DEVELOPMENT OF NONLINEAR PREDICTIVE MODEL-BASED FEEDFORWARD CONTROL FROM CLOSED-LOOP FREELY-EXISTING REAL DATA

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Introduction

The control of chemical processes in industry is a very important aspect of everyday operations. The ability to maintain control has an impact on process safety, product quality and plant profitability [1]. In recent years, many different advanced control techniques have been developed. Many chemical and biological processes exhibit nonlinear behavior, but model-based control schemes have often used linear models, which can be sufficient if the process is operated over a small range of inputs [2, 3]. Real processes also often exhibit complicated dynamic responses to changes in the process inputs, including nonlinear dynamics.

The performance of any model-based controller is highly dependent on the model that is used to predict process behavior. The procedures for developing the model can be time-consuming and costly, requiring the process to be perturbed in order to determine cause-and-effect behavior between the process inputs and outputs. It is desirable to be able to identify the process model without causing significant upsets to everyday operations. Ideally, historical data from the plant database could be used to develop the models to be used for prediction of process output response to changes in the inputs. The advantages of using this historical data are numerous. The data is readily available, is collected frequently, covers the “typical” operating space of the process, and does not require specific perturbations of the process inputs. However, several problems can be encountered if plant historical data is used. The process inputs are likely to be highly correlated, and the range of the inputs may not be very broad.

Distillation is an example of a process that would benefit from a model-based controller that can be built using plant historical data. The high degree of interaction between process variables makes it a complicated problem for control. There have been many applications of feedforward control to distillation processes. Among these, several have attempted to address the process response of product composition to various input disturbances such as feed flow and feed composition [4-6], but none have attempted to compensate for multiple input disturbances occurring simultaneously.

The purpose of this work is to demonstrate a method of developing a nonlinear process model under highly correlated inputs that can be used for a feedforward controller that will compensate for multiple input disturbances simultaneously. The model can be developed using historical plant data collected under closed-loop conditions and still effectively determine cause-effect behavior between the inputs and output of the process.

Methodology

Block-oriented models have been used to accurately describe many types of nonlinear process behavior. The two most common block-oriented models are the Hammerstein and Wiener models. In this paper, we will discuss the LNL block-oriented model which has a linear dynamic block followed by a nonlinear static block and then another linear dynamic block.

Closed-form solutions to the Hammerstein and Wiener processes have been proposed by Rollins et al. [7] and Bhandari and Rollins [8] for continuous-time modeling (CTM), and are called the H-BEST and W-BEST methodologies, respectively. A discrete-time modeling (DTM) method has also been developed by Rollins and Bhandari [9] that follows the CTM procedures for H-BEST and W-BEST. This work is an extension of the DTM method for the W-BEST methodology. This work also extends the developments of Rollins, et al. [10] in modeling diabetic subjects under free-living data collection to the modeling of real process data under freely existing conditions such as plant data. In addition, it applies the principles used by Rollins et al. [11] to address inputs that are serially correlated.

The Wiener model

Procedure for Model-Building

The following is the procedure we developed for model building under freely existing data, and is a modification of the experimental design method in Rollins et al. [11]:

1. Select the dynamic model form for Eq. 1, and estimate the static and dynamic model parameters under Model 1. This is repeated until an acceptable model form is found.
2. Using the residuals from step 1, determine the ARMA (p,q) form of Eq. 7 and estimates of the θ_p and ϕ_q parameters.
3. Simultaneously refit the dynamic, ultimate response, and ARMA parameters under Model 2 if necessary.
4. Check the residuals in step 3 for compliance to white noise

The form of the ARMA (p,q) model is found using the autocorrelation function (ACF) and partial autocorrelation function (PACF). Note that in Rollins et al. [11], statistical design of experiments (SDOE) was used to determine input changes to the process. In this case, we will be using historical plant data so no additional experiments need to be determined.

Feedforward Control Methodology

General Feedforward Controller Methods

The concept of feedforward control allows for theoretically perfect control of a process system. By measuring the disturbances (loads) of a process and modeling how these disturbances affect the process outputs, corrective action can be taken before the process outputs deviate from their desired values [1]. However, because there are many process disturbances that cannot be measured in a timely or efficient manner, feedforward control is typically used in conjunction with standard feedback control, which compensates for any deviation of the output variable from its setpoint, regardless of what caused the deviation.

The feedforward controller, G_f, is generally approximated by a linear model [12], but nonlinear process models can also be used [13, 14]. The model is found by determining how the process output responds to a given input disturbance.

In order for the feedforward/feedback controller to provide perfect control of the output variable Y, we must first find the closed-loop response to an arbitrary change in the disturbance variable X_i.

Some ideal feedforward controllers are physically unrealizable, in these cases, the feedforward controller is often approximated by a lead-lag unit [1]. We will discuss how this problem is addressed with the feedforward controller of the proposed approach in the next section.

Proposed Feedforward Controller Methodology

The block diagram for the feedforward/feedback controller under Wiener modeling has not been shown for space considerations. The first step in implementing feedforward/feedback control under Wiener modeling is to identify the model parameters for the process being studied. Once the model has been identified, the feedforward controller is designed.

As in the case of the traditional feedforward controller, we can find the closed-loop output response to a change in the input disturbance X_i.

The Distillation Process

The distillation process used was a pilot-scale methanol/water distillation column consisting of 12 trays, with an inside diameter of 6 inches. Feed was introduced at Tray 4 and had a concentration of 15% (mol) methanol. The column is connected to a DeltaV distributed control system from Emerson Process Management.

Open-Loop Model Building

Training Phase

In order to first determine the feasibility of developing a Wiener model under highly correlated inputs for the distillation process, training and test data were collected in the open-loop mode [15]. The input variables chosen for the experimental tests that were conducted included feed flow rate, feed temperature set point, reboiler level and reboiler steam pressure. Other variables that were measured on-line and used as input variables included reflux flow rate, column pressure, bottoms product flow rate, distillate product flow rate and overhead condensate temperature. The output response of the process was the top tray (Tray 12) temperature, which was also measured on-line.

During the experiment the feed temperature set point was the input variable, and the feed temperature displayed significant dynamic response to the set point changes and also to the feed flow changes. Because of this, we included dynamics on the feed temperature set point which relate the observed feed temperature with the feed temperature set point and feed flow changes. The other input changes displayed very little dynamic response to set point changes, so the measured values of those input variables were used directly in the model building process.

Testing Phase

In order to test the model that was built during the training phase, another series of input changes was made to the distillation process. In this case, a Box-Behnken design with four factors and three center points was run, but this time the correlation between the feed flow rate and feed temperature set point was zero. This was done to demonstrate that the model built under high correlation was able to determine accurate cause-and-effect behavior between the input and output variables. As in the training phase, only four inputs were deliberately changed, but an additional five inputs were measured on-line and used in the prediction of the output response.

PI controller vs. FFPI controller process responses

The feedforward/feedback controller that we developed was tested and compared to the feedback controller alone.

In order to quantitatively compare the results of implementing the feedforward controller, the average absolute error (AAE) term is used.

In the case of the PI controller, AAE=0.192, while in the case of the FFPI controller, AAE = 0.134. This represents a 42.8% reduction in the variability of the Tray 12 temperature.

Conclusions

In this paper, we have presented a methodology for developing a Wiener block-oriented model from plant data that accurately predicts process response behavior to multiple input disturbances that are occurring simultaneously. The model was implemented into a feedforward/feedback control scheme and demonstrated marked improvements over traditional feedback control. The ability to develop the model with plant historical data under closed-loop conditions represents a significant advantage over traditional model-building techniques, which require specific perturbations of the process that can affect plant operations.

This work will be extended to other types of chemical and biological process systems for further investigation. Specifically, the work done by Rollins et al. [24] to predict glucose response in type 2 diabetics will be extended to close the loop on glucose concentration. The implications of this for persons with type 1 and type 2 diabetes are tremendous, as the ability to control glucose levels at a desired level will greatly affect their longevity and quality of life.

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