standard PID and standard FOPID. The process in a microwave reactor is modeled, which mimics the nonlinear energy balance in the reactor. The model uses an Adaptive Neuro-Fuzzy Inference System (ANFIS), which acts as predict plant to mimic all the real-time variations, and deals with the incorporation of volumetric microwave heating and temperature, which dependent thermophysical properties of virgin oil that are difficult for transfer-function models to capture. The paper introduces a real-world monitoring and control system. ANFIS-FOPID and ANFIS-PID controllers are built based on a real-time LabVIEW environment that can directly interface with experimental hardware, making it easy to instantiate control. The Implementation tested the intelligent control under different disturbance conditions by changing the flow-rate randomly. Experimental results show ANFIS-PID and ANFIS -FOPID under stable operation. However, the ANFIS-FOPID controller gives faster attainment of steady-state conditions. Settling time is a small value, which leads to better process efficiency and saves energy in large-scale applications of microwave thermal systems, and keeps temperatures within the range necessary for antioxidant and phenolic compound preservation in virgin oil. These results validate the proposed approach to industrial processes meeting green chemistry criteria requiring reliable temperature control.

CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article.

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