1. Introduction

In many process applications such as distillation columns, reboilers, evaporators, crystallizers and in mixing tanks the level must be maintained accurately at a desired set point despite line and load fluctuations. In the last decade we have seen development of many system identification techniques for both linear and nonlinear systems to make the modeling of industrial processes simpler and faster. Though different types of methods are available for parametric and nonparametric model estimation, one has to study the adoptability of the existing models to a particular process.

Control-oriented model identification methods are gaining more importance in recent years. Model driven control strategies are commonly used for two major purposes. One is for improving the system performance by tracking the set point and the second one is for rejecting load disturbance.

This paper focuses on modelling of a laboratory scale liquid level setup using system identification Toolkit provided in LabVIEW graphical programming language. The importance of system identification, various available methods and procedure for system identification using LabVIEW were discussed in following sections. Any plant can be modelled by using both open loop as well as closed loop system identification techniques.

The three important ways by which the systems can be identified are application of step test in open loop method, application of step test in closed-loop method and by using another different approach called relay feedback method. The selection and tuning of controller in closed loop system identification becomes critical because the system stability is a dependent factor. For this reason, the closed-loop step test is usually preferred for online system identification. The derived model is further used to improve the performance of the control system for more reliable control of the plant. The open

Abstract

Objectives: Present work describes the development of a dynamic model of laboratory scale level process using System Identification toolkit from LabVIEW graphical programming language. Methods/Statistical analysis: The dynamic characteristics of industrial processes are affected when they are recognized with different operating conditions. It is always advantageous to have an efficient model to design and implement suitable control configuration to obtain better performance. The identification process has several stages. Findings: The first stage comprises design of experiment, conduction, collection of experimental data. Useful portion of the input output data is selected and preprocessed to eliminate any outliers. In the second stage the experimental data is prepared in to different datasets which are further used to estimate autoregressive exogenous (ARX) models. Application/Improvements: Estimated models are simulated in both direct and indirect methods and the results are compared to draw conclusions.

Keywords: ARX Model, Closed loop Step Response, Data Driven Modeling, Parametric System Identification, System Identification
loop identification is simpler comparatively. But delays and model uncertainties are better treated by closed loop identification methods.

The two ways to introduce step change into the closed loop are either by applying the step change at set point side or at process input side (controller output side) as depicted in Figure 1. The existing step identification method is designed to achieve robust identification with steady (zero initial) process conditions and the typical response is given in Figure 2.

Figure 1. Simple closed-loop system.

Figure 2. Typical process reaction curve and model parameters from step test.

The identification of linear process models using step identification methods are grouped into three categories. In the first method the model fitting is done with the help of dominant points identified from the transient response, in the second method the time integral estimation is used and in the third the frequency response technique is used. There are many algorithms available for applying two-point fitting to FOPDT model. For all the above said categories, individual identification algorithms are available.

To obtaining more robust identification based on step test, separate identification methods must be deployed to incorporate and to withstand with the influences of various disturbances viz. measurement noise, load disturbance, and unsteady initial operating conditions of the process that are common in industrial applications. The applied step change in the closed-loop control structure should be confined to set point to secure the stability.

In many cases, the process that is to be modeled is an element of closed-loop system. When safety is a major concern, or if the open-loop system is unstable, the regulator cannot be disabled while performing an identification experiment. These issues naturally lead to research into the identifiability of closed-loop systems. The step signal is applied at the set point side and experimental data is used to estimate models by applying different System Identification techniques. The estimated models must be validated before they are used in control system design.

Model estimation can determine the most suitable model confined to the prescribed model structure. It is not guarantee that the estimated models confirm the information regarding, accurate description of the system. Whereas validation of the model reveals the superiority of the model obtained with in prescribed structure. Model validation determines the appropriateness of the model to express the system.

2. Methods of System Identification

The typical process reaction curve of an FOPDT model for a step change is as shown in Figure 2. The model parameters such as static gain, dead time and the average residence time are determined from the step response. A general model is a combination of a number of ordinary differential equations or difference equations and set of parameters which have to be estimated. The model structure (as defined by the number of differential equations and the form of any associated algebraic relationships) also includes uncertainties. The most suitable structure has to be identified by thorough testing using different data sets.

2.1 ARX Mode

Auto-regressive model with exogenous inputs is the most commonly used model to represent many systems used in the chemical process control industry. Exogenous variables are determined outside of the process that is being modeled. This model allows estimation of both correlated variables and exogenous variables. Parametric identification methods are used to extract the elements of the adapted plant and noise models. The criterion used for parameter estimation in ARX model is based on
the prediction error framework, which minimizes the prediction errors even when the probability distribution is unknown. The model order is usually set greater than the real to reduce the computational error. However it is observed that increased model order will influence the extraction of dynamic characteristics and stability of the system. The basic structure and elements of an ARX model are as shown in Figure 3. Where $u(n)$ is the input to the system, $y(n)$ is the output and $e(n)$ is error. $A(q)$ and $B(q)$ are the polynomial equations of the system.

Figure 3. ARX model structure.

2.2 Procedure to collect experimental data
The experiments are carried on the level process to obtain preliminary model parameters such as steady state gain, time delay, rise time and time constants etc. The conclusions can be drawn from experimental data to determine more suitable and superior experimental settings that yield much useful data for identification. The obtained data is further used in System Identification Toolkit available in LabVIEW and MATLAB.

The typical steps involved in LabVIEW System Identification are shown in Figure 4. Various toolkits are available to carry out different steps starting from plant modeling, control design and simulating the models to comply with real-time module.

Figure 4. Plant modeling, control design, simulation and deployment.

Historical data is used for estimating standard models using both MATLAB and LabVIEW but this requires thorough study and extensive research for gathering requisite and relevant information and to pick up the most appropriate data which will possibly reveal the system characteristics; this involves careful segregation and formatting of the data. In the other method the experiment is conducted to obtain the statistics for analyzing the required system or its parameters.

3. Design of Experiment
An experiment was conducted on the level process and the experimental data was collected. The different steps involved in conducting the experiment are:

- The process to be identified was controlled using a PI controller.
- Then the process was tested by applying a standard input signal such as a step signal at set point side and the experimental data was collected.
- The data was preprocessed and used in LabVIEW to obtain ARX model.
- Simulation comparisons of these algorithms are used to confirm the identification accuracy and robustness against miscellaneous disturbances.
- The observations are tabulated to provide general perceptive of observations from each identification method assessed.

The experimental setup of level process station is shown in Figure 5. The process characteristics are estimated from the controller output and level readings. In the present closed loop identification the variation in the set point is applied to impose step change. The corresponding input (set point in cm) and output (level in process tank in cm) data is collected.

Figure 5. Experimental setup of the level process station.

The following are the Specifications of the level process station:
Process tank level: 70 cm.
Rota meter: 0-1000 LPH.
Transmitter: Capacitive level probe.
Current to Pressure converter (I/P):
Input= 4-20 mA
Output= 3-15 psi.
Controller: Proportional plus integral control.
Control valve Type: Plug type.
Action: Normally Close (air to open).

4. Model Extraction and Validation

After acquiring and preprocessing of the data is over the next step is estimation of the model. The two most commonly used techniques that characterize LTI systems are parametric and nonparametric. Estimation using nonparametric method is straightforward, competent but less accurate compared to parametric estimation. In this study we have used parametric model estimation. Parametric models are usually represented in terms of transfer functions and differential equations.

The two major categories of parametric models provided in LabVIEW system Identification Toolkit are state space model and polynomial models. The selection of accurate model type and suitable model order will lead to superior model estimation. After obtaining useful information about the model order and estimates of the delay, various model orders were tested to choose the best fit. The resulting model can be further tested for validation.

ARX model structure available in LabVIEW is used for analyzing the present system.

The identified models are the essential elements of the control system. The process is analyzed with the help of Bode diagrams and coefficients of the models are compared. The obtained ARX models were compared with results of co-simulations and are presented in following Figures 6 and 7.

There are three most regular validation methods available in System Identification Toolkit: first one is by simulating the model, the second is by using residual analysis, and the third one is prediction approach. Along with the above the methods like pole-zero approach, Nyquist and Bode analysis are used analyse the models estimated.

5. Results and Conclusions

The mathematical models identified from closed-loop step test are given in following equations. The Discrete-time ARX model obtained by using MATLAB System Identification Toolkit is given from (4) to (8).

\[
(1-0.998908z^{-1})y(k) = 9.08475E-5z^{-1}u(k) + e(k) \quad (4)
\]
\[
A(z) y(t) = B(z) u(t) + e(t) \quad (5)
\]
\[
A(z) = 1 - 0.9965 z^{-1} \quad (6)
\]
\[
B(z) = 0.001179 z^{-1} \quad (7)
\]
\[
(1 - 0.9965 z^{-1})y(t) = (0.001179 z^{-1}) u(t) + e(t) \quad (8)
\]

Figure 6. Bode plots of estimated ARX models.

Figure 7. Bode plots of simulated ARX models.
It is observed that model extraction using higher order will have impact on the stability of the model. The present model is estimated by using System Identification toolkits available in both LabVIEW and MATLAB. The coefficients of validated discrete models are compared in Table 1 and are found satisfactory.

Table 1. Comparison of ARX models

<table>
<thead>
<tr>
<th>System Identification Tool</th>
<th>A(z)</th>
<th>B(z)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MATLAB</td>
<td>0.9965</td>
<td>0.001179</td>
</tr>
<tr>
<td>LabVIEW</td>
<td>0.9989</td>
<td>9.08475E-5</td>
</tr>
</tbody>
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6. References