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Chemical Engineering Research and Design

journal homepage: www.elsevier.com/locate/cherdiChemE
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Block-oriented feedforward control with demonstration to nonlinear parameterized Wiener modeling

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ARTICLE INFO

Article history:

Received 21 July 2015

Received in revised form 1

December 2015

Accepted 10 February 2016

Available online 20 February 2016

Keywords:

Feedforward control

Model-based control

Wiener modeling

Block-oriented modeling

Nonlinear modeling

Nonlinear regression

ABSTRACT

Block-oriented modeling (BOM) is a multiple-input, multiple-output modeling approach for nonlinear dynamic processes. Current implementation of BOM into feedforward control (FFC) results in linearization of the model and decomposition into separate components for each input. This work presents a multiple-input BOM FFC approach that does not linearize and decompose the BOM into separate components for each input. This implementation uses a new FFC law that uses the complete BOM in the time domain. The approach is demonstrated with a Wiener model for a simulated continuous stirred tank reactor (CSTR) with four (4) measured inputs. The Wiener model is nonlinear in the physically-based dynamic parameters of the transfer functions and linear in the static parameters of the static gain function. The static gain function has a second order linear regression form with interaction and quadratic terms. The Wiener model is built under open-loop conditions using a Box-Behnken statistical experimental design consisting of 27 sequential step tests. Under a sequence of multiple input changes, the addition of this feedforward controller to the feedback controller reduced the standard deviation of the controlled variable from its set point by 70% in comparison to the response with only feedback control.

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1. Introduction

There are basically two types of control approaches – feedback control (FBC) and feedforward control (FFC). FBC is any control approach that determines the settings for the manipulated variable based on the deviation of the controlled variable from its target or set point (Y^{set}). This deviation can be at the current time instant, as in common FBC or a more sophisticated one like a Smith Predictor, or it can be a predicted deviation at some future time as in model predictive control (MPC). FFC differs from FBC in that it changes the manipulated variable based on the values of input variables and not the deviation from set point. More specifically, the FFC control

objective is to maintain the output of the FFC model, which consists of measured inputs only, at a constant value by changing the manipulated variable to “compensate” for changes in the measured inputs. Thus, to implement FFC effectively on the measured set of inputs, the model must be capable of accurate determination of the manipulated variable to “offset” the measured input changes while in an automatic control scheme. Approximations of the model to incorporate it into the control algorithm can also adversely affect control performance.

Some models for nonlinear gain behavior have been proposed for model-based controllers including radial basis functions (RBF) (Alexandridis and Sarimveis, 2005; Fischer

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<http://dx.doi.org/10.1016/j.cherd.2016.02.016>

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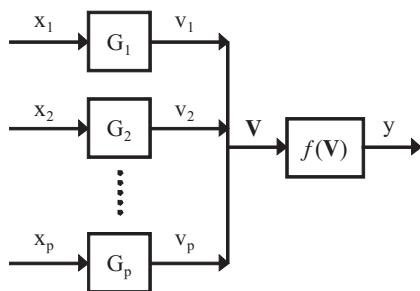


Fig. 1 – Block diagram for the Wiener network with p inputs and one output. Each input, x_i , is passed through their own unity gain linear dynamic block, G_i , after which these unobservable intermediate outputs are collected and passed through a single unrestricted static gain function, $f(V)$, to produce the output, y .

et al., 1998), genetic algorithms (GA) (Al-Duwaish and Wasif, 2001), Nonlinear Auto Regressive Models And exogenous inputs (NARMAX) models (Di Palma and Magni, 2004; Gao et al., 2003; Havlena and Findejs, 2005), and block-oriented models (BOMs) (Pearson and Ogunnaike, 1997; Rollins et al., 2003; Greblicki, 2000; Bhandari and Rollins, 2003, 2004; Chin et al., 2004). An important advantage of NARMAX and BOMs is that they can use transfer functions, i.e., linear dynamic equations with physically interpretable parameters. However, a limitation of the NARMAX structure is that all of its transfer functions have the same characteristic equation or denominator dynamics (Rollins et al., 2015a). BOMs use the outputs from blocks of dynamic (transfer) functions that are linear (L) differential equations as inputs to functions that can be nonlinear (N) with respect to static gain parameters. The simplest of the BOMs is the Hammerstein network (NL), which has an N block followed by an L block and the Wiener network (LN), which reverses the order of these two blocks. More complicated block-oriented structures include sandwich models such as an LNL network, which has linear dynamic blocks, followed by a nonlinear static block, followed by a second linear dynamic block. When the inputs can have different dynamic behavior, the Wiener network is the preferred choice over Hammerstein and is superior to NARMAX because the inputs can have completely different dynamic structures (Rollins et al., 2015a) as shown by its block diagram in Fig. 1.

A number of researchers have studied the identification of model parameters for the Hammerstein and Wiener networks, including Greblicki (1992, 2000), Eskinat et al. (1991), Shi and Sun (1991), and Al-Duwaish and Wasif (2001). Perhaps, due to its complexity, the LNL network has not gotten as much attention, but some have proposed methods for its parameter identification (Wills et al., 2013). There has been much progress over the last decade in the identification of BOMs (Wills et al., 2013; Biagiola and Figueroa, 2011; Romano and Garcia, 2011; Yu et al., 2013; Giri and Bai, 2010; Jing, 2011; Harnischmacher and Marquardt, 2007) and recently, by taking a nonlinear parameterized approach (Rollins et al., 2010) for estimation of the dynamic parameters, Rollins et al. (2015a) demonstrated accurate Wiener modeling using nine (9) inputs on a real distillation process with large variation due to unmeasured disturbances and with highly pairwise cross-correlation of the inputs. While there has been progress in the use of BOMs in model based control (Gregorčič and Lightbody, 2010; Kim et al., 2012; Ding and Ping, 2012), progress of FFC using BOMs

appears to have been limited to single input models (Reddy and Chidambaram, 1995; Dolanc and Strmčnik, 2008).

To implement a p -input nonlinear model structure the current FFC approach would linearize the structure, transfer it to the Laplace domain and decompose it into p FFC blocks. Additional approximations would be required for FFC blocks that are physically unrealizable to make them physically realizable. A numerical procedure (which is another approximation) such as Euler's method would be needed to obtain the output from each FFC block at each time instant. For the approach proposed in this work, a FFC law and methodology is presented that eliminates all these approximations. More specifically, the value of the manipulated variable to “offset” input changes at each time instant is obtained directly from the FFC model in the time domain in a root solving procedure and passing this solution through the inverse of the process transfer function. Since this procedure is done completely in the time domain the inverse of the process transfer function uses backward difference approximations for derivatives. Thus, an approximation to achieve a physically realizable transfer function is not needed for the proposed approach.

Thus, the objective of this work is the development of a general FFC framework for multiple-input BOMs in FFC with nonlinear static gain behavior. The BOM structure and identification will be demonstrated using a nonlinear parameterized Wiener model (Kotz et al., 2014; Rollins et al., 2010, 2015a) with a second-order static gain structure on a simulated CSTR. The Wiener model is built under open-loop conditions using a Box–Behnken statistical experimental design consisting of 27 runs or sequential step tests. The FFC model will be implemented using the proposed FFC approach discussed above. Under a sequence of multiple input changes, the addition of this feedforward controller to the feedback controller reduced the standard deviation of the controlled variable from its set point by 70% in comparison to the response with only feedback control.

2. Methodology

This section gives the methods used to develop and evaluate the BOM FFC approach with specific application to a CSTR. The general BOM FFC law is presented first and then its form specific to the Wiener modeling approach used in this work. This includes specification of the Wiener model (WM), its FFC law, and the parameter estimation approach. Lastly details of the CSTR are given in this section.

2.1. General FFC law

The concept of FFC appears to have been applied as early as 1925 to level control systems for boiler drums (Seborg et al., 2011). It allows for theoretically perfect control of a process system because it corrects for input disturbances before the process outputs deviate from their desired values. However, this requires timely and efficient measurement of all possible process disturbances, which is not likely in most applications, so it is commonly used in conjunction with FBC. The addition of FBC compensates for any deviation of the process output from its set point, regardless of the cause of the deviation. For each input, its FFC law is typically found independently of the other inputs from a function in the Laplace domain that uses an approximation to meet the requirement of physically reliability when necessary (Seborg et al., 2011). The joint FFC

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