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ESTIMATION OF LINEAR IDENTIFICATION OF MODELS OF DRY ELECTRICAL FILTER

Abstract. The aim of this paper is to estimate linear identification of dry electrical filter workflow process. This interest is due to the ability of providing accurate state-space models for multivariable linear systems directly from input-output data. The methods have their origin in classical state-space realization theory as developed in Matlab Ident tool application. The results show parameters of object. Given models are used for comparing different algorithms. The approach based on a linear model for performing errors with respect to prediction methods is established.

Keywords: system identification, work flow, Matlab ident tool, dry electrical filter, state-space, linear model.

Introduction. System identification is generally the art of mathematical modeling, given input-output measurements from a dynamical system. The problem is of interest in a variety of applications, ranging from work flow process simulation and control of identification of dry electrical filters. In the classical system, the problem of the input identification (the control signal) is known exactly, whereas the output signal may be corrupted by additive noise. The process can also have external unmeasurable inputs.

Estimating Linear Models Using Quick Start. The main aim is to estimate and validate simple, continuous-time transfer functions from multi-input/single-output (MISO) data to find the one that best describes the dynamics of the system [1-5].

Continuous-time process models are low-order transfer functions that describe the dynamics of the system using static gain, a time delay before the system output responds to the input, and characteristic time constants associated with poles and zeros. Such models are popular in the industry and are often used for tuning PID controllers. Parameters of process model have physical significance [6-11].

We specify different process model structures by varying the number of poles, adding an integrator or including a time delay or zero. The highest process model order you can specify in this toolbox is three, and the poles can be real or complex (underdamped modes).

In general, a linear system is characterized by a transfer function G, which is an operator that takes the input and to the output y:

$$y = Gu \tag{1}$$

For a continuous-time system, G relates the Laplace transforms of the input U(s) and the output Y(s), as follows:

$$Y(s) = G(s)U(s) \tag{2}$$

We estimate G using different process-model structures.

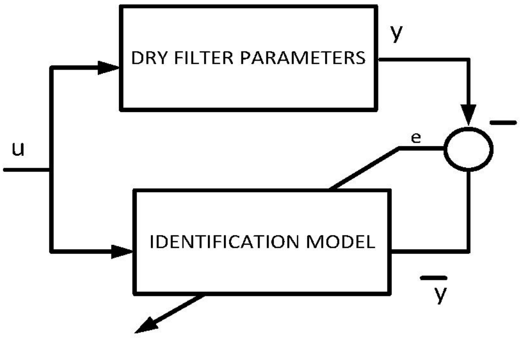

Figure 1 –
Model scheme of identification

Preparing Data for System Identification
– Loading Data into the MATLAB Workspace
– Opening the System Identification App
– Importing Data Objects into the System Identification App
– Plotting and Processing Data

We use system of Identification app to estimate linear models in Matlab. Identification tool might produce the final linear models we decide to use, or provide with information required to configure the estimation of accurate parametric models, such as time constants, input delays, and resonant frequencies [7-12].

Matlab ident tool estimates the following four types of models and adds the following to the System Identification app with default names:

imp – Step response over a period of time using the impulse algorithm.

spad – Frequency response over a range of frequencies using the spa algorithm. The frequency response is the Fourier transform of the impulse response of a linear system.

By default, the model is evaluated at frequency values, ranging from 0 to the Nyquist frequency.

arxqs – Fourth-order autoregressive (ARX) model using the arx algorithm.

This model is parametric and has the following structure:

$$y(t) + a1y(t-1) + nay(t-na) = \mathrm{b}1u(t-nk) + bnbu(t-nk-nb+1) + e(t) \quad (3)$$

$y(t)$ represents the output at time t, $u(t)$ represents the input at time t, n_a is the number of poles, n_b is the number of b parameters (equal to the number of zeros plus 1), n_k is the number of samples before the input affects output of the system it is called the *delay* or *dead time* of the model, and $e(t)$ is the white-noise disturbance. System Identification Toolbox software estimates the parameters $a1...an$ and $b1...bn$ using the input and output data from the estimation data set.

In arxqs, n_a=n_b=4, and n_k is estimated from the step response model impulse.

n4s3 – State-space model calculated using n4sid. The algorithm automatically selects the model order.

This model is parametric and has the following structure:

$$\mathrm{dydx} = \mathrm{Ax(t) + Bu(t) + Ke(t)}$$
$$\mathrm{y(t) = Cx(t) + Du(t) + e(t)} \quad (4)$$

$y(t)$ represents the output at time t, $u(t)$ represents the input at time t, x is the state vector, and $e(t)$ is the white-noise disturbance. The System Identification Toolbox product estimates the state-space matrices A, B, C, D, and K.

Validating the parameters of Model. We generate the following plots during model estimation to validate the quality of the models:
– Step-response plot
– Frequency-response plot
– Model-output plot

Algorithms of using methods

1. In the Import Data dialog box, specify the following options:

Object – Enter z as the name of the MATLAB variable that is the time-domain data object. Press **Enter.**

Data name – Use the default name z, which is the same as the name of the data object you are importing. This name labels the data in the System Identification app after the import operation is completed.

Starting time – Enter 0 as the starting time. This value designates the starting value of the time axis on time plots.

Sample time – Enter 1 as the time between successive samples in seconds. This value represents the actual sample time in the experiment.

We use following parameters of dry electronic filter work flow process [14-16]:

Table 1 – Input parameters for Identification process

№	MW	kPa	kPa	kPa	kPa	T left	T right
1	26,1	-0,186	-0,189	-0,197	-0,2	79,5	77,2
2	26,1	-0,186	-0,189	-0,197	-0,2	79,4	77
3	26	-0,186	-0,189	-0,197	-0,2	79,4	76,9
4	26	-0,181	-0,186	-0,193	-0,204	79,4	76,9
5	25,9	-0,176	-0,183	-0,189	-0,208	79,4	76,9
6	25,8	-0,176	-0,183	-0,189	-0,208	79,4	76,9
7	24,9	-0,177	-0,179	-0,188	-0,193	79,1	76,6
8	24,9	-0,177	-0,179	-0,188	-0,193	79,1	76,6
9	24,9	-0,175	-0,179	-0,187	-0,198	79,1	76,6
10	24,9	-0,173	-0,178	-0,186	-0,202	79,1	76,6
11	24,9	-0,173	-0,176	-0,181	-0,197	79,1	76,6
12	24,9	-0,174	-0,173	-0,176	-0,191	79,1	76,6
13	24,9	-0,174	-0,173	-0,176	-0,191	79,1	76,6
14	24,9	-0,175	-0,171	-0,177	-0,182	79,1	76,6
15	25	-0,175	-0,171	-0,177	-0,182	79,1	76,6
…	…	…	…	…	…	…	…
447	24,3	-0,194	-0,203	-0,208	-0,218	81,6	79
448	24,2	-0,194	-0,203	-0,208	-0,218	81,7	79,2
449	24,2	-0,194	-0,203	-0,208	-0,218	81,8	79,3
500	24,1	-0,201	-0,2	-0,21	-0,216	81,8	79,4

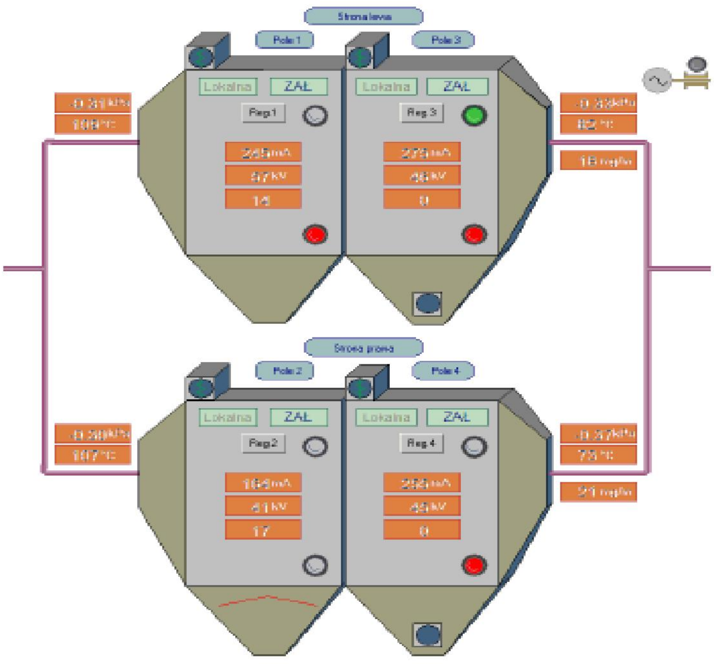

Figure 2 – Dry electronic filter contraction. Industry scheme

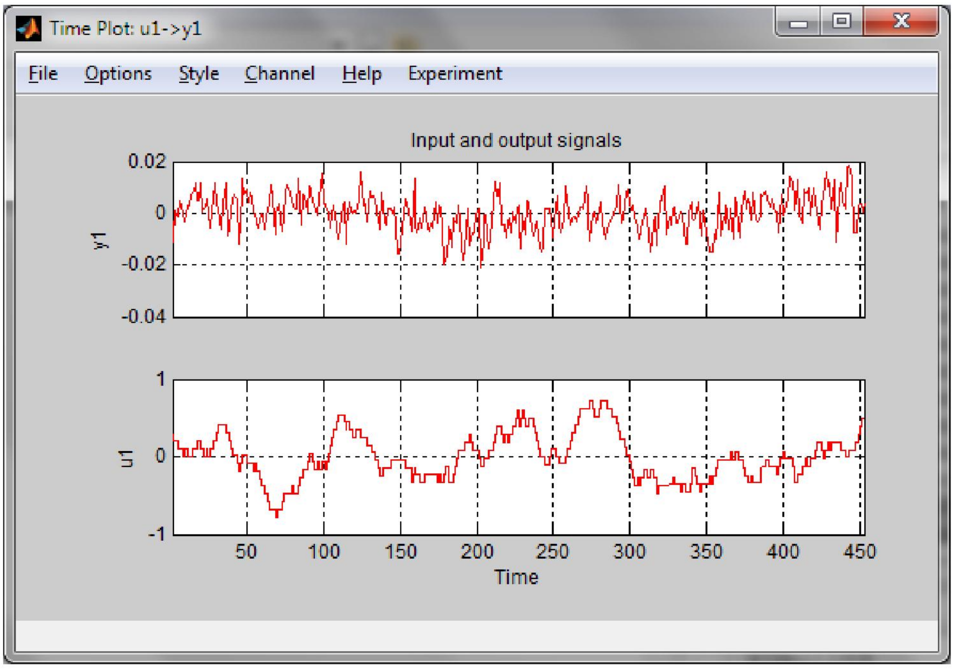

Figure 3 – Input parameters of dry electronic filter

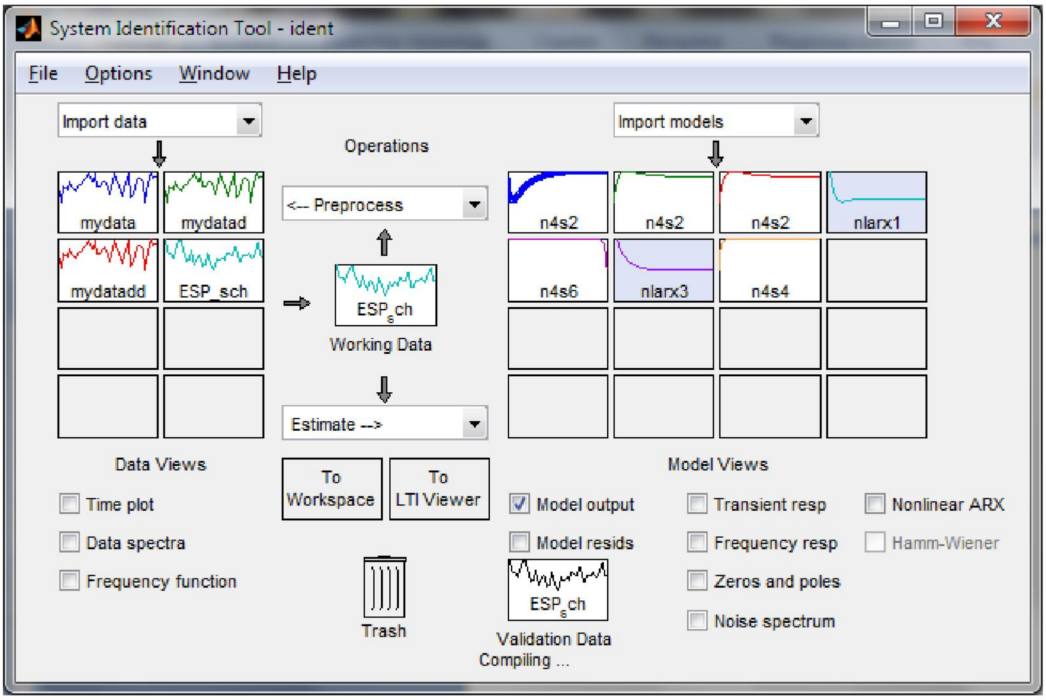

Figure 4 – Identification toolbox interface importing Data Arrays into the System Identification App

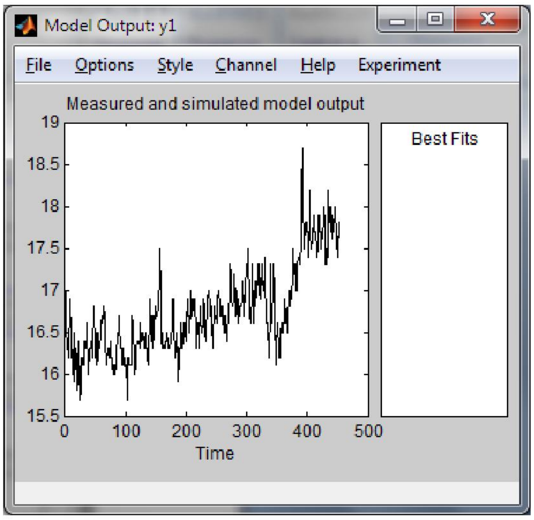

Figure 5 –
Measured and simulated model output parameters

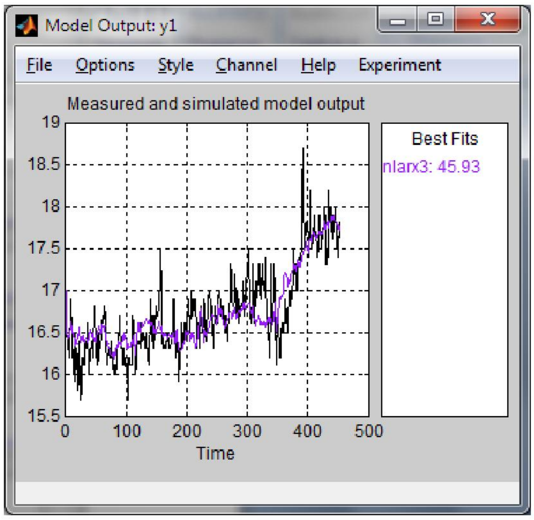

Figure 6 –
Comparison of state space and auto regression models

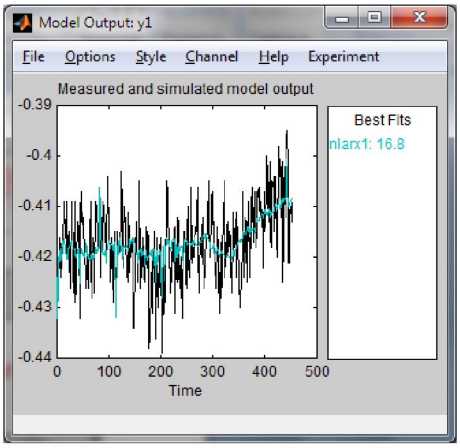

Figure 7 – Model input parameter and nonlinear regression models. Nonlinear ARX model with 6 outputs and 5 inputs of dry filter parameters

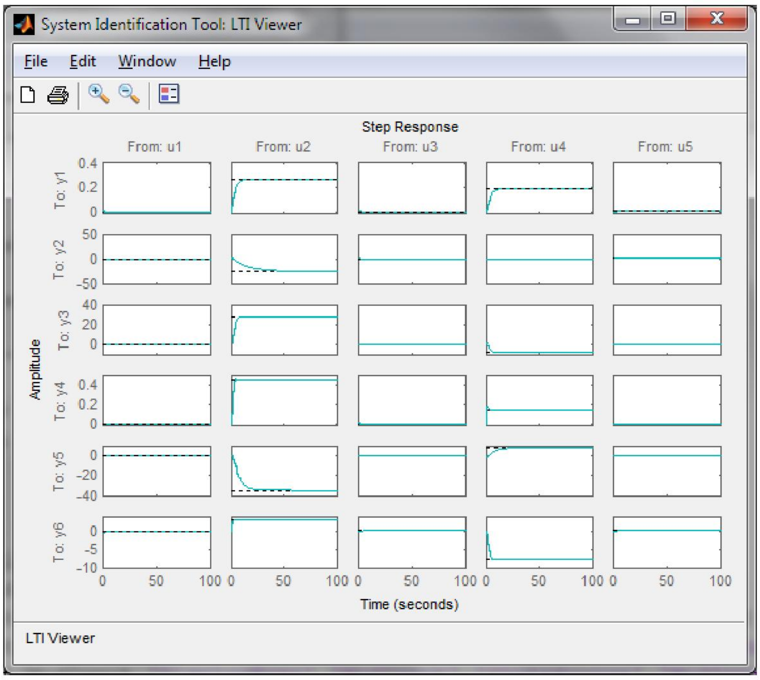

Figure 8 –
Step Response for imp, arxqs, and n4s3

Results of identification

n4s2 =

Continuous-time state-space model:

$$\begin{aligned} dx/dt &= A\,x(t) + B\,u(t) + K\,e(t) \\ y(t) &= C\,x(t) + D\,u(t) + e(t) \end{aligned} \quad (5)$$

A =

	x1	x2
x1	-0.05693 +/- 6.441e+09	0.01739 +/- 2.146e+10
x2	-0.005346 +/- 4.515e+10	-0.1786 +/- 6.441e+09

B =

	u1	u2
x1	0.0003299 +/- 1.234e+09	-0.001577 +/- 3.301e+10
x2	0.007712 +/- 3.181e+09	-0.2066 +/- 8.533e+10

	u3	u4
x1	-0.00341 +/- 5.44e+08	-0.1047 +/- 1.467e+10
x2	-0.001557 +/- 1.379e+09	0.005271 +/- 3.879e+10

	u5
x1	-0.003706 +/- 1.245e+09
x2	-0.007006 +/- 3.129e+09

C =

	x1	x2
y1	0.006681 +/- 1.08e+09	-0.001838 +/- 1.248e+09
y2	-5.027 +/- 1.056e+12	-1.897 +/- 1.175e+12
y3	-0.3289 +/- 5.391e+11	-1.44 +/- 6.024e+11
y4	0.01175 +/- 2.982e+09	0.006178 +/- 3.312e+09
y5	-5.484 +/- 1.201e+12	2.794 +/- 1.379e+12
y6	-1.924 +/- 2.819e+11	-0.1478 +/- 3.19e+11

D =

	u1	u2	u3	u4	u5
y1	0	0	0	0	0
y2	0	0	0	0	0
y3	0	0	0	0	0
y4	0	0	0	0	0
y5	0	0	0	0	0
y6	0	0	0	0	0

K =

	y1	y2
x1	0.1524 +/- 3.063e+10	-0.1131 +/- 2.835e+10
x2	-0.1409 +/- 8.319e+10	-0.1448 +/- 7.092e+10

	y3	y4
x1	-0.004747 +/- 1.622e+10	-0.1091 +/- 1.592e+10
x2	-0.1013 +/- 4.18e+10	-0.02567 +/- 4.1e+10

	y5	y6
x1	-0.09313 +/- 3.416e+10	-0.02387 +/- 4.575e+09
x2	0.1997 +/- 9.117e+10	0.02006 +/- 1.243e+10

Conclusion. The aim of this paper is to give a guided tour through the scattered land of subspace-based methods for system identification. In order to achieve this aim different methods have been grouped into the realization-based and the direct 4SID methods. The members of the former class explicitly form estimates of the step response parameters, whereas the direct methods were based on the input-output relation (2). A number of similarities between different methods were pointed out. In particular, the basic 4SID methods were considered in this paper.

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ҚҰРҒАҚ ЭЛЕКТРСҮЗГІНІҢ ПАРАМЕТРЛЕРДІҢ СЫЗЫҚТЫ ИДЕНТИФИКАЦИЯСЫН ЖАСАУ

Аннотация. Берілген негізгі жұмыстың мақсаты құрғақ электрсүзгсінің жұмыс үрдісін сызықты идентификацияда жасалып көрсетілген. Бұл қызығушылық моделдің кеңістік күйін дәл және берілген тәуелсіз кірісшығыс сызықты жүйедегі көпфакторлар үшін ұсынылған мүмкіндік. Кеңістік күйінің классикалық теориясының туындауын нақтылау әдісінде Matlab Ident бағдарламалық ортасында ұсынылған. Оъбектідегі параметрлерді зерттеу. Әртүрлі алгоритмдерді салыстыру үшін моделдеу келтіріліп қосылған. Негізгі сызықты моделдеуді орындау үшін қатынастық бойынша қателікті болжау әдістері шарт бойынша қолданылған.

Түйін сөздер: идентификация жүйесі, технологиялық үрдіс, Matlab iden ttool, құрғақ электрсүзгісі, кеңістік моделінің күйі, сызықты модель.

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ЛИНЕЙНАЯ ИДЕНТИФИКАЦИЯ ПАРАМЕТРОВ СУХИХ ЭЛЕКТРОФИЛЬТРОВ

Аннотация. Целью данной работы является линейная идентификация рабочего процесса сухого электрофильтра. Этот интерес обусловлен возможностью предоставления точных моделей пространства состояний для многофакторных линейных систем непосредственно от ввода-вывода данных. Методы имеют свое происхождение в классической теории пространства состояний реализации, разработанные в применении инструмента Matlab Ident. Исследование параметров объекта сухих электрофильторов. Приведенные моделирования включены для сравнения различных алгоритмов. Найден подход на основе линейной модели для выполнения по отношению к методам прогнозирования ошибок, при условии, что система должным образом эксплуатирована.

Ключевые слова: идентификация системы, технологический процесс, Matlab iden tool, сухой электрофильтр, модель пространства состояний, линейная модель.

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