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ARX MODEL IDENTIFICATION FOR THE REAL-TIME TEMPERATURE PROCESS WITH MATLAB-ARDUINO IMPLEMENTATION

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Abstract. *To date, research in system identification has been widely demonstrated in many applications via ARX modelling due to its simplicity and straight forward implementation. The model captured the dynamics behaviour of the temperature process plant using the Toolbox of System Identification in MATLAB2019a. The two-fold contribution of the current study focuses on developing the plant modelling using an AutoRegressive with eXogenous input (ARX) model and real-time data interfacing using MATLAB-Arduino of connecting between real plant and processing computer. The process model was analytically analysed with aims to achieve the estimated model, further validating and finally identifying the best fit identification model to possess a good criterion for the system performance. The results demonstrated the ARX model (3,3,1) of DS2 was identified to perform the best estimate and validation with the best fit at 98.01%, low MSE to approximate zero and passed the correlation test.*

Keywords: System identification, MATLAB-Arduino, Temperature process, ARX model

1. Introduction.

Temperature control is the most common process variable in the industrial process. Determining the dynamical behavior of a given temperature system involves derivation of equations that is based on mathematical relationship between system properties. This method will require in depth knowledge of physics of the system involved and the mathematical derivation on complex equations. Using system identification method, the dynamic modelling will not require such complex derivation. In fact, for any given unknown (or the so-called "black box") system, the system identification allows dynamic modelling without requiring extensive knowledge [1,2]. Hence this paper proposed the system identification using AutoRegressive with eXogenous input model or known as ARX to model a given temperature system. This model is categorized as basic Single Input Single Output (SISO) linear model and is formed through model structure selection, estimation and validation process [3,4]. The methodology of ARX model is well established and researched, making it widely used in various applications including medicine, business and economics, energy usage and science since the 1980's [5,6]. A mathematical notation for ARX model structure is as follows [7]:

$$y(t) + a_1 y(t-1) + \cdots + a_n y(t-n_a) = b_1 u(t-1) + \cdots + b_{n_b} u(t-n_k-n_b+1) + e(t) \quad (1)$$

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$$A(q) = 1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a} \tag{2}$$

$$B(q) = b_1 + b_2 q^{-1} + \cdots + b_{n_b} q^{-n_b+1} \tag{3}$$

where $y(t)$ is the discrete output, $u(t)$ is the discrete input, both n_a and n_b are the parametric pole and zero of the ARX model, n_k is the delay, $e(t)$ is the model error, q is the delay operator and both polynomials $A(q)$ and $B(q)$ are the estimated parameter of polynomial via least square technique. This has resulted in the following structure [8] of the ARX model and its transfer function represented as:

$$y(t) = \frac{B(q^{-1})}{A(q^{-1})} u(t) + \frac{1}{A(q^{-1})} e(t) \tag{4}$$

$$G(q) = \frac{B(q,\theta)}{A(q,\theta)} \text{ where } \theta = [a_1 \cdots a_{n_a} \quad b_1 \cdots b_{n_b}] \tag{5}$$

ARX structure has been a common choice for time series applications, as well as modelling structure and estimation that involves linear data relationships in their applications. Several authors have been known to successfully develop ARX model for prediction application. Fan et al. [9] have proposed using ARX model for building cooling load prediction. In this study, the new model, as opposed to previous developed model has shown better accuracy via improvements in variable selections that result from sensitivity analysis and inclusion of quadratic term to reduce the model error. Similar study conducted by Kandananond [10] and Potočnik et al. [11] respectively have proved the effectiveness of the electricity demand forecasting and indoor temperature prediction via ARX model structure as well. Application of ARX in modelling mechanical system has also been explored where the authors [12-14] have conducted system identification of the measured data involving several parameters such as speed, acceleration, and force using ARX as an alternative to mathematical modelling. In recent studies, current application of ARX system identification can be also hybridized with other sophisticated algorithms such as wavelet-ARX and RBF-ARX as found in [15,16]. These proposed models have shown a great deal of potential, but the method will not be applied in this paper due to consideration of the computational complexity involved. Considering the studies, this paper will choose a simpler ARX approach for temperature process modelling of a plant.

The novelty of this paper is to develop a low cost and user-friendly interfacing technique which is suitable for communicating the real-time temperature plant data to the processing computer with the prediction model. This work will propose using ARX modelling techniques on measured temperature readings from pilot temperature plant to generate prediction model. The model formed from this technique will then be evaluated to assess its performance. With the development of the simple low-cost interfacing circuitry, transferring the model to another plant is expected to be relatively straightforward. Hence, the application in various sectors that require the use of prediction model to analyse behaviour will be very crucial as it will help in monitoring and improving plant performance. The created setup will also be helpful in education, as an example case of applying ARX technique in prediction model.

The remaining of the paper will demonstrate the methods used to develop ARX model, followed by the presentation and discussion of the results and finally the conclusions and findings are summarized at the end of this paper.

2. Temperature Process Plant.

The overall framework of the research works is demonstrated in Figure 1. This framework is currently developed for modelling behavior of temperature plant, which is represented by a pilot scale equipment setup designated as LD-Didactic Temperature Plant. The equipment setup comprises of DC power supply, power amplifier, oven model, thermocouple unit, DC bridge amplifier and digital multimeter to simulate a functioning temperature plant. The DC power supply serves as an input into the system in the form of input voltage. The output of the system will be in the form of temperature of the oven, which is measured by the K-type thermocouple installed in the setup. The output of the thermocouple is then amplified through the DC bridge and displayed by the digital multimeter as the output display. The DC bridge also serves to linearize output voltage from the thermocouple with setting range of between -10V and $+10$V. The measured output will also be sent to PC pre-installed with MATLAB for data logging purposes. These data were collected modelled via ARX structure. The data communication between the plant and the PC is supported by the Arduino-ESP8266 as the interface.

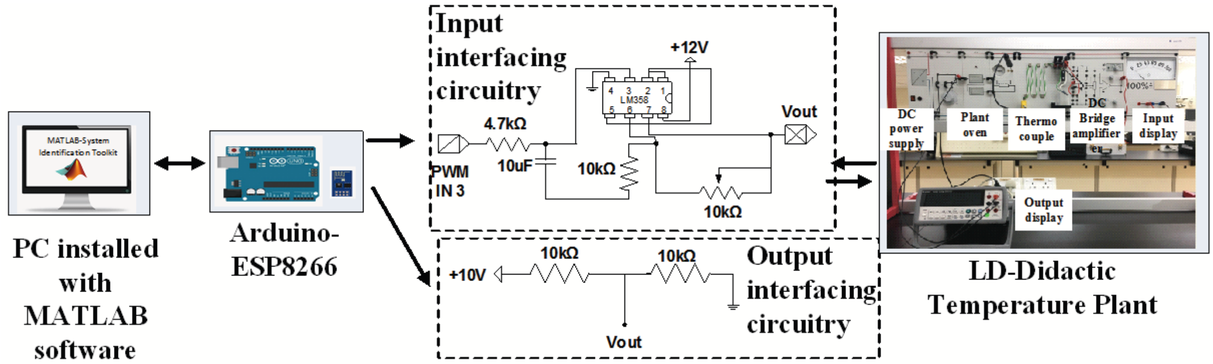


FIGURE 1. A methodology framework

The interfacing circuitry has been developed to enable input and output communication between PC and the simulated plant with the Arduino-ESP8266. Since the microcontroller board operates at 5V input of voltage supply, both input and output section are required to step down from 10V to 5V. Therefore, two additional circuitries must be included as voltage converter and voltage divider respectively representing the input interfacing circuitry and output interfacing circuitry. For voltage converter circuit, an LM358 amplifier in conjunction with 10μF low pass filter is used to step down the incoming voltage to 5V output. Input terminal interconnects the PWM pin 3 of the Arduino while the output communicates to the DC power supply. Once the temperature plant records the measurement activities, the process of data logging occurred. Direct output voltage that was measured as results of thermocouple measurements are further attenuated prior to be retrieved by the Arduino-ESP8266. In this case the attenuation of voltage via output circuitry of the voltage divider circuit enables the drop of voltage to not exceed the maximum voltage supported by the Arduino.

3. **Description of ARX Structure Modelling.** The dynamic response of the plant can be expressed by the input-output model structure in Equation (4) with block diagram representation as shown in Figure 2. The necessary parameters for system identification

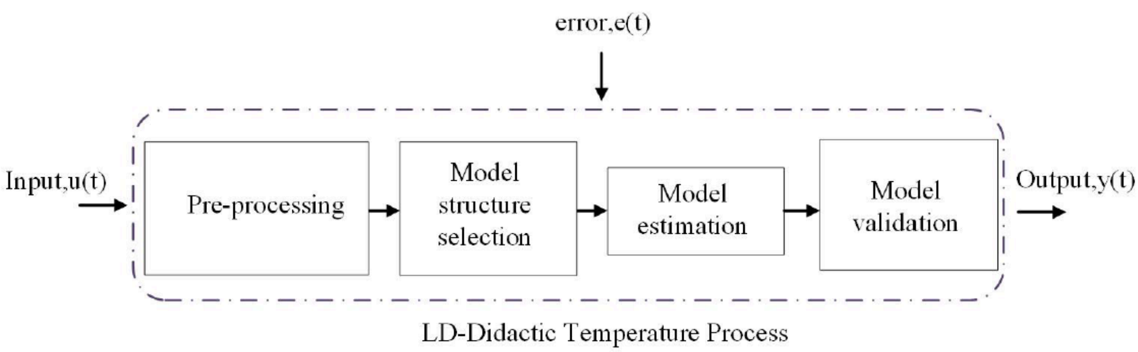


FIGURE 2. System identification block diagram

$A(q)$ and $B(q)$ were determined by analyzing the time response of the open loop temperature data. The MATLAB2019a of System Identification Toolbox has been used for computational analysis of real time temperature data. The data used for the experiment involved two data sets collected at different reference temperature of the thermocouple junction set at 0°C and 27°C.

3.1. **Input data pre-processing.** The open loop test has been executed by injecting a unit step response with a DC supply of 12V input signal. The oven temperature then increased from 0°C to 150°C and the temperature trend over time was captured and used as the input data for pre-processing. During pre-processing, data noise was filtered out from temperature data through outlier removal and magnitude scaling method. Time interval of temperature data comprising of input and output (u, y) was recorded at 1 sec collectively for 80 samples, then equally separated via interlacing technique into two sections namely estimation data, (z_{ue}, z_{ye}) and validation data, (Z_{ue}, Z_{ye}) respectively for odd number of sample and even number of sample. In this work, two groups of temperature data were experimented to be modeled using ARX estimation technique.

3.2. **Structure selection.** The choice to select suitable system identification is dependent on the system characteristics and suitable method. Therefore, the measured temperature data was pre-determined to fit accordingly to the ARX model due to its structure simplicity, low complexity and parameter estimation are efficient to analytically solve the linear regression equation. In this case, the parameters involved are estimated using the least square method.

3.3. **Model estimation.** This process involves parameters estimation with low residual which produces the small prediction error. The employed method of linear regression aims to minimize the sum of square residual and then followed by the output value, $y(t)$ which is calculated based on the previous value of output $y(t-1)$ and input $u(t)$. The identified parameters of $A(q)$ and $B(q)$ are further determined using the ordinary least squares method that minimizes the quadratic prediction error criteria which are referred to as Akaike's Final Prediction Error (FPE). The error computation will be subtracted between the actual output and the predicted output and then finally the resultant transfer function of the plant model is demonstrated as in Table 1.

3.4. **Validation.** For this process, validation is performed by evaluating the model output response with new input. When new input is provided, the predicted output from the model is compared with the actual output of the system. Several measures of performance can be used [4,9] to validate the response of the dynamic ARX model. In this paper, the performance parameter used for validation is percentage of best fit, Mean Square Error (MSE), Loss Function (LF), Final Prediction Error (FPE), Akaike Information Criterion (AIC) and one-step ahead prediction (1-SAP). The following notations are then used in the parameter calculations:

y = *actual output*, $\hat{y}$ = *average output*, $\bar{y}$ = *mean output*, $\hat{f}(\cdot)$ = *estimate of* $f(\cdot)$, N = *total set of data*, $d = n_a + n_b$

$$Best\ fit = 100\left[1 - \frac{norm\left(\widehat{\hat{y}-y}\right)}{norm(y-\bar{y})}\right] \tag{6}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}-y|^2 \tag{7}$$

$$LF = \left|\frac{1}{N}\sum_{1}^{N}\varepsilon(t,\theta_N)[\varepsilon(t,\theta_N)]^T\right| \tag{8}$$

TABLE 1. Comparison of simulated system identification model and its transfer function

Model name	*Estimated ARX model*		*Transfer function*
(n_a, n_b, n_k)	*Dataset1 (DS1)*	*Dataset2 (DS2)*	*(Estimation)*
$(1,1,1)$	$A(q) = 1 - 1.009q^{-1}$ $B(q) = 0.5799q^{-1}$	$A(q) = 1 - 1.009q^{-1}$ $B(q) = 0.5677q^{-1}$	$arx1_{\text{-}DS1} = \frac{(0.5799q^{-1})}{(1-1.009q^{-1})}$ $arx1_{\text{-}DS2} = \frac{(0.5677q^{-1})}{(1-1.009q^{-1})}$
$(2,2,1)$	$A(q) = 1 - 0.2532q^{-1} - 0.7594q^{-2}$ $B(q) = 98.7q^{-1} - 97.64q^{-2}$	$A(q) = 1 - 0.2001q^{-1} - 0.803q^{-2}$ $B(q) = 103q^{-1} - 101.7q^{-2}$	$arx2_{\text{-}DS1} = \frac{(98.7q^{-1}-97.64q^{-2})}{(1-0.2532q^{-1}-0.7594q^{-2})}$ $arx2_{\text{-}DS2} = \frac{(103q^{-1}-101.7q^{-2})}{(1-0.2001q^{-1}-0.803q^{-2})}$
$(3,3,1)$	$A(q) = 1 - 0.6183q^{-1} - 0.625q^{-2}$ $+ 0.2285q^{-3}$ $B(q) = -269.2q^{-1} + 504.1q^{-2}$ $- 234.3q^{-3}$	$A(q) = 1 - 0.2312q^{-1} - 0.7815q^{-2}$ $+ 0.007858q^{-3}$ $B(q) = 77.33q^{-1} - 53.75q^{-2}$ $- 22.35q^{-3}$	$arx3_{\text{-}DS1} = \frac{(-269.2q^{-1}+504.1q^{-2}-234.3q^{-3})}{(1-0.6183q^{-1}-0.625q^{-2}+0.2285q^{-3})}$ $arx3_{\text{-}DS2} = \frac{(77.33q^{-1}-53.75q^{-2}-22.35q^{-3})}{(1-0.2312q^{-1}-0.7815q^{-2}+0.007858q^{-3})}$
$(4,4,1)$	$A(q) = 1 - 0.9379q^{-1} - 0.03719q^{-2}$ $+ 0.6214q^{-3} - 0.6679q^{-4}$ $B(q) = -502.5q^{-1} + 1027q^{-2}$ $- 168.4q^{-3} - 355.5q^{-4}$	$A(q) = 1 - 0.2474q^{-1} - 0.1374q^{-2}$ $+ 0.1539q^{-3} - 0.7642q^{-4}$ $B(q) = 122.7q^{-1} - 99.82q^{-2}$ $+ 76.17q^{-3} - 96.63q^{-4}$	$arx4_{\text{-}DS1} = \frac{(-502.5q^{-1}+1027q^{-2}-168.4q^{-3}-355.5q^{-4})}{(1-0.9379q^{-1}-0.03719q^{-2}+0.6214q^{-3}-0.6679q^{-4})}$ $arx4_{\text{-}DS1} = \frac{(122.7q^{-1}-99.82q^{-2}+76.17q^{-3}-96.63q^{-4})}{(1-0.2474q^{-1}-0.1374q^{-2}+0.1539q^{-3}-0.7642q^{-4})}$
$(5,5,1)$	$A(q) = 1 - 0.98q^{-1} + 0.3771q^{-2}$ $+ 0.2049q^{-3} - 0.8205q^{-4}$ $+ 0.1931q^{-5}$ $B(q) = -770.1q^{-1} + 1491q^{-2}$ $- 793.5q^{-3} - 110.8q^{-4}$ $+ 184.4q^{-5}$	$A(q) = 1 + 0.3024q^{-1} - 0.2884q^{-2}$ $+ 0.2589q^{-3} - 0.4827q^{-4}$ $- 0.7778q^{-5}$ $B(q) = 146.2q^{-1} - 38.33q^{-2}$ $- 43.51q^{-3} + 46.61q^{-4}$ $- 106.9q^{-5}$	$arx5_{\text{-}DS1} = \frac{(-770.1q^{-1}+1491q^{-2}-793.5q^{-3}-110.8q^{-4}+184.4q^{-5})}{(1-0.98q^{-1}+0.3771q^{-2}+0.2049q^{-3}-0.8205q^{-4}+0.1931q^{-5})}$ $arx5_{\text{-}DS2} = \frac{(146.2q^{-1}-38.33q^{-2}-43.51q^{-3}+46.61q^{-4}-106.9q^{-5})}{(1+0.3024q^{-1}-0.2884q^{-2}+0.2589q^{-3}-0.4827q^{-4}-0.7778q^{-5})}$
$(6,6,1)$	$A(q) = 1 - 0.5693q^{-1} - 0.02939q^{-2}$ $+ 0.2165q^{-3} - 0.6478q^{-4}$ $+ 0.1988q^{-5} - 0.2119q^{-6}$ $B(q) = -731.7q^{-1} + 846.3q^{-2}$ $- 154.9q^{-3} - 235.8q^{-4}$ $+ 777.1q^{-5} - 499.7q^{-6}$	$A(q) = 1 + 1.185q^{-1} + 0.7971q^{-2}$ $- 0.05309q^{-3} - 0.199q^{-4}$ $- 1.094q^{-5} - 1.561q^{-6}$ $B(q) = 253.8q^{-1} + 27.66q^{-2}$ $+ 41.03q^{-3} - 133.6q^{-4}$ $+ 51.39q^{-5} - 229.3q^{-6}$	$arx6_{\text{-}DS1} = \frac{(-731.7q^{-1}+846.3q^{-2}-154.9q^{-3}-235.8q^{-4}+777.1q^{-5}-499.7q^{-6})}{(1-0.5693q^{-1}-0.02939q^{-2}+0.2165q^{-3}-0.6478q^{-4}+0.1988q^{-5}-0.2119q^{-6})}$ $arx6_{\text{-}DS2} = \frac{(253.8q^{-1}+27.66q^{-2}+41.03q^{-3}-133.6q^{-4}+51.39q^{-5}-229.3q^{-6})}{(1+1.185q^{-1}+0.7971q^{-2}-0.05309q^{-3}-0.199q^{-4}-1.094q^{-5}-1.561q^{-6})}$

$$FPE = V\left(\frac{1+\frac{d}{N}}{1-\frac{d}{N}}\right) \tag{9}$$

$$AIC = \lg V + \frac{2d}{N} \tag{10}$$

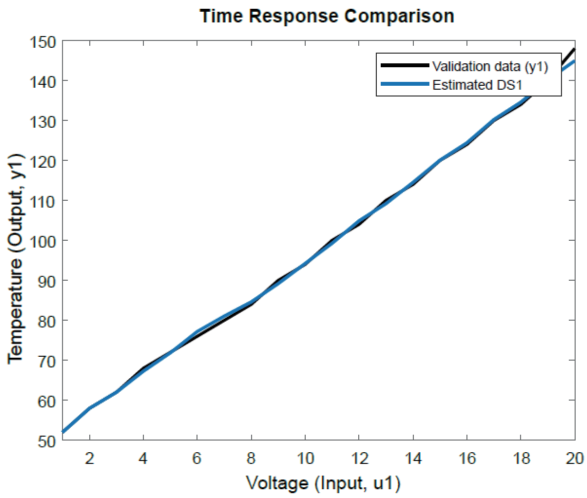
$$1-SAP, \hat{y} = \hat{f}\left(y(t-1),\ldots,y(t-n_y),u(t-1),\ldots,u(t-n_u),\varepsilon\left(t-1,\hat{\theta}\right),\ldots,\varepsilon\left(t-n_\varepsilon,\hat{\theta}\right)\right) \tag{11}$$

4. **Results and Discussion.** The results for the iterative variations in the model order and the corresponding performance measures for the ARX model are tabulated in Table 1 and Table 2 respectively.

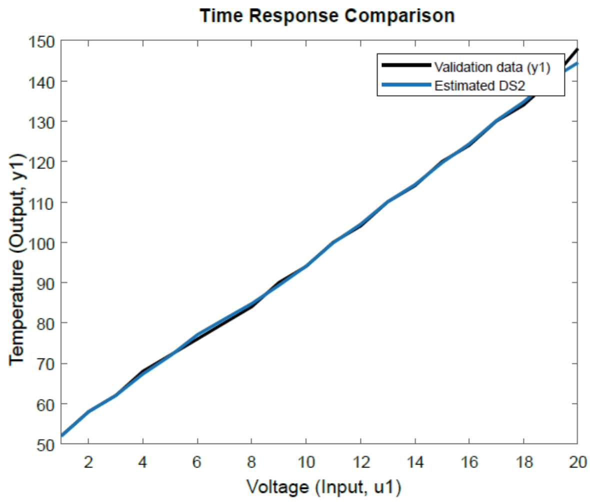
Table 2. Measure of performance for the estimated ARX model

Model name (n_a, n_b, n_k)	*Estimated ARX*	*Best fit (%)*	*1-SAP (%)*	*MSE*	*LF*	*FPE*	*AIC*
$(1,1,1)$	*DS1*	96.65	96.05	0.89	0.89	1.211	60.53
	DS2	96.65	96.05	0.89	0.89	1.21	60.52
$(2,2,1)$	*DS1*	97.73	96.58	0.41	0.41	0.77	51.02
	DS2	97.99	96.63	0.32	0.32	0.60	46.19
$(3,3,1)$	*DS1*	97.94	96.79	0.34	0.34	0.89	53.17
	DS2	98.01	96.73	0.32	0.32	0.83	51.70
$(4,4,1)$	*DS1*	98.20	96.70	0.26	0.26	1.03	53.74
	DS2	98.34	96.76	0.22	0.22	0.88	50.53
$(5,5,1)$	*DS1*	98.60	96.16	0.16	0.16	1.099	49.74
	DS2	98.61	96.79	0.15	0.15	1.09	49.49
$(6,6,1)$	*DS1*	98.96	96.34	0.09	0.09	1.63	43.65
	DS2	99.19	95.08	0.05	0.05	1.002	33.87

An iterative experimentation on the model order was conducted to find the best fit model with minimum order at the optimal performance. The identification process started with the simplest model order of $(1,1,1)$ and then progressively increased up to maximum of six number of poles and zeros. Selection of appropriate model is based on the parameters of best fit, MSE, LF, FPE and AIC, 1-SAP criterions. Best fit measures the validation percentage of estimation and validation data; therefore based on the tabulated data, the best fit percentage improves as the estimation model increased at higher order. Lower trend of FPE which is validated with MSE, LF, AIC has been observed. In fact, the trend of decreasing value of MSE also has been observed at highest possible model order to approach zero value. However, although FPE initially shows a downward trend as the model order progresses, this improvements peak at order $(3,3,1)$. Any further increase of order from this point shows an increase in FPE. The reliability of the ARX model is relatively unaffected by this observation as the FPE value is low. This finding indicates that the improvement in reliability of the estimated ARX model follows the increase of the model order. This was confirmed and validated as well with good agreement of the model closeness towards the output which measured by 1-SAP indicator. Subsequent residual analysis has been carried out based on the error between the projected model output and the actual measured output produced from the initial validation dataset. Therefore, the best estimated ARX model order of $(3,3,1)$ was illustrated in Figure 3. Subsequently, the correlation between residuals is checked using whiteness and independence test to validate the model as shown in Figure 4 and Figure 5. From this check, the correlation function is required to maintain within the boundaries of confidence intervals. This was observed for all order of the ARX model, in which residual is within the confidence region of ± 0.5. Taking into consideration with the other parameters, the model order $(3,3,1)$

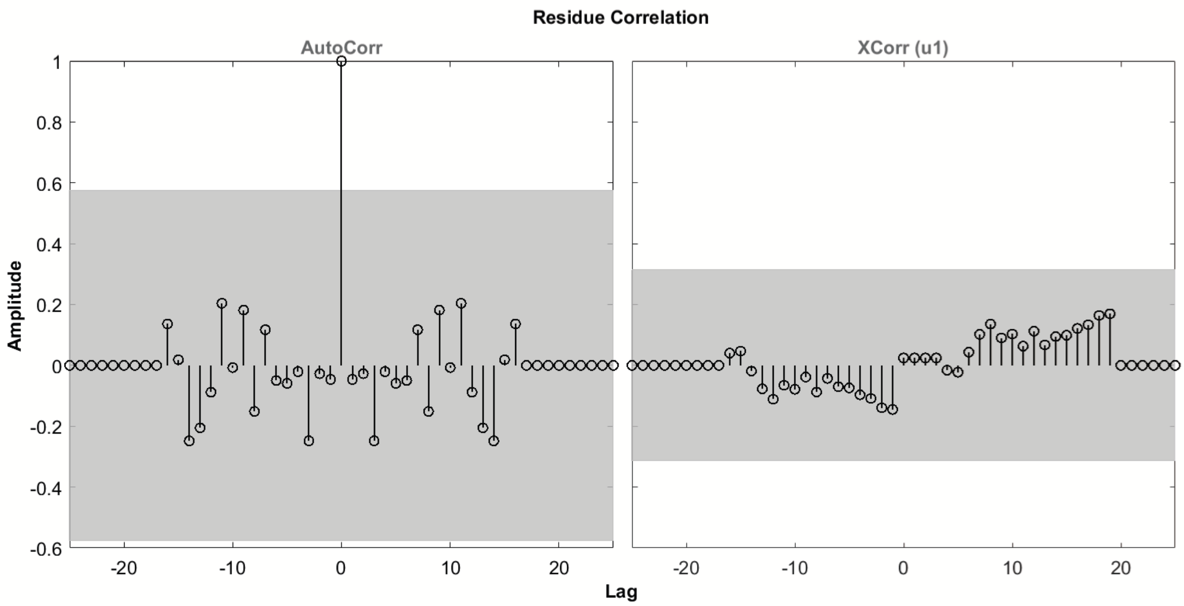


(a) Estimated ARX model for DS1



(b) Estimated ARX model for DS2

Figure 3. Residual analysis for the best ARX model

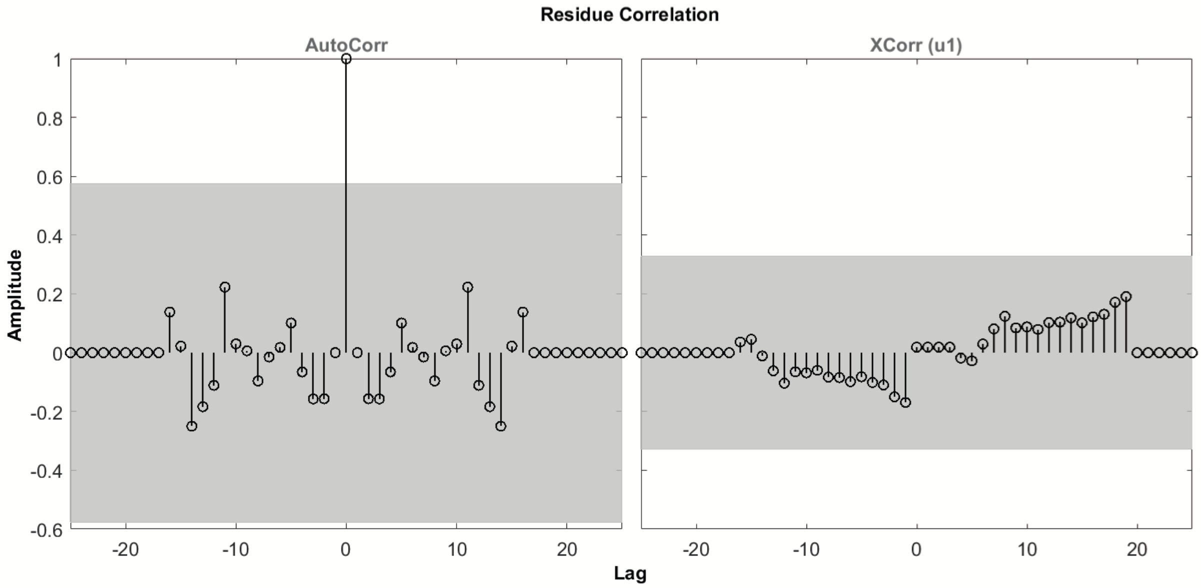


(a) (b)

Figure 4. Correlation test: (a) correlation function of residuals output for DS1, (b) cross correlation function between input and residuals output for DS1

has satisfactorily shown that prediction produced by this ARX model correctly follows the actual dynamic of the temperature process system.

5. **Conclusions.** Using system identification method, this proposed work has successfully demonstrated the use of ARX model in simulating the dynamic behavior of a temperature process system. Optimizing process had been performed to determine the best model order that produces the best measures of performance. As a result, the estimated ARX model of $(3, 3, 1)$ is capable to represent the dynamic model of the DS2 temperature pilot plant and achieved the best dynamic performance. The selected model order had the best results in best fit value, MSE, LF, FPE and AIC values of 98.01%, 0.32, 0.32, 0.83 and 51.70 respectively, indicating good reliability of the identified model with good



(a) (b)

FIGURE 5. Correlation test: (a) correlation function of residuals output for DS2, (b) cross correlation function between input and residuals output for DS2

agreement of 1-SAP validation model at 96.73%. Future work would involve the controller design with stable and robust characteristics, building on from inputs from this prediction model. This can be used as self-regulating temperature control system for plants.

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