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IDENTIFICATION OF NONLINEAR CASCADE SYSTEMS WITH NONINVERTIBLE PIECEWISE LINEAR INPUT AND BACKLASH OUTPUT NONLINEARITIES

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The paper deals with the parameter identification of cascade nonlinear dynamic systems with noninvertible piecewise linear input nonlinearities and backlash output nonlinearities. Application of the key term separation principle provides special expressions for the corresponding nonlinear model description that are linear in parameters. A least squares based iterative technique allows estimation of all the model parameters based on measured input/output data. Simulation studies illustrate the feasibility of proposed identification method.

K e y w o r d s: nonlinear systems, parameter estimation, least-squares, piecewise linear function, backlash

1 INTRODUCTION

Modeling and identification of nonlinear dynamic systems with both input and output nonlinearities is of great importance for control purposes. However, the choice of suitable mathematical models and estimation techniques for identified systems may be quite difficult in the case of special static nonlinearities (*eg* noninvertible) and dynamic nonlinearities (*eg* backlash or hysteresis). Three-block cascade models may be a good choice for appropriate description of the input (actuator) characteristics, system dynamics and output (sensor) characteristics of identified nonlinear dynamic systems.

Cascade models are a popular type of block-oriented models and the simplest types of cascade nonlinear models consist of two blocks. The so-called Hammerstein model consists of a static nonlinear block followed by a linear dynamic block and is supposed to represent actuator nonlinearities. The identification of nonlinear dynamic systems using the Hammerstein model with different types of input nonlinearities has been an active research area for many years and some recent works dealing with the Hammerstein models can be found *eg* in [1–7].

The so-called Wiener model consists of a linear dynamic block followed by a static nonlinear block and generally represents sensor nonlinearities. This type of two-block models was also studied and applied with different types of nonlinearities and estimation techniques, see *eg* [8–14].

If the systems to be identified contain nonlinearities with memory such as backlash or hysteresis [15], the choice of Hammerstein or Wiener models is not possible, because the nonlinear static block cannot characterize dynamic nonlinearities. Therefore, a special case of two-block models consisting of the cascade of linear dynamic and nonlinear dynamic blocks has to be used. For example, the cascade model structure consisting of a linear dynamic block followed by a nonlinear dynamic block was often used for the identification of nonlinear dynamic systems with output backlash [16–18].

However, in some cases of more complex nonlinear dynamic systems with input nonlinearities, the two-block cascade model may be not precise enough and it is appropriate to choose a three-block cascade model with combination of nonlinear static, linear dynamic, and nonlinear dynamic blocks [19]. It means, compared to the well-known structure of Hammerstein-Wiener model, see *eg* [20–23], that the input block contains static nonlinearities while the output block is describing assumed dynamic nonlinearities, *eg*, backlash or hysteresis. The three-block cascade models compared to the Hammerstein or Wiener models significantly extends the applicability of block-oriented models for identification of nonlinear dynamic systems with both actuator and sensor nonlinearities.

In this paper, the three-block cascade model is used to the parameter identification of nonlinear dynamic systems with a backlash output nonlinearity and a piecewise linear input nonlinearity. This extends the results from [19] and enables the identification of systems including noninvertible input characteristics. The previous results on the decomposition of compound operators using the so-called key term separation principle are applied with the aim to simplify the mathematical description of this complex system. The resulting input/output equation is without cross-multiplication of parameters; nevertheless, it contains more internal variables, which are generally unmeasurable. Application of a least squares based iterative algorithm enables estimation of internal variables and all the model parameters on the basis of measured

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Fig. 1. Three-block cascade system with output backlash

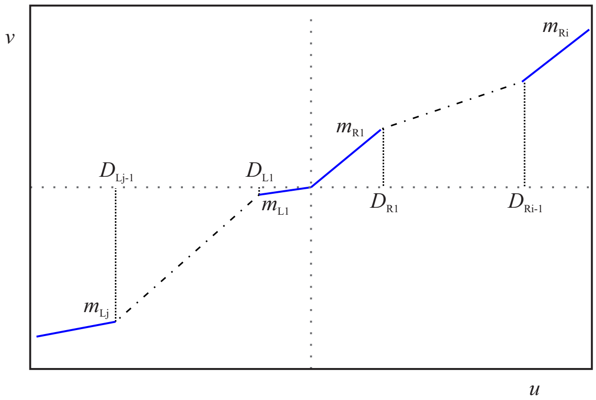

Fig. 2. Multi-segment piecewise linear function

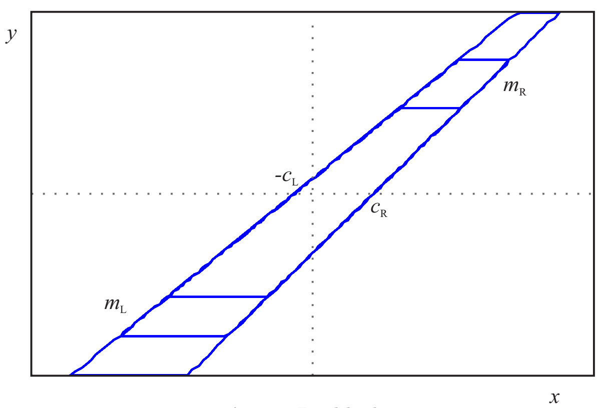

Fig. 3. Backlash

input/output data. Simulation studies of nonlinear dynamic systems identification with noninvertible piecewise linear inputs and output backlash characteristics are included and illustrate the feasibility of proposed identification method.

2 THREE–BLOCK CASCADE MODEL

Let a three-block cascade model be given by the cascade connection of a nonlinear static block followed by a linear dynamic block, which is followed by a nonlinear dynamic block according to Fig. 1. In the case of noninvertible nonlinear static characteristics, it is appropriate to choose piecewise linear characteristics for the description of nonlinear static blocks.

Let us assume the nonlinear static block NS with inputs $u(t)$ and outputs $v(t)$ can be described by the following general multisegment piecewise linear function (Fig. 2) given in a compact form as follows [24]

$$v(t)=\sum_{i=1}^{n_R}[u(t)-D_{R,i-1}]f_{1,i}(t)+\sum_{j=1}^{n_L}[u(t)-D_{L,j-1}]f_{2,j}(t) \tag{1}$$

where

$$\begin{aligned} f_{1,i}(t) &= (m_{R,i}-m_{R,i-1})h[D_{R,i-1}-u(t)] \\ &= M_{R,i}h[D_{R,i-1}-u(t)] \end{aligned} \tag{2}$$

$$\begin{aligned} f_{2,j}(t) &= (m_{L,j}-m_{L,j-1})h[u(t)-D_{L,j-1}] \\ &= M_{L,j}h[u(t)-D_{L,j-1}] \end{aligned} \tag{3}$$

and $h(\cdot)$ is a switching function defined as

$$h(s)=\begin{cases} 0 & \text{if } s\geq 0\,, \\ 1 & \text{if } s<0\,. \end{cases} \tag{4}$$

In this description, $|m_{R,i}|<\infty$, $|m_{L,j}|<\infty$ are the segment slopes, $0\leq D_{R,i}<D_{R,i+1}<\infty$ are the constants representing the partition of domain for the positive inputs, while $-\infty<D_{L,j+1}<D_{L,j}\leq 0$ are the constants representing the partition of domain for the negative inputs. It is assumed that $m_{R,0}=D_{R,0}=m_{L,0}=D_{L,0}=0$.

As the direct substitutions of (2) and (3) into (1) would lead to cross-multiplications of parameters, the key term separation principle will be applied to separate the parameters. After multiple half-substitutions of (2) for $f_{1,i}(t)$, *ie* only in the chosen key terms $f_{1,i}(t)u(t)$ and (3) for $f_{2,j}(t)$, *ie* only in the chosen key terms $f_{2,j}(t)u(t)$ in (1), the output equation for the general multisegment piecewise linear characteristics can be written as

$$\begin{aligned} v(t) &= \sum_{i=1}^{n_R}\left\{M_{R,i}h[D_{R,i-1}-u(t)]u(t)-D_{R,i-1}f_{1,i}(t)\right\} \\ &+\sum_{j=1}^{n_L}\left\{M_{L,j}h[u(t)-D_{L,j-1}]u(t)-D_{L,j-1}f_{2,j}(t)\right\} \end{aligned} \tag{5}$$

where all the parameters are separated.

The linear dynamic block LD of the three-block cascade model can be described by the following difference equation

$$x(t)=A(q^{-1})v(t)-B(q^{-1})x(t) \tag{6}$$

where $v(t)$ and $x(t)$ are the inputs and outputs, respectively, $A(q^{-1})$ and $B(q^{-1})$ are scalar polynomials in the unit delay operator q^{-1} (ie $q^{-1}x(t)=x(t-1)$)

$$A(q^{-1})=a_1q^{-1}+\cdots+a_rq^{-r}\,, \tag{7}$$

$$B(q^{-1})=b_1q^{-1}+\cdots+b_pq^{-p}\,. \tag{8}$$

Let the nonlinear dynamic block ND be a backlash shown in Fig. 3 with inputs $x(t)$ and outputs $y(t)$. The backlash can be described by the following first order nonlinear difference equation [18]

$$\begin{aligned} y(t) &= m_L[x(t)+c_L]g_1(t)+m_R[x(t)-c_R]g_2(t) \\ &\quad +y(t-1)[1-g_1(t)][1-g_2(t)] \end{aligned} \tag{9}$$

where $g_1(t)$ and $g_2(t)$ are internal variables defined as

$$g_1(t) = h\big\{[m_L x(t) + m_L c_L - y(t-1)]/m_L\big\}, \quad (10)$$

$$g_2(t) = h\big\{[y(t-1) - m_R x(t) + m_R c_R]/m_R\big\} \quad (11)$$

and $h(\cdot)$ is the switching function defined by (4).

The input-output equation of the three-block cascade model resulting from direct substitutions of the corresponding variables from (5) into (6) and then into (9) would be a very complex equation that is strongly nonlinear both in the variables and in the parameters, hence not very suitable for the parameter estimation. We will again apply the key-term separation principle to find a simpler form of this description. Note that the parameterization of the cascade connection of three blocks is not unique, as many combinations of parameters can be found. Therefore, in at least two blocks, one parameter has to be fixed. Choosing $m_L = 1$, we rewrite (9) as

$$y(t) = x(t)g_1(t) + c_L g_1(t) + m_R x(t) g_2(t) - m_R c_R g_2(t) + y(t-1)[1 - g_1(t)][1 - g_2(t)] \quad (12)$$

and we half-substitute $x(t)$ from (6) into (12), *ie* only for $x(t)$ in the first term on the right-hand side of (12) obtaining

$$y(t) = \sum_{i=1}^{r} a_i v(t-i) g_1(t) - \sum_{j=1}^{p} b_j x(t-j) g_1(t) + c_L g_1(t) + m_R x(t) g_2(t) - c g_2(t) + y(t-1)[1 - g_1(t)][1 - g_2(t)] \quad (13)$$

where

$$C = c_R m_R \,. \quad (14)$$

Then we can choose $a_1 = 1$, and half-substitute (5) into (13), *ie* only for the term with variable $v(t-1)$. This will lead to the three-block cascade model output equation

$$\begin{aligned} y(t) = \sum_{i=1}^{n_R} \big\{ & M_{R,i} h[D_{R,i-1} - u(t-1)] u(t-1) - D_{R,i-1} f_{1,i}(t-1) \big\} g_1(t) + \sum_{j=1}^{n_L} \big\{ M_{L,j} h[u(t-1) - D_{L,j-1}] u(t) - D_{L,j-1} f_{2,j}(t-1) \big\} g_1(t) \\ & + \sum_{i=2}^{r} a_i v(t-i) g_1(t) - \sum_{j=1}^{p} b_j x(t-j) g_1(t) + c_L g_1(t) + m_R x(t) g_2(t) - c g_2(t) + y(t-1)[1 - g_1(t)][1 - g_2(t)] + e(t) \quad (15) \end{aligned}$$

where $e(t)$ is a zero mean random disturbance (white noise) uncorrelated with $u(t)$ and assumed to be acting on the system output. It is also assumed that $u(t) = 0$ and $y(t) = 0$ for $t \le 0$. This equation is linear in all the model parameters, but nonlinear in some variables. The model inputs $u(t)$ and outputs $y(t)$ are available, while the internal variables $f_{1,i}(t)$, $i = 1, \dots, n_R$, $f_{2,j}(t)$, $j = 1, \dots, n_L$, $v(t)$, $x(t)$, $g_1(t)$ and $g_2(t)$ are not.

3 PARAMETER ESTIMATION

The above derived cascade model equation can be written in the following concise form

$$y_c(t) = y(t) - y(t-1)[1 - g_1(t)][1 - g_2(t)] = \varphi(t)\theta + e(t) \quad (16)$$

where

$$\begin{aligned} \varphi(t) = & \big[h[-u(t-1)]u(t-1)g_1(t), h[D_{R,1} - u(t-1)]u(t-1)g_1(t), \\ & \dots, h[D_{R,nR-1} - u(t-1)]u(t-1)g_1(t), -f_{1,2}(t-1)g_1(t), \\ & \dots, -f_{1,nR}(t-1)g_1(t), h[u(t-1)]u(t-1)g_1(t), \\ & h[u(t-1) - D_{L,1}]u(t-1)g_1(t), \dots, \\ & h[u(t-1) - D_{L,nL-1}]u(t-1)g_1(t), -f_{2,2}(t-1)g_1(t), \dots, \\ & - f_{2,nL}(t-1)g_1(t), v(t-2)g_1(t), \dots, v(t-r)g_1(t), \\ & -x(t-1)g_1(t), \dots, -x(t-p)g_1(t), g_1(t), x(t)g_2(t), -g_2(t) \big] \quad (17) \end{aligned}$$

is the vector of data,

$$\begin{aligned} \theta = \big[& M_{R,1}, \dots, M_{R,nR}, D_{R,1}, \dots, D_{R,nR-1}, M_{L,1}, \dots, \\ & M_{L,nL}, D_{L,1}, \dots, D_{L,nL-1}, \\ & a_2, \dots, a_r, b_1, \dots, b_p, c_L, m_R, c \big]^\top \quad (18) \end{aligned}$$

is the vector of parameters and $y_c(t)$ is the so-called corrected output.

As the variables $f_{1,i}(t)$, $i = 1, \dots, n_R$, $f_{2,j}(t)$, $j = 1, \dots, n_L$, $v(t)$, $x(t)$, $g_1(t)$ and $g_2(t)$ are not available and must be estimated, an iterative parameter estimation process has to be considered. The techniques presented in [18–20], which are based on the use of the preceding estimates of model parameters for the estimation of internal variables and vice-versa, can be easily extended to this three-block model. We replace the internal variables in (16) by their estimates defined as

$$^s f_{1,i}(t) = {^s M_{R,i}} h\big[{^s D_{R,i-1}} - u(t)\big], \quad (19)$$

$$^s f_{2,j}(t) = {^s M_{L,j}} h\big[u(t) - {^s D_{L,j-1}}\big], \quad (20)$$

$$\begin{aligned} ^s v(t) = & \sum_{i=1}^{n_R} \big\{ {^s M_{R,i}} h[{^s D_{R,i-1}} - u(t)] u(t) - {^s D_{R,i-1}} f_{1,i}(t) \big\} \\ & + \sum_{j=1}^{n_L} \big\{ {^s M_{L,j}} h[u(t) - {^s D_{L,j-1}}] u(t) - {^s D_{L,j-1}} f_{2,j}(t) \big\}, \quad (21) \end{aligned}$$

$$^s x(t) = {^s v}(t-1) + \sum_{i=2}^{r} {^s a_i} {^s v}(t-i) - \sum_{j=1}^{p} {^s b_j} {^s x}(t-j)\,, \quad (22)$$

$$^s g_1(t) = h\big({^s x}(t) + {^s c_L} - y(t-1)\big), \quad (23)$$

$$^s g_2(t) = h\big((y(t-1) - {^s m_R} {^s x}(t) + {^s m_R} {^s c_R}) / {^s m_R}\big), \quad (24)$$

$$^s y_c(t) = y(t) - y(t-1)\big(1 - {^s g_1}(t)\big)\big(1 - {^s g_2}(t)\big) \quad (25)$$

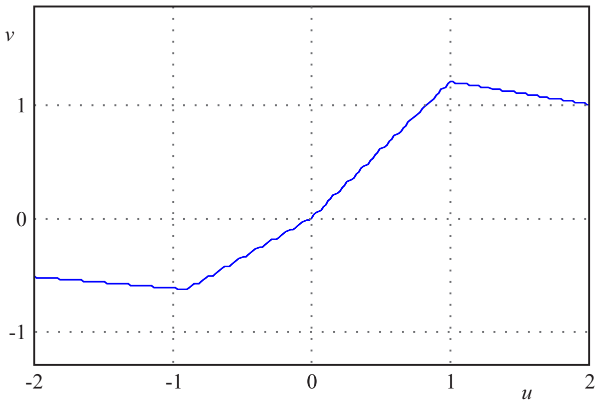

Fig. 4. Example 1 — noninvertible piecewise linear function

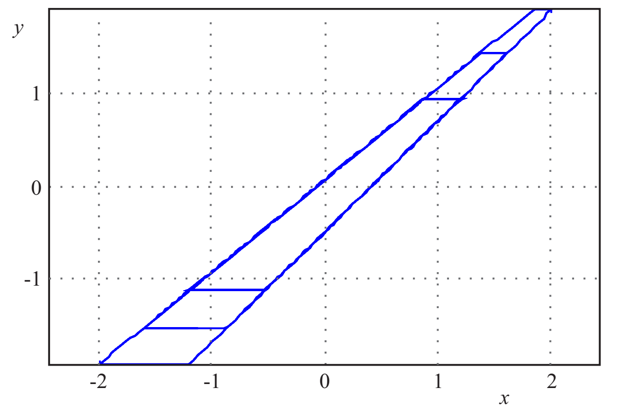

Fig. 5. Example 1 — output backlash

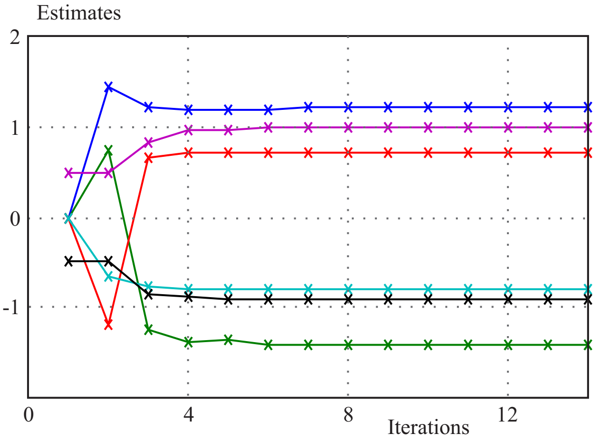

Fig. 6. Example 1 — the process of parameter estimation for the nonlinear static block

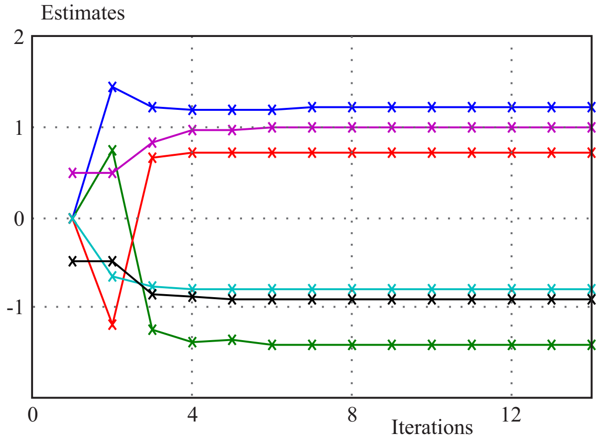

Fig. 7. Example 1 — the process of parameter estimation for the linear dynamic block

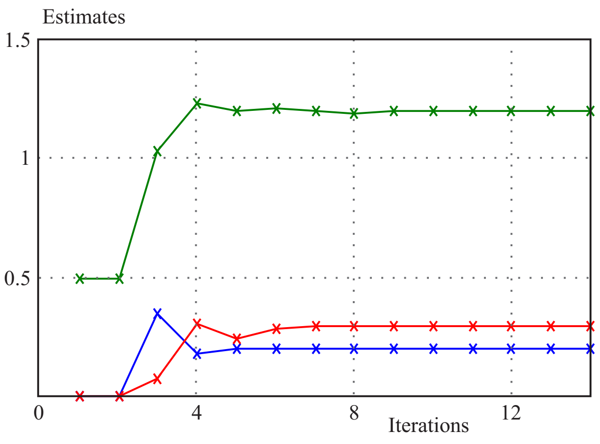

Fig. 8. Example 1 — the process of parameter estimation for the backlash

using the s-th estimates of corresponding parameters and variables. Assigning the s-th estimate of parameter vector as

$$
{}^s\theta = \left[{}^sM_{R,1}, \dots, {}^sM_{R,nR}, {}^sD_{R,1}, \dots, {}^sD_{R,nR-1}, {}^sM_{L,1}, \dots, {}^sM_{L,nL}, {}^sD_{L,1}, \dots, {}^sD_{L,nL-1}, {}^sa_2, \dots, {}^sa_r, {}^sb_1, \dots, {}^sb_p, {}^sc_L, {}^sm_R, {}^sc\right]^\top . \quad (26)
$$

The error to be minimized for the estimation procedure in the $(s+1)$-st iteration is

$$
{}^{s+1}\varepsilon(t) = {}^sy_c(t) - {}^s\varphi(t)^{s+1}\theta \,. \quad (27)
$$

If the mean squares error criterion is used, the following functional will be minimized with respect to the parameter vector

$$
{}^{s+1}J = \frac{1}{N}\sum_{t=1}^{N} {}^{s+1}\varepsilon^2(t) \quad (28)
$$

where N is the number of input/output samples. Then the iterative algorithm consists of the following steps:

a) The s-th estimates of internal variables, *ie*, ${}^sf_{1,i}(t)$, $i = 1, \dots, n_R$, ${}^sf_{2,j}(t)$, $j = 1, \dots, n_L$, ${}^sv(t)$, ${}^sx(t)$, ${}^sg_1(t)$, ${}^sg_2(t)$ and the corrected output ${}^sy_c(t)$ are computed using (19)–(25) with the recent estimates of corresponding parameters and the estimates of ${}^s\varphi(t)$ are evaluated.

b) Minimizing ${}^{s+1}J$ the estimates of parameters ${}^{s+1}\theta$ are computed using ${}^s\varphi(t)$ and ${}^sy_c(t)$ with the s-th estimates of internal variables.

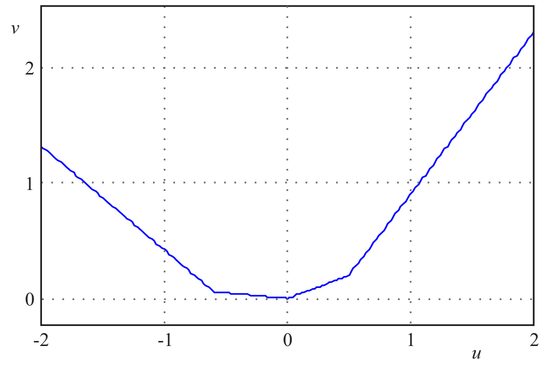

Fig. 9. Example 2 — noninvertible piecewise linear function

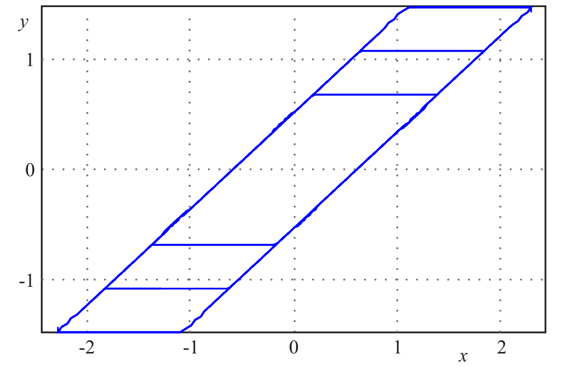

Fig. 10. Example 2 — output backlash

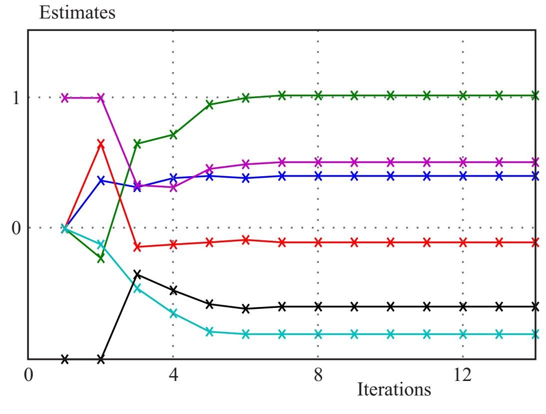

Fig. 11. Example 2 — the process of parameter estimation for the nonlinear static block

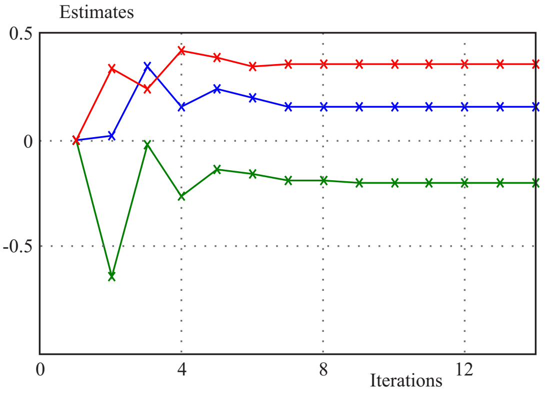

Fig. 12. Example 2 — the process of parameter estimation for the linear dynamic block

c) If the estimation criterion is met, *ie* the error is less than a predetermined value, the procedure ends, else it continues by repeating steps a) and b).

In the first iteration, only the parameters of nonlinear static block and the linear dynamic block are estimated where $v(t-i)$ is approximated by $u(t-i)$ and $x(t-j)$ is approximated by $y(t-j)$. Nonzero initial values of the parameters $D_{R,i}$ and $D_{L,j}$ have to be considered for evaluation of $f_{1,i}(t)$ and $f_{2,j}(t)$, while the initial values of the parameter estimates for other parameters in the nonlinear static and the linear dynamic blocks can be chosen zero. Then, nonzero initial values of the backlash parameters m_R, c_L and c_R have to be considered for evaluation of $g_1(t)$, $g_2(t)$ and $y_c(t)$.

4 SIMULATION STUDIES

The following examples of identification of simulated nonlinear dynamic systems with noninvertible piecewise linear input nonlinearity and output backlash illustrate the feasibility of proposed method.

Example 1. The noninvertible input static nonlinearity of the cascade system was described by the piecewise linear characteristic (Fig. 4) given by $M_{R,1} = 1.2$, $M_{R,2} = -1.4$, $M_{L,1} = 0.7$, $M_{L,2} = -0.8$, $D_{R,1} = 1.0$ and $D_{L,1} = -0.9$. The linear dynamic block was given by the difference equation

$$x(t) = v(t-1) + 0.15v(t-2) + 0.2x(t-1) - 0.35x(t-2)$$

and was followed by the output backlash (Fig. 5) characterized by the parameters $m_L = 1.0$, $m_R = 1.2$, $c_L = 0.2$, $c_R = 0.3$. The identification was performed on the basis of 4000 samples of uniformly distributed random inputs with $|u(t)| < 2.0$ and simulated outputs. Normally distributed random noise $e(t)$ with zero mean and signal-to-noise ratio $SNR = 25$ (the square root of the ratio of output and noise variances) was added to the outputs.

The iterative estimation algorithm was applied with the initial values $D_{R,1} = 1.0$, $D_{L,1} = -1.0$ for the first estimates of $f_{1,1}(t)$ and $f_{2,1}(t)$, and $m_R = 0.5$ and $c_L = c_R = 0.001$ for the first estimates of $g_1(t)$ and $g_2(t)$. The process of parameter estimation is shown in Fig. 6 for the nonlinear static block (the top-down order of parameters is: $M_{R,1}$, $D_{R,1}$, $M_{L,1}$, $M_{L,2}$, $D_{L,1}$, $M_{R,2}$), in Fig. 7 for the linear dynamic block (the top-down order of parameters is: b_2, a_1, b_1) and in Fig. 8 for the backlash (the top-down order of parameters is: m_R, c_R, c_L). The estimates meet the values of real parameters after about 6 iterations.

Example 2. The convex noninvertible input static nonlinearity of the three-block cascade system was described

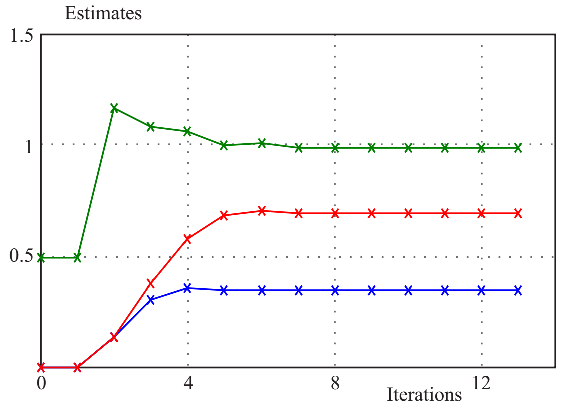

Fig. 13. Example 2 — the process of parameter estimation for the backlash

by the piecewise linear characteristic (Fig. 9) given by $M_{R,1} = 0.4$, $M_{R,2} = 1.0$, $M_{L,1} = -0.1$, $M_{L,2} = -0.8$, $D_{R,1} = 0.5$ and $D_{L,1} = -0.6$. The linear dynamic block was given by the difference equation

$$x(t) = v(t-1) + 0.15v(t-2) + 0.2x(t-1) - 0.35x(t-2)$$

and was followed by the output backlash (Fig. 10) characterized by the parameters $m_L = 1.0$, $m_R = 1.0$, $c_L = 0.35$, $c_R = 0.7$. The identification was performed on the basis of 2000 samples of uniformly distributed random inputs with $|u(t)| < 2.0$ and simulated outputs and under the same conditions as in Example 1. The process of parameter estimation is shown in Fig. 11 for the nonlinear static block (the top-down order of parameters is: $M_{R,2}$, $D_{R,1}$, $M_{R,1}$, $M_{L,1}$, $D_{L,1}$, $M_{L,2}$), in Fig. 12 for the linear dynamic block (the top-down order of parameters is: b_2, a_1, b_1) and in Fig. 13 for the backlash (the top-down order of parameters is: m_R, c_R, c_L). The estimates meet the values of real parameters after about 6 iterations.

5 CONCLUSION

The proposed approach to the modeling and identification of nonlinear dynamic systems with noninvertible piecewise linear inputs and output backlash is based on the three-block cascade model with static input and dynamic output blocks. To simplify the cascade model description the key term separation principle was applied to the original compound operator. The resulting mathematical model consists of the least possible number of parameters and is linear in all these parameters. For this model, an iterative least squares based parameter estimation algorithm with internal variables estimations was proposed. The feasibility of identification method is illustrated on representative examples of simulated nonlinear dynamic systems with different noninvertible piecewise linear input nonlinearities and output backlash.

The presented identification method is appropriate for systems with both actuator and sensor nonlinearities and can be easily extended for systems with the so-called general output backlash [25, 26]. Moreover, the proposed three-block cascade model can be applied for on-line identification of this type of nonlinear dynamic systems using the known recursive least-squares algorithm [27, 28].

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