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ScienceDirect
Journal of Process Control 17 (2007) 551–561
JOURNAL OF PROCESS CONTROL
www.elsevier.com/locate/jprocont

Modeling of pH process using wavenet based Hammerstein model

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Received 12 April 2006; received in revised form 30 October 2006; accepted 2 November 2006

Abstract

This paper outlines an approach for developing a Hammerstein model for nonlinear dynamic systems. The nonlinearity is sought to be captured through functional approximation using wavelets cast in a wavenet structure. Nonlinear block of wavenet at input side is cascaded with a linear dynamic block described by a state space model. A sequential approach is used for development of static nonlinear and linear dynamic parts of the model. Configuration and parameters of the nonlinear wavenet structure are determined from near steady state data extracted from dynamic test data while the state space model parameters of the linear dynamic part are obtained using a subspace identification approach. This approach has been applied for modeling a strongly nonlinear pH process operated over a wide range of operating conditions.

Keywords: Hammerstein; Wavenet; pH

1. Introduction

Most real-world processes are nonlinear and dynamic in nature. The nonlinear static block followed by dynamic block in the Hammerstein structure has been found to be a simple and effective representation for capturing the dynamics of typical chemical engineering processes such as distillation columns, heat exchangers [1] and pH systems [2]. Well established linear controller design methods can be employed once this model is available. There have been many variants to the Hammerstein model structure. The nonlinearity is represented either through algebraic polynomial expressions [3] or as neural network models [4]. Both iterative and noniterative methods have been used for determination of the parameters of the static-nonlinear and linear-dynamic parts of the model. To overcome the need for a priori assumption of order of the dynamic part Lakshminarayanan and co-workers [3] proposed the use of canonical variable analysis (CVA) method. In their method the unknown static nonlinear characteristics are assumed to be defined adequately by a polynomial expression. Problems involved in the use of a polynomial form for the nonlinearity include nonconvergence if the system is not of polynomial form, oscillatory behavior of high-degree polynomials, etc. As a solution, neural networks were proposed by Su and McAvoy [4], in which a two-step procedure is used to identify the nonlinear function separately from the linear part utilizing steady-state data and transient data, respectively. Fuzzy approaches such as in [5] have also been suggested for this case. Jia and co-workers [6] presented a clustering algorithm in order to identify the antecedent parameters, i.e., the centers and widths of a neuro-fuzzy-based Hammerstein model. They have used a special switched form of test signals so that the linear and nonlinear parts of the model could be identified in a sequential manner.

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doi:10.1016/j.jprocont.2006.11.001

Nomenclature

A	model dynamic matrix
b	bias
B_1	model input (feature vector) matrix
B_2	model input matrix
c_i	linear weights
c_{s1}, c_{s2}	constants relating derivative of signal to wavelet transforms
C	model output matrix
D_1	model direct feed through feature vector matrix
D_2	model direct feed through input matrix
d_{ij}	dilation values for data
D_c	dilation of data associated with scalons
D_i	dilation of data associated with wavelons
$F(\cdot)$	static nonlinear block
$f(t)$	signal
$H(\cdot)$	linear dynamic block
H, G	finite impulse response of (wavelet function) filters
i, j	index
I_i	quantization vector for data
J	objective function for minimization
k	actual sample time
l	level of frequency subspace
m	number of inputs
n	number of feature vector variables
NT_s	number of translations for scalons
N_L	number of levels associated with dilation
NT_i	number of translations
N	number of data points
s	characteristic scale
t_s	sampling interval
T_{sc}	translation vector associated with scalons
T_{it}	translation vector associated with wavelons
T_s	threshold for identification of steady state
T_w	threshold for identification of zero-crossing point of wavelet transform
u	input variable
U	input vector
U_s	steady state value of input
V_{l-1}	lower frequency subspace (approximation)
W_{l-1}	high frequency subspace (detail)
$W_s(t)$	wavelet transform of signal
$WW_sf(t)$	second order wavelet transform
w	weights relating feature vector variable to output
X	state vector
y	output
y_s	steady state value of output
y_target	actual value of output
z	feature vector variable
Z	feature vector
Z_s	steady state value of feature vector
Δ	derivative
Δ^2	double derivative

Greek symbols

$\beta(t)$	steady state index
Π	set of basis functions for nonlinear part
θ_i	parameter set associated with the function Π_i
Ψ	set of Mexican Hat wavelet functions
ψ	wavelet function
Φ	set of scaling functions used for Mexican Hat
φ	scaling function
σ_{W_s}	standard deviation of wavelet transform modulus $W_sf(t)$
σ_{WW_s}	median of second order wavelet transform modulus $WW_sf(t)$
ω	frequency of perturbation
τ	response time constant

Oussar et al. [7] presented a dynamic wavelets structure for capturing dynamics and nonlinearity simultaneously without a block-oriented cascaded structure. Here the order of dynamics of the process is assumed a priori. Gomez et al. [8] have used a Wiener model which uses a pseudo inverse procedure to develop an output feature vector and then applied CVA for identification of the dynamic part of the model relating the input to the output feature vector. Kalafatis et al. [9] have proposed a Wiener model structure with a set of frequency sampling filters with associated dynamics and polynomial form of inverse static output nonlinearity. They demonstrated that this structure could be used to model highly nonlinear processes such as the pH process of Henson and Seborg [10]. They showed that the model could be identified with a variety of test signals – single sinusoid, multiple sinusoids and random signal. In a subsequent paper [11], they have developed an online estimation approach for estimating the parameters of the Wiener model using only sinusoidal test signals. They were able to track the titration curve of the pH process of [10] for small changes in the buffer flow rate.

In a previous work, the authors [12] have used both recurrent network and wavenet for direct modeling of both the nonlinearity and dynamics of pH process. Though RNN structure had inherent capability to model the dynamics, it was found inferior to the wavenet in its ability to capture the nonlinear static characteristics of the pH process. The wavenet structure used did not have inherent capability to represent the dynamics of the process and it was necessary to incorporate the dynamic effects through the use of input sequences with a suitable set of delays. For buffer flow variations, the wavenet structure could