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Identification of extended Hammerstein systems for modeling sticky control valves under general types of input signals

FANG Lei[1], WANG Jiandong[1], ZHANG Qinghua[2]

1. College of Engineering, Peking University, Beijing, China 100871
E-mail: fanglei@pku.edu.cn, jiandong@pku.edu.cn

2. INRIA, Campus de Beaulieu, 35042 Rennes Cedex, France
E-mail: zhang@irisa.fr

Abstract: This paper is motivated by modeling the control valve stiction phenomena in feedback control loops. An extended Hammerstein system with discretized Preisach model as the input nonlinearity is proposed to capture hysteretic dynamic behaviors of cascading systems consisting of control valves followed by linear dynamic subsystems. An iterative method is presented to identify the extended Hammerstein systems. An informative input needs to have multiple local extreme values in order to ensure the discretized Preisach model identifiable. However, if only a single hysteresis loop of the discretized Preisach model is in active, then an oscillatory input with only two extreme values is shown to be persistently excited for identification. Hence, the proposed identification method for extended Hammerstein systems is applicable to general types of inputs as well as oscillatory ones. Two industrial examples are provided to demonstrate the effectiveness of the proposed identification method for extended Hammerstein systems.

Key Words: Nonlinear system identification, Hammerstein system, Preisach model, Control valve stiction, Persistent excitation

1 Introduction

Hammerstein systems are one typical class of block-oriented nonlinear systems in which a static input nonlinearity is followed by a linear time-invariant dynamic subsystem, and have been applied to describe many physical systems [1]. If the input nonlinearity contains some memory effects, instead of being limited to static ones, then the resulting system is referred to as an *extended Hammerstein system* in this context.

Our study on the identification of extended Hammerstein systems is mainly motivated by the problem of modeling the control valve stiction. The detection, quantification and compensation of control valve stiction have been very active research topics recently; see the collected results in [2]. The methods based on Hammerstein model identification are promising to detect the presence of control valve stiction. Srinivasan *et al.* [3] applied the idea of separable least squares to stiction models parameterized by one parameter for control valves. Jelali [4], Choudhury *et al.* [5], Karra & Karim [6] and Farenzena & Trierweiler [7] generalized the same idea to identify Hammerstein systems consisting of a two-parameter stiction model connected with a linear process model. In these works, the control valve stiction is represented by data-driven stiction models with one or two parameters, whose structure is rather confined; as a result, data-driven stiction models may not be flexible enough to describe the actual characteristics of sticky control valves in practice. For instance, some control valves exhibit sticky behaviors only in the process of opening and move smoothly in the closing process. Wang & Zhang [8] described the ascend and descend paths of input nonlinearity by two static nonlinear models, and exploited the oscillatory property of input to identify the two models in a separated manner. However, the proposed method in [8] requires the input to be oscillatory with only two extreme values, and cannot be applied to more general inputs.

The contribution of this paper is two-fold. First, we propose an extended Hammerstein model with an input nonlinearity described by the discretized Preisach model, and present an iterative method to identify the extended Hammerstein system. Comparing with the data-driven stiction models in [3][4][5][6][7], the discretized Preisach model is much more flexible, e.g., it can describe the asymmetric behaviors of opening and closing control valves. Comparing with our previous work in [8], the proposed extended Hammerstein system is applicable to more general types of input and does not require the input to be oscillatory with only two extreme values. The second contribution is to establish the persistently exciting (PE) condition of input for identification of discretized Preisach model for the case that the input is oscillatory with only two extreme values. Thus, the proposed extended Hammerstein system and its identification method are applicable to general types of inputs and oscillatory ones.

The rest of the paper is organized as follows. Section 2 formulates the identification problem. Section 3 proposes an iterative identification method. Section 4 establishes a PE condition for the oscillatory signals having only two extreme values. Two industrial examples are provided in Section 5. Some concluding remarks are given in Section 6.

2 Problem formulation

Consider an extended Hammerstein system, depicted in Fig. 1,

$$\begin{aligned} A(q^{-1})y(t) &= B(q^{-1})x(t) + e(t), \\ x(t) &= f\left(u(t)\right), \end{aligned} \tag{1}$$

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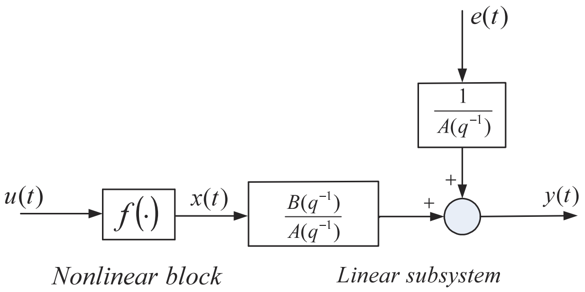

Fig. 1: The diagram of an extended Hammerstein system

with

$$\begin{aligned} A(q^{-1}) &= 1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a}, \\ B(q^{-1}) &= b_1 q^{-n_k-1} + \cdots + b_{n_b} a^{-n_k-n_b}. \end{aligned}$$

where $u(t)$, $y(t)$, $x(t)$ and $e(t)$ are the input, output, inner input and noise signals, respectively; $x(t)$ and $e(t)$ are not measurable. Symbol q^{-1} stands for a one-sample delay operator, e.g., $q^{-1}x(t) = x(t-1)$. The nonlinear block $f(\cdot)$ is a hysteresis nonlinearity described by the discretized Preisach model.

The discretized Preisach model is a superposition of many discretized relay operators [9]. Assume that the input $u(t)$ is located in a finite range $[u_{min}, u_{max}]$ where u_{min} and u_{max} are the minimum and maximum values of $u(t)$, respectively. Divide the input range $[u_{min}, u_{max}]$ uniformly into $L+1$ levels for a positive integer L, and denote the discretized thresholds u_i as

$$u_i = u_{min} + (i-1)\delta, \; i = 1, 2, \cdots, L+1, \tag{2}$$

with

$$\delta = (u_{max} - u_{min})/L. \tag{3}$$

Here L and δ are referred to as the discretization level and step size, respectively. With the discretized thresholds u_i, the discretized relay operator is define as

$$\gamma_{ij}(t) = \begin{cases} +1, & \text{if } u(t) > \frac{u_j + u_{j+1}}{2}, \\ -1, & \text{if } u(t) < \frac{u_i + u_{i+1}}{2}, \\ \gamma_{ij}(t-1), & \text{otherwise.} \end{cases}$$

for $i = 1, 2, \cdots, L, j = i, i+1, \cdots, L$. The discretized Preisach model is defined as

$$x(t) = \sum_{i=1}^{L} \sum_{j=i}^{L} \mu_{ij} \gamma_{ij}(t) \tag{4}$$

where μ_{ij} is the corresponding weighting parameter of $\gamma_{ij}(t)$ for $i = 1, 2, \cdots, L, j = i, i+1, \cdots, L$. Eq. (4) can be rewritten into a compact form,

$$x(t) = \gamma^T(t)\mu, \tag{5}$$

with

$$\begin{aligned} \mu &\triangleq [\mu_1, \mu_2, \cdots, \mu_K]^T \\ &\triangleq [\mu_{11}, \cdots, \mu_{1L}, \mu_{22}, \cdots, \mu_{2L}, \cdots, \mu_{LL}]^T \end{aligned}$$

and

$$\begin{aligned} \gamma(t) &\triangleq [\gamma_1(t), \gamma_2(t), \cdots, \gamma_K(t)]^T \\ &\triangleq [\gamma_{11}(t), \cdots, \gamma_{1L}(t), \\ &\quad \gamma_{22}(t), \cdots, \gamma_{2L}(t), \cdots, \gamma_{LL}(t)]^T, \end{aligned} \tag{6}$$

where $K = L(L+1)/2$ is the number of discretized relay operators.

The following assumptions are made throughout the paper:

A1 The noise $e(t)$ is zero-mean white noise and is independent of the input $u(t')$ for all $t \geq t'$.

A2 The linear subsystem is asymptotically stable, and the polynomials $A(q^{-1})$ and $B(q^{-1})$ are coprime.

A3 The nonlinear block $f(\cdot)$ belongs to the type of hysteresis nonlinearities that can be described by the discretized Preisach model.

Under Assumption A1, the linear subsystem (1) is an auto-regression with extra input model, possibly operating in a feedback control loop. Assumption A2 is standard for the identification of linear subsystems. Assumption A3 is satisfied by the hysteresis nonlinearities having the so-called wiping out property, congruency property and rate-independence property [9].

Based on the discretized Preisach model (5), the extended Hammerstein model (1) becomes

$$A(q^{-1})y(t) = B(q^{-1})x(t) + e(t), \tag{7}$$

$$x(t) = \gamma^T(t)\mu. \tag{8}$$

The objective is to design an identification method to estimate the unknown parameters of linear subsystem, $a \triangleq [a_1, \cdots, a_{n_a}]^T$ and $b \triangleq [b_1, \cdots, b_{n_b}]^T$ and the weighting parameter μ of discretized Preisach model, as well as the structure parameters (n_a, n_b, n_k) of the linear subsystem and the discretization level L, based on the measurements $\{u(t), y(t)\}_{t=1}^N$.

3 Identification method

This section proposes an iterative method for the identification of extended Hammerstein system.

Substituting (8) into (7) yields

$$y(t) = -\phi^T(t)a + b^T\Gamma(t)\mu + e(t), \tag{9}$$

where

$$\phi(t) = [y(t-1), \cdots, y(t-n_a)]^T,$$

$$\Gamma(t) = \begin{bmatrix} \gamma_1(t-n_k-1) & \cdots & \gamma_K(t-n_k-1) \\ \vdots & \ddots & \vdots \\ \gamma_1(t-n_k-n_b) & \cdots & \gamma_K(t-n_k-n_b) \end{bmatrix}.$$

If the structure parameters (n_a, n_b, n_k) and the discretization level L are known *a priori*, the estimation of the unknown parameter vectors a, b and μ is a bilinearly parameterized estimation problem [10]. The iterative method [11] is adapted here. Its main idea is to estimate the parameter vectors a, b and μ in two iterative steps in which the estimation problem is linear at each step.

Based on the measurements $\{u(t), y(t)\}_{t=1}^N$ and the model (9), define the loss function

$$J_N(a, b, \mu) = \frac{1}{N}\sum_{t=1}^{N}\left(y(t) + \phi^T(t)a - b^T\Gamma(t)\mu\right)^2.$$

The iterative method consists of the following steps:
Step 1. Select the initial estimates of linear subsystem

$$\hat{a}(0) = [0, 0, \cdots, 0]^T,\ \hat{b}(0) = [1, 0, \cdots, 0]^T.$$

Step 2. Estimate the parameter μ of the input nonlinearity $f(\cdot)$ in the k-th iteration ($k = 1, 2, \cdots$) by solving a linear least-squares problem,

$$\bar{\mu}(k) = \arg\min_{\mu} J_N(\hat{a}(k-1), \hat{b}(k-1), \mu)$$

where $\hat{a}(k-1)$ and $\hat{b}(k-1)$ are the estimates of a and b in the $(k-1)$-th iteration, respectively.
Step 3. Estimate the parameters a and b of the linear subsystem by solving another linear least-squares problem,

$$\{\bar{a}(k), \bar{b}(k)\} = \arg\min_{a,b} J_N(a, b, \bar{\mu}(k)).$$

Step 4. Normalize the above estimates in order to remove a gain ambiguity between the linear subsystem and input nonlinearity [12] by

$$\begin{aligned}\hat{\mu}(k) &= s(k)\bar{\mu}(k)\|\bar{b}(k)\|,\\ \hat{b}(k) &= \frac{s(k)}{\|\bar{b}(k)\|}\bar{b}(k),\\ \hat{a}(k) &= \bar{a}(k),\end{aligned}$$

where $s(k)$ is the sign of the first nonzero element of $\bar{b}(k)$, and $\|\cdot\|$ stands for the Euclidean norm of the operand.
Step 5. Stop the iteration if the estimated parameters satisfy the convergence criterion that monitors the relative percentage improvement of the estimated parameters:

$$\frac{\|\hat{\vartheta}(k) - \hat{\vartheta}(k-1)\|}{\|\hat{\vartheta}(k)\|} < \zeta, \tag{10}$$

where $\hat{\vartheta}(k)$ stands for the estimated parameter vector composed by $\hat{a}\,(k)$, $\hat{b}\,(k)$ and $\hat{\mu}\,(k)$, and ζ is a small positive real number close to zero, e.g., $\zeta = 0.01$. If the convergence criterion (10) is not satisfied, set $k = k+1$ and go to Step 2.

The structure parameters (n_a, n_b, n_k) of the linear subsystem and the discretization level L are determined by a grid search for the minimum of a Akaike's information criterion (AIC) [13],

$$\begin{aligned}&\mathrm{AIC}\,(n_a, n_b, n_k, L)\\ =\ & N\log\frac{1}{N}\sum_{t=1}^{N}\left(y\,(t) - \hat{y}_p\,(t)\right)^2 + 2\dim\left(\hat{\vartheta}(k)\right),\end{aligned}$$

where $\hat{y}_p\,(t)$ is the predicted output, $\hat{y}_p\,(t) = -\phi^T(t)\hat{a}\,(k) + \hat{b}^T\,(k)\,\Gamma(t)\hat{\mu}\,(k)$, and $\dim\left(\hat{\vartheta}(k)\right)$ stands for the dimension of the estimated parameter vector $\hat{\vartheta}(k)$.

4 Theoretical analysis

This section establishes the persistently exciting (PE) condition of input for identification of discretized Preisach model.

In order to obtain consistent estimates of the unknown parameters, it is necessary that the input $u(t)$ is PE so that the discretized Preisach model (8) is identifiable. Tan & Baras [14] have established the PE condition of $u(t)$ for identification of the discretized Preisach model (8). However, the established PE condition is not satisfied for the inputs being oscillatory with only two extreme values, which often are arisen from sticky control valves in feedback control loops. Hence, it is necessary to generalize the PE condition of $u(t)$ to the case that the input varies with only two extreme values.

First, the definition of PE condition is recalled [13].

Definition 1. A signal $u(t)$ is PE of order n if there is an integer $N > 0$ and two constants $c_1 > 0$ and $c_2 > 0$ such that for all t_0,

$$c_1 I \le \sum_{t=t_0}^{t_0+N-1} U(t)U^T(t) \le c_2 I$$

where $U(t) = [u(t-1), \cdots, u(t-n)]^T$ and I stands for the identity matrix.

Next, a PE equivalence class of signals defined in [14] is introduced as follows. Consider an input sequence $\{u(t)\}_{t=t_a}^{t_b}$ with $t_a < t_b$. If there exist t_1, t_2, t_3 and t_4 satisfying $t_a \le t_1 < t_2 \le t_3 < t_4 \le t_b$ such that $\gamma(t_1) = \gamma(t_3)$ and $\gamma(t_2) = \gamma(t_4)$ ($\gamma(t)$ is defined in (6)), another sequence $\{u'(t)\}_{t=t_a}^{t_b}$ can be obtained by swapping $\{u(t)\}_{t=t_1}^{t_2}$ with $\{u(t)\}_{t=t_3}^{t_4}$. That is, the new sequence $\{u'(t)\}_{t=t_a}^{t_b}$ is constructed by connecting the five data segments $\{u(t)\}_{t=t_a}^{t_1-1}$, $\{u(t)\}_{t=t_3}^{t_4}$, $\{u(t)\}_{t=t_2+1}^{t_3-1}$, $\{u(t)\}_{t=t_1}^{t_2}$ and $\{u(t)\}_{t=t_4+1}^{t_b}$ in order. The two sequences $\{u(t)\}_{t=t_a}^{t_b}$ and $\{u'(t)\}_{t=t_a}^{t_b}$ are said to be PE equivalent since the two sequences include the same information for the purpose of identification of the discretized Preisach model. All possible input sequences like $\{u'(t)\}_{t=t_a}^{t_b}$ obtained from $\{u(t)\}_{t=t_a}^{t_b}$ as explained above form a PE equivalence class denoted as $\{\underline{u(t)}\}_{t=t_a}^{t_b}$. For instance, Fig. 2 presents two inputs being PE equivalent.

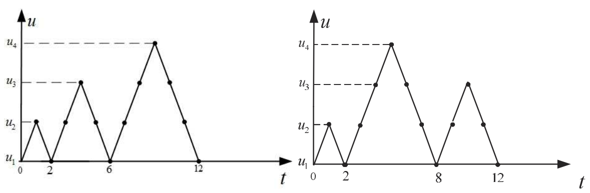

Fig. 2: Two inputs for $L = 3$ being PE equivalent

The PE condition established by Tan & Baras [14] is restated in the next Theorem.

Theorem 1 *The difference sequence of* $\gamma(t)$ *in (6),*

$$\gamma_d(t) \triangleq \gamma(t) - \gamma(t-1)$$

is PE, if there exists a positive integer N*, such that for any* t_0*, one can find a sequence* $\{u'(t)\}_{t=t_0}^{t_0+N-1}$ *belonging to its PE equivalence class* $\{\underline{u(t)}\}_{t=t_0}^{t_0+N-1}$ *satisfying the following* *conditions: There exist time indices $t_0 \le t_a \le t_1^- < t_1^+ < t_2^- < t_2^+ < \cdots < t_i^- < t_i^+ < \cdots \le t_b \le t_0 + N - 1$ or $t_0 \le t_a \le t_1^+ < t_1^- < t_2^+ < t_2^- < \cdots < t_i^+ < t_i^- < \cdots \le t_b \le t_0 + N - 1$, such that $u'(t_i^+)$ is a local maximum and $u'(t_i^-)$ is a local minimum of $\{u'(t)\}_{t=t_0}^{t_0+T-1}$ for each i, these local maxima and minima include all discretized input u_i, $i = 1, 2, \cdots, L+1$ in (2), and either of the following two cases holds:*

Case-I: $\{u'(t_i^+)\}$ is non-increasing, $u'(t_i^+) \ge u'(t)$ for $t_i^+ < t \le t_b$, $u'(t_i^+)$ differs from $u'(t_{i+1}^+)$ by no more than the discretization step size δ defined in (3); $\{u'(t_i^-)\}$ is non-decreasing, $u'(t_i^-) \le u'(t)$ for $t_i^- < t \le t_b$, $u'(t_i^-)$ differs from $u'(t_{i+1}^-)$ by no more than δ;

Case-II: $\{u'(t_i^+)\}$ is non-decreasing, $u'(t_i^+) \ge u'(t)$ for $t_i^+ > t \ge t_a$, $u'(t_i^+)$ differs from $u'(t_{i+1}^+)$ by no more than δ; $\{u'(t_i^-)\}$ is non-increasing, $u'(t_i^-) \le u'(t)$ for $t_i^- > t \ge t_a$, $u'(t_i^-)$ differs from $u'(t_{i+1}^-)$ by no more than δ.

Proof: See Theorem 3.2 in [14] for the proof. □

According to Theorem 1, if the discretization level L is greater than 2, then the oscillatory input $u(t)$ is not PE with sufficient order, so that the parameters of the discretized Preisach model are not identifiable. However, in this case that $u(t)$ is oscillatory with two extreme values, the discretized Preisach model has a single hysteresis loop in active. It is then necessary to establish a relaxed version of Theorem 1 for identification of the discretized Preisach model restricted to a single active hysteresis loop.

Theorem 2 *If the discretization level is L and the input $u(t)$, being oscillatory with only two extreme values u_{max} and u_{min}, varies no more than one discretization step size δ defined in (3) between two consecutive samples, then the single active hysteresis loop is identifiable in the form of the discretized Preisach model using $2L$ parameters.*

Proof: Let us extract some consecutive samples of $\{u(t)\}$ as a sequence $\{u(t)\}_{t=t_0}^{t_0+N-1}$ such that the sequence covers a full circle of the active hysteresis loop. Without loss of generality, $\{u(t)\}_{t=t_0}^{t_0+N-1}$ starts from $u(t_0) = u_{min}$ to $u(t_1) = u_{max}$ for some time instant $t_1 \in (t_0, t_0 + N - 1)$ and goes back to $u(t_0 + N - 1) = u_{min}$. In the time interval $t \in [t_0, t_1]$, the input $u(t)$ increases no more than one step size δ between consecutive samples. If $u(t-1) \le \frac{u_j + u_{j+1}}{2}$ and $u(t) > \frac{u_j + u_{j+1}}{2}$ with the discretized threshold u_j defined in (2), then only the relay operators associated with $\mu_{ij}, i = 1, \cdots, j$, give the outputs -1 at the time instant $(t-1)$, and $+1$ at the time instant t, and other relay operators keep their outputs same with the ones at the time instant $(t-1)$, so that a set of L parameters $\mu_{\beta j}$ for $j = 1, 2, \cdots, L$ can be uniquely determined as

$$\mu_{\beta j} \triangleq \sum_{i=1}^{j} \mu_{ij} = \frac{f(t) - f(t-1)}{2}.$$

Similarly, in the time interval $t \in [t_1, t_0 + N - 1]$, the input $u(t)$ decreases no more than one step size δ between consecutive samples. If $u(t-1) \ge \frac{u_i + u_{i+1}}{2}$ and $u(t) < \frac{u_i + u_{i+1}}{2}$, then another set of L parameters $\mu_{i\alpha}$ for $i = 1, 2, \cdots, L$ can be uniquely determined,

$$\mu_{i\alpha} \triangleq \sum_{j=i}^{L} \mu_{ij} = \frac{f(t) - f(t-1)}{2}.$$

Based on the above analysis, the single active hysteresis loop can be completely described by the $2L$ parameters $\mu_{i\alpha}$ and $\mu_{\beta j}$, and the oscillatory input $u(t)$ is sufficient to yield unique estimates of these $2L$ parameters. □

5 Examples

This section presents two industrial examples to illustrate the effectiveness of the proposed identification method for extended Hammerstein systems.

Example 1: An international database accompanied with the book [2] is available online[1] for academic research on the detection and diagnosis of oscillation and control valve stiction. An industrial feedback control loop labelled *cdata.chemicals.loop23* in the database is investigated here. The measurements of input $u(t)$ and output $y(t)$ are shown in Fig. 3, which clearly shows that the input $u(t)$ is oscillatory with two extreme values. The sampling period is 10 sec. As commented by the data provider (Dr. C. Scali), the control valve is (likely) with stiction, while the actual valve position is not available.

Based on the collected data $\{u(t), y(t)\}_{t=1}^{N=1500}$, the proposed iterative method is applied to obtain the estimation of an extended Hammerstein system. The results of structure parameters are $\hat{n}_a = 1$, $\hat{n}_b = 1$, $\hat{n}_k = 0$ and $\hat{L} = 14$. The estimated input nonlinearity $f(\cdot)$ and the step response of estimated linear subsystem are shown in Fig. 4, where the estimated input nonlinearity reveals that the control valve does have the stiction problem. The estimated model quality is quantitatively measured by the fitness between the simulated output $\hat{y}_s(t)$ and measured output $y(t)$,

$$\text{Fitness} = 100\left(1 - \frac{\|\hat{y}_s(t) - y(t)\|}{\|y(t) - E\{y(t)\}\|}\right),$$

where $\|\cdot\|$ is the Euclidean norm, and the simulated output $\hat{y}_s(t)$ is obtained as

$$\hat{y}_s(t) = \frac{\sum_{j=1}^{n_b} \hat{b}_j q^{-j-n_k}}{1 + \sum_{i=1}^{n_a} \hat{a}_i q^{-i}} \gamma^T(t)\hat{\mu}.$$

The fitness between $\hat{y}_s(t)$ and $y(t)$ shown in Fig. 5 is 75.7605%, and $\hat{y}_s(t)$ can well capture the main dynamic variations of $y(t)$. The obtained results are in line with Theorem 2 that the oscillatory input $u(t)$ in Fig. 3 is informative enough to estimate the single active hysteresis loop. Note that this medium fitness value 75.7605% is due to the presence of significant high-frequency noise components in $y(t)$, because the high-frequency variations are absent in $u(t)$. The same example was presented at [8], where the estimated input nonlinearity is similar to that in Fig. 4, and the fitness between the measured and simulated outputs is 73.6054%.

Example 2: Another industrial control loop labelled *cdata.chemicals.loop19* in the international database introduced

[1] http://www.ualberta.ca/∼bhuang/book2.htm

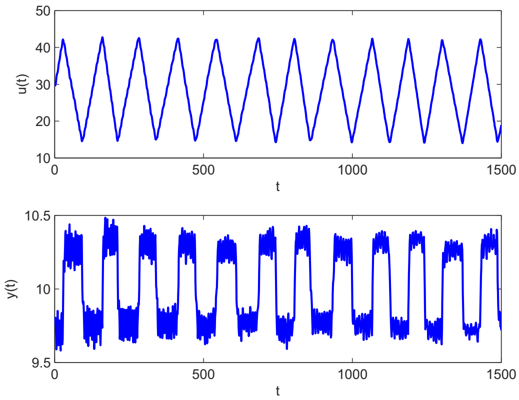

Fig. 3: The input $u(t)$ and output $y(t)$ of an industrial feedback control loop for Example 1

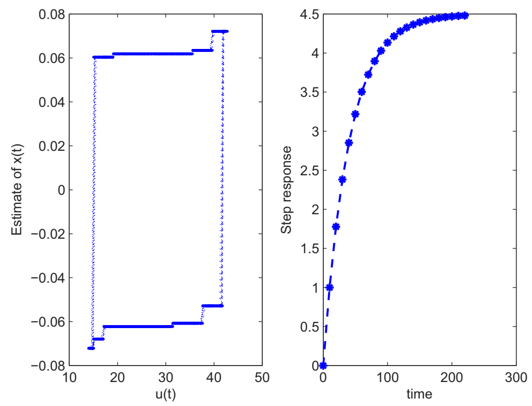

Fig. 4: The estimated input nonlinearity (left) and the step response of estimated linear subsystem (right) for Example 1

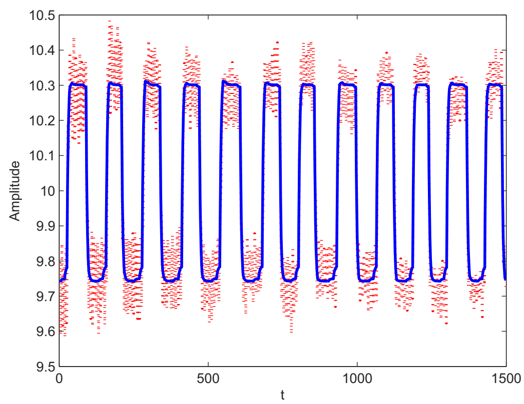

Fig. 5: The measured output $y(t)$ (dash) and simulated output $\hat{y}_s(t)$ (solid) of the extended Hammerstein system for Example 1

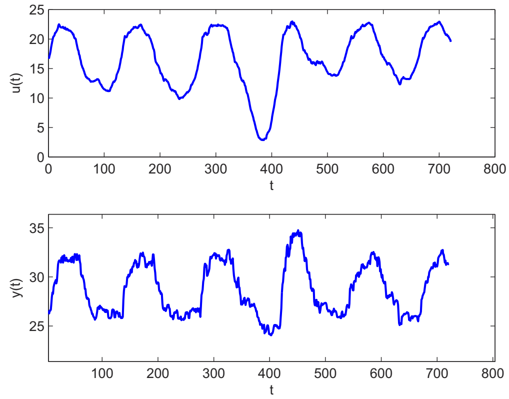

Fig. 6: The input $u(t)$ and output $y(t)$ of an industrial control loop for Example 2

in Example 1 is considered. The measurements of input $u(t)$ and output $y(t)$ are shown in Fig. 6. The sampling period is 12 sec. Similar to Example 1, the actual valve position is not available and the data provider (Dr. C. Scali) commented that the control valve is (likely) with stiction.

Based on the collected data $\{u(t), y(t)\}_{t=1}^{N=721}$, the proposed iterative method is applied to build an extended Hammerstein model. The structure parameters are determined as $\hat{n}_a = 1$, $\hat{n}_b = 1$, $\hat{n}_k = 0$ and $\hat{L} = 26$. The estimated input nonlinearity $f(\cdot)$ and the step response of estimated linear subsystem are shown in Fig. 7. The measured output $y(t)$ and the simulated output $\hat{y}_s(t)$ are shown in Fig. 8 with the fitness 74.410%. The estimated input nonlinearity demonstrates several hysteresis loops, and the simulated output can well capture the main dynamic variation of $y(t)$. Note that the peak of $y(t)$ around $t = 450$ is due to an external disturbance additive to $y(t)$, since the input $u(t)$ around $t = 450$ does not have a related variation.

The input $u(t)$ in Fig. 6 is more general than that in Fig. 4, and varies among several local maximum and minimum values. As a result, the required assumptions in [8] are no longer valid so that the extended Hammerstein model proposed in [8] would introduce some modeling errors if it is applied to the collected data $\{u(t), y(t)\}_{t=1}^{N=721}$ in Fig. 6. This is confirmed by the results shown in Fig. 9, where the input nonlinearity is incorrectly concluded to be absent and the step response of the estimated linear subsystem has some erroneous overshooting behavior. The simulated output has some large discrepancies with the measured output as shown in Fig. 10; the corresponding fitness is 64.7295%. Therefore, the proposed extended Hammerstein system in this paper is more effective in the case that the input $u(t)$ is in the general shape.

6 Conclusions

In this paper, the discretized Preisach model was introduced as the input nonlinearity to formulate an extended Hammerstein system. The discretized Preisach model is flexible; in particular, it is suitable to describe the complex characters of sticky control valves. The iterative method was proposed to estimate the model parameters. The oscillatory input with only two extreme values was shown to be PE in Theorem 2. Two industrial examples supported the valid-

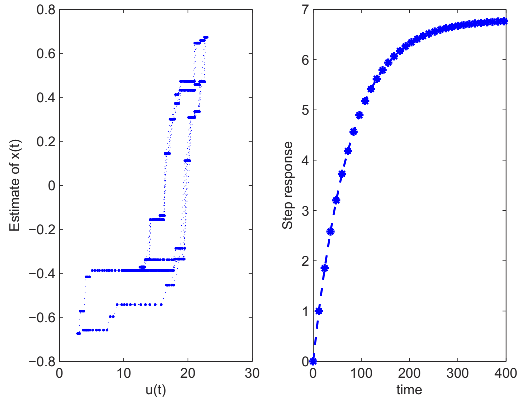

Fig. 7: The estimated input nonlinearity (left) and the step response of estimated linear subsystem (right) for Example 2

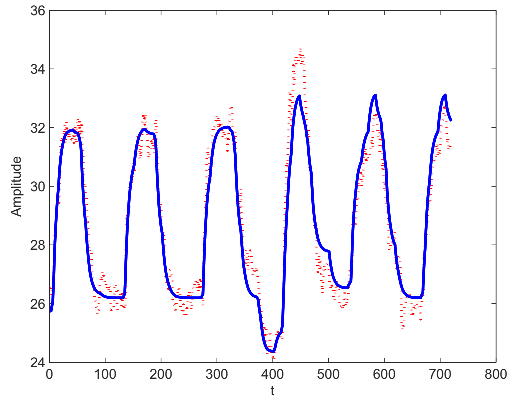

Fig. 8: The measured output (dash) and simulated output (solid) of the extended Hammerstein system for Example 2

ness of the proposed extended Hammerstein system with the discretied Preisach model as the input nonlinearity and illustrated the effectiveness of the proposed iterative method.

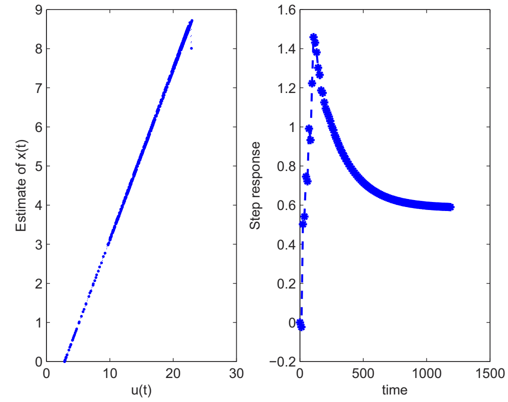

Fig. 9: The estimated input nonlinearity (left) and the step response of estimated linear subsystem (right) using the model in [8] for Example 2

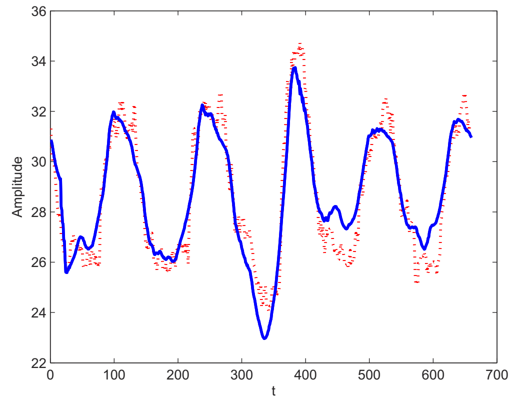

Fig. 10: The measured output (dash) and simulated output (solid) of the extended Hammerstein system using the model in [8] for Example 2

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