Implementation of Fuzzy PID Controller on Hot Air Blower System

Atiqah Liyana Md Said, Norlela Ishak* and Mazidah Tajjudin

***Abstract*—This paper focuses on the modeling, development, and implementation of a Fuzzy PID controller in controlling the heating system. This study will look into the effectiveness of a fuzzy Proportional Integral Derivative (PID) control scheme for this application. Instead of using a trial-and-error method for the controller tuning, this study proposes a fuzzy PID control to tune the controller parameters and to improve the conventional PID controller transient response. Modeling of the PT326 heating system is required before designing the controller. Through the MATLAB System Identification Toolbox, a discrete-time model is obtained and represented by an ARX model structure. A simulation study had been implemented on a unit step input. The results demonstrated that the system shows positive improvement in terms of rise time and settling time when fuzzy PID controller was applied.**

***Index Terms*—ARX model, Fuzzy PID, hot air blower, PID controller, process trainer, PT326, system identification.**

I. Introduction

PT326 the process trainer, depicted in Fig. 1, is a self-contained piece of process and control equipment. Air is drawn from the atmosphere by a centrifugal blower and driven past a heater grid and through a length of tubing before being returned to the atmosphere. An inlet throttle attached to the blower can be used to adjust the velocity of the air stream. The process involves heating the air flowing through the tube to the desired temperature level, and the control equipment's purpose is to measure the air temperature, compare it to a value set by the user, and generate a control signal that determines the amount of electrical power supplied to a correcting element. In this case, a heater is installed next to the blower. The PT326 process trainer works by heating the air flowing through the tube to the desired temperature.

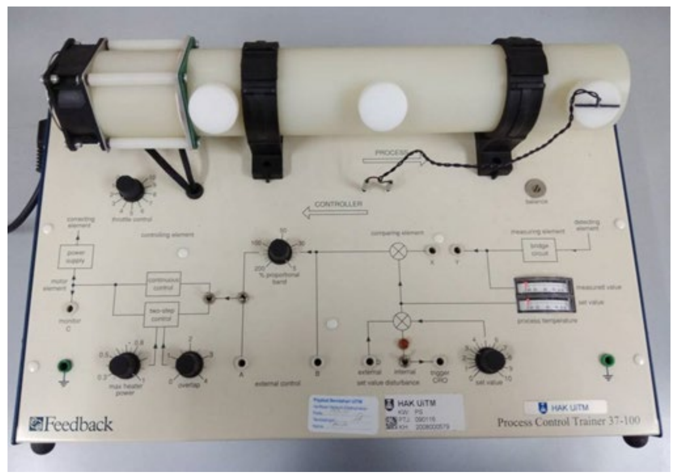

Fig. 1.PT326 process trainer heating system.

The control equipment's purpose is to measure the air temperature, compare it to a user-specified value, and generate a control signal that determines the amount of electrical power supplied to a correcting element. In this case, a heater is installed next to the blower [1]. As seen in previous studies [2]–[11], the PT326 process trainer or hot air blower system can be used for a variety of reasons and applications.

The problem of developing mathematical models of dynamical systems based on observed data from the system is addressed by system identification. A system is an object that interacts with variables of various types to produce observable signals. The observable signals that are of interest to us are typically referred to as outputs. The system is also influenced by external stimuli. The observer can manipulate inputs, which are external signals. Disturbances are another term for other types of signals. Disturbances are classified as either directly measured or observed only through their influence on output. The difference between inputs and measured disturbances is frequently insignificant for the modelling process [12]. When the current output value of a system is dependent not only on the current external stimuli but also on their previous values,

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the system is said to be dynamical [12], [13]. Essentially, a model must be built from data that has been observed [12].

There are two methods for building mathematical models which are mathematical modelling and system identification. Mathematical modelling is an analytic approach that uses basic physics laws to describe the dynamic behavior of a process or phenomenon. Meanwhile, system identification is an experimental technique in which various tests are done on the system before fitting a model to the recorded data by assigning appropriate numerical values to its parameters [13].

II. SYSTEM IDENTIFICATION

Modeling and identifying nonlinear dynamic structures are a difficult task due to the fact that nonlinear processes are unique in the sense that they do not share many properties. The primary goal of any nonlinear system modelling and identity scheme is universality: the capability of describing a vast array of structurally distinct structures.

The task of system identification is depicted in Fig. 2. For the sake of simplicity, it is assumed that the process has only one output. It is simple to extend to the case of multiple outputs. A model should be as accurate as possible in representing the behavior of a process. Typically, model quality is expressed as a function of the difference between the (disturbed) process output and the model output. This error is used to fine-tune the model's parameters [14], [15].

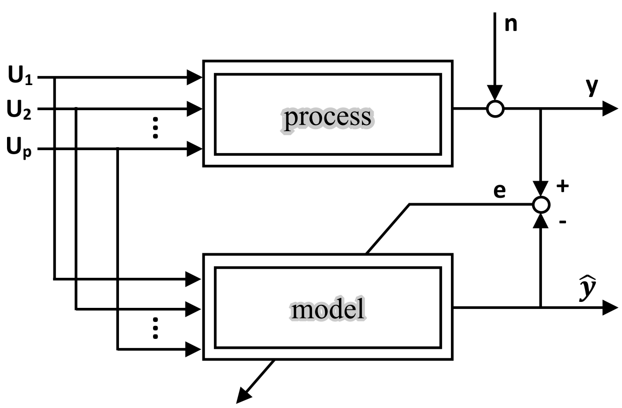

Fig. 2. System Identification block diagram.

A. Model Identification

To obtain the parametric model structure, the input and output data were run through the identification system in the MATLAB GUI. Due to its basic and simple model compared to the other models, the Auto Regressive with Exogenous Input (ARX) model was used as the parametric model in this study. Fig. 3 depicts a block diagram of the PT326 heating system. Table 1 shows four different models obtained from PT326 were chosen for this study, which are ARX221, ARX331, ARX441, and ARX551. Fig. 4 depicts the input and output signals generated by the identification system in the MATLAB GUI toolbox for model identification.

TABLE 1
ARX MODEL REPRESENTATION WITH BEST FIT CRITERIA

Plant Model	Polynomials	Best Fits (%)
ARX 221	$\frac{B(z)}{A(z)} = \frac{0.003592z^{-1} + 0.04372z^{-2}}{1 - 1.6805z^{-1} + 0.7299z^{-2}}$	71.93
ARX 331	$\frac{B(z)}{A(z)} = \frac{0.002666z^{-1} + 0.001748z^{-2} + 0.07142\, z^{-3}}{1 - 1.6395z^{-1} + 0.8776z^{-2} - 0.1597z^{-3}}$	84.71
ARX 441	$\frac{B(z)}{A(z)} = \frac{0.001943z^{-1} + 0.003348z^{-2} + 0.06328z^{-3} + 0.05455z^{-4}}{1 - 1.121z^{-1} + 0.09012z^{-2} + 0.2189z^{-3} - 0.06088z^{-4}}$	85.31
ARX 551	$\frac{B(z)}{A(z)} = \frac{0.001688z^{-1} + 0.003451z^{-2} + 0.06452z^{-3} + 0.06223z^{-4} + 0.022}{1 - 0.9646z^{-1} + 0.05961z^{-2} - 0.01838z^{-3} + 0.1405z^{-4} - 0.058}$	85.36

In general, an identification experiment is carried out by exciting the system with an input signal such as a step, a sinusoid, or a random signal and observing its input and output over a time interval. The system is subjected to an input signal step in this study. Normally, these signals are recorded in a computer mass storage for later "information processing." The recorded input and output sequences will then be used to fit a parametric model of the process. The first step is to determine an appropriate form of the model, which is typically a linear difference equation of a certain order. The second step is to use a statistically based method to estimate the model's unknown parameters, such as the coefficients in the difference equation. In practice, structure and parameter estimations are frequently done iteratively. This means that a preliminary structure is chosen, and the associated parameters are estimated. The obtained model is then tested to see if it is an accurate representation of the system. If this is not the case, a more complex model structure must be considered, its parameters estimated, and the new model validated, among other things [11], [16]–[18].

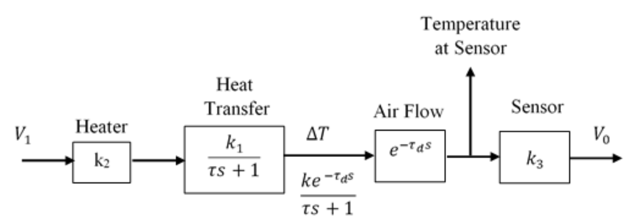

Fig. 3. Block diagram of PT326 heating system.

The plant models in the form of discrete-time transfer functions were given to MATLAB System Identification Toolbox, and the best fits obtained are shown in Table 1. A portion of the experimental data that was not used will be used in the model validation section. Several criteria, including Akaike's Final Prediction Error, Akaike's Information Criteria, and best fit, will determine whether the obtained model is accepted or rejected [12], [19], [20].

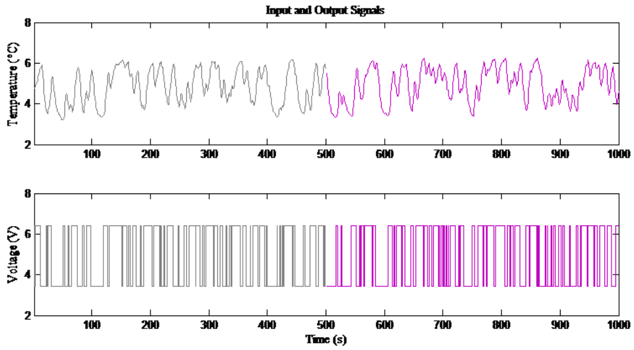

Fig. 4.Input and output signal for model identification.

Fig. 5 shows the zero and pole plots for ARX221, ARX331, ARX441 and ARX551 respectively. Based on Fig. 5, the models obtained are a non-minimum phase model considering that there are zeros situated outside the unity circle.

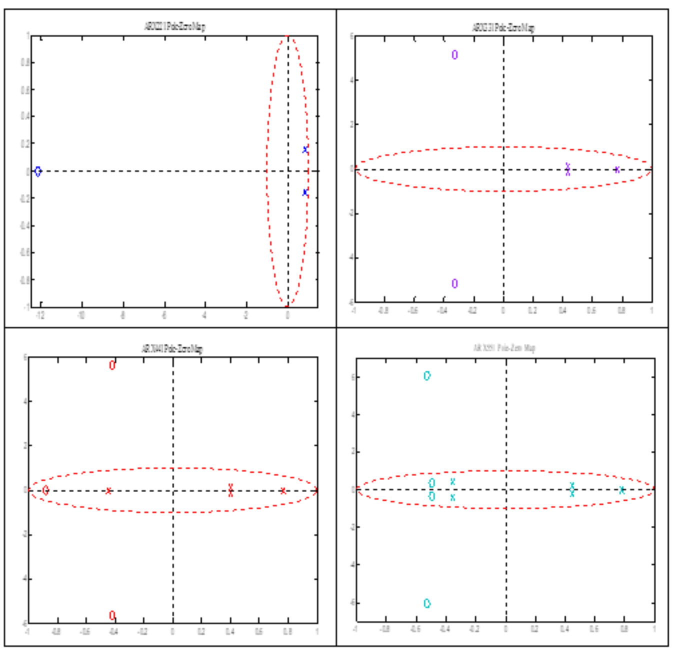
Fig. 5. Zeros and poles plots of ARX models.

III. PID CONTROLLER

Proportional-Integral-Derivative (PID) control is the most widely used control algorithm in industry and is widely accepted in industrial control. PID controllers' popularity can be attributed to their robust performance in a wide range of operating conditions, as well as their functional simplicity, which allows engineers to operate them in a simple, straightforward manner [11]. The PID algorithm, as the name implies, is made up of three basic coefficients: proportional, integral, and derivative, which are varied to achieve the best possible response.

The basic idea behind a PID controller is to read a sensor and then compute the desired output by calculating proportional, integral, and derivative responses and summing those three components. In a PID controller, you must decide which parameter to use and specify its correct value. This is due to the fact that incorrect parameter values can have an impact on the controller's performance [21].

With the passage of time, the "trial and error" method, which was once used to tune the PID parameters, has come to be regarded as a time-wasting method. This is because PID controller performance can now be improved with automatic tuning, automatic generation of gain schedules, and continuous adaptation.

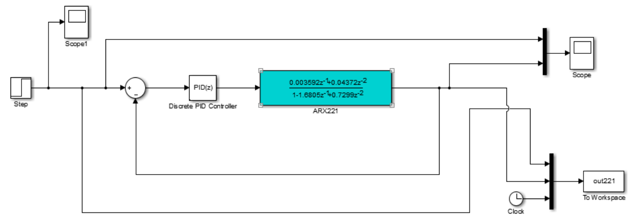

Fig. 6.PID controller Simulink block diagram.

The Simulink block diagram of the PID controller is shown in Fig. 6. The gains of a PID controller were calculated using the PID tuner in MATLAB/Simulink, and this method is easier to use because the tuning is shown graphically rather than manually. The controller parameters are optimized by varying the response time between slower and faster values, as well as the transient behavior, which can be aggressive or robust. The gains parameters obtained from the simulation depicted in Fig. 6 are summarized in Table 2. The transient response parameters obtained from the simulation are summarized in Table 3.

TABLE 2
SUMMARIZES OF PID GAINS

PID Gain	Parameters			
	ARX221	ARX331	ARX441	ARX551
Kp	0.031	0.381	0.412	0.353
Ki	0.062	0.088	0.097	0.084
Kd	0	0	0	0

Based on previous researches such as[5], [9]–[11], [20], [21] it shows that the PID controller can be used on the hot air blower system i.e. PT326 process trainer. Nevertheless, the PID controller can also be applied to other plant and it has been proven according to previous researches in [22]–[31].

TABLE 3
PERFORMANCE TABLE OF CONVENTIONAL PID CONTROLLER

PID	Parameters		
	Rise Time, Tr (s)	*Settling Time, Ts(s)*	*Overshoot, %OS (%)*
ARX221	37	73	0
ARX331	16	32	0
ARX441	14	26	0
ARX551	17	32	0

IV. FUZZY PID CONTROLLER

The fuzzy PID control evolved from traditional PID. Based on fuzzy control theory, the fuzzy relationship between three PID parameters Kp, Ki, and Kd and the error 'e' and error change rate 'dedt' can be established. When the PID parameters are adjusted using fuzzy control, the conventional PID controller is transformed into the fuzzy PID controller. Fig. 7 depicts the MATLAB Simulink block diagram of the fuzzy PID controller used in this project, and Fig. 8 depicts the subsystem of the block model components under the fuzzy PID block. Each polynomial model's PID parameter was tuned using the MATLAB Simulink PID tuning extension toolbox for fuzzy PID and PID Simulink models.

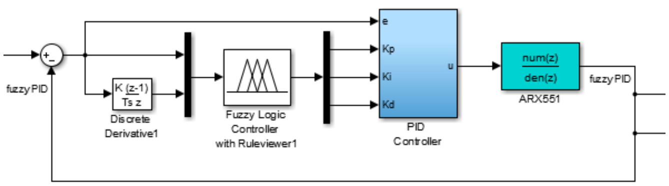

Fig. 7.Fuzzy PD Simulink block diagram.

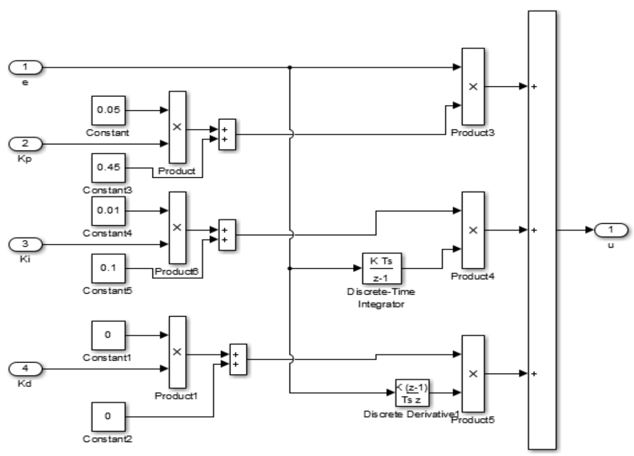

Fig. 8.PID controller block model components under fuzzy PID block.

The fuzzy logic consists of two inputs and three outputs of the fuzzy logic interference engine, as shown in Fig. 9 where the Mamdani model is used in this study as a fuzzy inference structure. This paper uses this model to find the best values for Kp, Ki, and Kd.The feedback error e(t) and the derivative of error de(t)/dt are the inputs, and the outputs are Kp, Ki, and Kd.

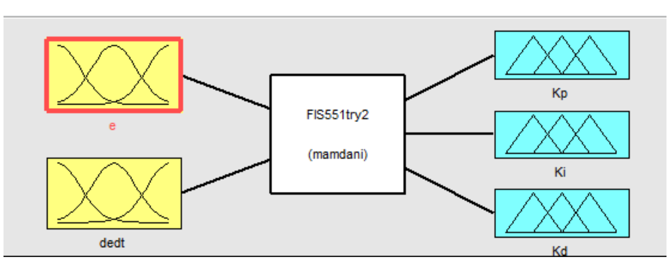

Fig. 9.Fuzzy logic control system.

It is assumed that Kp, Ki, and Kd are within the specified ranges [Kpmin Kpmax], [Kimin Kimax], and [Kdmin Kdmax]. They are normalized into the range between zero and one for convenience using the following linear transformation [32].

$$\text{Initial proportional gain, } Kp' = \frac{Kp - Kp_{min}}{Kp_{max} - Kp_{min}} \tag{5.1}$$

$$\text{Initial integral gain, } Ki' = \frac{Ki - Ki_{min}}{Ki_{max} - Ki_{min}} \tag{5.2}$$

$$\text{Initial derivative gain, } Kd' = \frac{Kd - Kd_{min}}{Kd_{max} - Kd_{min}} \tag{5.3}$$

Where the initial PID parameters are Kp′, Ki′, and Kd′, and the adjusted PID parameters are Kp, Ki, and Kd. The initial PID parameters determine the ranges of Kp, Ki, and Kd as [0.45 0.50], [0.10 0.11], and [0 0.000000001], respectively.

The input and output ranges were determined using the previous conventional PID controller experiment. These values are then substituted into equation (5.1), (5.2), and (5.3), respectively, to compute the coefficients Kp, Ki, and Kd. The fuzzy membership rules were built using the conventional PID controller, as shown in Table 4. Small (S), Medium Small (MS), Medium (M), Medium Big (MB), and Big (B) were the linguistic variables used. Since the variables were set to five, the system used 25 fuzzy rules.

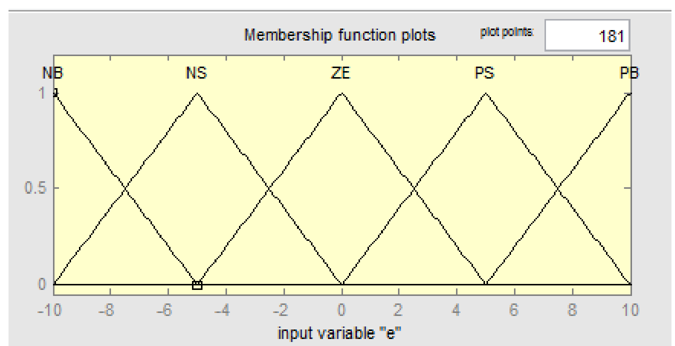

Fig. 10. Input membership function for error in temperature.

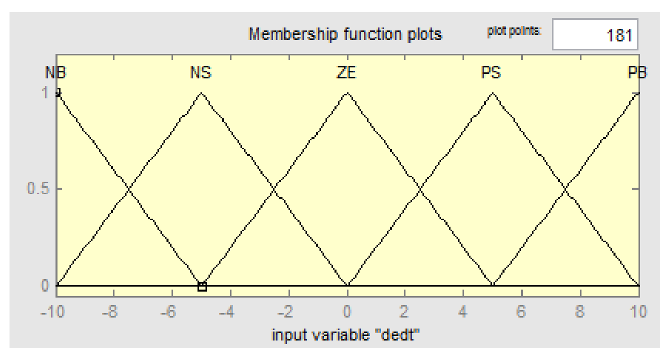

Fig. 11. Input membership function for error rate in temperature.

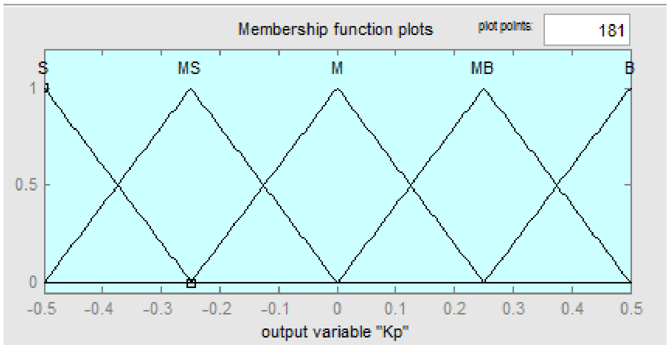

Fig. 12. Output membership function variable "Kp".

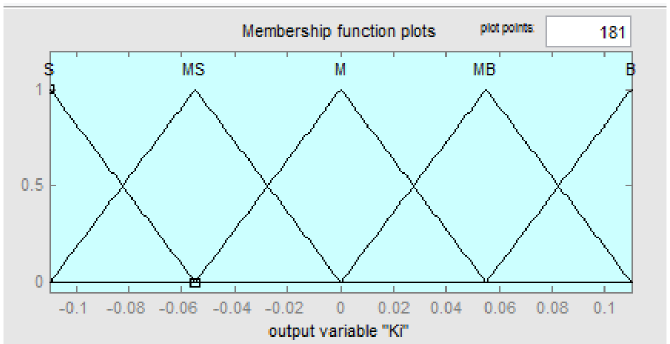

Fig. 13. Output membership function variable "Ki".

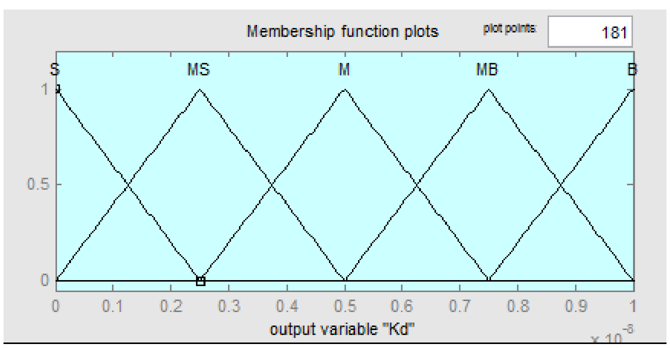

Fig. 14. Output membership function variable "Kd".

TABLE 4

FUZZY INFERENCE RULES

de/dt	Error (e)				
	NB	NS	ZE	PS	PB
NB	S	S	MS	MS	M
NS	S	MS	MS	M	MB
ZE	MS	MS	M	MB	MB
PS	MS	M	MB	MB	B
PB	M	MB	MB	B	B

The rules are developed in accordance with the characteristics of the process transfer function and the PID controller's properties. E in the domain of "e" linguistic variables and dedt in the domain of "dedt" linguistic variables were defined. The deviation "e" basic domain and error change rate "dedt" basic domain was set as {el,eh}={-10,10} and {ecl,ech}={-10,10} respectively. Typically, the fuzzy inference system (FIS) inputs are the signals of error "e" and change of error "dedt". The configuration of FIS for the fuzzy controller used is shown in Fig. 9. Meanwhile, Fig. 10, 11, 12, 13, and 14 depict the membership functions of the inputs and outputs. Centroid method defuzzification was used to obtain the definite values that were sent to the PID controller. The entire system was built with MATLAB Simulink.

V. RESULTS AND DISCUSSION

This section discusses the simulation results of the fuzzy PID controller system and the PID controller system using Simulink within the MATLAB application. Step response, disturbance rejection, and parameter variation (robustness) of the closed loop system are used to analyze the simulation. Simulink is a toolbox extension for the MATLAB programming language. It is a programmed used to simulate dynamic systems. Simulink has the advantages of being able to simulate complex dynamic systems, having a graphical environment with visual real-time programming, and having a large selection of toolboxes. Its graphical interface allows for the selection of functional blocks, their placement on a worksheet, the interactive selection of functional parameters, and the description of signal flow by connecting their data lines. Simulink simulates both analogue and discrete digital systems.

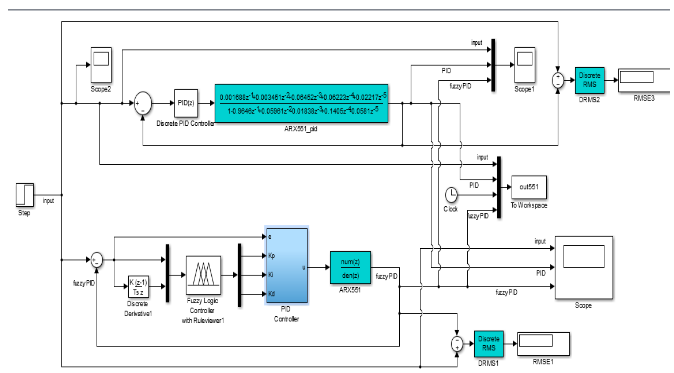

Fig. 15. Overall Simulink model of fuzzy PID and PID controller.

The overall MATLAB Simulink model of both fuzzy PID and PID controllers for the hot air blower system, PT326 process trainer is shown in Fig. 15. Meanwhile, Fig. 16 shows the conventional PID controller simulation for every model. As observed and illustrated in Fig. 16 and Fig. 17, with the MATLAB Simulink tool, the fuzzy tuned PID controller the step response of the system decreased in settling time and increased in rise time. Therefore, the designed fuzzy PID controller can be concluded as acceptable and successfully developed.

As illustrated in Fig. 17, it is observed that the ARX221 model produced the slowest settling time among the other models. This is due to the fact that the location of zero of ARX221 model is very far from the unity circle as shown in Fig. 5. It also demonstrates that the system becomes more unstable and difficult to control as the non-minimum phase or non-stable zero moves away from the unit circle.

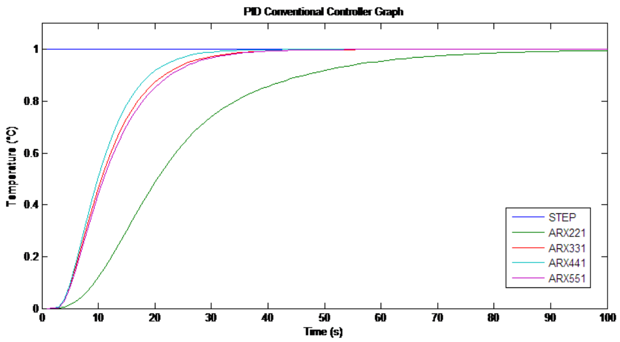

Fig. 16. Response of conventional controller.

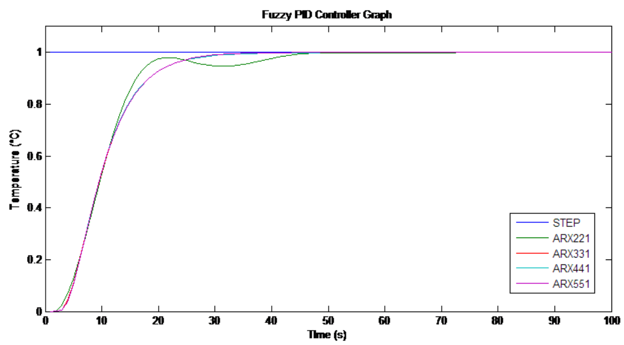

Fig. 17. Response of fuzzy controller.

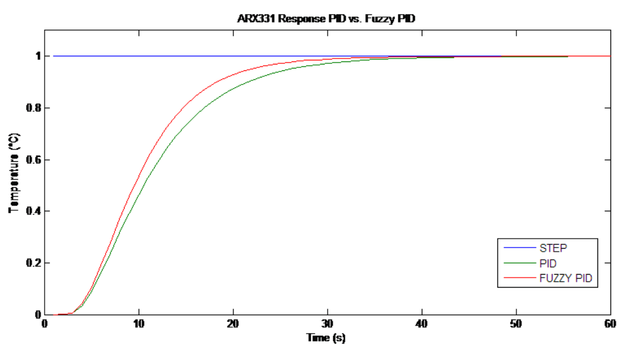

Fig. 18. ARX331 response of conventional controller and fuzzy controller.

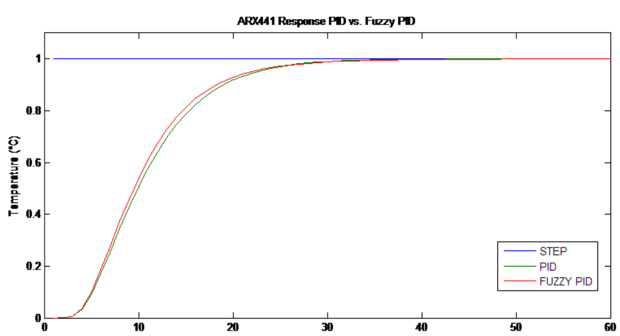

Fig. 19. ARX441 response of conventional controller and fuzzy controller.

TABLE 5
SUMMARIZATION OF THE RMSE BETWEEN BOTH CONTROLLERS

PLANT MODEL	RMSE (°C)	
	PID	FUZZY PID
ARX221	0.1782	0.1588
ARX331	0.1753	0.1207
ARX441	0.1288	0.1207
ARX551	0.1293	0.1208

TABLE 6
SUMMARIZATION OF THE CONVENTIONAL PID CONTROLLER PERFORMANCE

PLANT MODEL	RISE TIME (S)	SETTLING TIME (S)	OVERSHOOT (%)
ARX221	36.10	49.69	0
ARX331	30.13	33.78	0
ARX441	17.40	22.68	0
ARX551	17	32	0

TABLE 7
SUMMARIZATION OF THE FUZZY PID CONTROLLER PERFORMANCE

PLANT MODEL	RISE TIME (S)	SETTLING TIME (S)	OVERSHOOT (%)
ARX221	19.02	18.41	0
ARX331	13.14	16.10	0
ARX441	13.03	16.22	0
ARX551	13.13	15.92	0

It can be observed in Table 5 that fuzzy PID controller has lower root mean square error (RMSE) compared to the conventional PID controller after fuzzy control was implemented. Based on Table 6 and Table 7, it can be observed that there is improvement in controller performance after implementing fuzzy control on the controller. The calculated percentages of improvement for ARX221, ARX331, ARX441 and ARX551 in term of rise time are 89.8%, 129.3%, 33.54% and 29.47% respectively after fuzzy controller was implemented. The calculated percentage of improvement in term of settling time for ARX221, ARX331, ARX441, and ARX551 are 169.91%, 109.81%, 39.83%, and 101.01% respectively after fuzzy controller was implemented. Hence, according to these findings it is concluded that the fuzzy controller has been successfully implemented on the hot air blower system and improved the conventional PID controller.

VI. CONCLUSION

In conclusion, the fuzzy PID controller has been successfully implemented in this paper. Plant modeling from input-output experimental data is successfully obtained and presented using MATLAB System Identification Toolbox. The models are also successfully tested using a Fuzzy PID controller, with excellent results. The simulation results show that the RMSE for the fuzzy PID controller is lower and hence better than that of conventional PID controller. It also demonstrates that the system shows positive improvement in terms of rise time and settling time when fuzzy PID controller was applied. For future work recommendation, this controller can be implemented with model reference adaptive controller.

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