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Advanced model structures applied to system identification of a servo-hydraulic test rig

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Analysis and modelling

ABSTRACT

Purpose: This paper deals with a method for the parametric system identification of a nonlinear system to obtain its parametric representation using a linear transfer function. Such representation is applicable in off-line profile correction methods minimizing the error between a reference input signal and a signal performed by the test rig. In turn, a test signal can be perfectly tracked by a servo-hydraulic test rig. This is the requirement in massive production where short test sequences are repeated to validate the products.
Design/methodology/approach: A numerical and experimental case studies are presented in the paper. The numerical study presents a system identification process of a nonlinear system consisting of a linear transfer function and a nonlinear output component, being a static function. The experimental study presents a system identification process of a nonlinear system which is a servo-hydraulic test rig. The simulation data has been used to illustrate the feasibility study of the proposed approach, while the experimental data have been used to validate advanced model structures under operational conditions.
Findings: The advanced model structures confirmed their better performance by means of the model fit in the time domain.
Research limitations/implications: The method applies to analysis of such mechanical and hydraulic systems for which measurements are corrupted by residual harmonic disturbances resulting from system nonlinearities.
Practical implications: The advanced model structures are intended to be used as inverse models in off-line signal profile correction.
Originality/value: The results state the foundation for the off-line parametric error cancellation method which aims in improving tracking of load signals on servo-hydraulic test rigs.
Keywords: System identification; Mechanical system; Hydraulic system; Parametric model

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1. Background

The crucial stage of the shock absorber manufacturing is the validation process . Shock absorbers are evaluated regarding comfort and noise using a synthesized or road load data. A sequence load has to be accurately tracked by test rigs which are most frequently used in the validation process of a shock absorber. While performing either durability or comfort evaluation tests obtaining repeatable and reproducible results is one of the most important steps in automotive shock absorbers development. In this case, the frequent problem is to applied to a shock absorber the test sequence minimizing the error between a reference and a measured signal.

In literature several papers [6-12,14,20] discuss offline feedback or feed-forward controllers to tackle this problem. The controllers perform iterative off-line correction process with the use of an inverse model of the plant [16]. The plant model is typically identified using system identification techniques [13,15]. The aim of this paper is to propose a model structure which provides the best results by means of the fit measure in the time domain for the identified model of the plant [15].

The content of the paper is divided into five sections. The second and third sections of the paper present the fundamentals of advanced model structures in system identification and estimation theory. Section fourth and fifth state the main goal of this paper, i.e. the presentation of numerical and experimental results from the analysis of a sensitivity model of a structure's influence. The paper ends with the Summary section.

2. Advanced model structures in system identification

The system theory approach to modeling considers three essential principles, consisting of sub-system isolation, input-output selection, and the model economy. The model formulation task requires the ability to separate one part of a physical environment, called a system, from the rest (Fig. 1). In the physical world, mutual interaction exists and influences the system behavior to a smaller or greater extent. Therefore sub-system isolation is required when there are a number of interaction types existing between a system and its surrounding environment. This implies that in system analysis only the most relevant and important interactions in the form of inputs and outputs should be considered [18,20]. Due to the principles of isolation and selection, a model is always simplified according to the purpose of modeling. Economic principles necessitate the simplicity of the structure and the minimum number of considered parameters and state variables. When the number of inputs and outputs is reduced, an additional disturbance path can be included to describe the effects of an incomplete model structure (Fig. 2). This is possible with the use of a parametric system identification approach and advanced model structures, which allow harmonic and stochastic disturbances to be separated from an input-output path [[15]].

A parametric time domain system identification approach has been under development since the 1970s. Interested readers are referred to the work of Aström, Box-Jenkins [1], Ljung [15], Södrström [5] and Stoica for details. In this paper, available model structures are classified with respect to the complexity of the disturbance model and special focus is placed on the Box-Jenkins (BJ) model structure [15].

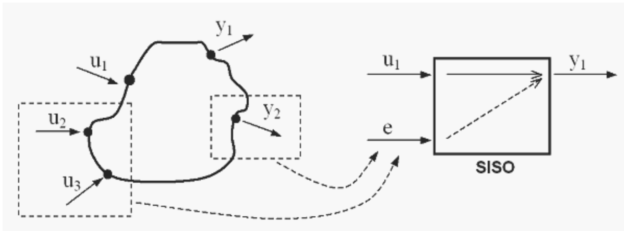

Fig. 1. Working principle of a double tube damper

A transfer function model is parameterized with $G(z^{-1})$, input-to-output, and $H(z^{-1})$, disturbance-to-output, transfer functions, which are also called paths in reference to its graphical representation (Fig. 2). A diagrammatic representation of the model structured (1) of an input-to-output dynamical system is depicted in Fig. 2.

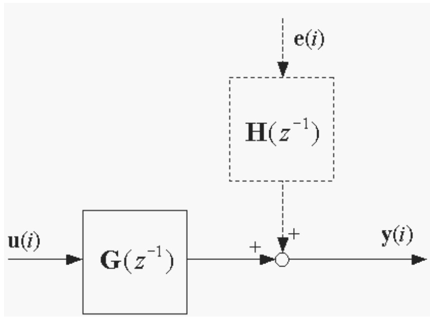

Fig. 2. Input-to-output path (control channel) and disturbance-to-output path (disturbance channel)

The transfer functions $G(z^{-1})$ and $H(z^{-1})$ are rational functions of the operator z^{-1} of the form

$$G(z^{-1}) = \frac{B(z^{-1})}{A(z^{-1})F(z^{-1})} \text{ and } H(z^{-1}) = \frac{C(z^{-1})}{A(z^{-1})D(z^{-1})}, \quad (1)$$

related to one another via the equation

$$y(i) = G(z^{-1})u(i) + H(z^{-1})e(i) \quad (2)$$

where

$$\begin{aligned} A(z^{-1}) &= 1 + a_1 z^{-1} + a_2 z^{-2} +,...,+ a_{nA} z^{-nA}, \\ B(z^{-1}) &= b_0 + b_1 z^{-1} + b_2 z^{-2} +,...,+ b_{nB} z^{-nB}, \\ C(z^{-1}) &= 1 + c_1 z^{-1} + c_2 z^{-2} +,...,+ c_{nC} z^{-nC}, \\ D(z^{-1}) &= 1 + d_1 z^{-1} + d_2 z^{-2} +,...,+ d_{nD} z^{-nD}, \\ F(z^{-1}) &= 1 + f_1 z^{-1} + f_2 z^{-2} +,...,+ f_{nF} z^{-nF}, \end{aligned} \quad (3)$$

are polynomials used for model parameterization. Special cases of the SISO structure (2) are [15]:

$$\begin{aligned} &\mathrm{PEM}(nA, nB, nC, nD, nF, k)\\ &\mathrm{BJ}(nB, nF, nC, nD, k)\\ &\mathrm{ARMAX}(nA, nB, nC, k)\\ &\mathrm{ARARX}(nA, nB, nD, k)\\ &\mathrm{OE}(nB, nF, k)\\ &\mathrm{ARX}(nA, nB, k) \end{aligned} \tag{4}$$

where nA, nB, nC, nD, nF are polynomial orders and k is input-to-output delay.

The ARX model constitutes a basic structure applicable to systems in which input-to-output data is not significantly corrupted by measurement noise. The disturbance-to-output path is integrated with the input-to-output path using the common poles of the polynomial $A(z^{-1})$. The ARMAX model introduces a separate description of disturbances in the form of the numerator $C(z^{-1})$ in the path of the $H(z^{-1})$ disturbance-to-output transfer function. This model structure can be used when dominating disturbances, so-called load disturbances, enter at the input [15]. The OE model does not include the $H(z^{-1})$ disturbance-to-output transfer function and the disturbance source e(i) affects only the output. The BJ model yields separate descriptions of the $G(z^{-1})$ input-to-output path and the $H(z^{-1})$ disturbance-to-output path, filtering disturbances through the $H(z-1)=C(z^{-1})/D(z^{-1})$ transfer function. Filtration using the numerator and denominator provides additional flexibility for modelling the noise and harmonic disturbances. BJ models are recommended when the noise does not enter at the input, but is primarily a measurement disturbance [15]. Finally, the PEM model provides free parameterization of the $G(z^{-1})$ and $H(z^{-1})$ paths. Because this structure is too general in most cases, one or several of the polynomials are typically set to unity in applications. A diagram of a general model structure is shown in Fig. 3. The OE structure includes B and F polynomials, and the BJ structure contains B, F, C and D polynomials [15]. In cases where the disturbances enter the system at the input, it is preferable to use polynomial $A(z^{-1})$ zeros which correspond to poles common for the input-to-output model and the disturbance-to-output model. $F(z^{-1})$ determines the poles that are unique to the input-to-output dynamics, and $D(z^{-1})$ determines the poles that are unique to the disturbance-to-output dynamics [15]. The PEM model structure facilitates common parameterization of the input-to-output and the disturbance-to-output poles using the polynomial $A(z^{-1})$ and independent parameterization of the input-to-output and disturbance-to-output poles using the polynomials $F(z^{-1})$ and $D(z^{-1})$, respectively. Such a representation increases the economy of the structure by decreasing the number of parameters in the model.

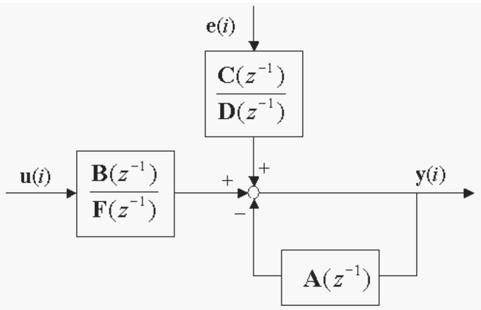

Fig. 3. Regressive model structure of an input/output model

In the state-space formulation, the relationship between the input, disturbances and output signals is written as a system of first order difference equations. The model is parameterized as the State-Space Innovations Form (SSIF)

$$\begin{aligned} x(i+1) &= \mathbf{A}x(i) + \mathbf{B}u(i) + \mathbf{K}e(i)\\ y(i) &= \mathbf{C}x(i) + \mathbf{D}u(i) + e(i) \end{aligned} \tag{5}$$

where **A**, **B**, **C**, **D** are the system matrices, K is the disturbance matrix, y is the output, u is the input, and e is the disturbance input. Fig. 4 presents the diagrammatic representation of the state space model expressed in the State-Space Innovations Form (SSIF).

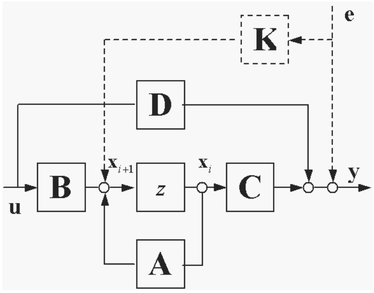

Fig. 4. Structure of a model in the form of state equations

A linear model structure can be extended to a nonlinear one using static or dynamic nonlinear mapping methods. One of the most general mapping functions is an artificial neural network (ANN) [16], which is a nonlinear weighted sum of inputs. For identification purposes, the weights of an ANN are treated as adjustable parameters and estimated by means of one of the numerous conventional optimization methods [15] or by artificial intelligence ones [16]. A multiple model, or the so-called hybrid approach, is often considered [2], e.g. a Takagi-Sugeno fuzzy multiple model involving fuzzy-weighted combinations of local ARX/ARMAX-like models. These nonlinear models are general-purpose ones if a priori knowledge is not available. On the other hand, rotating machines, consisting of a rotor and supporting bearing system, are typical mechanical structures for which different models are derived in numerous theoretical and experimental studies. It allows a grey-box nonlinear model that includes first principle modeling to be used [17]. Difficulties typically encountered in choosing an appropriate structure of the black-box model, which are caused by the uncertainty related to the complexity and structure of the unknown dynamics, is justification for using a grey-box model. From the point of view of this paper, the Hammerstein-Wiener model [15] describing dynamical systems by means of input and/or output static nonlinear mapping functions, in serial combinations with a linear transfer function, constitutes an interesting class of nonlinear models.

One can use advanced linear models (e.g. BJ, OE and PEM) to parameterize the disturbance-to-output transfer function and decouple disturbances from the input-to-output transfer function. Availability of a priori knowledge, e.g. the form of nonlinearity, number of residual harmonics, etc., facilitates parameterization.

In the case of control applications, utilization of all the relevant, that is, with physical interpretation, information obtained from the process is essential. For instance, a BJ model structure has a disturbance-to-output transfer function consisting of a numerator and denominator. The denominator $D(z^{-1})$ is the key polynomial that allows disturbing harmonics with a minimal number of parameters to be captured as an Infinite Impulse Response (IIR) filter. On the other hand, the numerator polynomial $C(z^{-1})$ may capture potential white noise disturbances with a minimal number of parameters as a Finite Impulse Response (FIR) filter.

3. Estimation theory

The most essential stages of a system identification procedure are summarized as follows, i.e. (i) formulate a model structure , and (ii) define the $V(\theta)$ error function between the data acquired and the model parameters.

The objective of the estimation is to minimize the $V(\theta)$ error function comprising the individual model parameters. The Least Squares method is applicable when the error is a linear function of model parameters. In other cases, a numerical optimization method is required. This refers to all prediction error methods (PEM), with the exception of AR/ARX models. The minimization methods applicable for an error function are as follows:

- Simple direct seek methods,
- First-order methods based on the information provided by the first derivative (gradient) of the $V(\theta)$ error function (e.g. reverse propagation method),
- Second-order methods based on the information regarding the first and second derivative (gradient and Hessian form) of the $V(\theta)$ error function (e.g. Newton method, the Newton quasi-method, Gauss-Newton method, pseudo-method of Newton, Levenberg-Marquardt). These second order methods differ in their simplification when determining the second derivative influencing the convergence and speed of a selected algorithm.

The iterative methods designed to seek a minimum of the error function have a number of drawbacks, to mention only a few:

- Low sensibility level in the initial parameter values,
- Frequently occurring problems while reaching the algorithm convergence,
- It is likely that the local minima of the objective function may appear.

Taking into account the selected model structure, the following two basic criteria of a model error formulation are commonly applied. The former criterion refers to the Prediction Error Method (PEM)

$$\hat{\varepsilon}(i) = y(i) - \varphi^T(i)\hat{\theta}(i) \qquad (6)$$

$$V(\theta) = \sum_{i=1}^{N} \varepsilon^2(i,\theta) \qquad (7)$$

while the latter one refers to the Least-Square (LS)

$$\hat{\varepsilon}(i) = y(i) - \varphi^T(i)\hat{\theta}(i) \qquad (8)$$

$$V(\theta) = \sum_{i=1}^{N} \varepsilon^2(i) \qquad (9)$$

The prediction error method may be readily used as an implementation for the identification of a general PEM model structure and other particular solutions, such as the OE and BJ models. The $H(z^{-1})$ transfer function or **K** matrix (gain matrix of a Kalman's filter) are applied, when the response of a true system is biased by disturbances occurring at the model output or state variables.

If a priori information of the model order is unavailable, a model structure can be evaluated and accurately selected from the data. For instance, the AIC and BIC methods [15]] allow us to detect under- and over-estimated model structures.

4. Results of numerical investigations

A sensitivity study on the influence of the model structure on the system identification results is presented in the subsequent section (Figs. 5-10). The objective of this study is to confirm the performance of BJ structures in modelling disturbances and to rank model structures in order to evaluate data fitting accuracy (Table 1). For the purpose of determining model quality in regard to the input-to-output transfer function, a series of Bode diagrams in the frequency domain was prepared. Subsequently, in order to evaluate separated disturbances regarding the error-to-output transfer function, a corresponding series of power spectra was obtained. The ARMAX structure, inadequate for modelling harmonic (deterministic) disturbances, was not considered. A nonlinear continuous-time system was used to produce data (Figs. 11, 12) suitable for system identification of advanced model structures. The linear part of the system is described by the following transfer function:

$$H(s) = \frac{1}{s^2 + 10s + (2\cdot\pi\cdot 30)^2} + \frac{1}{s^2 + 2s + (2\cdot\pi\cdot 80)^2} \qquad (10)$$

The output of the nonlinear system is given as follows

$$y = 10^9\left[L^{-1}\{H(s)\cdot u(s)\}\right]^3 \qquad (11)$$

An excitation is assumed as a harmonic function

$$u(t) = \sin(2\cdot\pi\cdot 60t) \qquad (12)$$

where sampling frequency is f_p=500 [Hz].

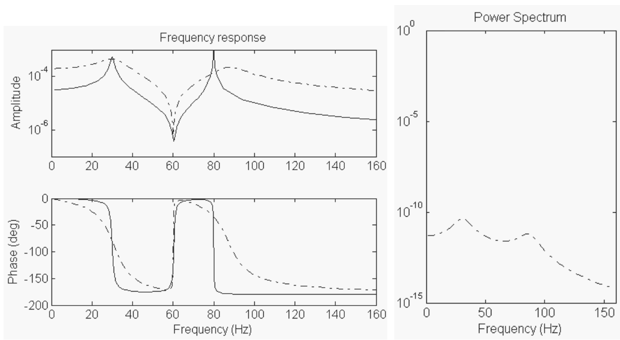

Fig. 5. Identified ARX(4,3,1) model (solid line – reference model, dotted line – identified model), amplitude in logarithmic scale

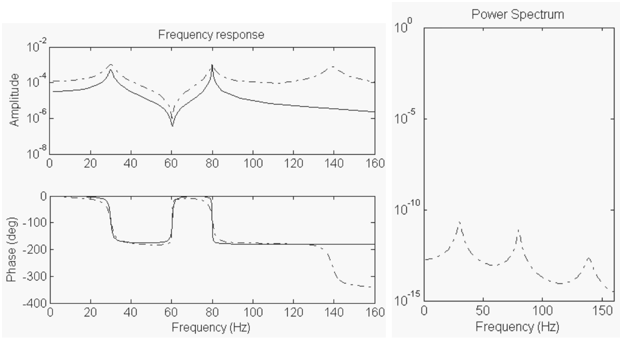

Fig. 6. Identified ARX(10,6,1) model (solid line – reference model, dotted line – identified model), amplitude in logarithmic scale

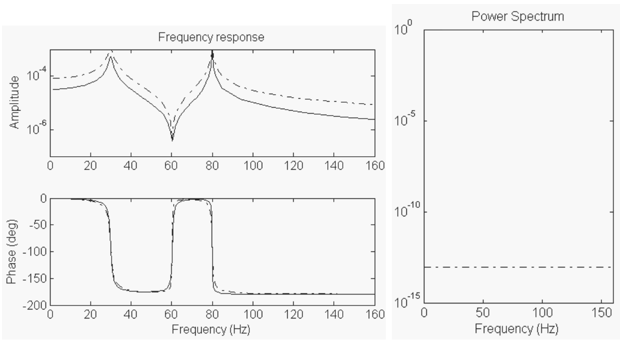

Fig. 7. Identified OE(3,4,1) model (solid line – reference model, dotted line – identified model), amplitude in logarithmic scale

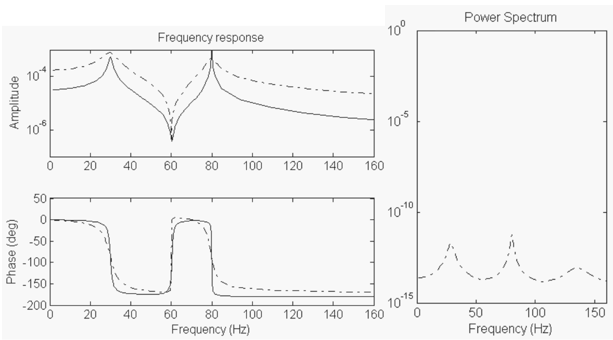

Fig. 8. Identified BJ(4,2,8,4,1) model (solid line – reference model, dotted line – identified model), amplitude in logarithmic scale

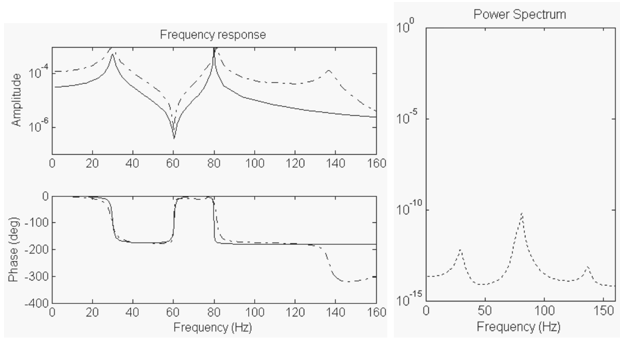

Fig. 9. Identified N4SID(13) model (solid line – reference model, dotted line – identified model), amplitude in logarithmic scale

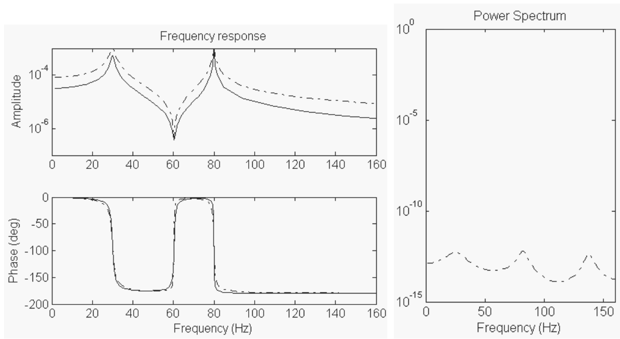

Fig. 10. Identified BJ(3,2,8,4,1) model (solid line – reference model, dotted line – identified model), amplitude in logarithmic scale

Table 1.
The model data fitting results in the time domain (one-step ahead predicted output)

Model	best fit [%]
ARX(4,3,1)	32 %
ARX(10,6,1)	71 %
OE(3,4,1)	64 %
BJ(4,2,8,4,1)	84 %
state-space SSIF(12)	82 %
BJ(3,2,8,4,1)	87 %
Hammerstain-Wiener ARX(4,3,1)	75 %

All models were identified using the 'ident' application available in the System Identification Toolbox in the Matlab package [1,3-4]. Model performance can either be evaluated by visual inspection of the plots or by numerical value [15]:

$$R^2 = 1 - \frac{\frac{1}{N}\sum_{i=1}^{N}\left|y(i) - y^*(i)\right|^2}{\frac{1}{N}\sum_{i=1}^{N}\left|y(i)\right|^2} \quad (13)$$

where y is the reference amplitude, and y^* is the predicted amplitude. R is the part of the model output explained by the model. This measure is usually used in the Matlab System Identification Toolbox [[1]] and, for convenience, R is expressed in %.

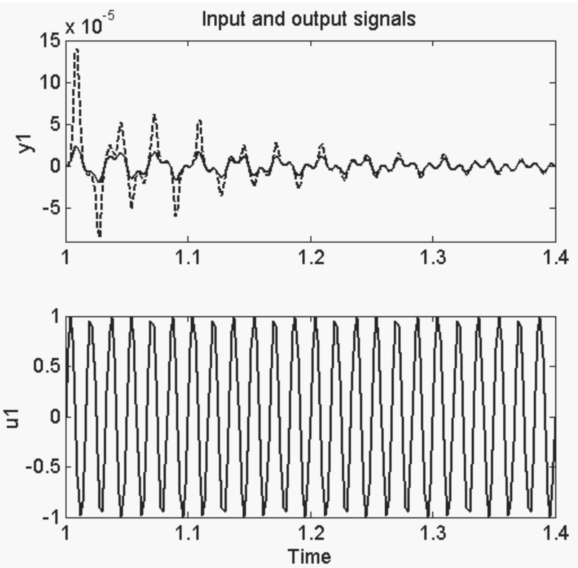

Fig. 11. The simulated model input u1, and output y1 (solid – linear model, dotted – nonlinear model)

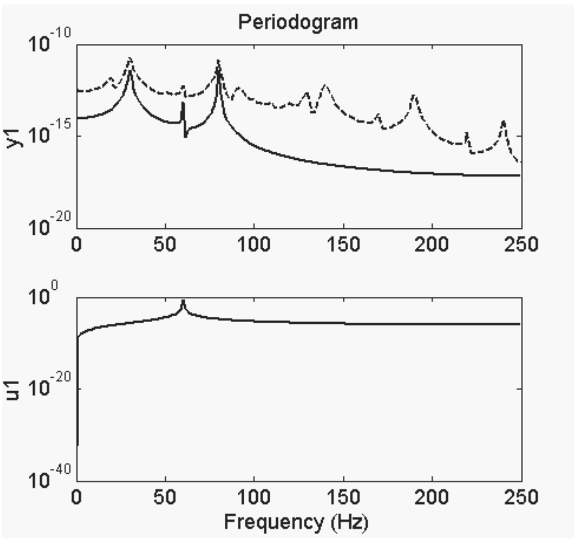

Fig. 12. Logarithmic power spectra of the model input u1, and the output y1 (solid – linear model, dotted – nonlinear model)

The ARX(4,3,1) structure is insufficient to capture nonlinearities, and only an overparametrized ARX(10,6,1) structure provides results which closely fit the average results of other models (Figs. 6-7; above 60%). The OE(3,4,1) structure gave good accuracy and qualitatively reproduced the linear behaviour of the reference system, however, it did not estimate the model disturbance (Fig. 7). The BJ structure is very sensitive to overparametrization, e.g. the case of BJ(4,2,8,4,1), however, the correct polynomial orders, i.e. BJ(3,2,8,4,1) provided excellent quality of amplitude-phase reproduction as well as model accuracy (Figs. 8, 10). The state-space model SSIF(13) demanded an enormously high order to provide acceptable quality of amplitude-phase reproduction (Fig. 9). The Hammerstain-Wienner model was considered as an alternative. The model structure consisted of a linear part in the form of the ARX(4,3,1) model and a sigmoidal output static nonlinear function. This model enabled nonlinearities to be captured and provided good quality fitting.

5. Results of experimental investigations

Experimental tests were performed on a servo-hydraulic test-rig Hydropuls® MSP25 equipped with the electronic controller IST8000 (Fig. 13).

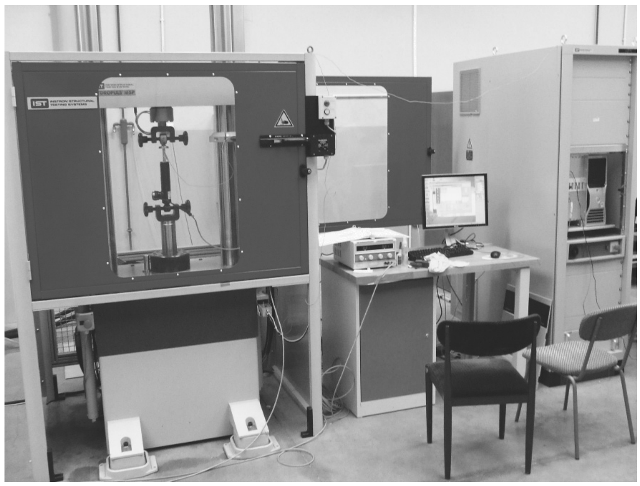

Fig. 13. A servo-hydraulic test-rig used in experimental investigations

The test rig was used to load a shock absorber and capture its dynamical characteristic, i.e. displacement vs. force. Data acquisition [19] was performed with the 8-channel ICP amplifier manufactured by LMS. The test rig is equipped with an oil supplying system (so called servo-pack) that provides a pressure of 28 MPa at a flow-rate of 90 l/min. The actuator provides 25 kN force at the rod, while the maximum stroke is 250 mm at the maximum achievable velocity of 2 m/s. The actuator rod is coupled to the adapter which transfers the force to a shock absorber mounted on a test rig. The main components of the servo-hydraulic system are the hydraulic actuator with the integrated displacement transducer in a piston-rod assembly (IST-Schenk) and three-stage servo-valve system. The test rig is equipped with a servo-hydraulic system and the PID-FF controller. The feed-forward (FF) section in this controller passes a proportion of the command signal to the controller output through a high-pass filter to block the command mean level. Different control settings are used depending on a type of excitation signal. The excitation signal is converted into a voltage applied to the servo-valve which controls the amount of oil supplied to the chambers of the actuator.

The purpose of system identification is to identify a transfer function between the reference and the measured displacement signal, i.e. uniformly distributed white noise. A fourth order discrete transfer function was chosen as a parametric representation of the test rig dynamics. The actuator is equipped with a damping throttle block with is the bypassing orifice between actuators' chambers. The important function of this bypass is to provide a little damping to the actuator and decrease its oil resonance peak amplitude by adjusting the throttle.

The system identification was performed for two cases, i.e. opened and closed throttle valve, respectively. In Fig. 14. were shown results of the difference between the opened and the closed throttle valve. These exemplary results were obtained with the use of ARX(4,4,1) model (Fig. 14). The remain results are presented in Tables 2-3.

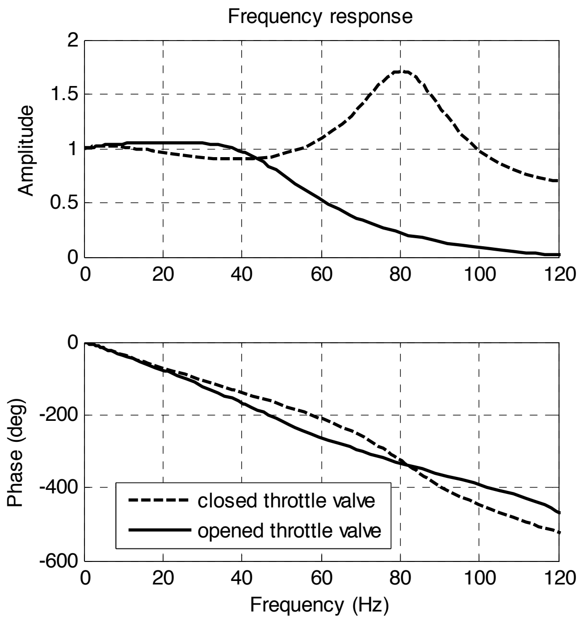

Fig. 14. A servo-hydraulic test-rig used in experimental investigations

Table 2.
The model data fitting results in the time domain for the opened throttle valve (one-step ahead predicted output)

Model	best fit [%]
ARX(4,3,1)	67%
ARX(10,6,1)	77%
OE(3,4,1)	87%
BJ(3,3,4,4,1)	89%
PEM(4)	86%
ARMAX(4,4,4,1)	81%

Table 3.
The model data fitting results in the time domain for the closed throttle valve (one-step ahead predicted output)

Model	best fit [%]
ARX(4,3,1)	62%
ARX(10,6,1)	78%
OE(3,4,1)	85%
BJ(3,3,4,4,1)	91%
PEM(4)	85%
ARMAX(4,4,4,1)	80%

6. Conclusions

The aim of this paper is to discuss a parametric identification method in the study of nonlinear systems using advanced model structures. The nonlinear system was simulated to generate data intended to be used for the purpose of system identification. On the other hand a servo-hydraulic test rig was selected as an example of an experimental nonlinear system. The models obtained in the results of system identification based on numerical and experimental data were ranked using the 'best fit' criterion. The numerical and experimental analysis confirmed that advanced model structures may provide better separation of disturbances from the input-to-output model dynamics.

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