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Original Article

Fuzzified Control in Band Dryer System

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Abstract: *Temperature control plays a crucial role in industrial processes that involve air drying. Drying is the process of removing moisture from materials, and the temperature during this process significantly impacts its overall performance. This manuscript proposes a hybrid technique for precise temperature control in band dryer systems, aiming to ensure product quality, process efficiency, and energy conservation. The Proposed Hybrid method is the combined execution of both the Giant Armadillo Optimization (GAO) and fuzzy logic-based PID controller (FL-PID) to optimize temperature control in band dryer systems. Hence, it is named GAO-FL-PID Approach. The proposed GAO algorithm is used to optimize the parameter of the PID controller and FL-PID controller is used to predict the uncertainties within the system. Traditional Proportional-Integral-Derivative (PID) controllers often struggle with the nonlinearities, uncertainties, and disturbances inherent in these systems. This research investigates the application of a fuzzy logic based PID controller to achieve robust and adaptive temperature control in a band dryer system. In this approach, a set of fuzzy rules, based on expert knowledge and process dynamics, dynamically adjusts the PID parameters in real-time based on the temperature error and its rate of change. The hybrid approach combines the strengths of fuzzy logic and PID control, and simulation work is conducted using MATLAB Simulink platform and compared with various existing approaches. The result demonstrates that the adaptive tuning enables the controller to quickly respond to disturbances and maintain tight temperature tracking, minimizing overshoot and settling time. The proposed method shows low settling time of 0.1 S and minimum overshoot of 0.4% compared with other existing methods such as Particle swarm optimization (PSO), Wild horse optimization (WHO), and Seagull Optimization Algorithm (SOA) respectively.*

Keywords: *Temperature Control, Band Dryer System, Fuzzy Logic Controller, Fuzzy-Logic Based PID Controller, Product Quality, Cohen-Coon Method.*

I. INTRODUCTION

Industrial drying plays a central role in various manufacturing processes, contributing to the preservation and quality of end products. A band dryer system is a type of drying equipment used in various industrial processes to remove moisture from materials such as food products, chemicals, and pharmaceuticals. It has become well-known among the many drying technologies available because of its adaptability and efficiency in various industries. The main component of a band dryer system is a continuously moving conveyor belt, or band, on which the material to be dried is placed. The drying process involves the application of heat to the material as it moves along the conveyor belt, allowing moisture to evaporate and escape. Hot air, infrared radiation, steam, and other heating techniques are used to provide the heat required for moisture evaporation during the drying process. Need for Control in Band Dryer System is required to ensure optimal drying efficiency and product quality, precise control is essential in a band dryer system. [1]

Traditional control methods, such as PID controllers, have been commonly used in band dryer systems. As maintaining optimal temperature conditions is critical for effective drying, PID controllers in band dryer systems modulate heating elements based on proportional error, integral of error over time, and derivative of error, ensuring that the system adapts to varying conditions and achieves the desired temperature setpoints. However, PID controllers may not be able to meet the accuracy requirements in certain industry cases due to the non-linear and complex nature of the drying process. Fuzzy logic control has emerged as a promising alternative due to its ability to handle imprecise information and complex dynamics. Even in the absence of accurate mathematical models, it can transfer the expert knowledge of operators into control actions. Fuzzy logic can be integrated with PID controllers to create a hybrid control system that benefits from the advantages of both techniques [2].

A. Background of the Recent Research Work

Recent research indicates that constant-temperature control systems comprise the majority of drying temperature control systems in use today. However, there aren't many reports on temperature-variable processes using drying temperature control systems. Varying-temperature drying techniques are no longer compatible with the existing drying temperature control systems due to their lack of specificity. The sophisticated and efficient proportional-integral-derivative (PID) controller is used for the linear combination of system errors. It returns to the object that is in control. The PID controller's derivative, integral, and proportional parameters must be pre-set via human experience; the control effect is left to the individual's judgment. The PID controller is not able to make real-time adjustments to the controller parameters and lacks control flexibility. The control effect is rarely satisfactory for complex non-linearity control systems. This is where the nifty PID algorithm comes into play, able to instantly change the PID controller's settings. Numerous control industries have used PIDs, including PIDs for particle swarm optimization, fuzzy, neural networks, and genetic algorithms. Because neural networks have a special capacity for learning and non-linear processing, they are frequently utilized for PID controller parameter tuning. On the other hand, neural networks have a slow convergence rate and are prone to local optimization during training as opposed to global optimization. Improved neural network training can greatly increase the neural network's capacity to control PID parameters. Research in this area aims to address the challenges and drawbacks associated with the hybrid method of temperature control in a band dryer system.

II. PROCESS DESCRIPTION

An industrial drying device called a band dryer system is made to remove moisture effectively and continuously from bulk materials. This kind of dryer is extensively employed in many different industries to dry a wide range of commodities, including textiles, chemicals, food items, minerals, and more. The basic working principle of a band dryer is moving material through a drying chamber continuously on a conveyor belt while heating it to promote moisture evaporation [3].

A. Operating Principle

The convective mass transfer theory supports the band dryer's operation. On the conveyor belt, hot air from the AHU is driven through the material bed. The heat transfer from the hot air causes the moisture in the wet material to evaporate, and the humid air is subsequently released through the exhaust vents. The material is continuously moved by the conveyor belt through the drying chamber, where it is exposed to hot air and effectively removed moisture. Until the intended final moisture content is reached, the drying process is continued [4].

III. PID CONTROLLER

In dynamic systems, the most used controller is the proportional-integral-derivative (PID) controller. For every control, there might be a single closed loop PID control. PID controller implementation has progressed from early pneumatic and mechanical designs to transistor-based analog circuits and, more recently, microprocessor and digital systems [9]. Digital signal processors (DSPs) and low-cost, high-performance microprocessors allowed digital control to become a competitive option. Furthermore, because FPGAs can do multiple tasks at once, digital controller architectures can be designed in parallel. One of the most often used controllers in the market is PID. It is often utilized in processes with up to medium order and little time delays because of its great stability.

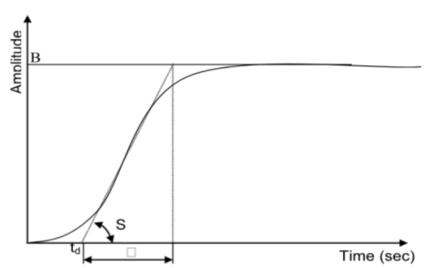

Figure 1: Open Loop Sigmoidal Curve

The gain form of PID controller is given as,

$$G(s) = K_p + \frac{K_i}{s} + K_d S (1)$$

In the above equation, the G(s) is the gain of the controller, K_p, K_i, K_d are the proportional, integraland derivative gains respectively. It is to be noted that the gain parameters in PID controller are manually tuned using tuning rules. In MATLAB, Cohen-Coon method is used to auto the PID Controller [5].

B. Cohen-Coon Method

This is also known as a process response curve or an open loop curve. Compared to the ZN technique, this procedure is simpler, but it still involves some computational complexity.

The actions that need to be done are as follows:

- The open loop test is performed and a sigmoidal curve is obtained.
- From the sigmoidal curve the gain K, time constant τ and deadtime t d values are found.
- K is found by the point at which the curve attains steady state, τ is the 63% of the controller output, and t d is the point on the time axis formed when tangential line to the curve which cuts the x axis.

By the obtained values, we can obtain the gain values by substituting and computing in the respective formula.

Table 1: Parameters of Cohen-Coon Method

Parameter	Formula
K_p	$K_P = \frac{1}{K}\frac{\tau}{t_d}\left[\frac{4}{3}+\frac{t_d}{4\tau}\right]$
T_i	$T_i = t_d\left[\frac{32+6\frac{t_d}{\tau}}{13+8\frac{t_d}{\tau}}\right]$
T_d	$T_d = t_d\left[\frac{4}{11+2\frac{t_d}{\tau}}\right]$

Where K is gain, τ is time constant, $t_d$is dead time. The gain formulae vary for every type of controller. For PID controller the gain is calculated from these values and is substituted in the Functional Block Parameter of PID Controller [1].

IV. GAO-FL-PID BASED TEMPERATURE CONTROL IN BAND DRYER SYSTEM

In this paper, GAO-FL-PID for precise temperature control in band dryer systems used in industries. The proposed method combines Giant Armadillo Optimization (GAO) and fuzzy logic-based PID controller (FL-PID) technique. The controller's parameter is optimized through the application of the proposed GAO algorithm, namely $K_p, K_i \text{ and } K_d$ensuring an efficient and robust control strategy and FL-PID controller is used to predict the uncertainties within the system. The aim of this research is to enhance product quality and energy conservation by achieving precise temperature control. The following is a detailed explanation of the proposed technique's justification:

A. Giant Armadillo Optimization

Each member of the GAO population represents a giant armadillo's location in the wild, and the problem-solving space in the GAO algorithm corresponds to the giant armadillo's natural habitat. Every participant embodies a potential resolution to the issue under investigation. The GAO algorithm mimics the movement and interaction of the giant armadillos in the wild to search for optimal solutions [10]. All things considered, the GAO approach builds an efficient metaheuristic algorithm for problem-solving by drawing on the natural behavior of the giant armadillo, specifically its attack strategy on termite mounds and its digging for food. Next, a mathematical representation of the two stages of the process of updating candidate solutions—exploration and exploitation—is provided.

Step 1: Initialization

Set the system's input parameters to zero. Set the PID controller's gain parameters during this phase using fuzzy logic.

Step 2: Random Generation

After initialization, the random vectors produce the input parameters at random.

$$Z = \begin{bmatrix} Z_1 \\ Z_2 \\ Z_3 \end{bmatrix}_{M\times N} = \begin{bmatrix} Z_{1,1} & Z_{1,G} & Z_{1,N} \\ Z_{j,1} & Z_{j,G} & Z_{j,N} \\ Z_{M,1} & Z_{M,G} & Z_{M,N} \end{bmatrix}_{M\times N} \quad (2)$$

Here, Z represent the population matrix of GAO, represent the j^{th} participant in the GAO, $Z_{j,G}$ denotes the search space's G^{th}dimension, M is denoted as the quantity of enormous armadillos, N is represent as the quantity of variables used in the decision.

Step 3: Fitness Function

The objective function determines fitness. It is defined as the fitness function.

$$Fitness = MIN(Error) \quad (3)$$

Step 4: Attack on Termite Mounds (Exploration Phase)

The 1st stage of GAO involves modelling the attack of a massive armadillo on termite mounds during hunting, which is employed to alter the population's locations within the problem-solving area. Each member of the population has a new position calculated for them based on a model of giant armadillos moving toward termite mounds. If this new position enhances the objective function's value, it takes the place of the corresponding member's former position.

$$Z_{j,i}^{P1} = Z_{j,i} + R_{j,i}.\left(STM_{j,i} - I_{j,i}.Z_{j,i}\right) \quad (4)$$

$$Z_j = \begin{cases} Z_j^{P1}, & E_j^{P1} \leq E_j \\ Z_j, & else \end{cases} \quad (5)$$

Here, STM_j represent the giant armadillo's selected termite mound, $STM_{j,i}$ is its i^{th} dimension, Z_j^{P1} represent the new location determined by using the attacking phase of the proposed GAO for the j^{th} giant armadillo, $Z_{j,i}^{P1}$ is the i^{th} dimension, E_j^{P1} denotes the value of the objective function.

Step 5: Digging in termite Mounds (Exploitation Phase)

The population members' locations within the problem-solving area are modified by imitating the giant armadillo's habit of burrowing into termite mounds to feed on termites during the second phase of GAO. For every individual in the population, a new position is calculated using a model that mimics the giant armadillo's digging prowess. The corresponding member's prior position is replaced if the new position improves the value of the objective function.

$$Z_{j,i}^{P2} = Z_{j,i} + \left(1 - 2R_{j,i}\right).\frac{Va_i - la_i}{t} \quad (6)$$

$$Z_j = \begin{cases} Z_j^{P2}, & E_j^{P2} \leq E_j \\ Z_j, & else \end{cases} \quad (7)$$

Here, Z_j^{P2} represent the new location determined for the j^{th} giant armadillo using the proposed GAO's digging phase, $Z_{j,i}^{P2}$ is the i^{th} dimension, E_j^{P2} denotes the iterative counter, and The objective function's value is represented by t.

Step 6: Repetition Process

The first iteration of GAO ends when all giant armadillos' positions in the problem-solving space have been updated during the attack and digging phases. After that, the algorithm moves on to the following iteration, until the final iteration, the locations of the giant armadillos within the problem-solving area are updated. The position of the top GAO member has been updated and saved as the best candidate solution at the end of each iteration.

Step 7: Termination Criteria

Check the criteria for termination; if it is met, the best possible solution has been found; if not, repeat the procedure.

V. FUZZY LOGIC CONTROLLER

Fuzzy logic (a way of AI) is mainly designed by simulating human brain's reasoning ability and decision-making ability and composed of fuzzy rule base, fuzzification, fuzzy inference and defuzzification. The operator's technical knowledge is translated into forms of fuzzy rules and composes a fuzzy rule base. The precise input signal becomes fuzzy input signal after fuzzy processing. Then fuzzy input signal is dealt through fuzzy inference in fuzzy rule base to get fuzzy conclusions. One method that creates the most useful fuzzy rules is the “IF-THEN” rule statement which has been used in PID drying Controller, intelligent monitoring, and parameter optimization etc.

The fuzzification process should be concerned with two aspects, viz, fuzzy set whose general way is Zadeh representation and sequence pair representation and gauss function are used as a membership function. The fuzzy inference is a method to get fuzzy conclusions by calculating the membership degree of the input to the related fuzzy sets according to fuzzy rules and generally used the maximum and minimum synthesis regulation. The commonly used methods for defuzzification process are centre of gravity (COG), central mean (CA), the maximum criterion method and the mean value method of maximum value. After defuzzification of fuzzy conclusions, the system gives precise and specific output data. [6]

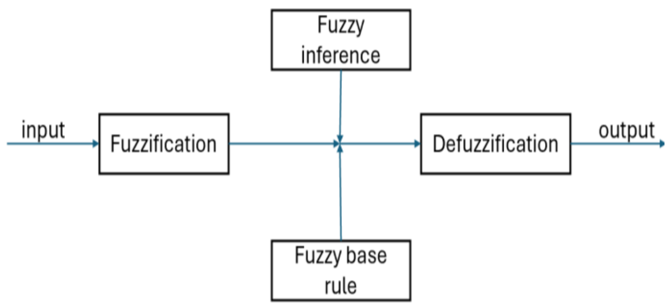

Figure 2: Schematic Diagram of Fuzzy Logic

B. Selection of Fuzzy Variables

The fuzzy input and output variables, namely Error, Variation in Error and Variation in output, are divided into five linguistic (fuzzy) variables namely VL (Very Low), L (Low), M (Medium), H (High) and VH (Very High).

a) Data Base and Rule Base of Fuzzy Logic Controller for Band Dryers:

Functions of membership for the input and output variables containing errors, as well as the error and controller output variations, are provided. Figure 3 illustrate the analysis of fuzzy logic input error. At very low error the value is initially start from 1 at 0 input variable and then the value is gradually decreased to reach 0 at the input variable of 1. At low error the value is initially start from 0.1 at the input variable of 0 and then the value is gradually increase and decrease to reach till 0 at the input variable of 1. At medium error the value is initially start from 0 at the input variable of 0 and then the value is gradually increase and decrease to reach till 0 at the input variable of 1. At high error the value is initially start from 0 at the input variable of 0.5 and then the value is gradually increase and decrease to reach 0.5 at the input variable of 1. Figure 4 illustrate the analysis of fuzzy logic derivative error. At very low error the value is initially start from 0.8 at 0 input variable and then the value is gradually decreased to reach 0 at the input variable of 1. At low error the value is initially start from 0.1 at the input variable of 0 and then the value is gradually increase and decrease to reach till 0 at the input variable of 1. At medium error the value is initially start from 0 at the input variable of 0 and then the value is gradually increase and decrease to reach till 0 at the input variable of 1. At high error the value is initially start from 0 at the input variable of 0.5 and then the value is gradually increase and decrease to reach 0.5 at the input variable of 1.

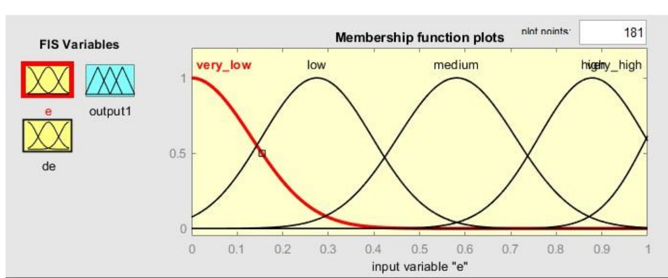

Figure 3: Analysis of Fuzzy Logic Input Error

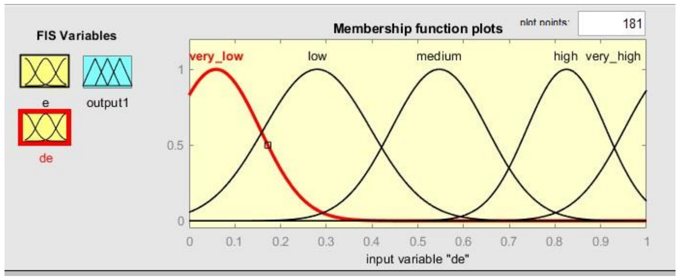

Figure 4: Analysis of Fuzzy Logic Derivative Error

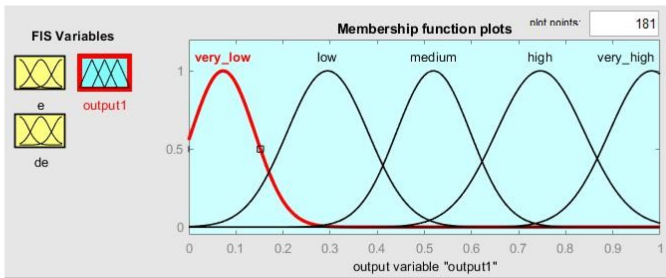

Figure 5: Analysis of Fuzzy Logic Output

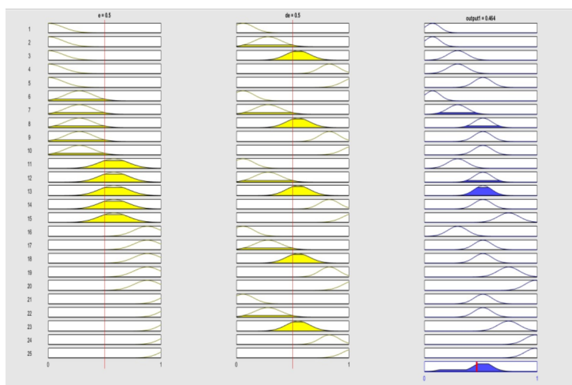

Figure 6: Analysis of Rule Base Fuzzy Logic Controller

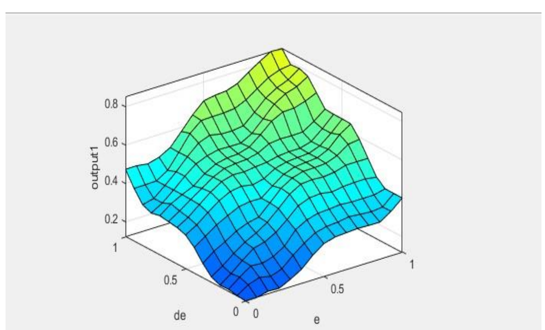

Figure 7: Surface View of Rule Based Fuzzy Logic Controller

Figure 5 illustrate the analysis of fuzzy logic output. At very low error the value is initially start from 0.6 at 0 input variable and then the value is gradually decreased to reach 0 at the input variable of 1. At low error the value is initially start from 0 at the input variable of 0 and then the value is gradually increase and decrease to reach till 0 at the input variable of 1. At medium error the value is initially start from 0 at the input variable of 0 and then the value is gradually increase and decrease to reach till 0 at the input variable of 1. At high error the value is initially start from 0 at the input variable of 0 and then the value is gradually increase and decrease to reach 0 at the input variable of 1. Figure 6 illustrate the analysis of rule base fuzzy logic controller. Figure 7 illustrate the analysis of surface view of rule based fuzzy logic controller.

Table 2: Fuzzy Access Memory Table for Fuzzy Controller

e→ de↓	**VL**	**L**	**M**	**H**	**VH**
VL	VL	VL	L	L	M
L	VL	L	M	M	M
M	L	M	M	M	H
H	L	M	H	H	VH
VH	M	M	H	VH	VH

Table 2 represents the fuzzy access memory table (FAM table). It is an easy way to represent the rules in the form of a table. It shows the output of different input combinations of the system. Figure 6 represents the surface view and Figure 5 represents the rule view. As their name indicates, they both are read only tools. Surface view is a 3D representation of dependency of output on inputs. Rule view is used to view the detailed behavior of fuzzy inference system.

VI. FUZZY TUNED PID CONTROLLER

Fuzzy Tuned PID (FL-PID) control emerges as a powerful solution to address these challenges. It combines the strengths of both PID control and fuzzy logic.

A. Working of FL-PID Band Dryer

a) Fuzzy Rule Base:

A set of rules defines the relationship between process variables (e.g., temperature error, rate of change of error) and adjustments to PID gains. These rules are based on operator experience and capture the non-linear dynamics of the drying process.

b) Fuzzy Inference Engine:

Continuously monitors process variables and activates relevant fuzzy rules based on their degree of truth (fuzzification). These activated rules are then aggregated (e.g., AND, OR) to form a single fuzzy output representing the recommended adjustments to the PID gains.

c) Defuzzification:

Converts the fuzzy output into a crisp numerical value that can be directly applied to modify the PID parameters (K_p, K_i, K_d). Different methods exist (e.g., centroid average, mean of maxima) with varying effects on controller behaviour.

B. Benefits of FL-PID in Band Dryers

a) Improved Temperature Tracking:

By dynamically adjusting PID gains, FL-PID achieves tighter control over the drying temperature, minimizing overshoot and settling time.

b) Enhanced Robustness:

Fuzzy logic's ability to handle uncertainties and nonlinearities makes FL-PID less susceptible to disturbances and variations in the drying process, leading to more consistent product quality.

c) Reduced Energy Consumption:

Precise temperature control optimizes energy usage by avoiding unnecessary heating and over drying.

d) Operator Knowledge Integration:

Fuzzy logic captures the valuable insights of experienced operators, translating their expertise into actionable control strategies.

Overall, FL-PID controllers offer a promising approach for advanced temperature control in band dryer systems. They combine the strengths of traditional PID control with the adaptability and robustness of fuzzy logic, leading to improved performance, efficiency, and product quality.

C. Selection of Variables

The fuzzy input and output variables, namely Error, Variation in Error and Variation in output, are divided into three linguistic (fuzzy) variables namely L (Low), M (Medium) and H (High).

D. Data Base and Rule Base of Fuzzy Logic Controller for Band Dryers

The error, error variation, and controller output variation membership functions are provided for the input and output variables. Figure 8illustrates the analysis of FL-PID input error. At low error the value initially starts from 1 at 0 input variable and then the value gradually decrease to reach 0 at the input variable of 1. At medium error the value is initially start from 0.1 at the input variable of 0 and then the value is gradually increase and decrease to reach till 0.1 at the input variable of 1. At high error the value is initially start from 0 at the input variable of 0 and then the value gradually increases to reach 1 at the input variable of 1. Figure 9illustrates the analysis of FL-PID derivative error. At low error the value initially starts from 1 at 0 input variable and then the value gradually decreases to reach 0 at the input variable of 1. At medium error the value initially starts from 0 at the input variable of 0.1 and then the value gradually increases and decreases to reach up to 0.1 at the input variable of 1. At high error the value is initially start from 0 at the input variable of 0 and then the value is gradually increased to reach 0.5 at the input variable of 1.

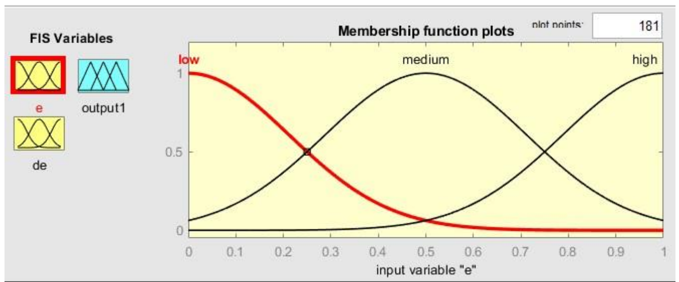

Figure 8: Analysis of FL-PID Input Error

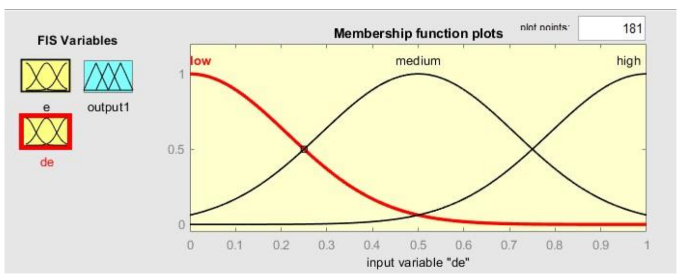

Figure 9: Analysis of FL-PID Derivative Error

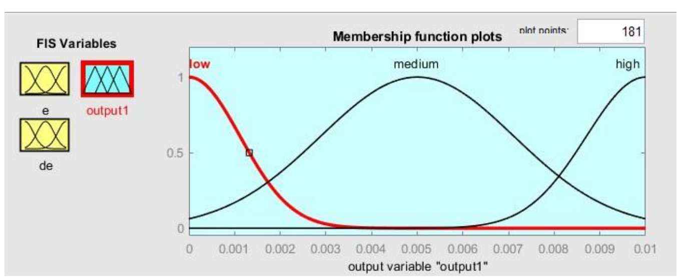

Figure 10: Analysis of FL-PID Output

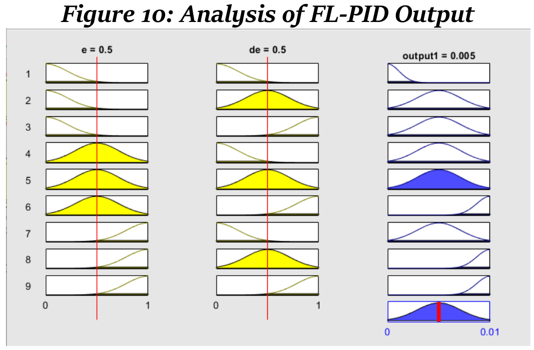

Figure 11: Analysis of Rule Base FL-PID Controller

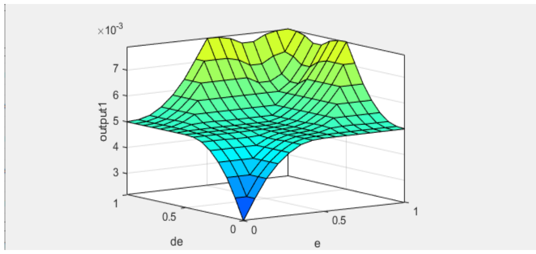

Figure 12: Surface View of Rules

Figure 10illustrates the analysis of FL-PID output. At very low error the value is initially start from 1 at 0 input variable and then the value is gradually decreased to reach 0 at the input variable of 0.01. At medium error the value is initially start from 0.1 at the input variable of 0 and then the value gradually increases and decreases to reach up to 0.1 at the input variable of -0.01. At high error the value is initially start from 0 at the input variable of 0 and then the value gradually increases and decreases to reach 1 at the input variable of 0.01. Figure 11illustrates the analysis of rule base fuzzy logic controller. Figure 12illustrates the analysis of surface view of rule-based FL-PID controller.

Table 3: Fuzzy Access Memory Table for Fuzzy Tuned PID Controller

e→ de↓	L	M	H
L	L	M	M
M	M	M	H
H	M	H	H

VII. RESULT AND DISCUSSION

The error and the variation in error is observed as the input data and level of the temperature is observed as the output data for the Band Dryer System. Data assortment is done by manual means and the system identification algorithms are established using MATLAB. The identified transfer function for the Band Dryer System using system identification tool is:

$$U(t)= \frac{0.1552}{S+0.001569}$$

The above transfer function is then taken for controller tuning and PID control algorithm is implemented. Cohen-Coon tuning method is being utilized and the PID values calculated for the process are K_p = 3.95, K_i =0.67, K_d = 0.1925

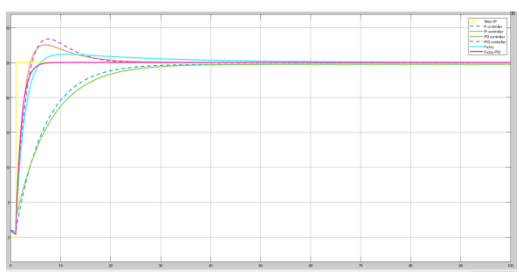

Figure 13: Simulation Result Comparison of Various Controllers for Band Dryer System

From figure 13, Comparing the proposed fuzzy and fuzzy tuned PID controller to the standard P, PI, PD, and PID controller, it is found that the latter effectively reduces overshoot.

Table 4: Evaluation Criteria of Different Controllers

Controller	Rise Time	Overshoot	Undershoot	Settling Time	IAE	ISE	ITAE
P- controller	12.694 s	0.501%	1.727%		163.9	1747	2113
PI- controller	2.057s	10.795%	-0175%	30s	49.61	392.1	314.7
PD- controller	14.852 s	0.500%	1.526%		177.9	1768	2452
PID- controller	2.395 s	14.535%	0.613%	24s	57.55	473.6	340.3
Fuzzy logic controller	3.144 s	4.787%	0.929%		67.47	477.8	984
FL- PID controller	2.371 s	0.511%	1315%	8.5s	2.23	324	111.2

Table 5: Analysis of Controller Performance

Solution Approach	Settling time (S)	Overshoot (%)	Rise Time (S)
Proposed	0.1	0.4	0.036
PSO	0.25	0.54	0.0085
WHO	0.33	0.62	0.0093
SOA	0.46	0.78	0.023

Table 4 illustrate the Evaluation Criteria of different Controllers. Table V displays an analysis of controller performance. In comparison to the other three approaches, the one proposed has a shorter settling time (0.4%) and a shorter rise time (0.036). There are three methods: PSO, WHO, and SOA. When compared to existing methods, the proposed method exhibits lower settling and rise times. Better outcomes are shown by the proposed approach in every approach.

VIII. CONCLUSION

This study proposes a hybrid approach combining the Giant Armadillo Optimization (GAO) algorithm and a Fuzzy Logic-PID controller (FL-PID) to optimize temperature control in band dryer systems. The objective was to enhance product quality and conserve energy by achieving precise temperature control in the drying process. This study aimed to address the limitations of traditional PID controllers in handling the nonlinearities, uncertainties, and disturbances inherent in such systems. The proposed FL-PID controller utilized a set of expert-derived fuzzy rules to dynamically adjust the PID gains (K_p, K_i, K_d) based on real-time measurements of temperature error and its rate of change. Furthermore, the FL-PID controller offered the advantage of incorporating operator knowledge and experience into the control logic through the fuzzy rule base. This facilitated a more intuitive and adaptable control system, reducing reliance on complex mathematical models and simplifying parameter tuning. The improved product quality, optimized energy usage, and reduced operational complexity offer significant benefits for industrial applications. Through simulation experiments using MATLAB Simulink, the performance of the hybrid GAO-FL-PID approach was evaluated. The results demonstrated improved temperature tracking, minimized overshoot and settling time, and enhanced disturbance rejection capabilities compared to traditional PID controllers. This demonstrates how well the proposed approach works to optimize temperature control in band dryer systems. To believe that the further research and development in this area can pave the way for wider adoption of fuzzy logic-based control strategies in various industrial processes, fostering enhanced sustainability and performance. In conclusion, the proposed approach has a 0.1 settling time, a 0.4% overshoot, and a 0.036 rise time when compared to the other three approaches. There are three methods: PSO, WHO, and SOA. When compared to existing methods, the proposed method exhibits lower settling and rise times. The proposed method shows better results in all approaches.

IX. REFERENCES

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