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Model predictive control with exogenous auto-regressive model to improve performance in the CO_2 removal

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Abstract
Model predictive control (MPC) is used in the CO_2 removal process in the Subang field to improve its control performance. MPC is used to maintain the CO2 concentration at the sweet gas output by controlling the feed gas pressure (PIC-1101), makeup water flow rate (FIC-1102), and amine flow rate (FIC-1103). The empirical model applied to MPC to represent the process model is the auto-regressive exogenous (ARX) model. The ARX model is compared with the first order plus dead time (FOPDT) model based on the root mean square error (RMSE) between the model and the actual process, then MPC parameters are tuned which include sampling time (T), prediction horizon (P) and control horizon (M) to control for the three variables. Improved control performance is measured based on the integral square error (ISE). The results show that the ARX model is the best model for the CO_2 removal process with an RMSE value of 35%-91% smaller than the FOPDT model. The optimal control parameters Prediction Horizon (P), Control Horizon (M) and Sampling Time (T) in the CO_2 removal process are 75, 25 and 1 on PIC-1101, 25, 10 and 1 on FIC-1102, and 30, 25 and 1 on FIC-1103. The MPC-ARX (MPC using ARX model) can improve the control performance of 33% in the servo control and 6-56% on the regulatory control. However, not all of them showed an increase in control performance improvement from previous studies even though they had used the best model (ARX). This is due to the MPC parameter setting that is not yet appropriate, so it needs to be retuning.

Keywords:
Auto-Regressive Exogenous;
CO2 removal;
Model predictive control;
Regulatory control;
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INTRODUCTION

Since 2004 Indonesia has become a net importer of oil due to the decline in oil production while public consumption continues to increase. It was recorded that in 2021, Indonesia imported 88.08 million barrels of oil per day to help meet the people's fuel consumption needs [1]. One solution that can be offered to assist Indonesia in overcoming this problem is by processing natural gas which can also act as a fuel that tends to be cleaner and more abundant in Indonesia. In 2021, Indonesia produces natural gas by 64% of the total oil and gas production in Indonesia, and by 2050 it is estimated to increase to 86% [2]. Because gas can be sure to run out slowly, the existing gas processing must be maximized so that it gets effective fuel. Therefore, controllers are needed to maintain optimum factory conditions so that the desired results are obtained [3].

The difference in the characteristics of natural gas and the design stage of a natural gas field project will affect the series of treatments carried out on natural gas [4]. One of the industries that process natural gas in Indonesia is PT. X Subang Field with natural gas characteristics in the form of high CO_2 content and low sulfur content. Therefore, the gas sweetening process in this industry only focuses on removing CO_2 and is referred to as CO_2 Removal Unit. The process of removing acid gas is carried out by absorption and regeneration processes. Acid gas in natural gas will be absorbed by certain solvents, then the solvent is regenerated for reuse. However, in the PT. X in the Subang field, during the regeneration process, problems often occur in the form of loss of several hydrocarbons. To overcome these problems, optimization of conditions and the use of appropriate controllers are carried out.

Previously, several researchers had conducted research on controlling the CO_2 removal unit process. Wahid and Mahdi [5] re-tunes the PI controller, Wahid, Meizvira, and Wiranoto [6] use multivariable model predictive control, Manap, Abdul Wahab, and Zuki [7] uses online self-tuning fuzzy-PID controller to control CO_2 exchange process in membraneoxygenator. Aripin et al [8] analyzed level control using conventional PID (proportional-integral-derivative) controllers. Li [9] analyzed the MPC model for level control. Wahid and Wiranoto [10] conducted a study using MPC. However, the model used in this study uses an approach model or FOPDT (first-order dead time). This FOPDT model is limited to models based on changes in MV (manipulated variable) to CV (control variable). The use of the FOPDT model will only simplify the actual process, so this model is not suitable for use in complex processes and will cause inaccuracies.

Due to these limitations, a different approach is needed in the dynamic model that can accurately represent the real process of CO_2 removal compared to the FOPDT model. The Auto-Regressive Exogenous (ARX) model is a linear representation of the dynamic system that is useful for modeling time series data. The ARX method involves a regression method so that the experimental data is represented according to the real process. The ARX model solves the problem by minimizing the error function by assuming unknown parameters in the model. Compared to other types of polynomial models, the estimation of the ARX model is more efficient because the results of solving linear regression equations are analytic. For high-order process structures, the ARX model is a popular or frequently used model because it can model complex processes more precisely without reducing the level of model accuracy.

MATERIAL AND METHODS

FOPDT and ARX models

System identification based on input-output data have three forms: a low order transfer function (first and second order plus dead time, FOPDT and SOPDT), state-space models and input-output polynomial models such as Autoregressive Exogenous (ARX), Autoregressive Moving Average Exogenous (ARMAX), Box-Jenkins (BJ) and Output-Error (OE). Each model has a numerical difficulty, compactness, and consistency in different closed-loop test [11][12].

The first order plus dead time (FOPDT) model is used to represent the behavior of many processes. This is because the response model like this can provide a good approximation to the actual response of many systems and sub-systems found in industrial process control applications. In addition, the FOPDT model is considered to have simple computations and the general utility of the first-order model makes it very practical. With the FOPDT model, the process model will be assumed to have a first-order structure even though the process has a different order [13][14]. This is a weakness that causes the FOPDT model to be inaccurate for high-order process models. The FOPDT model is formulated with the equation:

$$G(s) = \frac{K_p e^{-\theta s}}{\tau s+1} \qquad (1)$$

where K_p is gain, τ is time constant, and θ is dead time.

In contrast to the FOPDT model, ARX is a model that can measure the output of the system at any time t, if the initial value of the system is known. For that, the input value can be used at the current time and the previous time value (u(t), u(t-1), ...) and the output value at the previous time (y(t-1), y(t-2), …) in the case of the regression model. The advantages of ARX compared to FOPDT include having a higher fit between the model and the real process including in the CO_2 removal. Its application in MPC provides excellent control performance so it is used in this study [15, 16, 17]. The model is formulated in the following polynomial form [18][19]:

$$A(q)y(t) = B(q)u(t-nk) + e(t) \qquad (2)$$

where u(t) = system input, y(t) = system output, nk = time delay, e(t) = disturbance and A(q) &

B(*q*) = polynomial. The equations for *A*(*q*) and *B*(*q*) are defined by:

$$A(q) = 1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a} \tag{3}$$

$$B(q) = 1 + b_0 q^{-1} + \cdots + b_{n_a} q^{-n_b} \tag{4}$$

where q^{-1} represents the delay operator.

From this, the ARX model describes the relationship between disturbance, input signal and output signal. This is due to a linear equation where the output is given by the unit time *t*, calculated as a linear combination of the previous input and output. In general, the main purpose of the ARX model is to determine the model structure and its parameters using input and output data.

Steady state modeling and simulation

Make a model that fits the PFD model on the CO_2 removal unit in the Subang Field using HYSYS. In actual conditions in the field, the equipment used consists of CO_2 Absorber, heater, valve, LP Flash Column, CO_2 Cooler, KO Drum, Pump, and Makeup. Figure 1 shows the relationship process flow diagram. Then the simulation is carried out in a steady state (steady state). Steady state simulation is a flow simulation in the production process that does not consider disturbances and does not change with time [20]. In this study, control will be carried out on the PIC-1101, FIC-1102, and FIC-1103. All three are important variables that greatly affect the removal of CO_2 so that this research is focused on. Meanwhile, other controls such as FIC-1101 and TIC-1106 are carried out manually by the industry due to the high fluctuation factor that causes valve openings to be more frequent. And the controllers LIC-1101, LIC-1104, LIC-1105, and LIC11-9 are not the focus of research because a more in-depth approach and data matching are needed in the field.

Changing to dynamic simulation

After getting the same actual condition as the steady state, then the simulator mode at the steady state condition is changed to a dynamic condition. In dynamic conditions, the system will consider changes in the incoming flow due to external disturbances.

Retrieve PRBS (Pseudo-Random Binary Sequence) data

Before identifying the model, first collect input and output data from the system. In this study, in collecting data used an input signal in the form of PRBS. PRBS is a popular type of input signal because the variation of the signal consists of two values, namely the power spectrum and the signal can be concentrated in frequency [21].

Creating an ARX model using the System Identification toolbox

To get the best model that fits the plant, it is necessary to identify it with the MATLAB System Identification Toolbox by adding the data obtained through the HYSYS simulation by following these steps:

a) Adding input and output data in the form of time (t) and CV by using the MATLAB editor and then running it to enter the Workspace from MATLAB.
b) On the APPS tab at the top of MATLAB, click “System Identification”.
c) After the System Identification toolbox appears, at the top left click "Import data" and select "Time domain data".

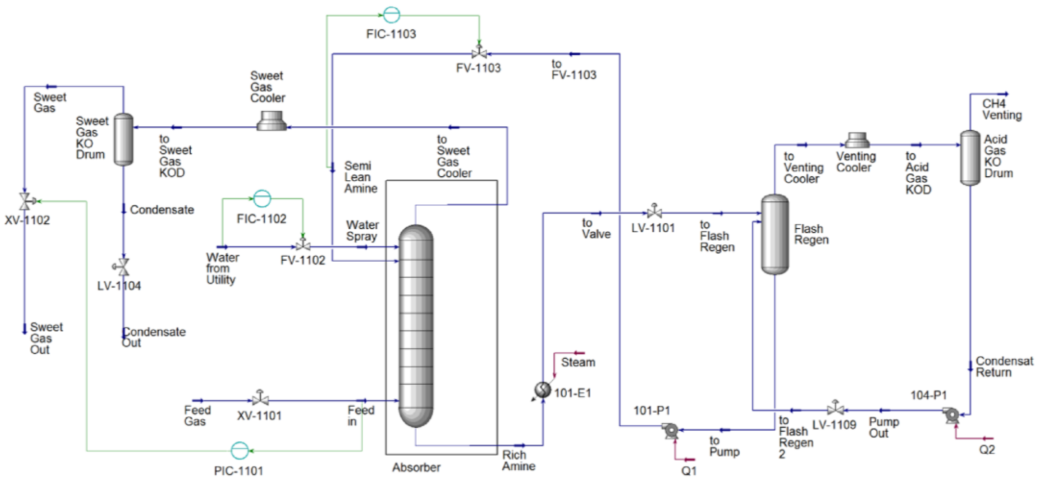

Figure 1. CO_2 removal process control system [10]

d) Import input and output data by writing the variable name in the “Workspace Variable” box.
e) Click the “Estimate” tab and select “Polynomial Models.”
f) Select the order of the ARX model and add it to the "Order" box in the order na, nb, nk (nk is the dead time of the process). In the "Focus" box, select "Prediction", then click the "Estimate" button to create a process model.
g) Then double-click on the obtained model, then click the “Present” button to bring up the model and fit estimation model in the MATLAB common window.

Comparing the fitness curve of the ARX model with the FOPDT model

Curve fitness is the process of approaching the trend of the data in the form of an equation of the mathematical model. At this stage, the process of adapting the model to the data and analyzing its suitability will be carried out. The comparison will be displayed with the number of each data response, and the size of the root mean square (RMSE). RMSE is a measurement method that measures the difference in model predictions and observed values [22]. Models with good estimation accuracy are characterized by small RMSE values. Analysis of the fit of the curve is carried out until the ARX model represents data better than the FOPDT model, or the RMSE ARX value is smaller than the RMSE FOPDT value. The FOPDT model used as a comparison is the FOPDT model by [10].

MPC Tuning

After the controller is installed, tuning can be done to obtain the optimal value. In tuning, model testing will be carried out using the close loop method. MPC tuning is mainly done in the time domain where optimization is performed. In general, the MPC controller has certain parameters to achieve optimal performance. The MPC control parameters that were tuned were T (sample time), P (prediction horizon), and M (control horizon) [23][24].

Control Performance

Control simulation is carried out by changing the setpoint value by ±15% to determine the controller's ability to handle setpoint changes. In addition, simulations were also carried out by providing ±15% disturbances to the system to determine the controller's ability to handle disturbances. After the previous parameters have been reached, further analysis of the controller performance can be carried out by comparing the ISE values. The ISE value in this study will be compared between MPC based on ARX model (MPC-ARX), MPC based on FOPDT model using Matlab (MPC-FOPDT1), and MPC based on the FOPDT model using HYSYS as has been studied by [10] (MPC-FOPDT2). The calculation of this value aims to determine the accuracy of MPC performance between the expected SP and the actual controlled output.

RESULTS AND DISCUSSION

System Identification

To obtain a system model, data-driven modeling is carried out, where the measured data from the system obtained through a simulation process using HYSYS, will be processed to form a model using Data-driven tools, namely the MATLAB System Identification toolbox. To get the best model, trial-and-error was carried out on the ARX model with different orders, and the best model was obtained with the highest fit estimation results. Fit estimation describes how close the model's output is to the system's output.

The PIC-1101 controls the pressure difference that occurs between the bottom and the top of the absorber column, and to maintain the sweet gas pressure. The modeling was carried out using the PRBS testing model by changing the MV value by -10%, based on previous research. Figure 2 shows the interaction that occurs when MV is lowered to CV, namely an increase in pressure. Based on Figure 1, the changes given to the XV-1102 valve opening cause an increase in pressure. In the step response graph, the controller immediately responds to changes given to the system. The results of the modeling system obtained an ARX model with an order of na = 15 nb = 15 nk = 0 and a fit estimation value of 99.98%.

Before the ARX model is determined as a model that represents the plant, it is necessary to verify the actual plant data first. To verify, RMSE (root mean square error) calculation is used, with the aim of evaluating the accuracy of the model to be used. In this process, a comparison of the RMSE values will also be made between the ARX and FOPDT models. The comparison is determined using the RMSE parameters that have been prepared in the form of a MATLAB script. The model with a lower RMSE value shows that the model tends to have similarities with the actual data. Figure 3 is the result of a comparison between the model and the actual plant data.

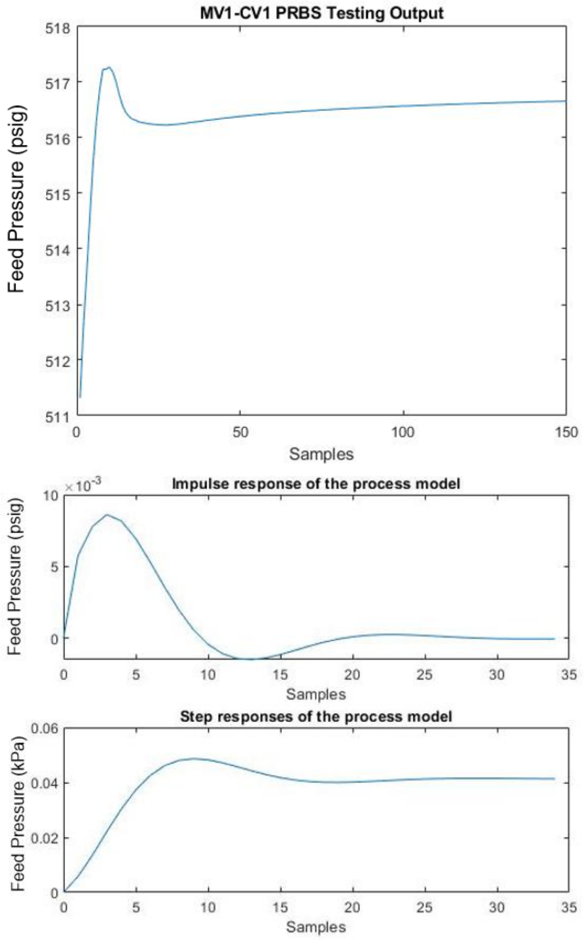

Figure 2. Output and step response of PIC-1101

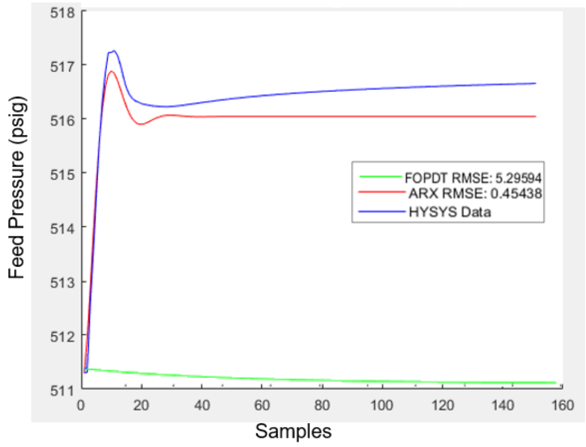

Figure 3. Verification of FOPDT and ARX models of PIC-1101

The blue color shows the actual plant data, the red color shows the ARX model, and the green color shows the FOPDT model. Based on the results of the comparison of the RMSE values, the ARX model has a smaller value than the FOPDT model. This huge difference is caused by the formed PRC having an under-damped second-order model behavior as indicated by the overshoot [25]. The FOPDT model cannot capture this behavior because the firs-order model does not have an overshoot, while ARX can capture this overshoot so that it is closer to actual.

FIC-1102 is a controller that is installed with the aim of maintaining the quality of the amine that will be used to bind the acid gas. The amine solution used consisted of a mixture of aMDEA and piperazine with water. To maintain the quality of amine strength from water evaporation during the regeneration process, makeup water is needed. At least 2-4 m^3/h of makeup water is required to maintain amine strength in the range of 45%.

The modeling is done through the PRBS model testing process using HYSYS by changing the MV value by +10%. Figure 4 shows the interaction of MV changes to the makeup water flow rate. Based on Figure 1 the changes given to the FV-1102 valve opening cause an increase in the makeup water flow rate. The step response graph shows that it takes 0.1 s before the input of the response reacts.

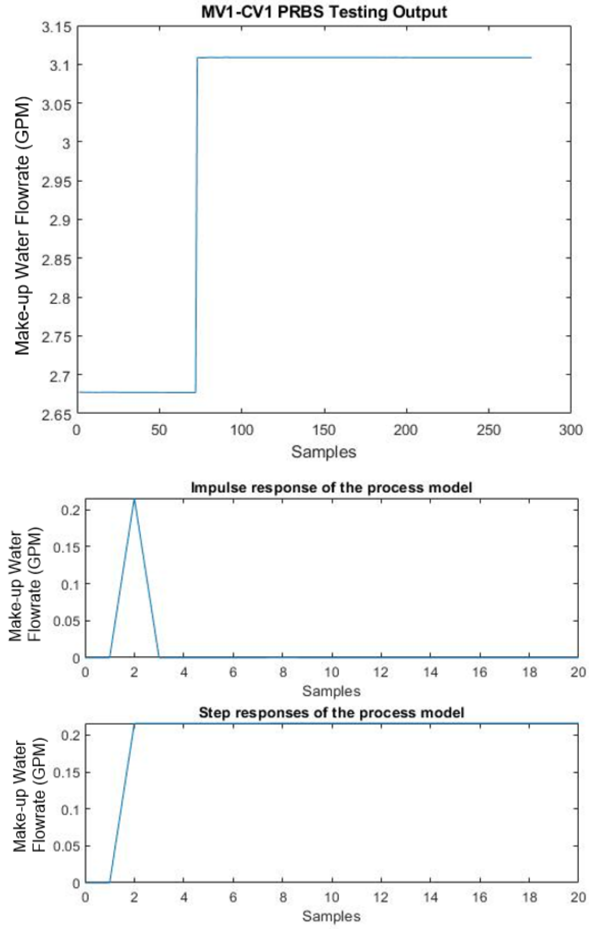

Figure 4. Output and step response of FIC-1102

The results of the modeling system obtained an ARX model with an order of na = 8, nb = 8, nk = 0 and a fit estimation value of 99.99%.

The best model that has been obtained, then validated the data between the model and the system. Validation was carried out on the ARX model and the FOPDT model obtained in previous studies based on the RMSE value. Figure 5 is the result of a comparison between the model and the actual plant data. Based on the comparison results, the ARX model has a smaller RMSE value than the FOPDT model. This shows that the ARX model has a response that is more like the response of the actual plant data.

The FIC-1103 is a controller that is used to control the flow rate of the amine to the absorber. FIC-1103 and FIC-1102 controllers have the same role, namely, to maintain amine quality or amine strength. To maintain the amine concentration at 45%, it is necessary to at least 650 – 700 m^3/h for the amine flow rate.

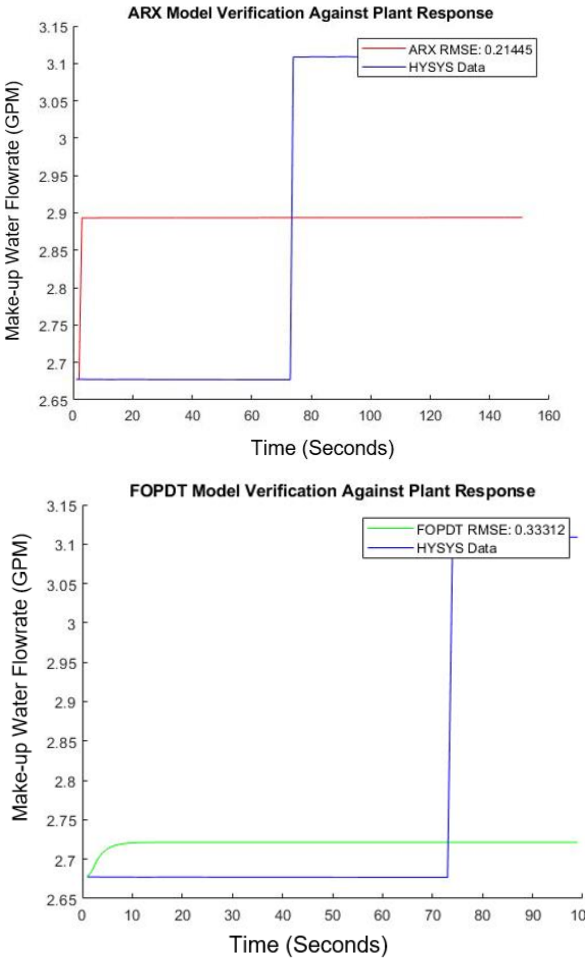

Figure 5. Verification of ARX and FOPDT models of FIC-1102

The MV change value used in the testing model is +10%. Figure 6 shows the interaction of MV changes with CV or amine flow rate.

Based on Figure 1 the changes given to the FV-1103 valve opening cause the amine flow rate. In the step response graph, the controller immediately responds to changes given to the system. The results of the modeling system obtained an ARX model with the order na = 14 nb = 14 nk = 0 and the fit estimation value is 87.87%. Then do data validation between the model and the system. Validation was carried out on the ARX model and the FOPDT model obtained in previous studies based on the RMSE value. Figure 7 is the result of a comparison between the model and the actual plant data. Based on the graph below, the RMSE value of the ARX model is smaller than the FOPDT model.

Control Performance Evaluation

After tuning the MPC parameters (shown by Table 1, further testing is carried out on the performance of the controller.

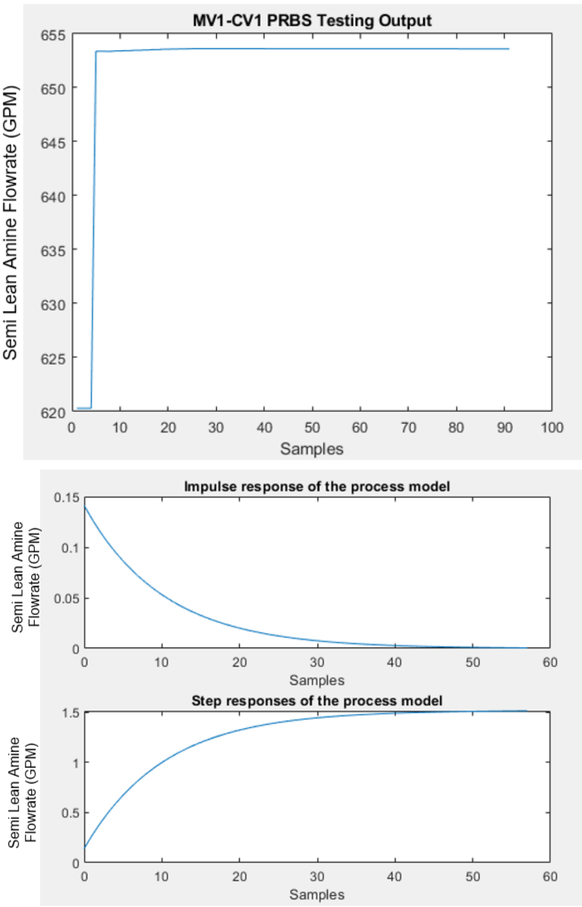

Figure 6. Output and step response of FIC-1103

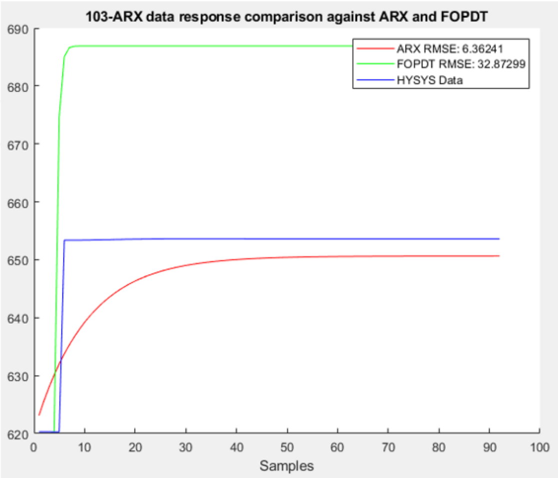

Figure 7. Verification of ARX and FOPDT models of FIC-1103

This test involves the effect of the set point tracking and the disturbance rejection. Set point tracking is done by changing the set point on each controller. While the disturbance rejection is done by reducing the feed gas flow rate by 5 MMSCFD. Tests conducted based on previous research [10].

In the PIC-1101, SP change is 2 psig, while the disturbance rejection is as described above. The effects that occur due to changes in set points and disturbances along with the comparison between using MPC-ARX and MPC-FOPDT1 are shown in Figure 8 and Figure 9, respectively. MPC-FOPDT2 does not display the response, only ISE values are taken from [10]. This applies to the following tests on FIC-1102 and FIC-1103. MPC-ARX is better than MPC-FOPDT1, but worse than MPC-FOPDT2, both servo and regulatory, as shown in Table 2.

In the FIC-1102, a test was carried out by performing a set point tracking by changing the SP of 0.5 m^3/h. The disturbance was given as in the previous test.

Table 1. MPC parameter tuning results

Model		T	P	M
PIC-1101	ARX	1	75	25
	FOPDT	1	90	31
FIC-1102	ARX	1	25	10
	FOPDT	1	110	25
FIC-1103	ARX	1	30	25
	FOPDT	5	40	10

Table 2. ISE value servo and regulatory control in PIC-1101

Model		Servo	Regulatory
PIC-1101	ARX	37.4	2.1
	FOPDT	$3.1x10^3$	$3.0x10^3$
	[9]	7.7	0.947

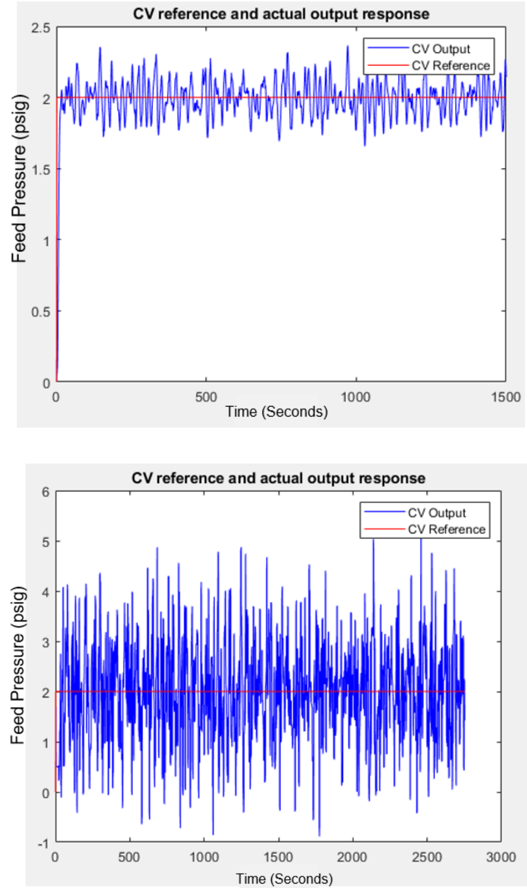

Figure 8. Servo control in PIC-1101: ARX (above), FOPDT (below)

The effect that occurs due to changes in SP and the given disturbance is depicted in the response comparison graph which can be seen in Figure 10 and Figure 11.

In the FIC-1102, a test was carried out by performing a set point tracking by changing the SP of 0.5 m^3/h. The disturbance was given as in the previous test. The effect that occurs due to changes in SP and the given disturbance is depicted in the response comparison graph which can be seen in Figure 10 and Figure 11. MPC-FOPDT2 does not display the response, only ISE values are taken from [10]. MPC-ARX is better than MPC-FOPDT1 and MPC-FOPDT2, both servo and regulatory with improvement of 6% and 33%, respectively, as shown in Table 3.

Table 3. ISE value servo and regulatory control in FIC-1102

Model		Servo	Regulatory
FIC-1102	ARX	$4.5x10^{-2}$	$16x10^{-2}$
	FOPDT	$1.7x10^4$	$1.0x10^4$
	[9]	$1.9x10^{-1}$	$2.4x10^{-1}$

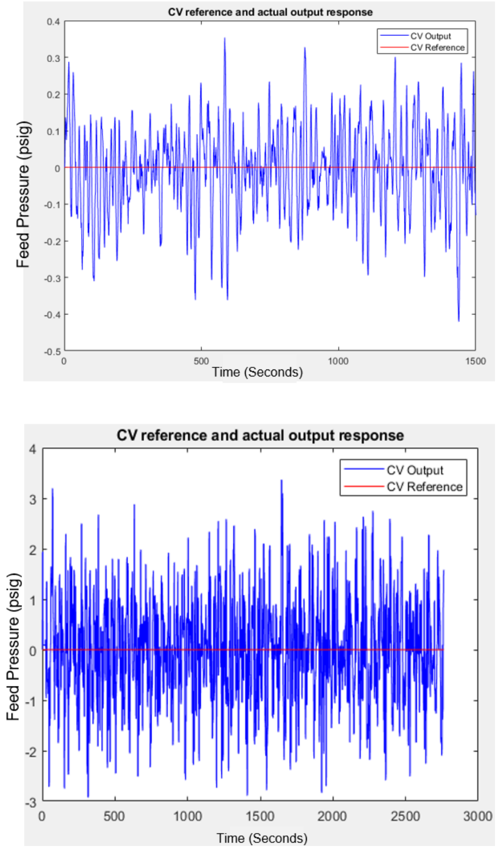

Figure 9. Regulatory control in PIC-1101: ARX (above), FOPDT (below)

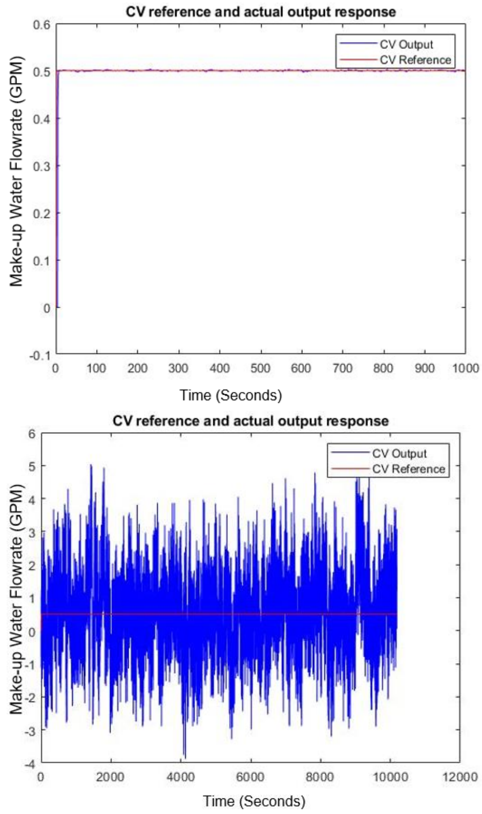

Figure 10. Servo control in FIC-1102: ARX (above), FOPDT (below)

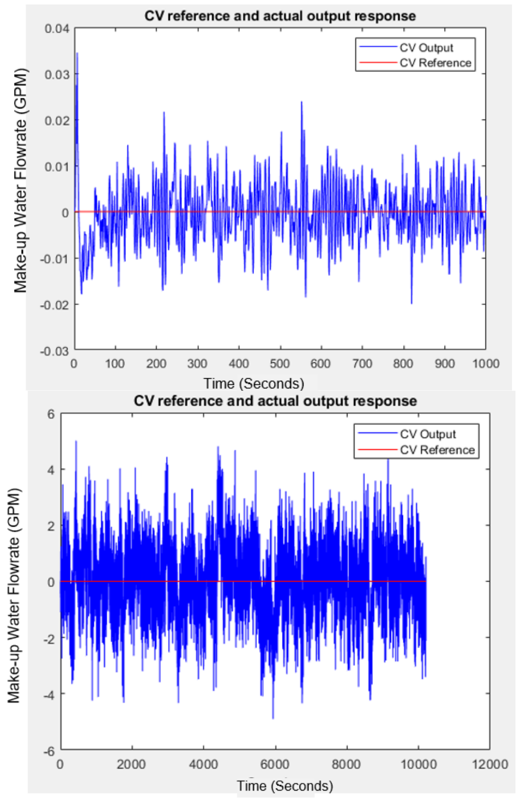

Figure 11. Regulatory control in FIC-1102: ARX (above), FOPDT (below)

In the FIC-1103, a test was carried out by performing a set point tracking by changing the SP 30 m^3/h to be able to see the response of the controller. The disturbance was given as in the previous test. The effect that occurs due to changes in SP and the given disturbance is illustrated in the response comparison graph which can be seen in Figure 12 and Figure 13. Control performance using FOPDT is not displayed because the MMPC failed to run. This failure occurs when the FOPDT model is used very badly as shown in Figure 7, the model error is very high. MPC-ARX is better than MPC-FOPDT1 and MPC-FOPDT2 (in servo control with improvement of 56%), but worst in regulatory control, as shown in Table 4.

Table 4. ISE value servo and regulatory control in FIC-1103

Model		Servo	Regulatory
FIC-1103	ARX	140.7	13.6
	FOPDT	Fail	5.7×10^5
	[9]	318	0.4

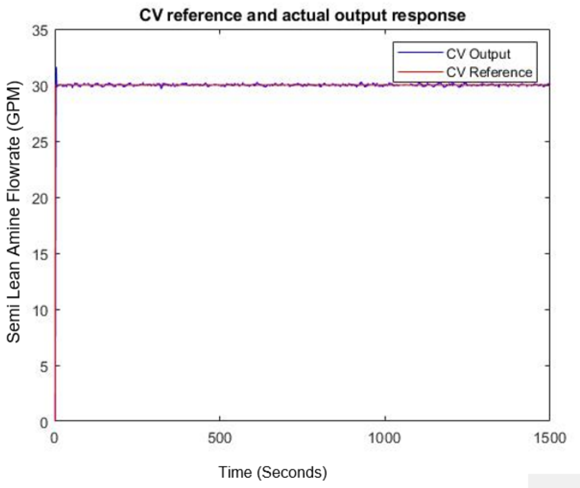

Figure 12. Servo control in FIC-1103 (ARX)

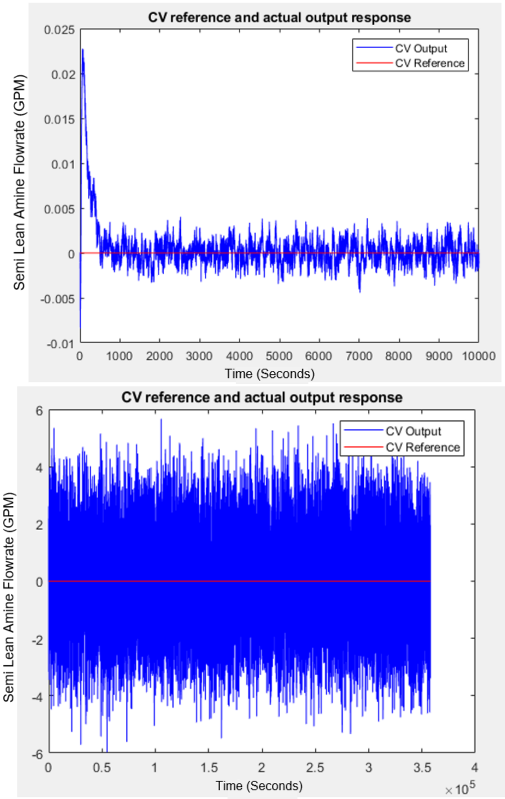

Figure 13. Regulatory control in FIC-1103: ARX (above), FOPDT (below)

From the three tests above, they do not show that using the best model will produce the best control performance as well as has been proven by previous research [26]. This is most likely caused by improper tuning of MPC parameters so that better adjustments must be made [27, 28, 29, 30]. In all the tests conducted, MPC-FOPDT1 showed very poor control performance so it was not used as a comparison. The cause of this very poor performance is most likely due to improper MPC parameter settings, too.

CONCLUSION

The ARX model is the best model for the CO_2 removal process with an RMSE value of 35%-91% smaller than the RMSE value of the FOPDT model. The optimal control parameters Prediction Horizon (P), Control Horizon (M) and Sampling Time (T) in the CO_2 removal process are 75, 25 and 1 on PIC-1101, 25, 10 and 1 on FIC-1102, and 30, 25 and 1 on FIC-1103. The MPC-ARX can improve the control performance of 6-56% on the regulatory control and 33% in the servo control. However, not all of them showed an increase in control performance improvement from previous studies even though they had used the best model (ARX). This is due to the MPC parameter setting that is not yet appropriate, so it needs to be retuning.

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