MODELING AND CONTROLLER DESIGN FOR THE VVS-400 PILOT SCALE HEATING AND VENTILATION SYSTEM

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Abstract- In this paper, a heating and ventilation model VVS-400 from Instrutek, Larvik, Norway is modeled using ARX model structure and linear black-box technique. The conventional PID controller and artificial Fuzzy controller are designed based on the approximated plant model and real plant model. The approximated plant model is estimated using System Identification approach while the real plant model is developed by interfacing the Real-time Windows Target toolbox in Matlab with real VVS-plant by using data acquisition (DAQ) card PCI-1711. An artificial Fuzzy controller approach is incorporated in two ways which are conventional Fuzzy logic controller (FLC) and a replacement of conventional fuzzy controller known as Single input fuzzy logic controller (SIFLC). Simulations and experiment validate the equivalency of both controllers. Results reveal that SIFLC found to be better than FLC due to its less computation time compared to conventional FLC.

Index terms: System identification, estimation, ventilation, VVS-400, Autoregressive with exogenous input (ARX), PID, Fuzzy logic controller, Single input fuzzy logic controller

I. INTRODUCTION

The heating and ventilating system is a common process in our daily life where certain desired temperature is controlled. In industries such as pharmaceutical, ability to control temperature is crucial to ensure the quality of the product always within control. However, most of heating and ventilation plants are complex with higher-order systems, which leads to unsatisfactory performance.

Therefore, in the recent years, there are many emerging control strategy approaches for controller's design of heating and ventilation systems such as robust PID controller [1], fuzzy immune PID controller [2], multiple model predictive control (MMPC) [3] and advanced PID auto-tuner [4]. For example, Kasahara [1] propose a robust PID control system which can cope with the changes in the plant characteristic which suitable for practical applications. Another example is an auto tuner for PID controller, both for SISO and MIMO processes which developed by Bi and Cai [4].

In some cases, an artificial approach such as Fuzzy logic control (FLC) has gain interest in control systems design. For instance, Rafael [5] has proposed a combination of weighted linguistic fuzzy rules together with a rule selection process in heating and ventilation system in order to maintain its indoor temperature. However, it is known that conventional FLC has to deal with fuzzification, rule base, inference engine and defuzzification operation. Larger sets of rules will produce longer computational time for conventional FLC. Usually, a complicated system as heating and ventilation system require many rules to perform this conventional FLC. These will results large computational time to accomplish the control algorithm. Therefore, Single input fuzzy logic controller (SIFLC) has been introduced to solve the conventional FLC problem. The SIFLC has only one input variable which significantly produce less number of rules compared to conventional FLC. Tabakova [6] has presented the implementation of the SIFLC and its effectiveness which has less computation time in the real time application.

However, in order to design very efficient controller with high quality system performance, the system must be modeled in a proper way. For unknown system which has unknown parameters, it can be called as black-box model. The mathematical modeling of this black-box model system can be obtained using System Identification (SI) technique. SI technique provides an efficient approach and proved to be very significant in practical applications. There are two methods to perform the system modeling, which are using theoretical and experimental design. The overall step of system identification procedure can be found in [7]. Only experimental approach is considered in this paper where the system model is referred as a black-box model (Section III). In this approach, the persistently excitation of input signal is crucial, since it influences data sufficiency. Often, Pseudo-Random Binary Sequences (PRBS) input were chosen due to its large energy content in a large frequency range [8]. Further details in choosing the appropriate input can be found in [9]. Controller design is also included in this paper through

Matlab simulation (Section IV) and online implementation using Real-time Windows Target toolbox (Section V). Finally, discussion and conclusion are drawn.

II. SYSTEM DESCRIPTION OF THE VVS-400

In this study, VVS-400 is used as a model system. The VVS-400 plant is a pilot scale of heating and ventilation system developed by Instrutek A/S, Larvik, Norway [10]. The schematic diagram of this system is shown in Figure 1. This plant can operate in three different modes: 1) Temperature control, 2) Flow control and 3) Cascade control. In this paper, only temperature control is studied (constant air flow rate). This model consists of a fan and heating element which is controlled by TRIAC. The fan blows air through the flow tube over the heating element. The temperature sensor, RTD platinum is located at the end of the tube. This plant model is also equipped by two independent local PID controllers to control the temperature and flow processes. However, in this study, local PID controller for temperature will be set as "off mode" which creates an open loop system for temperature while the air flow rate is fixed to a certain number and controlled by flow local PID controller.

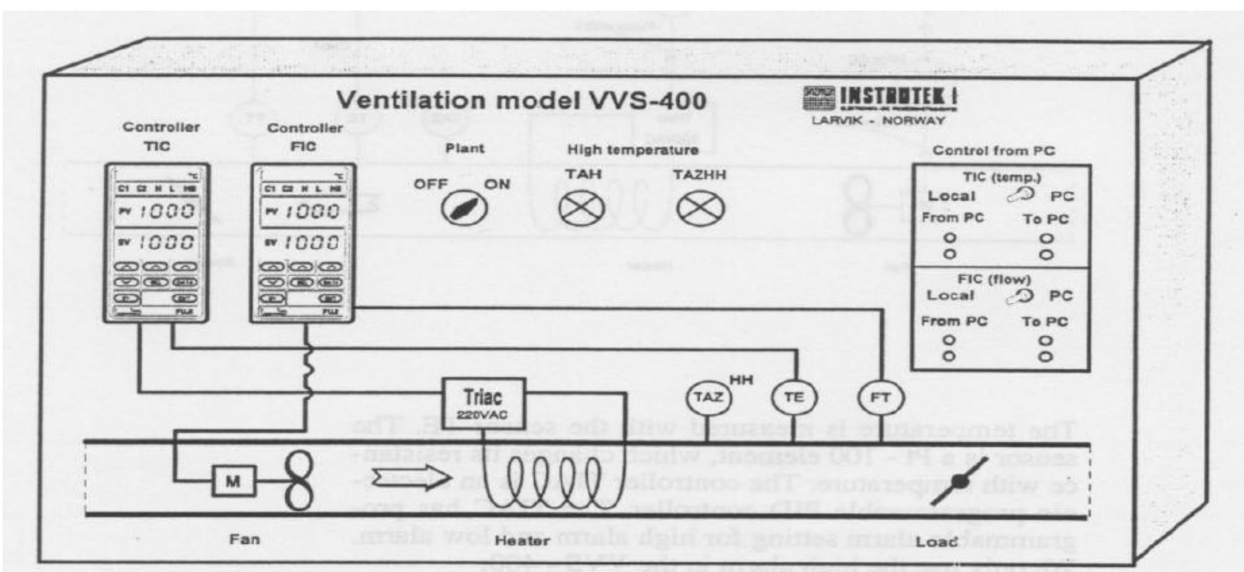

Figure 1: Schematic diagram of the VVS-400 heating and ventilation model

After model calibration, the relationship between voltage and temperature is obtained and is plotted as shown in Figure 2. This is done by observing the output temperature with different input voltage as shown in Table 1.

Table 1: Input voltage and output temperature

Voltage(V)	Temperature(Celcius)
2.5	50
2.8	56
3	60
3.1	62
3.3	66
3.4	68
3.5	70
3.6	72
3.8	76
4	80
4.1	82
4.2	84
4.3	86
4.4	88
4.5	90

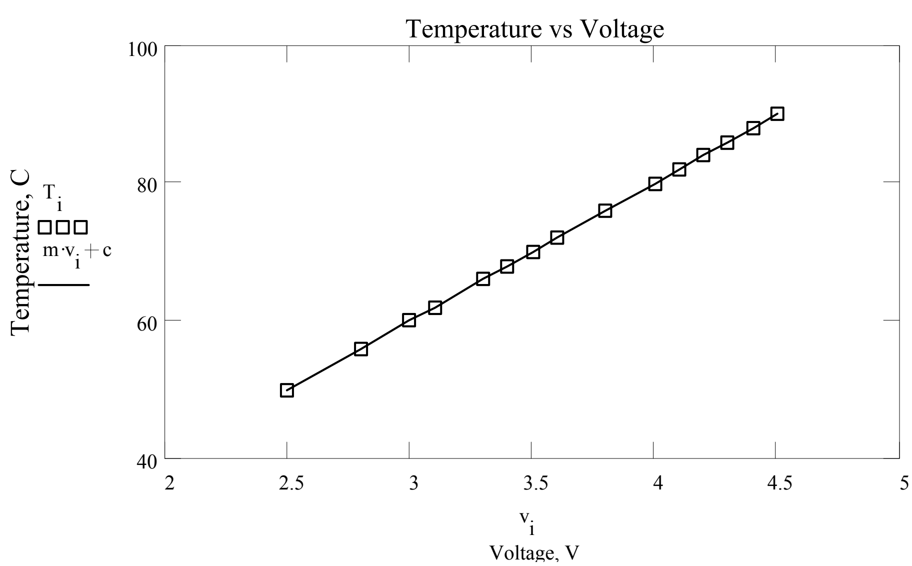

Figure 2: Relationship between temperature and voltage

From Figure 2, it can be noted that

$$\text{Temperature}(^\circ\text{C}) \ \alpha \ K \times \text{Voltage}(V) \qquad (1)$$

$$K = \text{constant} = \text{gradient} = 20$$

Hence,

$$\text{Temperature } (^\circ\text{C}) = 20 \times \text{Voltage } (V)$$

$$T_i = 20V_i \qquad (2)$$

where i = nth data

Therefore, process output must be multiplied with constant 20, since the output from the approximated plant and data acquisition (DAQ) card is in voltage. Temperature process study of VVS-400 plant has been conducted in [11] which reveal the temperature process is continuously nonlinear.

III. PROCESS MODEL IDENTIFICATION EXPERIMENT

Initially, system model must be determined before control technique is applied. The system modeling part is the most challenging and vital part in designing the control system of VVS-400 due to its large time constant and slow process response [8]. In order to obtain a particular model for this system, the open loop identification experiment has been done using parametric approach. In this experiment, a system model is identified using data collected when the Pseudo Random Binary Sequence (PRBS) is perturbed into the system as can be seen in Figure 3. From Figure 3, there are 2297 samples of data with 2 seconds sampling interval. The PRBS input is generated in Matlab. The collection of data was performed by PCI-1711 interface card. The input-output data is then be analyzed by System Identification toolbox in Matlab [12].

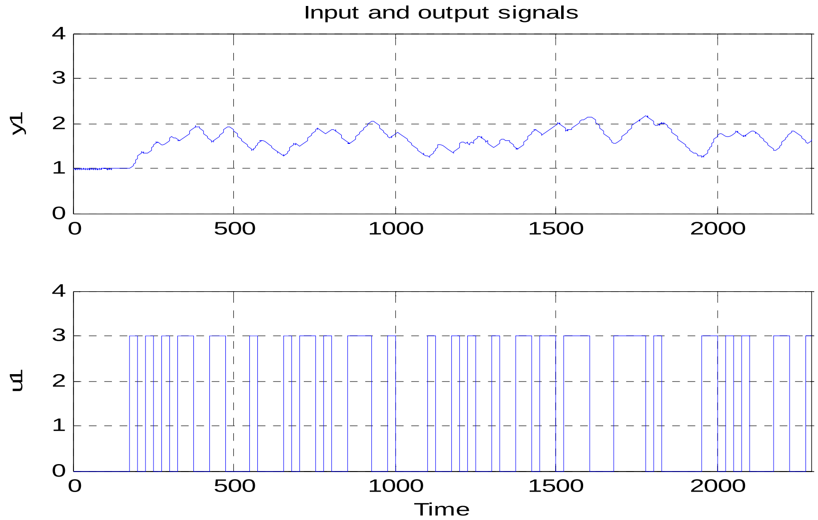

Figure 3: The input-output data set

From the set of input-output data in Figure 3, it was divided into two parts. The first part is the training data and the second is for testing or validation data. In this paper, the VVS-400 system is modeled based on Autoregressive with exogenous input (ARX) model structure with sixth order. The best fit of output model is 82.84% as depicted in Figure 4. Its polynomial structure can be written as

$$A(q)y(t) = B(q)u(t) + e(t) \tag{3}$$

$$A(q) = 1 - 0.4776q^{-1} - 0.441q^{-2} - 0.774q^{-3} + 0.4322q^{-4} + 0.1352q^{-5} + 0.1308q^{-6} \tag{4}$$

$$B(q) = 0.0002502q^{-3} + 0.0008348q^{-4} + 0.0003908q^{-5} + 0.0003052q^{-6} + 0.0006835q^{-7} + 0.000266q^{-8} \tag{5}$$

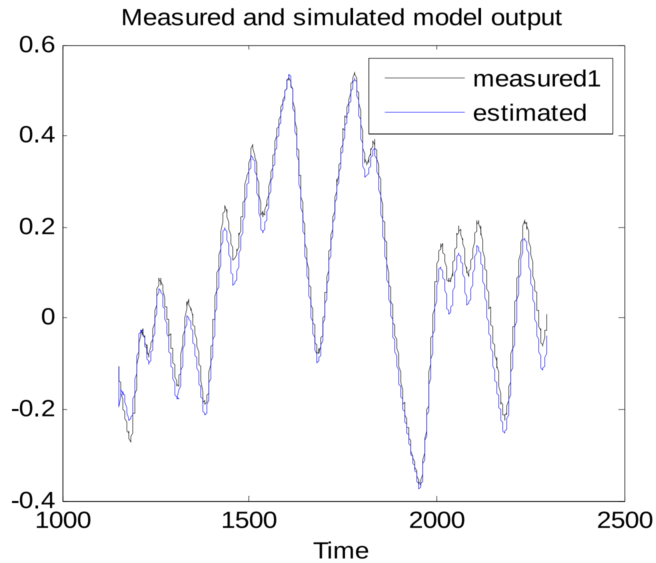

Figure 4: Measured and simulated model output

Then, Loss function = 0.0000123078 and Akaike's Final Prediction Error (FPE) = 0.000012567. Therefore, the pilot scale heating and ventilation VVS-400 plant can be approximated modeled by this following equation

$$\frac{B(q)}{A(q)} = \frac{0.0002502q^{-3} + 0.0008348q^{-4} + 0.0003908q^{-5} + 0.0003052q^{-6} + 0.0006835q^{-7} + 0.000266q^{-8}}{1 - 0.4776q^{-1} - 0.441q^{-2} - 0.774q^{-3} + 0.4322q^{-4} + 0.1352q^{-5} + 0.1308q^{-6}} \tag{6}$$

Hence, based on this approximated plant model, conventional PID and artificial Fuzzy logic controller will be designed to perform the closed loop system simulation. The approximated plant gives a higher order model where an excess model order is usually represent the noise. Since the ARX model incorporate with noise in the system model, the model might be influenced by this noise [13].

Next, by observing the pole-zero plot of the model, there is one zero outside the unit circle of the z-domain as shown in Figure 5. This specific zero is called non-minimum phase model. For a non-minimum phase process the converse is true, a non-minimum phase pole will tend to cause a +90º phase shift, and a non-minimum phase zero will tend to cause a -90º phase shift. Since the system is assumed to be stable, all the poles will have negative real parts.

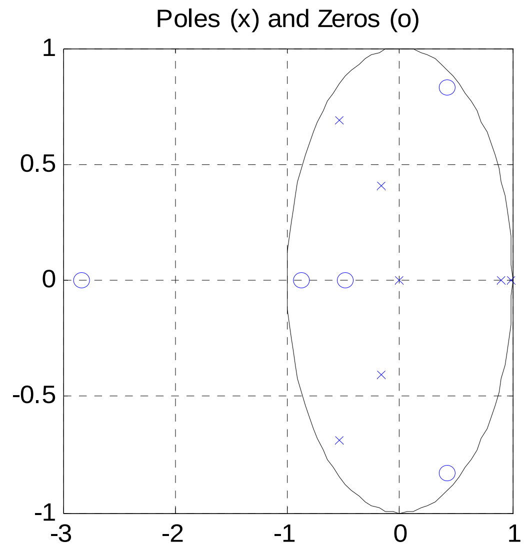

Figure 5: Pole-zero plot

IV. CLOSED- LOOP SIMULATION AND PERFORMANCE ANALYSIS

Before the real process implementation, a simulation is carried out for each controller to verify the propose controller design. The aim of simulation is to give emphasis to the designing of the conventional proportional-integral-derivative (PID) and artificial Fuzzy Logic controllers. To ensure stability, only closed loop controller is considered. The step input is applied to the system as a reference input with a set point of 60.

The PID controller is often implemented for industrial practice since it has a simple structure, straightforward implementation and easy to tune [2]. In this paper, the PID controller is designed using the parameters of K_p (proportional gain), K_i (integral gain) and K_d (derivative gain) tuned by Ziegler-Nichols method. The discrete-time expression of PID controller has the following form:

$$u(k) = K_p e(k) + K_i T_s \sum_{i=1}^{n} e(i) + \frac{K_d}{T_s} \Delta e(k) \tag{7}$$

where $u(k)$ is the control signal, $e(k)$ is the error between the reference input and the process output and T_s is the sampling time for the controller.

However, finding an optimum adjustment for this system is not trivial. Fine tuning is required for an optimum result.

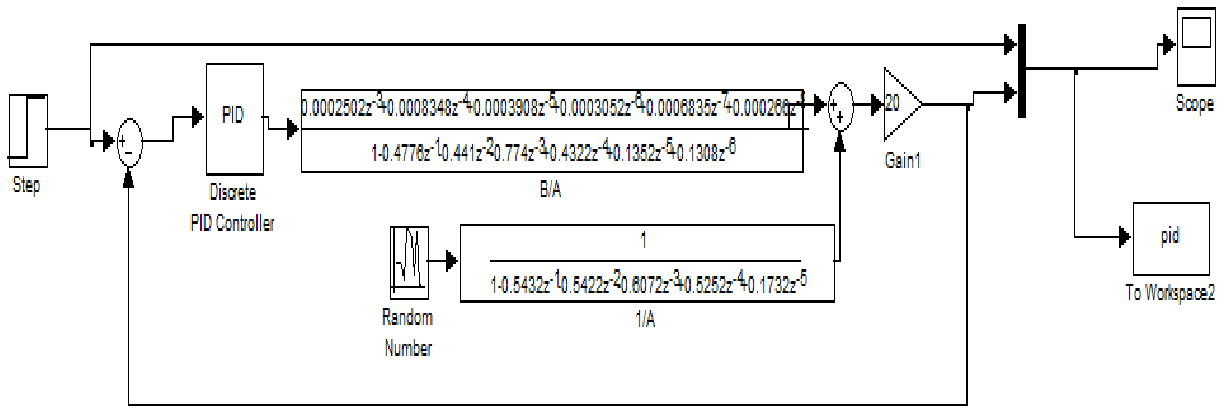

Figure 6: Simulink block diagram with PID controller

Figures 6 and 7 show the Simulink block diagram with PID controller and the process output, respectively. From Figure 7, the process output shows high overshoot with settling time is 100 seconds corresponding to step input reference. It can be seen that the response of this proposed controller is satisfactory.

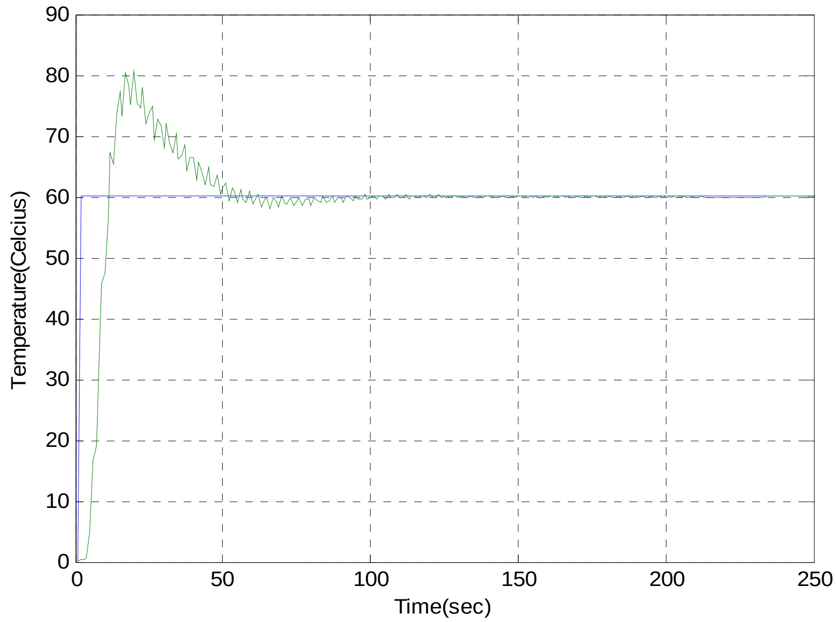

Figure 7: Temperature process response from simulation with PID controller

Even though the PID controller is widely used in industrial process, the tuning of PID parameters is a crucial issue in particular for the system's characteristic which has large time delay and high order system [14]. Commonly in industrial process, only an expert or experience workers are able to monitor and tune the PID parameters based on their experience. Therefore, in certain cases where there is deficient of experience with the processes, it is sometimes quite impossible to achieve a satisfactory performance. For these reason, it is desirable to introduce other types of controller such as an artificial conventional Fuzzy logic controller (FLC) or Single input fuzzy logic controller (SIFLC).

The conventional FLC has two inputs which are error, e and derivative error, $\dot{e}$ and only one control input, Δu as represented in Figure 8. The SIFLC has only error, e as an input. For the FLC control design structure, it involves three main stages:1) fuzzification, 2) rule base, and 3) defuzzification [15]. The rule base is extracted from the knowledge or experience about the system itself. In fuzzy control, the membership function, rules and scaling factor (gain) are tuning parameter. The membership function of error, e , derivative error, $\dot{e}$ and control input, Δu are assigned as NL: Negative large, NM: Negative medium, NS: Negative small, Z: Zero, PS:

Positive small, PM: Positive medium, and PL: Positive large as can be seen in Figure 9. The ranges of this membership function are -10 to 10.

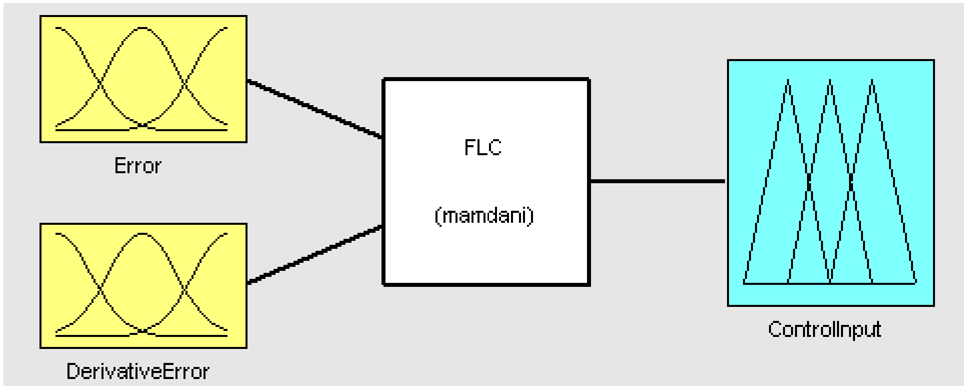

Figure 8: Fuzzy inference block

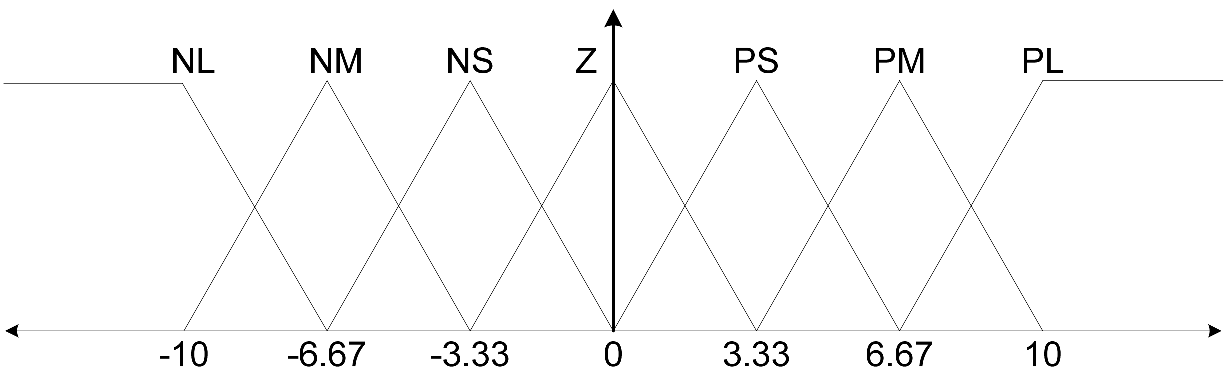

Figure 9: Membership function of error (e), derivative of error ($\dot{e}$) and control input, Δu

Since we have 7 variables for each fuzzy input, it gives 49 fuzzy rules as illustrated in Table 2. The rules are written as;

IF error, e is PL AND derivative error, $\dot{e}$ is NL, THEN control input, Δu is Z

Therefore, 49 fuzzy rules in Table 2 must be reads as mentioned and be performed in rule viewer of FIS editor in Fuzzy Matlab.

Table 2: Rules table of fuzzy

e \ $\dot{e}$	PL	PM	PS	Z	NS	NM	NL
NL	Z	NS	NM	NL	NL	NL	NL
NM	PS	Z	NS	NM	NL	NL	NL
NS	PM	PS	Z	NS	NM	NL	NL
Z	PL	PM	PS	Z	NS	NM	NL
PS	PL	PL	PM	PS	Z	NS	NM
PM	PL	PL	PL	PM	PS	Z	NS
PL	PL	PL	PL	PL	PM	PS	Z

Figure 10 shows the Simulink block diagram of the system with fuzzy controller. There are two scaling factors at the input and one scaling factor at the output of conventional FLC. Step input is performed in order to obtain the output response of the system.

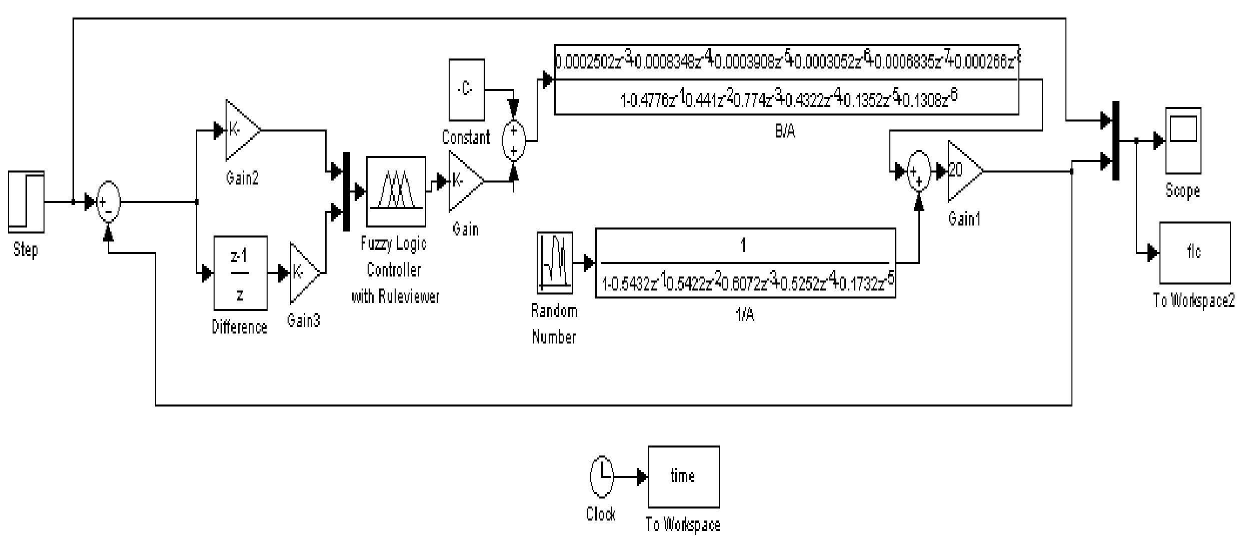

Figure 10: Simulink block of the system and conventional FLC

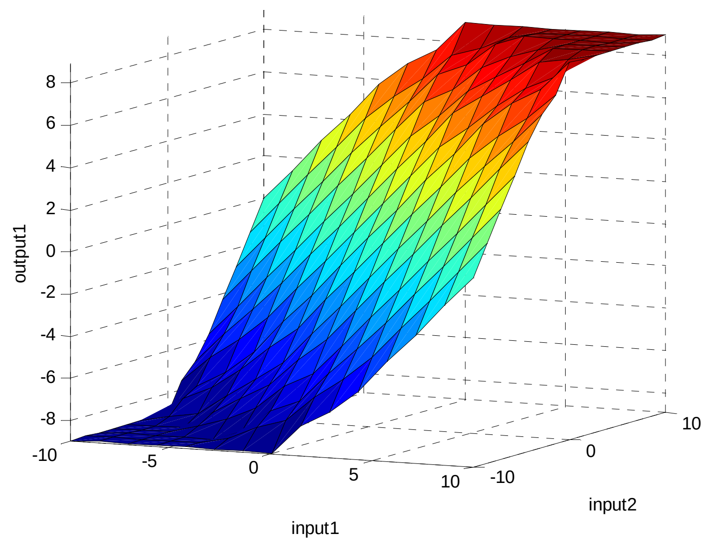

Figure 11: Linear control surface of Conventional FLC

The control surface of the conventional FLC is shown in Figure 11. This control surface represents the correlation between input and output in three-dimensional plot. From this figure, it is clear that conventional FLC behaves as linear controller.

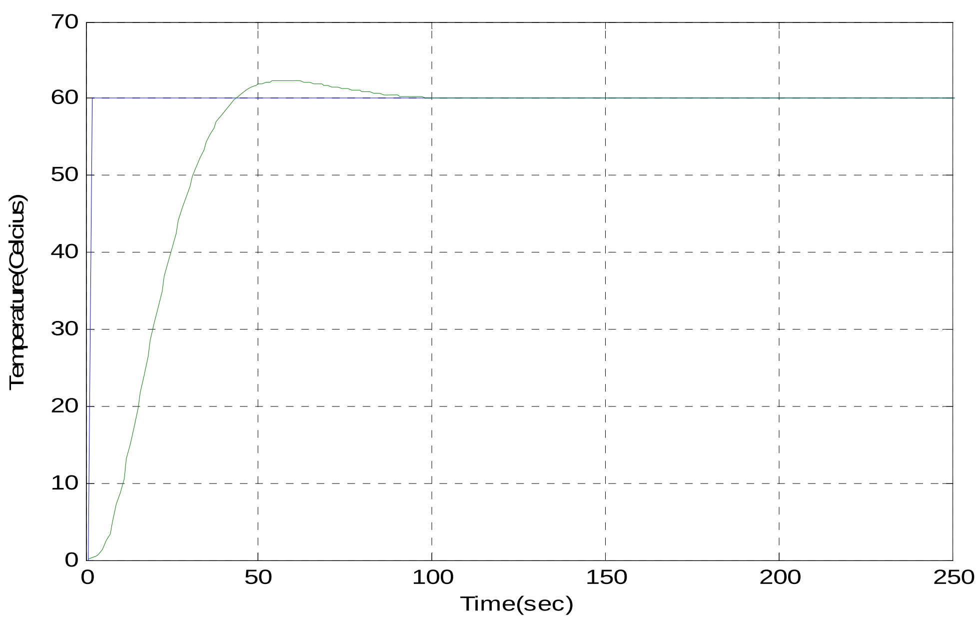

Figure 12: Temperature process response from simulation with conventional FLC

Figure 12 shows the output response of conventional FLC with small overshoot. Although the output response has less overshoot, this approach takes a longer computation time (95 seconds) to accomplish the controller algorithm. In fuzzy control, the computation time depends on the number of rules used. More rules will result the longer computation time. This problem can be solved by replacing the conventional FLC into Single-input FLC (SIFLC), where there are no rules at all [16]. In this approach, the rules are computed into constant number using a specific equation and will be performed using Look-up Table.

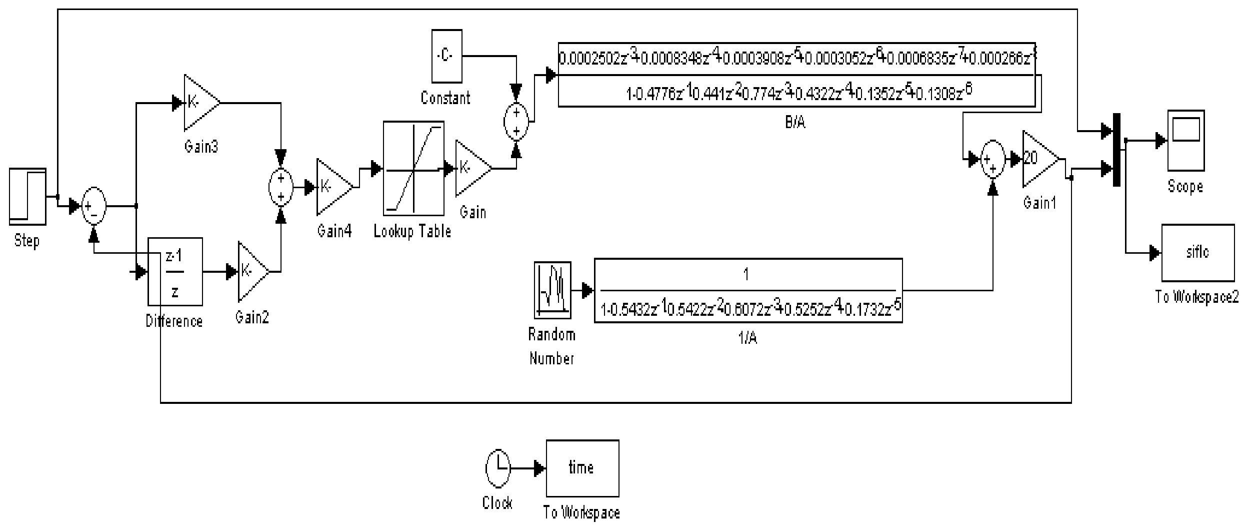

Figure 13: Simulink block of the system and SIFLC

The design of SIFLC for this system employs Signed Distance method and the Simulink block diagram is shown in Figure 13. From Table 2, it is common to have same output membership function in a diagonal direction. Then, each diagonal line has a magnitude which proportional to the distance from its main diagonal line. Instead of using two inputs ($e, \dot{e}$) in the conventional FLC, this method simplifies the number of input into one single input known as distance, *d*. The distance represents the absolute distance magnitude of the parallel diagonal lines (in which the input set of e and $\dot{e}$ lies) from the main diagonal which can be written as follows

$$d = \frac{\dot{e} + \lambda e}{\sqrt{1+\lambda^2}} \tag{8}$$

with slope of diagonal line, λ is equal to “1”.

In order to obtain the distance, *d* value, the diagonal lines need to be calculated. The output of rule table for conventional FLC as shown in Table 2 can be represented in the constant number as follows

$$\dot{e} + \lambda e = 0$$
$$\dot{e} + e = 0 \tag{9}$$

Then, equation (9) will results seven diagonal lines correspond to seven input values that can be seen in Table 3. Therefore, *d* can have positive or negative values. The diagonal line that result "0" is called main diagonal line.

Table 3: The rule table with Toeplits structure

e / $\dot{e}$	PL "10"	PM "6.67"	PS "3.33"	Z "0"	NS "-3.33"	NM "-6.67"	NL "-10"
NL "-10"	0	-3.33	-6.67	-10	-10	-10	-10
NM "-6.67"	3.33	0	-3.33	-6.67	-10	-10	-10
NS "-3.33"	6.67	3.33	0	-3.33	-6.67	-10	-10
Z "0"	10	6.67	3.33	0	-3.33	-6.67	-10
PS "3.33"	10	10	6.67	3.33	0	-3.33	-6.67
PM "6.67"	10	10	10	6.67	3.33	0	-3.33
PL "10"	10	10	10	10	6.67	3.33	0

Saturation region

The derivation of distance, *d* input variable results in one dimension rule table compared to conventional FLC which have many rules. The rule table is depicted in Table 4 with the output of corresponding diagonal lines, u_o .

Table 4: The reduce rule table of SIFLC

$d = \frac{\dot{e} + \lambda e}{\sqrt{1+\lambda^2}}$	-10	-7	-4.66	-2.33	0	2.33	4.66	7	10
$u_o = \dot{e} + \lambda e$ (rule table)	-9.9	-9.9	-6.6	-3.3	0	3.3	6.6	9.9	9.9

All input, *d* and output, u_o values are formed using a look-up table. Figure 16 shows the output of the system with SIFLC with less overshoot.

Figure 14: Temperature process response from simulation with SIFLC

As shown in Figure 14, the SIFLC control performance (in terms of output results) is almost the same as the FLC controller in Figure 12. However, SIFLC provides much better performance in computation time, which is less than 1 second for the same computation that took

FLC 95 seconds. This comparable performance is achieved by reducing the number of rules from 49 rules in FLC to 7 rules in SIFLC.

V. CONTROLLER IMPLEMENTATION IN A REAL VVS-400 SYSTEM

In the previous section, three types of controller have been designed via simulation. However, it was not enough to ensure that all the design controllers are exactly capable to control the VVS-400 system model until it was implemented to perform an online control. This real system implementation is done using Real Time Windows Target (RTWT) toolbox in Matlab [17]. Two blocks called Analog Output and Analog Input from RTWT connect the Simulink Matlab to the VVS-400 plant using data acquisition (DAQ) card PCI-1711. The controller will respond to the online process with 2 seconds sampling interval. The output of the controller will be fed into the Analog Output and the process output is generated from the Analog Input. Since only voltage is applicable in this RTWT toolbox, the output from the Analog Output need to be converted into temperature by multiply with constant, 20 as given in the previous section. The simulink block diagram of the system with PID, conventional FLC and SIFLC controller are represented in Figure 15, 17, and 19, respectively. The system output with PID, conventional FLC and SIFLC controllers are shown in Figure 16, 18 and 20, respectively. However, to satisfy the output, tuning parameter requires a little adjustment since the simulation tuning parameter is designed based on the approximated plant.

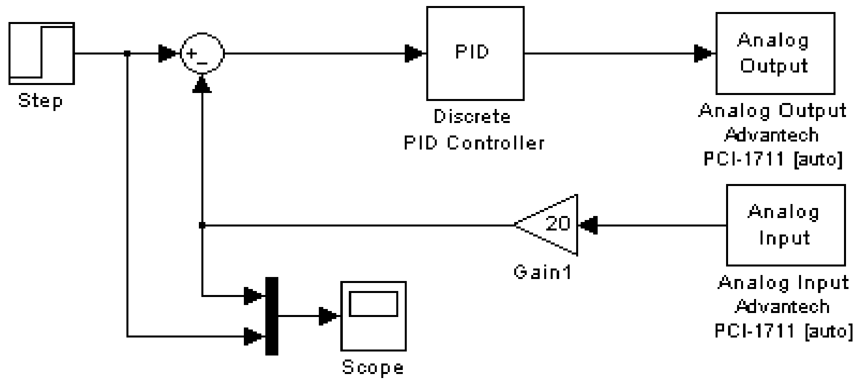

Figure 15: Simulink block diagram of real plant implementation with PID

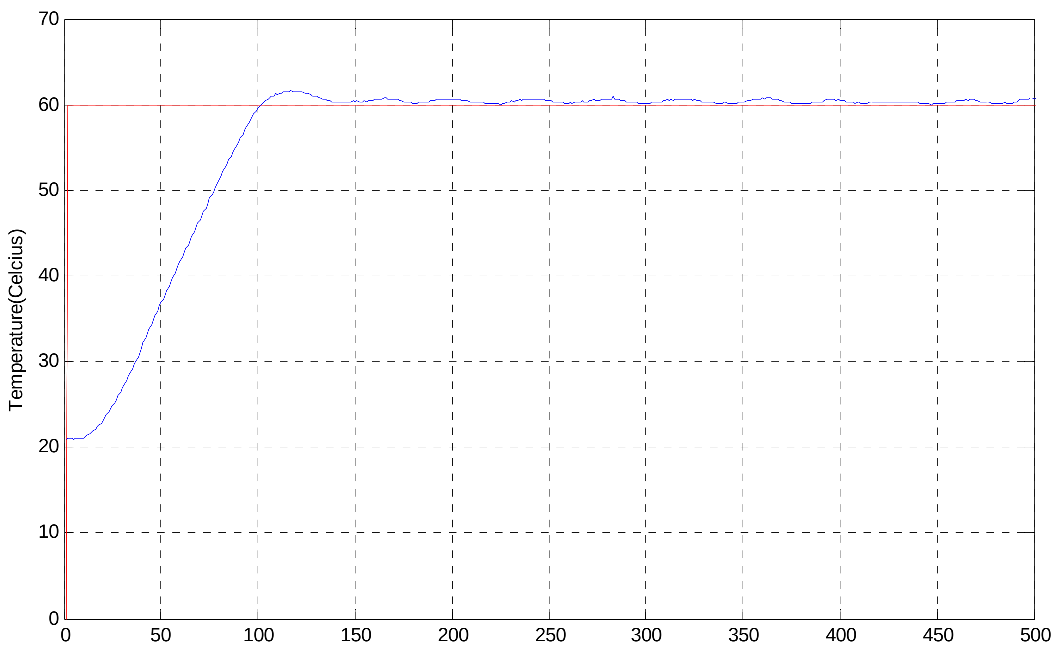

Figure 16: Temperature process response from experiment with PID

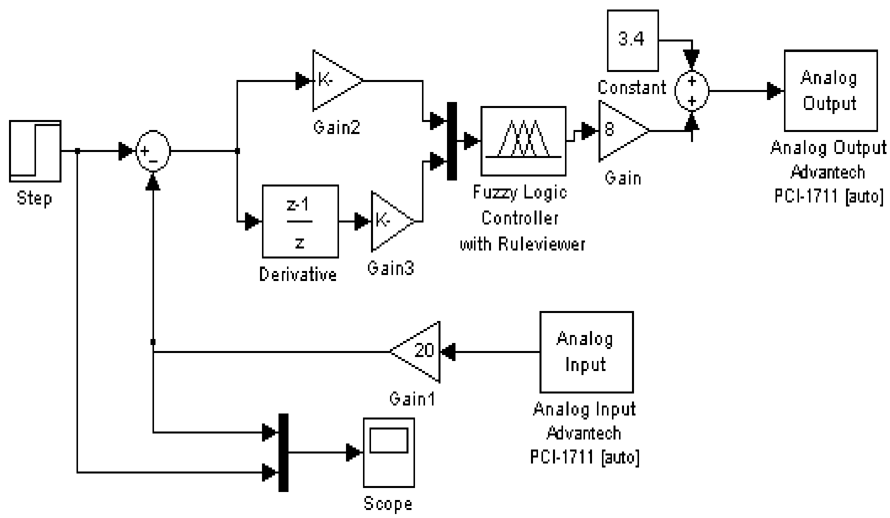

Figure 17: Simulink block diagram of real plant implementation with conventional FLC

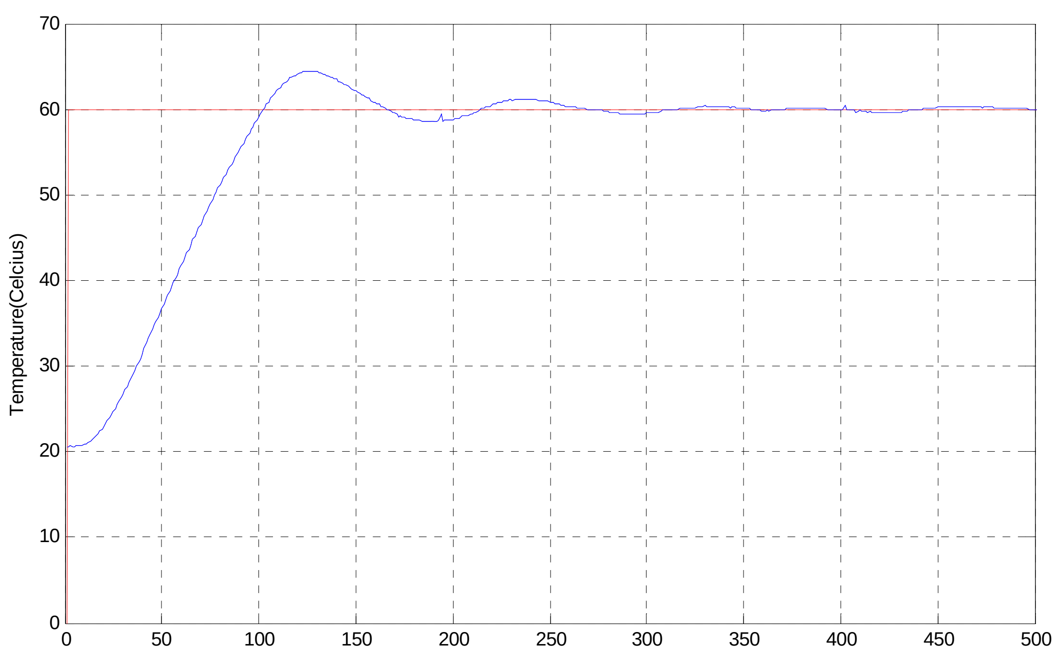

Figure 18: Temperature process response from experiment with conventional FLC

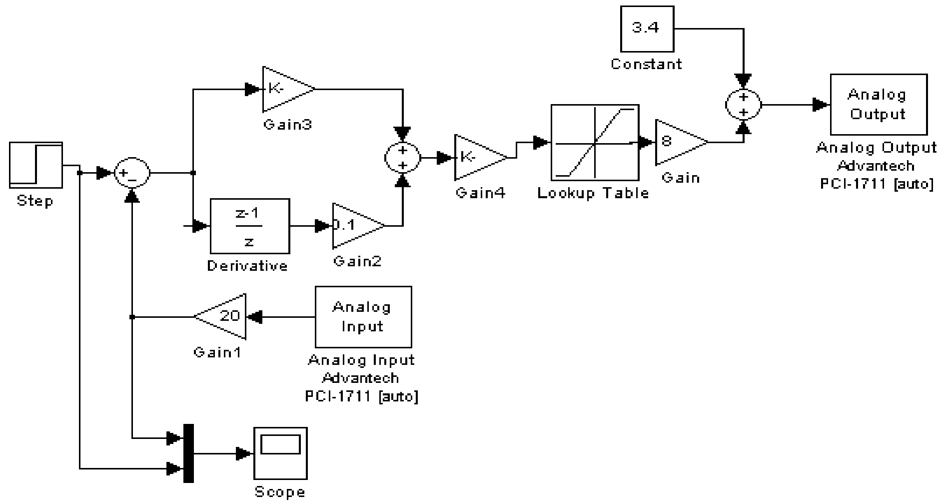

Figure 19: Simulink block diagram of real plant implementation with SIFLC

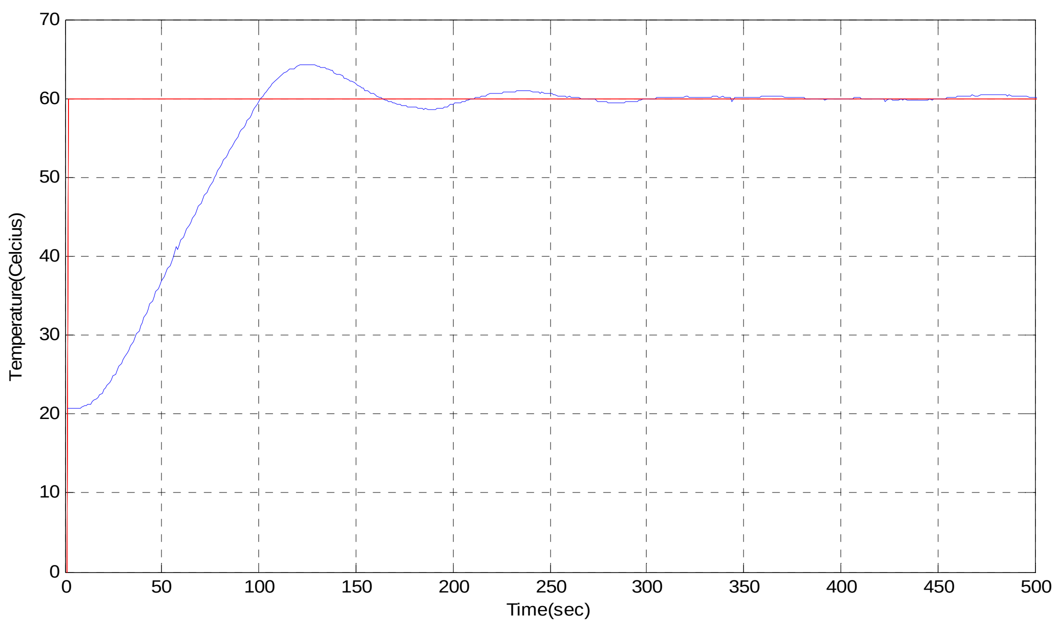

Figure 20: Temperature process response from experiment with SIFLC

By comparing the Figures 18 and 20, it shows that SIFLC capable to provide almost similar result as conventional FLC with less number of rules. The computation time for SIFLC is 974 seconds which is less than FLC (1002 seconds).

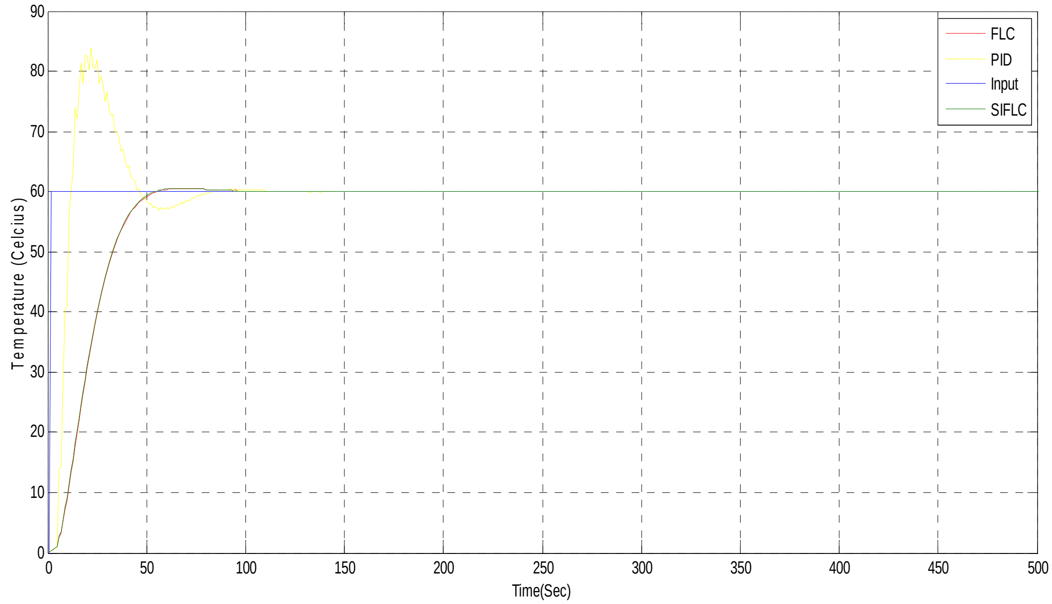

Figure 21: Temperature process response from simulation

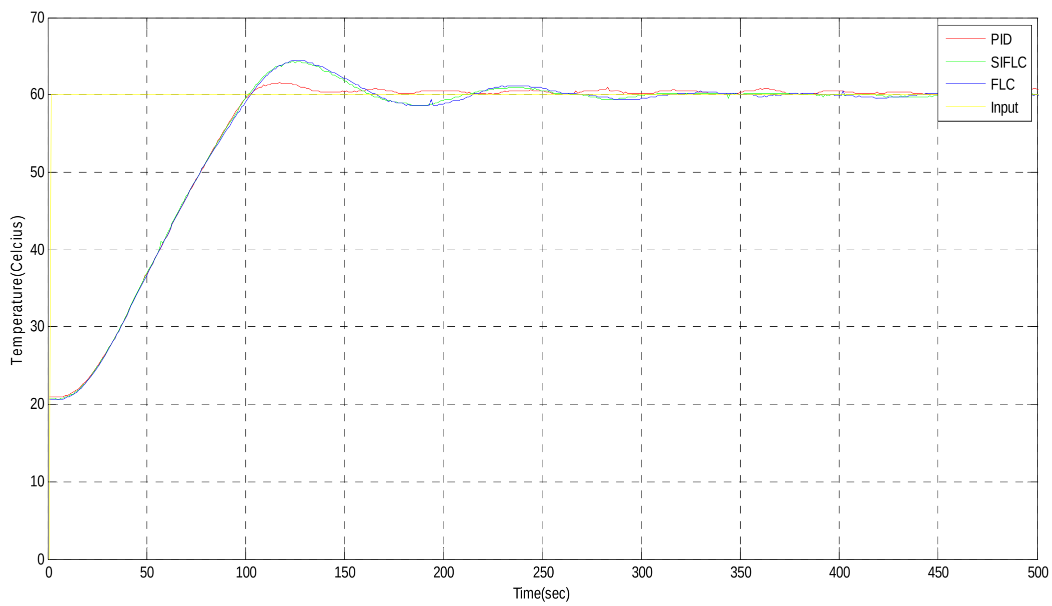

Figure 22: Temperature process response from real VVS-400 plant

The overall system outputs are shown in Figures 21 and 22. The PID controller gives high overshoot in the simulation result compare to FLC and SIFLC. In contrast, in the online implementation with a real VVS-400, PID controller has less overshoot compare to FLC and SIFLC after re-tuning. The FLC and SIFLC produced almost similar result with SIFLC has less computation time than FLC.

VI. CONCLUSION

In this paper, the pilot scale of heating and ventilation VVS-400 plant has been successfully modeled by ARX model structure using system identification approach. The PID, conventional FLC and SIFLC controllers are developed on this plant. These controllers are not only designed by an approximated model plant but also have been implemented to the VVS-400 plant. From this study, it can be clearly seen that SIFLC is better than FLC with respect to the computation time due to the number of rules that can be significantly reduced. Though, both controllers produced almost similar results, the computation time is also considered as vital part of choosing suitable controller.

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