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Procedia Computer Science 105 (2017) 119 – 124

Procedia Computer Science

2016 IEEE International Symposium on Robotics and Intelligent Sensors, IRIS 2016, 17-20 December 2016, Tokyo, Japan

U-Model based Adaptive Control of Gas Process Plant

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Abstract

Industrial process control holds great importance while dealing with nonlinear control. System modeling and controller design is considered to be a critical challenge for researchers as well as plant operators. Resultantly, significant amount of research work has been prompted in the area of Adaptive Control. Their biggest advantage is that unknown system parameters are tuned online and adjusted adaptively. In this research work, an adaptive controller, based upon a recently developed U-Model is suggested. U-Model is a simplified polynomial structure that adaptively adjusts system parameters online. Being less complex in structure, design and development of U-Model based controller is simple. Previously, it has performed well in different applications regarding system identification and controller design. This motivates us to undertake a Gas Process Plant for our research work using U-Model. The proposed control strategy is verified by a simulation.

Peer-review under responsibility of organizing committee of the 2016 IEEE International Symposium on Robotics and Intelligent Sensors(IRIS 2016).

Keywords: Adaptive; Gas Process Plant; Industrial Process Control; Newton-Raphson Controller; System Identification; U-Model;

1. Introduction

Nonlinear control is given high priority by the researchers in order to improve process control methods. Process control industry can be greatly benefited by effective control strategies. There are quite some control techniques commonly used for controller design and development. They usually have high count of parameters and variables with lagged input in time domain[1]. As a result, the system structure gets complex, slow and expensive[2]. Another demerit with several controllers is that unknown system parameters are tuned manually and offline. This may result in compromised controller performance at different scenarios. All this gap paves the way out for deployment of Adaptive Control Methods not only for researchers as well as industrial operators. Unlike other controllers, adaptive control methods tunes system parameters online and adjusts them adaptively[3]. This lessens the probability of human error during tuning process. Adaptive control methods greatly depend upon model selection[4]. Appropriate model that can model the system efficiently can lead to a robust controller synthesis and implementation[5].

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Peer-review under responsibility of organizing committee of the 2016 IEEE International Symposium on Robotics and Intelligent Sensors(IRIS 2016).
doi:10.1016/j.procs.2017.01.186

Model structure is a vital part of adaptive control strategies. It provides basis for a simplified controller design. A good model is considered to be simple, having less number of parameters, variables, and not lagging greatly in time domain. It also needs to be reliable by ensuring the overall system stability. Many modeling techniques have been used extensively over wide range of applications. NARMAX (Nonlinear Autoregressive Moving Average with Exogenous inputs)[6], ARX[7] or ARMAX[7] are some of the commonly used adaptive models. A considerable variety of nonlinear systems can be represented using these models[8]. Having substantial number of parameters and variables, they lead to complexity in system identification and controller design. The Artificial Neural Network is a time-taking multi-stage process. It requires high computational resources that may slow down the overall process[9]. One of the widely used method Fuzzy Logic also utilizes high time and resources, having absence of set-of-rules at times[10,11].

Based upon an appropriate model, a controller can be designed and implemented easily. There is a wide range of controllers used in process control industry. One of the most common controller, PID, has been extensively used in different applications and processes. However, not being adaptive in nature, its parameters needs to be tuned manually and offline. This invites the probability of compromised controller-performance due to possibly inappropriate parameter-tuning. State-Space and Sliding Mode controllers lack in terms of providing a non-complex structure for controller design[12,3]. Model Predictive Control is also used in process control applications. The disadvantage associated to MPC is complex nonlinear algebraic solutions when it comes to plant inverse solution. Due to number of parameters and variables, it is time-taking and resource-taking[13]. NARMAX[7] and Hamerstein[4] based inversion techniques also show similar behavior.

The importance of adaptive model and efficient controller cannot be ignored in nonlinear process control. Keeping in view the simplicity and stability needed for controller design and development, the adaptive U-Model was introduced[7]. The main advantage U-Model offers is reduced number of parameters and variables, resulting in a simple model structure. It sets the basis for an easy synthesis of control law. Though U-Model is a recently developed method, it has given encouraging results in different scenarios[1,12,9,11,6,14,15,16,17]. Its successful and recent implementation to various real-time processes motivates us to apply it on Gas Process Plant located in UTP, Block 23. Previously, the similar plant has been controlled using MPC[13]. However, U-Model has a simpler model structure than MPC. This paper focuses on design and development of U-Model based adaptive controller for Gas Process Plant.

U-Model based control method in this research work will be verified by simulation. Paper is organized as Section 2 describing U-Model method. Gas Process Plant is briefed in Section 3, followed by Results discussion in Section 4. The work is concluded in Section 5.

2. U-Model Structure

U-Model is a polynomial structure that comprises of time-varying system parameters. It was originally developed by Zhu[18] and can represent a wide range of nonlinear systems of the similar class. We have used Internal Model Control (IMC) structure in overall control loop as shown in Fig. 1a[19]. Control signal is fed into the plant as well as U-Model. The adaptive process keeps updating system parameters and identifies the plant online as shown in Fig. 1b. Once the system has been identified, the plant inverse, or the controller is obtained using Newton-Raphson root solving method.

The SISO generalized U-Model output equation with respect to current control signal $u(t-1)$ can be written as[5]:

$$y_m(t) = \sum_{j=0}^{M} \alpha_j u^j(t-1) \tag{1}$$

where, M is the degree of polynomial. α_j is the time-varying system parameters that are past inputs and past outputs except $u(t-1)$. The parameter function can be represented as:

$$\alpha_j(t) = [\alpha_1, \alpha_2, \alpha_3, ..., \alpha_M] \tag{2}$$

System parameters are adjusted adaptively using Normalized Least Mean Square (nLMS) principle[20]. The model update equation is:

$$\alpha_j(t+1) = \alpha_j(t) + \mu(t) error(t) u^j(t) \tag{3}$$

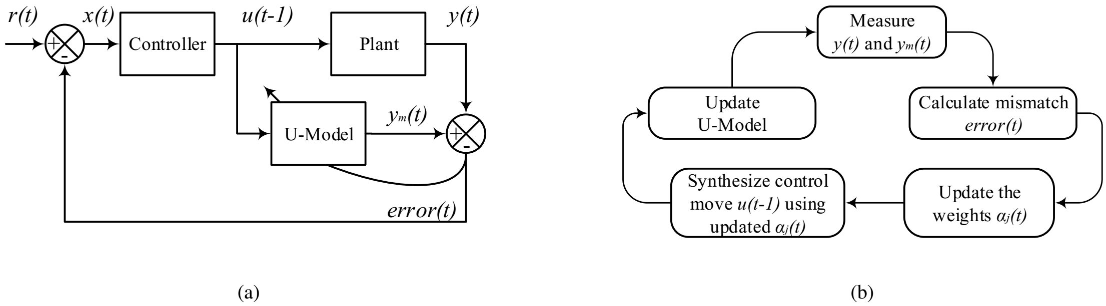


Fig. 1: (a) U-Model based IMC Loop. (b) U-Model Adaptive Update Algorithm.

where, $\mu(t)$ is the learning rate and is usually set between 0 to 1. $error(t)$ is the plant model mismatch error:

$$error(t) = y(t) - y_m(t) \tag{4}$$

If the model output $y_m(t)$ excites the controller via feedback, the controller output $u(t-1)$ will force the model and the plant to produce $y_m(t)$. Therefore, the input to controller $x(t)$ can be set to $y_m(t)$[21]. Replacing $y_m(t)$ using equation 1, and rearranging it, we get:

$$x(t) - \sum_{j=0}^{M} \alpha_j u^j(t-1) = 0 \tag{5}$$

In order to obtain the plant inverse, solution of equation 5 with respect to $u(t-1)$ is needed. In other words, we need to solve the polynomial equation using some root solving technique. The ease in determining control law is offered by the simplicity in U-Model structure. Since initial solution in U-Model can be taken as previous control input, the Recursive Newton-Raphson method can perform effectively in solving equation 5 for the control signal[14]:

$$u_{i+1}(t-1) = u_i(t-1) - \frac{y_m(t) - x(t)}{y_m'(t)} \tag{6}$$

where, i is the iteration index.

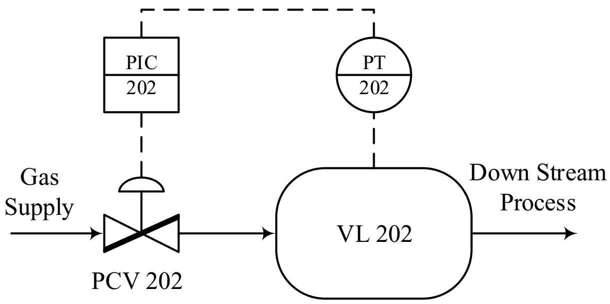
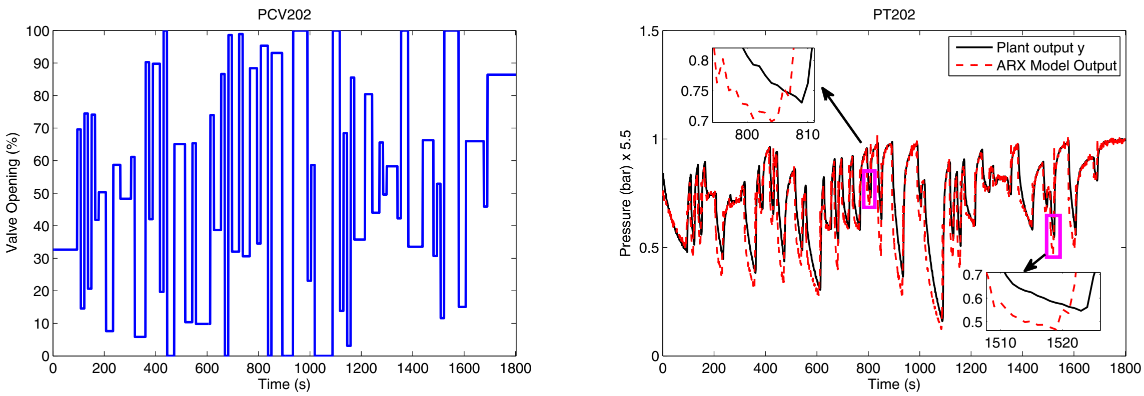


Fig. 2: P&ID of SISO Gas Process Plant.

3. Gas Process Plant

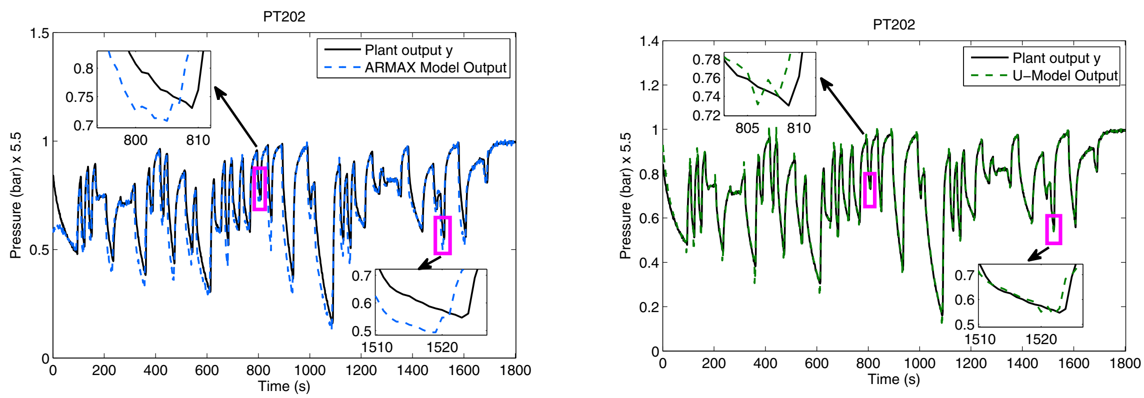
Fig. 2 shows piping and instrumentation diagram of SISO Gas Process Plant. Gas is continuously fed into the plant by upstream gas compressor. The pressure desired by Downstream Process, needs to be regulated in Buffer Tank VL202. U-Model based online controller PIC202 sends control signals to adjust the opening percentage of valve PCV202 ranging from 0% to 100%. Pressure sensor PT202 gives feedback to the controller for adjustment of the control signal. Control signals as well as feedback is given via Data Acquisition Units (DAQs). They can operate at 1kHz and can receive signals from current driven instruments ranging 4-20 mA.

4. Results and Discussion



(a) (b)

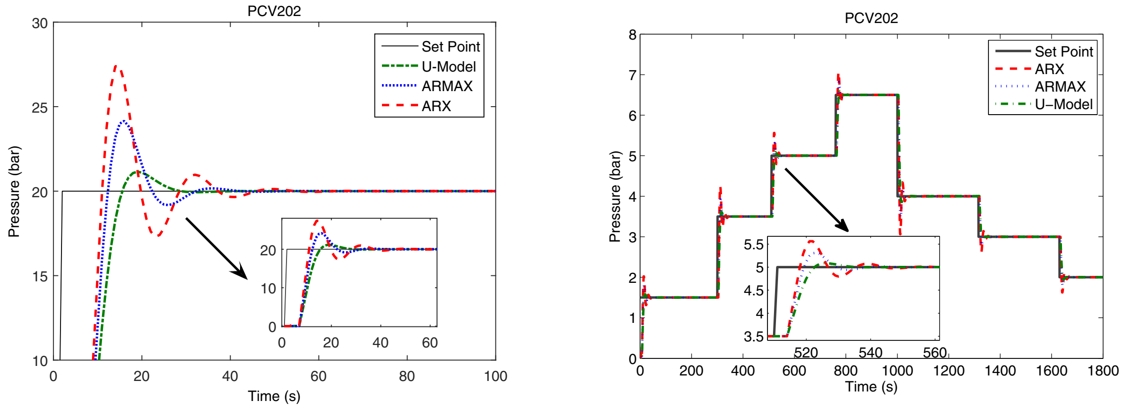
Fig. 3: (a) Gas Process Plant Input. (b) System Identification using ARX.



(a) (b)

Fig. 4: (a) System Identification using ARMAX. (b) System Identification using U-Model.

U-Model based online controller is designed and verified by simulation. The control system has two parts, system identification and controller implementation. We have utilized online data for system modeling that has been normalized between 0 to 1. Fig. 3a shows manipulated variable PCV202 signals. Simulation is carried out for 1802



(a) Fixed Set Point.

(b) Varying Set Point.

Fig. 5: Reference Tracking

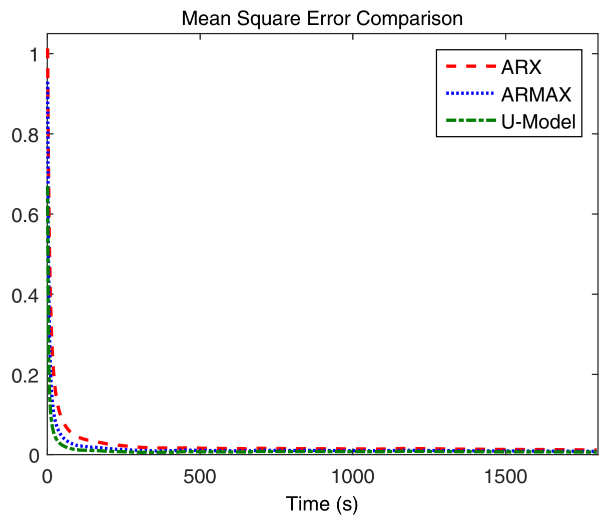


Fig. 6: Comparison in Tracking Error.

seconds and 3rd order ARX, ARMAX and U-Model have been used for system identification. Fig. 3b, Fig. 4a and Fig. 4b shows simulation results for controlled variable PT202 using ARX, ARMAX and U-Model respectively. It can be seen clearly that output tracking using U-Model has shown better results than ARX and ARMAX. To justify the claim, some intervals on the plot have also been elaborated by a close view. At around 800 seconds and 1500 seconds, U-Model based learning is quicker, without showing abrupt behavior unlike ARX and ARMAX. Moreover, as shown in Fig. 6, Mean Square Error (MSE) has been used as performance indicator for comparison between them.

The online controller using U-Model is also verified by a simulation. U-Model based online controller is compared with ARX and ARMAX based controllers on similar system. Reference tracking using the aforementioned controllers can be seen in Fig. 5a and 5b. It can be seen that U-Model based controller has converged quicker than other controllers. Moreover, ARX and ARMAX have high overshoots as compared to U-Model. It is worth mentioning here that the overshoots and high settling-time not only affects the control performance, but it may also damage the hardware. U-Model based controller is simple, robust and rapid. Performance indicator is the MSE shown in Fig. 6.

5. Conclusion

This paper has presented the design and development of U-Model based online controller. Suggested method is an adaptive model based strategy that involves system identification as well as controller design and development. ARX and ARMAX have been used in comparison to U-Model for verification purposes. Results have clearly shown that U-Model has performed better than the aforementioned techniques. It has depicted promising behaviour in system modelling as well as controller development. In the next phase, a real-time controller shall be designed and developed using U-Model. Its implementation will be done on the similar plant.

Acknowledgements

Author would like to thank Universiti Teknologi PETRONAS for their financial assistance and working facility provided to conduct research.

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