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# Identification of paper machine process models using MLBS excitation signal

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## 1 Introduction

Paper machines are complex applications of process industry which are typically controlled by model predictive controllers (MPC). The MPC predicts the output of the process by using process models that describe the interactions between the control variable and the desired manipulated variable. Typically, these models are identified by making step changes to the system, which are commonly known as bump tests. Sometimes these tests fail to give a response good enough for the identification due to disturbances or other interactions between the process variables. So, there is a need for an alternative way of identifying the models.

This paper studies a method of using a Maximum Length Binary Sequence (MLBS) in the identification of low-order transfer function models such as FOTD (First-Order Time Delay) and SOTD (Second-Order Time Delay). MLBS is a deterministic periodic broadband excitation signal which can be used to estimate the frequency response of the studied system. The estimated frequency response specifically called empirical transfer function estimate (ETFE) can then be used in a curve fitting problem. Low-order transfer function model's frequency response is fitted to the ETFE by minimizing error function between the two. In the context of process industry, the amplitude of the signal is important factor when running the tests and the fine part of using MLBS signal is its relatively small amplitude, which in theory would not disturb the process significantly during the identification.

#### 2 Aims of the study

This study's aim is to find out if MLBS excitation signal is applicable in the context of paper machines and process industry. The second goal is finding general principles needed in the generation of proper MLBS excitation signal. The paper also studies how well MLBS signal handles different disturbances and how their effect could be compensated with data handling techniques.

### 3 Materials and methods

MLBS is an excitation signal which has power on a frequency band, which can be designed by a set of parameters. Because MLBS is a deterministic excitation signal, the tests conducted with it are replicable. Figure 1 shows MLBS excitation signal in time and frequency domain.



Fig. 1. MLBS excitation signal in time and frequency domain

The signal is generated by a logic circuit called the shift register and the signal can be generated online or offline. Even though the name suggests that the signal is binary, it can also change between any other two values. It is common to choose the signal levels so that the signal has close to zero mean value. The transfer function models of FOTD and SOTD are given by equations 1 and 2

$$G_{\rm FOTD} = \frac{K}{\tau s + 1} e^{-ds},\tag{1}$$

$$G_{\text{SODT}} = \frac{K}{(\tau_1 s + 1)(\tau_2 s + 1)} e^{-ds}, \qquad (2)$$

where  $K \neq 0$  is the DC gain,  $\tau > 0$  is the time constant and d > 0 is the time delay. Both models have poles at the negative real axis and the models' step responses are monotonic.

The aims of this study are pursued through by identifying the low-order transfer function models from simulated process data. A simulator capable of simulating linear low-order systems with disturbances has been implemented in MathWorks' Simulink. To estimate the systems frequency response, MLBS excitation signal is generated and used to perturb the desired system. The collected data is used for the calculation of ETFE and then the low-order transfer function model parameters are calculated by minimizing a fit error between the model and ETFE. The minimization is performed by using Levenberg–Marquardt algorithm.

First the excitation signal's generation principles are studied. The effect of generation frequency's location to the identification is determined by using a set of MLBS excitation signals, which are located before and after the system's corner frequency. To improve the parameter fitting on higher frequencies an additional gain compensation algorithm is introduced.

The number of shift register bits affect the frequency domain properties of the excitation signal. The second test studies the effect of the shift register bit number and the location of the generated signal with simple placement rules. The tests are conducted with and without the gain compensation algorithm.

The final part of the paper studies the effect of different disturbances in the identification. The disturbances are made so that they resemble disturbances encountered in real processes. The simulated disturbances are zero-mean white noise, external step signal and external multi-sine.

## 4 Results

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The parameter fitting task was successful for studied linear models and simple rules for MLBS signal generation were found. Figure 1 shows an example how the generation frequency affects the FOTD model identification and the precise results can be seen from table 1. The results showed that data handling is a crucial



Fig. 2. The effect of generation frequency  $f_{gen}$  to the results.

part of identification and its importance becomes more obvious when disturbances are perturbing the system. From the results it was clear that the system's corner frequency and the MLBS excitation signal's effective frequency band played a significant role in the parameter fitting task. By prioritizing lower frequencies gain parameter was identified with better accuracy. The delay parameter was identified better, when MLBS excitation signal was on the higher frequencies of the studied band.

Table	1.	Models	of	figure	2.
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Compensation factor	$f_{gen}[Hz]$	t[s]	K	$\tau[s]$	d[s]	IAE
Not in use	$1.000 \cdot 10^{-3}$	377900	1.200	178.495	159.649	1.769
Not in use	$10.000 \cdot 10^{-3}$	37790	1.200	180.320	109.951	0.411
Not in use	0.100	3779	0.609	96.844	106.935	434.656
In use	$1.000 \cdot 10^{-3}$	377900	1.200	178.495	159.649	1.769
In use	$10.000 \cdot 10^{-3}$	37790	1.200	180.320	109.951	0.411
In use	0.100	3779	1.189	179.113	105.523	7.953
Exact model	_	_	1.200	180.000	105.000	_