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PARAMETER ESTIMATION FOR ENGINEERS: A NEW TOOL FOR EFFECTIVE SEARCH FOR SIMULINK MODEL PARAMETERS

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Abstract: *An estimation of Simulink model parameters is very important problem in field of system identification in mechatronics. This paper describes features and advantages of the New Parameter Estimation Tool developed with respect to particular engineering needs. Among other things, the tool allows to use the arbitrary combination of a model and a measured data for the construction of cost function of the optimization process. This enables to formulate various tasks briefly outlined in this paper including comparison of several candidate models or performing estimations of models with shared parameters. Furthermore, all temporary simulation results are stored and later can be browsed and viewed by user. This enables to get very clear visual insight into the estimation problem and especially increases the usefulness of the Brute force method use. Finally, the tool allows to cope actively with the problem of initial guesses of an optimization method. As a result, user can automate and control parameter estimations for time-consuming and demanding problems.*

Keywords: Parameter estimation, Simulink, Optimization, Software tool.

1. Introduction

The field of system identification is very important in many specific areas of modelling, testing, signal processing and control design in mechatronics. In engineering practice, many problems are formulated through creation of simulation models with given structure and system identification is then reduced to the parameter estimation. Typically, these models are implemented in MATLAB/Simulink and consequently the Simulink Parameter Estimation (SPE) tool is used to search for parameters based on measured data.

The SPE does not analyze in any way the structure of a simulation model and uses it as a black box with mathematical optimization to find the set of parameters. Selected parameters in simulation blocks are adjusted by the optimization algorithm and simulation is performed. Next, the cost function is calculated expressing the difference (MSE) between simulated and measured data. Further, the parameters are again modified by algorithm and simulation runs again. Finally, if optimization converges, the minimum of parameter vector is found. An example of simulation model with highlighted parameters is shown in Fig. 1. Generally, the estimated parameters can also include initial states of the model.

Although the SPE is very useful and widely used tool, from the practical point of view, it lacks several important features. In this paper, a New Parameter Estimation Tool (NPET) is introduced and briefly described.

The rest of the paper is organized as follows: first, the motivation for the use of several models in one optimization problem definition is described in Sec. 2. Next, in Sec. 3, other important features are mentioned. Finally, the GUI is shown in Sec. 4.

2. The parameter estimation problem: mass-spring-damper system with dry friction example

To demonstrate several aspects of practical approach to parameter estimation, a linear mechanical mass-

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spring-damper system with nonlinear (dry) friction is used. The simulation model of this system is shown in Fig. 1.The equation of motion

$$m\ddot{x} + kx + b\dot{x} + T\,\mathrm{sgn}(\dot{x}) = cu \tag{1}$$

contains five unknown parameters (mass *m*, stiffness *k*, viscous damping *b*, dry friction *T*, actuator constant *c*). Input system variable *u* is known.

2.1. How many parameters can be estimated?

The *n* = 5 parameters above have specific physical meaning and from engineering point of view it would be beneficial to be able to estimate all of them. However, only four (*n* - 1) parameters in this equation can be estimated independently, typically the equation should be rewritten in the form:

$$p_1\ddot{x} + p_2 x + p_3\dot{x} + p_4\,\mathrm{sgn}(\dot{x}) = u \tag{2}$$

These redefined parameters can be estimated but with lost physical meaning.

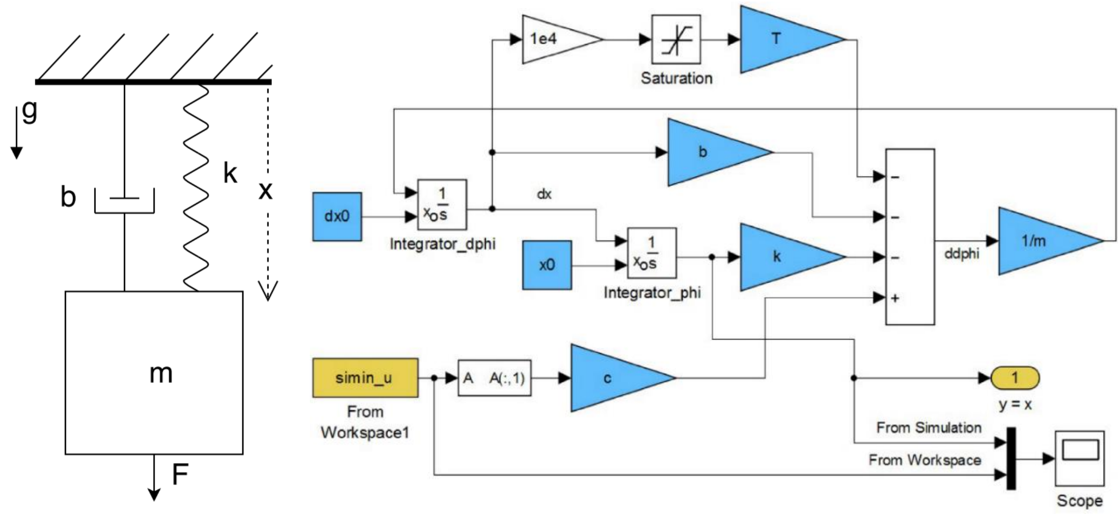

Fig. 1: Schematic and Simulink model of mass-spring system.

2.2. Modification of experimental setup

To solve the described problem, a certain modification of real experimental setup can often be done. The simplest example is to add an extra mass *M* (known) to the system:

$$(m + M)\ddot{x} + kx + b\dot{x} + T\,\mathrm{sgn}(\dot{x}) = cu \tag{3}$$

Such experimental arrangements provide in fact two different physical systems with five shared parameters (*m*, *k*, *b*, *c*, *T*). Combining these two systems (1) and (3) all five parameters can be estimated.

The procedure of the estimation can be clearly shown on simplified example:

$$\begin{aligned} m\,\ddot{x} &= cu \\ (m + M)\,\ddot{x} &= cu \end{aligned} \tag{4}$$

By minimizing the number of parameters, the (4) can be rewritten in the form:

$$\begin{aligned} p_1\,\ddot{x} &= u \\ p_2\,\ddot{x} &= u \end{aligned} \tag{5}$$

With known input *u* and measured $\ddot{x}$, both parameters p_1 and p_2 can be uniquely determined. Next, the calculation of *m* and *c* is just solution of two equations (with p_1, p_2 and *M* known):

$$\begin{aligned} p_1\,c &= m \\ p_2\,c &= m + M \end{aligned} \tag{6}$$

leading to result:

$$c = \frac{M}{p_2 - p_1} \tag{7}$$

Obviously, in real-world examples, the derivation of resulting parameters will not be so clearly understandable. To automate this process (4)-(7), the two independent systems (4) can simply be estimated using optimization methods while parameters *m* and *c* are shared. The SPE tool can utilize described approach only if the user includes both systems (4) into one Simulink model.

3. Overview of main NPET features

3.1. Estimation using combination of several models and measured data

Previous section shows the potential usefulness of the combination of several simulation models (M) and measured data set (D) in one optimization. Generally, the NPET allows arbitrary combination of several Simulink models (independent files) with sets of measured data. The cost function *e* of the optimization method can be constructed according to the user`s needs.

There are two basic applications:

1) **Combination of several modified experimental setups with shared parameters** (previous Section describes it in details). In such example, the cost function can have following form:

$$e = w_1 m_1(p_1, p_2, p_3) + w_2 m_2(p_3, p_4) \tag{8}$$

2) **Testing of several model candidates for the best fidelity**: In real life, the structure of the system model is never exactly known. Considering the example of mass-spring system, user can create many variants of simulation model including (3), model without dry friction (T = 0), model with quadratic damping and many others. The parameters of these candidate models can then be estimated and the model with the best fitting parameters (measuring the fidelity by MSE) can be selected. In such case, there are several competing cost functions:

$$\begin{aligned} e_1 &= m_1(p_1, p_2, p_3) \\ e_2 &= m_2(p_3, p_4) \end{aligned} \tag{9}$$

In the SPE tool the (M, D) couples can be arbitrarily combined using weights, logical and algebraic functions which allow very rich possibilities of task formulation.

3.2. Automated repetitive start from different initial condition

One of the most typical problems of the gradient (but also gradient-free) optimization methods use is the freezing in local minimum. Because avoiding this problem is very difficult (despite the optimism of GA fans), it is much easier to simply overcome the problem with repetitive starting of the algorithm from different (random) initial condition. The NPET allows to define the conditions to restart the optimization with respect to computation time and precision.

3.3. Storing temporary simulation results in memory

One of the best engineering approaches to optimization is Brute force method. It can of course be utilized only in case of middle-size problems, but then it could be very useful. In NPET, user can start the Brute force search which takes several days, all results (not necessary the simulated trajectories but the set parameter – MSE) are stored and available for later browsing. Such starting search can also be useful to get an overview of the properties of parameter state space.

Not only Brute force but all optimization methods store their results in NPET. Very often, the evaluation of model with specific set of parameters is computationally costly. In such case, it is better to search for already performed simulations in a database than calculate it again.

From the engineering perspective, the ability to explore the searched space visually (see Fig. 2) is one of the crucial advantages of NPET. The right side of GUI shows the plot of measured and simulated data with the possibility to limit the number of plots via MSE. On the left side, the corresponding parameter sets are drawn. User can clearly see how intense the performed search was in particular part of an optimization state space. This allows to analyze the stored simulation results with high level of comfort.

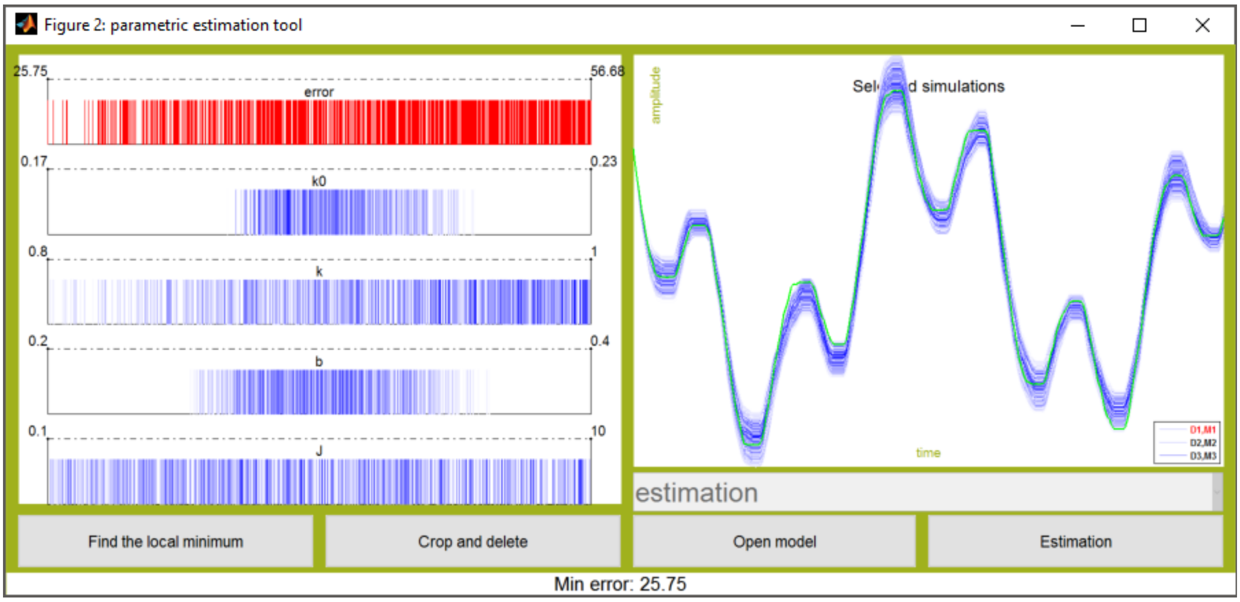

Fig. 2: Main GUI of NPET.

4. Conclusions

The NPET described briefly in this paper was used for estimating several nonlinear system models including nonlinear systems such as BLDC pump, electromagnetic levitation experimental setup and electronic throttle (Grepl, 2010). The estimated results, insensitivity to wrong initial guess and general user comfort of the use were very satisfactory and promising.

The software was implemented in MATLAB using object oriented programming as a result of a thesis (Appel, 2016). Besides the main estimation engine, several optimization methods were implemented or adapted for use in the NPET which allows to use the tool without the need of MATLAB Optimization Toolbox or Global Optimization Toolbox.

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References

Appel, M. (2016) Application of Optimization Methods for Parameters Estimation of Simulation Models, master thesis, FME, Brno University of Technology, (in Czech).

Grepl, R. and Lee, B. (2010) Modeling, parameter estimation and nonlinear control of automotive electronic throttle using a Rapid-Control Prototyping technique Int. J. of Automotive Technology, Vol. 11, pp. 601-610.

Nelles, O. (2001) Nonlinear System Identification, ISBN 978-3-662-04323-3.

Ljung, L. (2010) Perspectives on system identification, Annual Reviews in Control. Vol. 34, pp. 1-12.