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Identification of Complex Systems with the use of Interconnected Hammerstein Models

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Abstract

In the paper we consider the problem of identification of large-scale interconnected systems. Accurate models of complex nets are needed especially for optimal control in production and transportation systems. The specifics lay in the fact that individual elements cannot be disconnected and excited by arbitrary input processes for identification purposes. Moreover, structural interactions cause correlations between interaction signals. In particular, any output random disturbances can be transferred into the other inputs. It leads to cross-correlation problems, very difficult from the effective modelling point of view. First attempts made in 1980's were limited to static linear blocks, and in practice the results were rather devoted to linear dynamic systems working in steady state. In this paper we generalize the approach for components, which are both dynamic and nonlinear. All blocks are represented by two-channel Hammerstein systems (used e.g. in modelling of real heating processes). The least squares estimate is applied to identify unknown parameters of a system. The parameters of particular elements are obtained in singular value decomposition procedure. The algorithm as a whole is illustrated in simple simulation example.

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Keywords: Hammerstein system, Wiener system, system identification, least squares, instrumental variables

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1. Introduction

1.1. Identification of complex systems

The purpose of system identification is to build the model, which describes relation between the input and output processes, using the prior knowledge of the system characteristics (e.g. laws of physics) and the measurement data. Adequate models allow for system simulation, design of optimal decision and control, fault detection and forecasting of system behavior. It is often of crucial meaning from the economical point of view. Correct decisions made in the system input allow to save time, energy and money. As regards the state of the art in system identification framework, we have a lot of identification methods elaborated over the last decades (Söderström and Stoica, 1989). Starting from the traditional least squares and correlation based estimates applied to linear dynamic system identification, the ideas were generalized towards the least possible a priori restrictions imposed on the system characteristics. In particular, the nonlinear models represented by Volterra series expansions were first considered. Owing to high computational complexity they were displaced with the conception block- oriented models i.e. Hammerstein systems and Wiener systems, including serial connections of static nonlinear and linear dynamic blocks (Mzyk, 2014b and Giri and Bai, 2010). Nevertheless, the identified plants were usually considered separately, in the sense that the input process could be freely generated and the object could work independently of the other ones. In practice, the object input process depends on the outputs of the other cooperating elements. It leads to serious limitations making the identification problem more difficult. In particular, the input process as the output of other dynamics can by correlated and application of traditional procedures can be excluded. This aspect is very important and often met in production and transportation systems. It was shown in Hasiewicz (1987 and 1989), that even for the static linear blocks, identifiability of individual element in complex system depends on both the interconnection structure and the values of parameters of complementary blocks. Moreover, the random disturbances present on outputs can be transferred to the inputs by the structural feedback. In consequence, standard theory cannot be directly applied for complex system identification. The control of complex system problem was raised and analyzed in 1980s by the team of prof. W. Findeisen (1980). The whole system was splitted into smaller subproblems (Fig. 1), and the control quality indexes were optimized separately (and in parallel) under the supervising coordination layer. Similar strategy is proposed in this paper. Thanks to the knowledge of the system structure, the inputs are evaluated for individual blocks and next, the least squares are applied for its identification.

The paper is focused on the system including two (or more) mutually dependent nonlinear dynamic objects. Both the object and the dependencies are represented with the use of Hammerstein model. The proposed algorithm makes generalization of the methods proposed in Mzyk (2012, 2014a) towards nonlinear dynamic blocks. Hammerstein branches are identified by the concept presented in Bai (1998) and Mzyk (2013, 2015). The main contribution of the paper is application of least squares method for complex nonlinear dynamic systems.

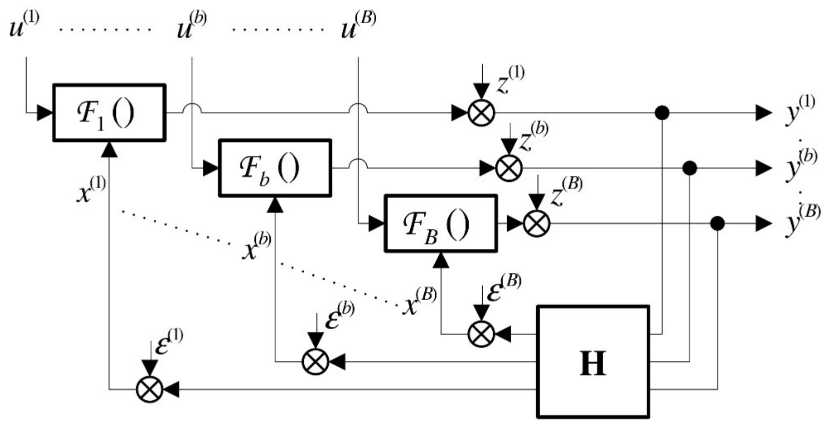


Fig. 1. Complex system.

1.2. Block-oriented models – approaches of identification and applications

Block-oriented models have been considered and used in many applications since early 1980's. They consist of the combination of interconnected static nonlinear and linear dynamic blocks. In many cases linear representation of real process is not sufficient. The model of the process can be displaced then by cascades: Hammerstein or/and Wiener structures (or more complex combinations of them). Two kinds of philosophies are proposed and widely considered in identification procedures of the models. Firstly, in the parametric approach, characteristics of the particular blocks are assumed or priori known. They are described with the use of finite numbers of unknown parameters. The purpose of identification is then recover of them by e.g. least squares and instrumental variables methods. Recently, the nonparametric (e.g. kernel regression, orthogonal expansion) are focused on nonparametric representation of both static characteristic and the finite impulse response of linear block, under poor prior knowledge about the examined process. The newest strategies use combined parametric-nonparametric methods, in which data with the use of nonparametric techniques are filtered what supports model selection (i.e. number of parameters describing the system) and decomposing the complex system identification into smaller subproblems.

Models with block structures are widely applied to different branches of engineering and science, e.g.: automation, robotics, telecommunication, electronics, signal processing, chemistry, physics and other. There are many known uses of them, i.e. modelling of pH neutralization (Hermansson and Syaffie, 2015) and pasteurization (Ibarrola *et al.*, 2002). One of the latest applications is modelling of heating process observed in Differential Scanning Calorimeter (DSC) presented by Kozdras and Mzyk, 2016. Device is used to determine some thermal properties of physical materials (i.e. glass/softening temperature in chalcogenide glasses). In the process, required in thermal analysis, block Hammerstein structure is selected to describe both dynamic and nonlinear properties of phenomenon. In particular, block-oriented structures could be selected in approximation of black-box models with possible non-linearity existence in process. However, the problem of their effectively identification is still open, because most of common used identification routines are restricted to specific subclasses of input signal (i.e. Gaussian process or sine wave) and nonlinear characteristics (e.g. polynomials). The specifics lay in fact that blocks cannot be disconnected and internal signals can be unmeasurable.

2. Statement of the problem

2.1. Identified component

Consider the two-channel, discrete-time and asymptotically stable dynamic system shown in Fig. 2 which is a part of the complex system (Fig. 1).

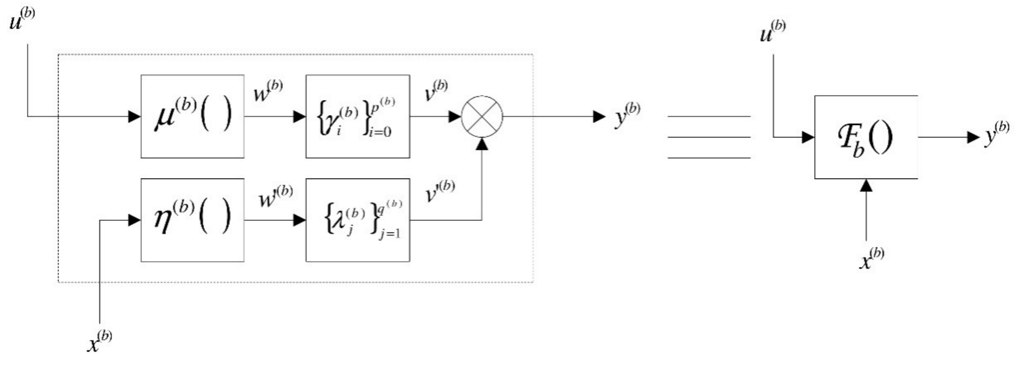


Fig. 2. Single *b*-th subsystem with output noise.

The subsystem contains two Hammerstein branches and can be described by the following equation (Bai, 1998).

$$y_k^{(b)} = \sum_{i=0}^{p^{(b)}} \gamma_i^{(b)} \mu^{(b)}(u_{k-i}^{(b)}) + \sum_{j=1}^{q^{(b)}} \lambda_j^{(b)} \eta^{(b)}(x_{k-j}^{(b)}) + z_k^{(b)}, \tag{1}$$

where $\mu(u)$ and $\eta(u)$ are the nonlinear characteristics of the static blocks, with unknown parameters

$$\mathrm{c}^{(b)} = (c_1^{(b)}, c_2^{(b)}, ..., c_m^{(b)})^T, \mathrm{d}^{(b)} = (d_1^{(b)}, d_2^{(b)}, ..., d_n^{(b)})^T \tag{2}$$

and

$$\Gamma^{(b)} = (\gamma_0^{(b)}, \gamma_1^{(b)}, ..., \gamma_p^{(b)}), \Lambda^{(b)} = (\lambda_1^{(b)}, \lambda_2^{(b)}, ..., \lambda_q^{(b)}), \tag{3}$$

denote the impulse responses of linear components. The signals $u_k^{(b)}$, $x_k^{(b)}$, $z_k^{(b)}$ and $y_k^{(b)}$ are the k-th ($k = 1,2,...,N$, where N is the number of measurements) external input, interaction input, block output noise and measured output respectively. We assumed the following parametric representations of the nonlinear characteristics

$$\mu^{(b)}(u) = c_1^{(b)} f_1(u) + ... + c_m^{(b)} f_m(u), \tag{4}$$

$$\eta^{(b)}(x) = d_1^{(b)} g_1(x) + ... + d_n^{(b)} g_n(x), \tag{5}$$

where $f_1(),..., f_m(), g_1(),..., g_n()$ are priori known linearly independent basic functions. The overparametrization technique was applied and the following vector of aggregated parameters (mixed products) could be identified:

$$\theta^{(b)} = (\gamma_0^{(b)} c_1^{(b)},.., \gamma_0^{(b)} c_m^{(b)},...., \gamma_p^{(b)} c_1^{(b)},.., \gamma_p^{(b)} c_m^{(b)},$$

$$\lambda_1^{(b)} d_1^{(b)},.., \lambda_1^{(b)} d_n^{(b)},...., \lambda_q^{(b)} d_1^{(b)},.., \lambda_q^{(b)} d_n^{(b)})^T. \tag{6}$$

Introducing the respective generalized input vector

$$\phi_k^{(b)} = (f_1(u_k^{(b)}),.., f_{m^{(b)}}(u_k^{(b)}),...., f_1(u_{k-p}^{(b)}),.., f_{m^{(b)}}(u_{k-p}^{(b)}),$$

$$g_1(x_k^{(b)}),.., g_{n^{(b)}}(x_k^{(b)}),...., g_1(x_{k-q}^{(b)}),.., g_{n^{(b)}}(x_{k-q}^{(b)}))^T \tag{7}$$

the equation describing a single block (1) can be simplified to the form

$$y_k^{(b)} = \phi_k^{(b)T} \theta^{(b)} + z_k^{(b)}, \tag{8}$$

what means that the model remains linear in-parameters. The aim is to estimate parameters (2) - (5) of the block with the use of the set of data $\{(u_k^{(b)}, \mathrm{y}_k)\}_{k=1}^N$ collected in the experiment.

2.2. Complex system

Let's consider the special case (Fig. 3) of the complex system from Fig. 1.

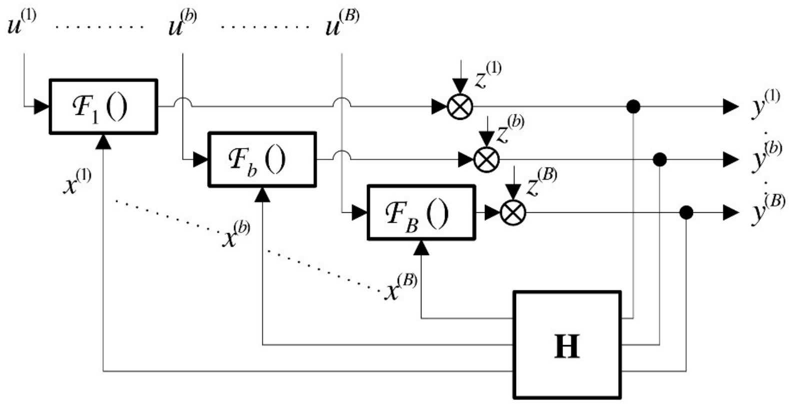


Fig. 3. Complex system with output noise only.

It consists of B ($b = 1, 2, \dots, B$) subsystems shown in Fig. 2, where

$$\mathrm{u}_k = \left(u_k^{(1)},\dots,u_k^{(b)},\dots,u_k^{(B)}\right)^T,\ \mathrm{x}_k = \left(x_k^{(1)},\dots,x_k^{(b)},\dots,x_k^{(B)}\right)^T,\ \mathrm{y}_k = \left(y_k^{(1)},\dots,y_k^{(b)},\dots,y_k^{(B)}\right)^T, \tag{9}$$

are the external inputs, interaction inputs and system outputs in time k. The output of b-th block can be determined with the use of equation (8). The block $\mathbf{H}$ determines the system structure in the following way

$$\mathrm{x}_k^{(b)} = \mathbf{H}_b \mathbf{y}_k, \tag{10}$$

where $\mathbf{H}_b$ is the b-th row of the binary, square matrix $\mathbf{H}$ (i.e. $\mathbf{H}_{b,i} = \mathbf{0}$ – no connection between $y^{(i)}$ and $x^{(b)}$, $\mathbf{H}_{b,i} = \mathbf{1}$ – connection).

The correlation between the external inputs and the outputs is zero, but the values of interaction inputs are dependent on the outputs. Hence, the output values in the particular subsystems are correlated with the input values. The noises from output are added to the input values.

The purpose of identification is to determine (recover) unknown vector of aggregated parameters $\Theta^{(b)}$ of the individual single blocks b using input and output measurements from the whole system.

We assume that:

- **Assumption 1**The structure of the system (i.e. the matrix $\mathbf{H}$) is known.
- **Assumption 2** The orders ($p^{(b)}$ and $q^{(b)}$) of linear dynamic subsystems in single blocks are known.
- **Assumption 3** The input process $u_k^{(b)}$ is a sequence of i.i.d bounded random variables, i.e., there exists $u_{\max}$, such that $|u_k^{(b)}| < u_{\max} < \infty$.
- **Assumption 4** The random noise process $\{z_k\}$ is stationary, zero-mean and independent of $\{u_k\}$.
- **Assumption 5** Only $\{u_k^{(b)}\}$ and $\{y_k^{(b)}\}$ can be observed.
- **Assumption 6** The blocks are asymptotically stable. For each block the nonlinear characteristic $\eta()$ is a Lipschitz function, i.e., $|\eta(y_1^{(b)}) - \eta(y_2^{(b)})| \le r\,|(y_1^{(b)}) - (y_2^{(b)})|$ and $\eta(0) = 0$. Moreover, the constant $r \ge 0$ is such that $\alpha = r\sum_{j=1}^{q^{(b)}} |\lambda_j^{(b)}| \le 1$.

We assume that the system structure and true values of parameters guarantee the identifiability of particular blocks, i.e. persistent excitation of the interaction inputs x. Establishing of formal sufficient conditions for a general class of nonliner dynamic systems is problematic. Owing to this fact we limit ourselves to some special cases with polynomial nonlinearities and FIR linear dynamic elements.

3. The algorithms

3.1. Least squares methods

The parametric LS algorithm can be used to identify unknown parameters of the complex system. It is currently one of the leading available approaches. It is based on the least squares estimation of the aggregated parameter vector. In order to make the model linear in the parameters, overparametrization of the single block is required. Firstly the LS estimate (6) of the aggregated $\theta^{(b)}$ is computed

$$\hat{\theta}_{LS}^{(b)} = \left(\frac{1}{N} \sum_{k=1}^{N} \phi_k^{(b)} \phi_k^{(b)T} \right)^{-1} \left(\frac{1}{N} \sum_{k=1}^{N} \phi_k^{(b)} y_k^{(b)} \right), \tag{11}$$

where N is the number of measurements. The estimate is the sum of the true parameter and an error $\hat{\theta}_{LS}^{(b)} = \theta^{(b)} + \Delta^{(b)}$, where ϕ_k is a vector (regressor) containing values of base functions calculated with the use of interaction inputs which are correlated with the noise values. The estimate (11) provides satisfying, but biased results. Even if the noise is zero-mean, the estimation error does not tend to zero

$$\frac{1}{N} \sum_{k=1}^{N} \phi_k^{(b)} z_k^{(b)} \to E\phi_k^{(b)} z_k^{(b)} , \tag{12}$$

due to correlation between noise $\{z_k\}$ and interaction input $\{x_k\}$ signals. The expected value is not equal to zero ($E\phi_k^{(b)} z_k^{(b)} \neq 0$). Hence the least squares estimator is biased with respect to the analysed complex system. It is impossible to recover the true values of parameter θ.

3.2. Singular Value Decomposition

Estimates of unknown parameters of the complex system can be obtained with the use of Singular Value Decomposition (SVD) algorithm. The algorithm has the following steps. Vector of aggregated parameters describing one single block can be transformed to matrices $\Theta_{\Gamma c}$ and $\Theta_{\Lambda d \Gamma}$

$$\Theta_{\Gamma c}^{(b)} = \begin{bmatrix} \gamma_0^{(b)} c_1^{(b)} & \gamma_0^{(b)} c_2^{(b)} & \cdots & \gamma_0^{(b)} c_m^{(b)} \\ \gamma_1^{(b)} c_1^{(b)} & \gamma_1^{(b)} c_2^{(b)} & \cdots & \gamma_1^{(b)} c_m^{(b)} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_p^{(b)} c_1^{(b)} & \gamma_p^{(b)} c_2^{(b)} & \cdots & \gamma_p^{(b)} c_m^{(b)} \end{bmatrix}, \tag{13}$$

$$\Theta_{\Lambda d}^{(b)} = \begin{bmatrix} \lambda_1^{(b)} d_1^{(b)} & \lambda_1^{(b)} d_2^{(b)} & \cdots & \lambda_1^{(b)} d_n^{(b)} \\ \lambda_2^{(b)} d_1^{(b)} & \lambda_2^{(b)} d_2^{(b)} & \cdots & \lambda_2^{(b)} d_n^{(b)} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_q^{(b)} d_1^{(b)} & \lambda_q^{(b)} d_2^{(b)} & \cdots & \lambda_q^{(b)} d_n^{(b)} \end{bmatrix}, \tag{14}$$

which are the products of

$$\Theta_{\Gamma c}^{(b)} = \Gamma^{(b)} c^{(b)T} \text{ and } \Theta_{\Lambda d}^{(b)} = \Lambda^{(b)} d^{(b)T}. \tag{15}$$

Each matrix being the product of two vectors has the rank equal to 1, and only one singular value is non-zero, i.e.,

$$\Theta_{\Gamma c}^{(b)} = \sum_{i=1}^{\min(p^{(b)}, m^{(b)})} \sigma_i^{(b)} \mu_i^{(b)} v_i^{(b)T}, \Theta_{\Lambda d}^{(b)} = \sum_{i=1}^{\min(q^{(b)}, n^{(b)})} \delta_i^{(b)} \xi_i^{(b)} \zeta_i^{(b)T}, \tag{16}$$

and

$$\sigma_1^{(b)} \neq 0, \sigma_2^{(b)} = \cdots = \sigma_{\min(p^{(b)}, m^{(b)})}^{(b)} = 0, \quad \delta_1^{(b)} \neq 0, \delta_2^{(b)} = \cdots = \delta_{\min(q^{(b)}, n^{(b)})}^{(b)} = 0. \tag{17}$$

Thus

$$\Theta_{\Gamma c}^{(b)} = \sigma_1^{(b)} \mu_1^{(b)} v_1^{(b)T} \text{ and } \Theta_{\Lambda d}^{(b)} = \delta_1^{(b)} \xi_1^{(b)} \zeta_1^{(b)T}, \tag{18}$$

where $\| \mu_1^{(b)} \|_2 = \| v_1^{(b)} \|_2 = 1$ and $\| \xi_1^{(b)} \|_2 = \| \zeta_1^{(b)} \|_2 = 1$. The representations of $\Theta_{\Gamma c}^{(b)}$ and $\Theta_{\Lambda d}^{(b)}$ given by (18) are always unique. To obtain $\Gamma^{(b)}$ one of equalities can be taken: $\Gamma^{(b)} = \mu_1^{(b)}$ or $\Gamma^{(b)} = -\mu_1^{(b)}$. The remaining part of decomposition allows for computing of $c^{(b)}$. The vectors of $\Lambda^{(b)}$ and $d^{(b)}$ can be determined in the same way.

4. Simulation example

In this section we present the performance of the algorithm on the example of the simple, two-element complex system (Fig. 4).

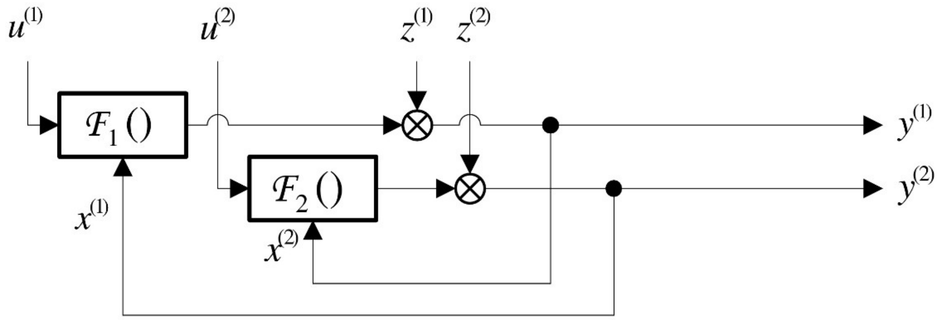


Fig. 4. The two-element system used in simulation.

Both single blocks are dependent on each other. The interconnections are coded as follows

$$\mathbf{H} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix},\ x^{(1)} = y^{(2)},\ x^{(2)} = y^{(1)}. \tag{19}$$

The parameters of the linear subsystems in the single blocks have been set to

$$(\gamma_0^{(1)}, \gamma_1^{(1)}) = (\gamma_0^{(2)}, \gamma_1^{(2)}) = (1{,}0.5) \to (p^{(1)}, p^{(2)}) = (1{,}1), \tag{20}$$

$$(\lambda_0^{(1)}, \lambda_1^{(1)}) = (\lambda_0^{(2)}, \lambda_1^{(2)}) = (0.1{,}0.05) \to (q^{(1)}, q^{(2)}) = (2{,}2). \tag{21}$$

The nonlinearities were chosen as follows

$$\mu^{(1)}(u) = \mu^{(2)}(u) = u^2 + 2u^3 \to (c_1^{(1)}, c_2^{(1)}) = (c_1^{(2)}, c_2^{(2)}) = (1{,}2), \tag{22}$$

$$\eta^{(1)}(x) = \eta^{(2)}(x) = 0.1x^2 + 0.2x^3 \to (d_1^{(1)}, d_2^{(1)}) = (d_1^{(2)}, d_2^{(2)}) = (0.1{,}0.2). \tag{23}$$

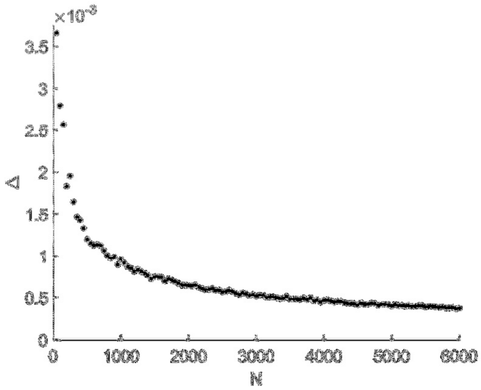
The system was excited by two independent uniformly distributed random processes

$$u^{(1)}, u^{(2)} \sim \mathcal{U}(-1{,}1). \tag{24}$$

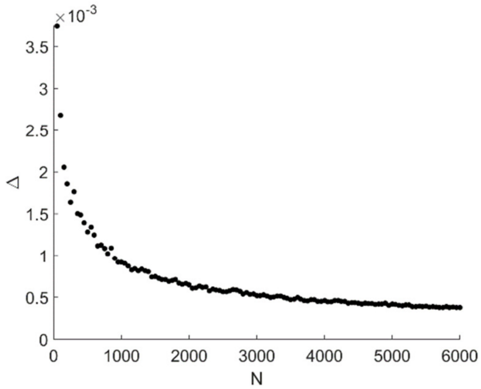
The simulation tests were performed with the use of 10% output

$$z^{(1)}, z^{(2)} \sim \mathcal{U}(-0.1, 0.1). \tag{25}$$

For both subsystems the least squares approach were used to compute estimates of parameters. In Fig. 5 the Euclidean norms of the errors Δ were presented.



(a) The first subsystem



(b) The second subsystem

Fig. 5. The estimation errors for different number of measurements N.

5. Conclusions

The idea of least squares estimate was successfully applied to the complex, interconnected system. Production and transportation systems usually work in steady state. In the paper more complex dynamic systems were considered. The proposed least squares algorithm recovers parameters of single blocks used in complex system with small error. We emphasize that the used method works for any structure of the system (for any interconnection matrix) and for any distribution of the random output noises. The identification procedure can be shortly implemented and automated in system controllers. If it is required, the small estimate error can be reduced to zero with the use of instrumental variables approach described below in the next section.

The procedure of identification has been tested in the practical example (heating process) with the use of Differential Scanning Calorimeter (Kozdras and Mzyk, 2016). Design of the device introduces nonlinearieties to unknown process which was approximated with the use of Hammerstein model. Comparing real measured values from process output and estimated data gives satisfying results. The Hammerstein model and least squares method could be used with success in real applications with nonlinearieties.

5.1. Instrumental variable method

The bias of the LS estimator can be reduced with the use of instrumental variables method, known from linear system theory. Assume that it is possible to generate additional vectors of instrumental variables $\psi_k^{(b)}$ with the same dimensions as $\phi_k^{(b)}$, i.e.,

$$\psi_k^{(b)} = (\psi_{k,1}^{(b)}, \psi_{k,2}^{(b)}, ..., \psi_{k,m(p+1)+nq}^{(b)})^T. \tag{26}$$

They fulfill the following conditions for each b

- **Condition 1** $\psi_k^{(b)}$ are jointly bounded, i.e., there exists $0 < \psi_{max} < \infty$ such that $|\psi_{k,j}| \leq \psi_{max}$ $(k = 1, ..., N$ and $j = 1, ..., m(p + 1) + nq)$ and $\psi_{k,j}$ are ergodic, not necessarily zero-mean processes.
- **Condition 2** There exists $P\lim(\frac{1}{N}\sum_{k=1}^{N}\psi_k^{(b)}\phi_k^{(b)T})) = E\psi_k^{(b)}\phi_k^{(b)T}$ and the limit is not singular, i.e., $det\{E\psi_k^{(b)}\phi_k^{(b)T}\} \neq 0$.
- **Condition 3** $P\lim(\frac{1}{N}\sum_{k=1}^{N}\psi_k^{(b)}z_k^{(b)T})) = E\psi_k^{(b)}z_k^{(b)} = = cov(\psi_k^{(b)}, z_k^{(b)}) = 0$.

As the result the IV estimate is given as

$$\hat{\theta}_{IV}^{(b)} = \left(\frac{1}{N}\sum_{k=1}^{N}\psi_k^{(b)}\phi_k^{(b)T}\right)^{-1}\left(\frac{1}{N}\sum_{k=1}^{N}\psi_k^{(b)}y_k^{(b)}\right). \tag{27}$$

Taking into account the conditions (C1)–(C3), a natural idea is to replace the LS estimate (11) with the IV estimate (38). The SVD decomposition can be made the similarly as for the LS estimator. The estimate error is equal to

$$\Delta_{IV}^{(b)} = \left(\frac{1}{N}\sum_{k=1}^{N}\psi_k^{(b)}\phi_k^{(b)T}\right)^{-1}\left(\frac{1}{N}\sum_{k=1}^{N}\psi_k^{(b)}z_k^{(b)}\right). \tag{28}$$

Due to condition (C3), the estimation error ($\Delta_{IV}^{(b)}$) tends to zero

$$\frac{1}{N}\sum_{k=1}^{N}\psi_k^{(b)} z_k^{(b)} \to E\psi_k^{(b)} z_k^{(b)} = 0. \tag{29}$$

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