Transactions of the VŠB – Technical University of Ostrava, Mechanical Series
No. 2, 2012, vol. LVIII
article No. 1923

Emmanuel PLACIER-ZAVALA, Viktor PLAČEK*

USABILITY OF LOW-PASS FILTERS ON BIOMASS COMBUSTION QUANTITIES

VYUŽITÍ FILTRŮ TYPU DOLNÍ PROPUST PŘI SPALOVÁNÍ BIOMASY

Abstract

Quantities measured during biomass combustion experiments are heavily burdened with a considerable noise. Usage of common linear low-pass filters is able to smooth measured time rows but it also introduces typical dynamic delay of filtered data. The article presents comparison of three commonly used linear filters – Butterworth, Bessel and Chebishev. An effort to smooth measured data without introducing dynamic delay led us to use some of less common non-linear filters. The article further presents usage of Threshold and Gaussian weighted average non-linear filters and compares them with the linear ones.

Abstrakt

Veličiny sledované při experimentech se spalováním biomasy jsou zpravidla významně zatížené silným šumem. Použití běžných lineárních filtrů s dolní propustí sice dokáže vyhladit průběhy měřených veličin, ale zavádí do filtrovaného signálu typické dynamické zpoždění. Tento článek porovnává použití tří běžně používaných lineární filtrů - Butterworthův, Besselův a Čebiševův. Další snaha o vyhlazení měřených dat bez zatížení dynamickým zpožděním vedla autory k použití méně běžných nelineárních filtrů. Článek tedy dále srovnává použití prahového filtru a filtru založeném na Gaussovo křivkou váženém průměru.

1 INTRODUCTION

A good portion of our work consists of experiments carried out on a small-scale biomass boiler. During the experiments many variables are measured, and almost all of the measured data is burdened with noise of varied magnitude. Some noise has its source in the measuring circuit and it can be handled by a change in the sensor connection. Nevertheless, a substantial part of the noise originates in the measured process itself. The non-homogenous combustion of solid fuels is a strongly non-deterministic process which creates severe disturbances to measured values.

When trying to indentify a system from measured data time rows with sufficiently smooth data is needed. Unfortunately, common linear filters when used for data smoothing, weight the data down with additional dynamic delay. When the filtered variable responds quickly to its excitation, the subsequent dynamic delay can considerably lurk away the instants of change. The dynamic delay thus distorts input data used for the system identification.

As an example, an experiment is introduced where a step change is made in frequency of asynchronous motor frequency changer driving intake air fan and observing changes in the temperature of flue gases in a stack entrance. As the frequency change is abrupt, the changes in observed values are equally fast. The measured data of temperature is strongly burdened with noise sourcing in the combustion process itself. In order to perform the identification of the air flow impact on the boiler performance, it is necessary to filter the signal without loosing the sudden changes in

* Emmanuel PLACIER-ZAVALA, Ing. Viktor PLAČEK, CTU in Prague, Faculty of Mechanical Engineering, Department of Instrumentation and Control, Technická 4, 166 07 Praha 6, eplacier@hotmail.com, viktor.placek@fs.cvut.cz

the measured variable as a reaction to the step changes of an excitation signal. Standard filters such as Butterworth, Bessel and Chebyshev are tested and their results are compared with two non-linear filters.

2 COMMON SIGNAL FILTERS

As an example of a measured signal, a part of an experiment is discussed where the combustion process in a small-scale boiler is excited by the air flow change. The air flow to both a primary and a secondary channel is changed in steps every time when the control algorithm detects finished transition from previous step (Fig. 1). Further information about the boiler, its configuration and control, can be found in [PLAČEK et. al., 2011], [HAAPA-AHO et. al., 2011].

Three of the most common continuous linear filters were used. Discrete filter was first converted to continuous using zero-order hold and then transformed using common differential equation with parameters got from the respective filter. The cutoff frequencies for the filters were chosen in a way that each filter would cover a range limited by a smooth and slow response to a poor smooth and fast response.

The result of using Bessel filter is in Fig. 2, Butterworth filter is in Fig. 3 and Chebyshev filter is in Fig. 4. The comparison of all three filters with optimal cutoff frequency is in Fig. 5. From the comparison it can be seen that all three filters use as high a cutoff frequency that the filtered signal is still rippled. But despite the high cutoff frequency of the filters, the filtered transitions still have significant dynamic delay.

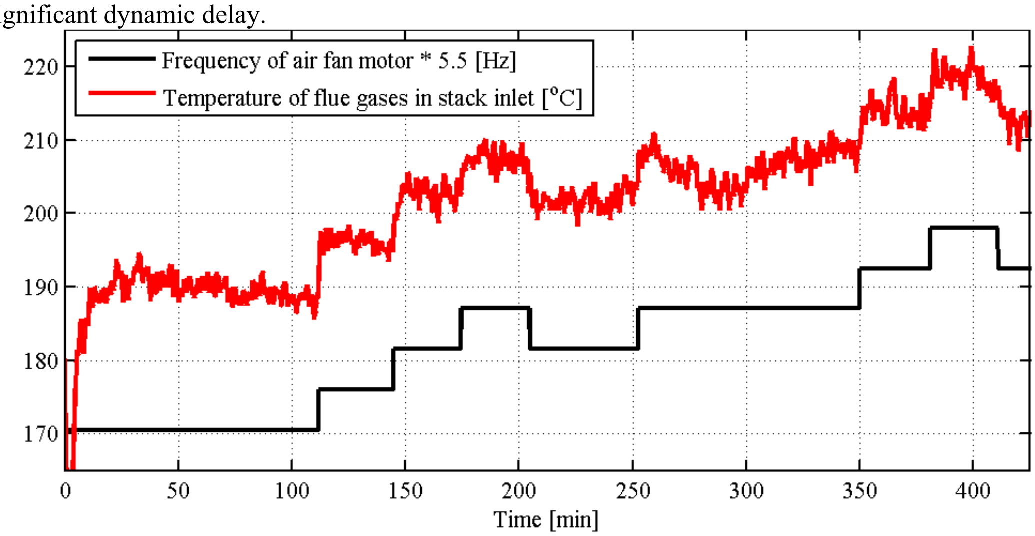

Fig. 1. Example of measured data for filtering. Black line is excitation signal and red line is time response.

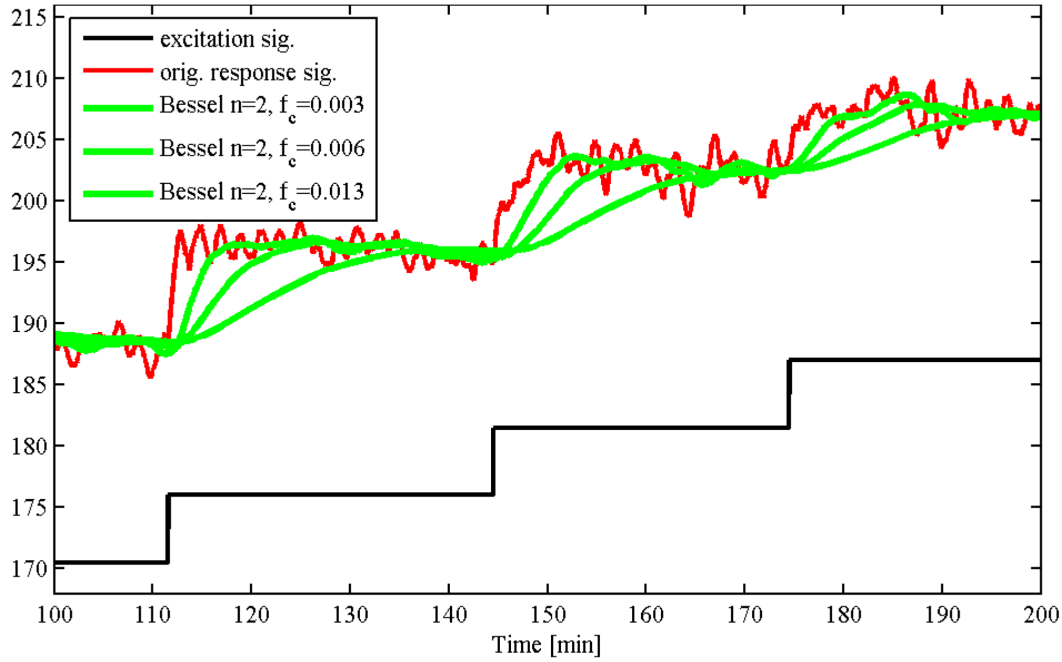

Fig. 2. Detail of the filtered response using Bessel filter of 2nd order with three different cutoff frequencies (in rad/s).

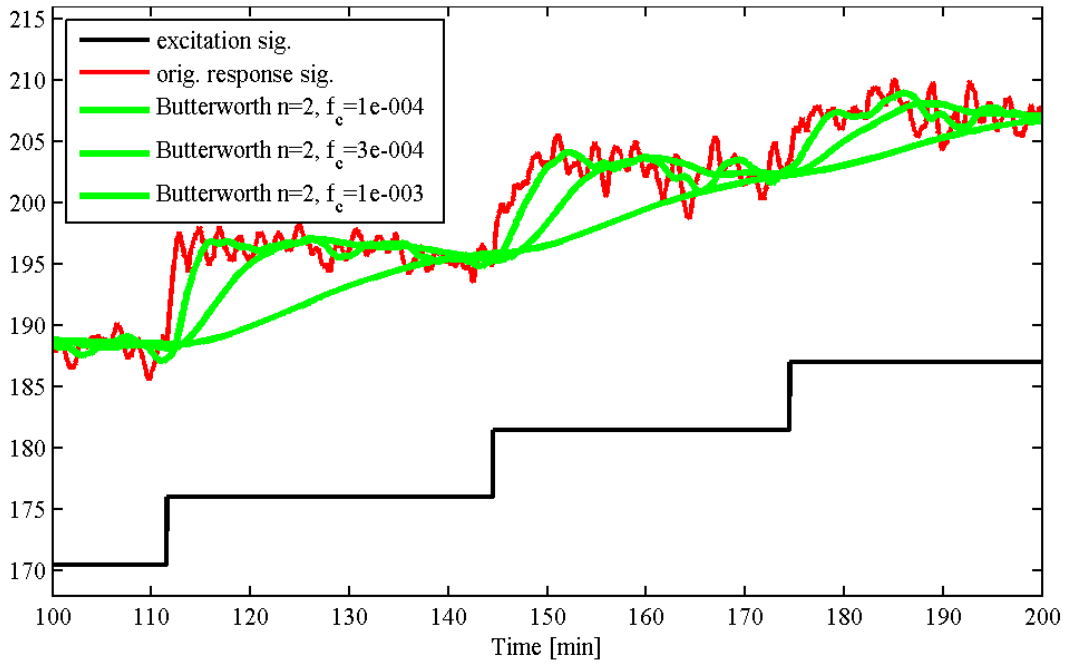

Fig. 3. Detail of the filtered response using Butterworth filter of 2nd order with three different cutoff frequencies (in rad/s).

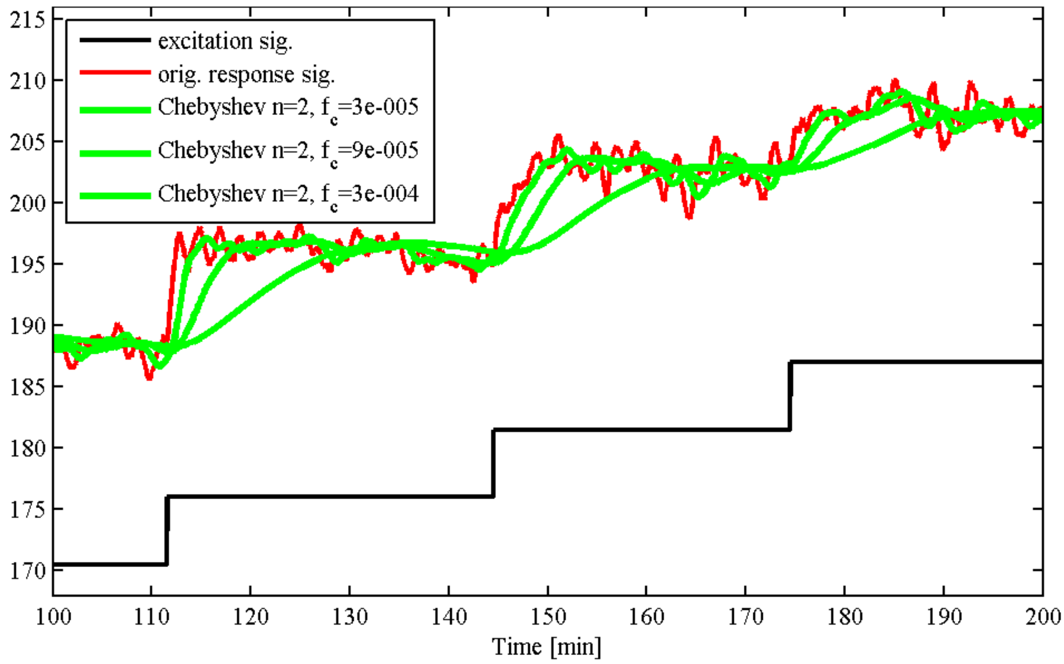

Fig. 4. Detail of the filtered response using Chebyshev filter of 2nd order with three different cutoff frequencies (in rad/s).

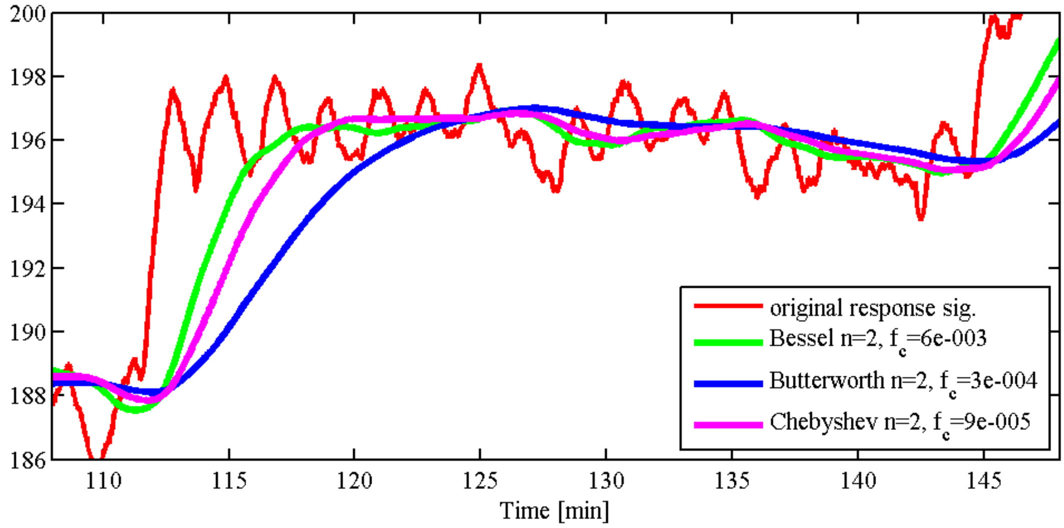

Fig. 5. Detail of the filtered response using three common linear filters.

3 CUSTOM FILTERS

Due to the inaccuracies discussed in the previous section, it was decided to use less common discrete filters. The first filter was Threshold filter. It is basically a non-linear modification of any of previous linear filters. The Threshold filter introduces a threshold element that allows filtering source signal only when the difference between source and filtered signal is smaller than defined threshold (Fig. 6).

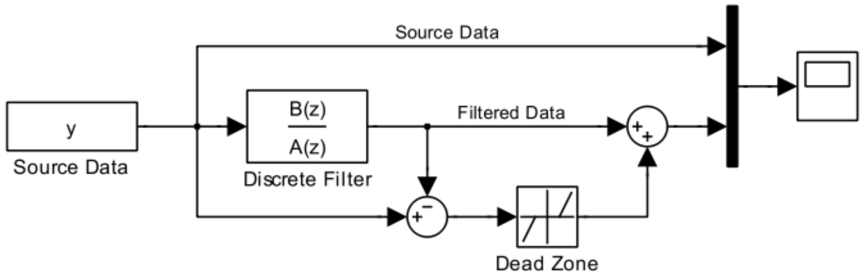

Fig. 6. Schematic view of Threshold filter algorithm.

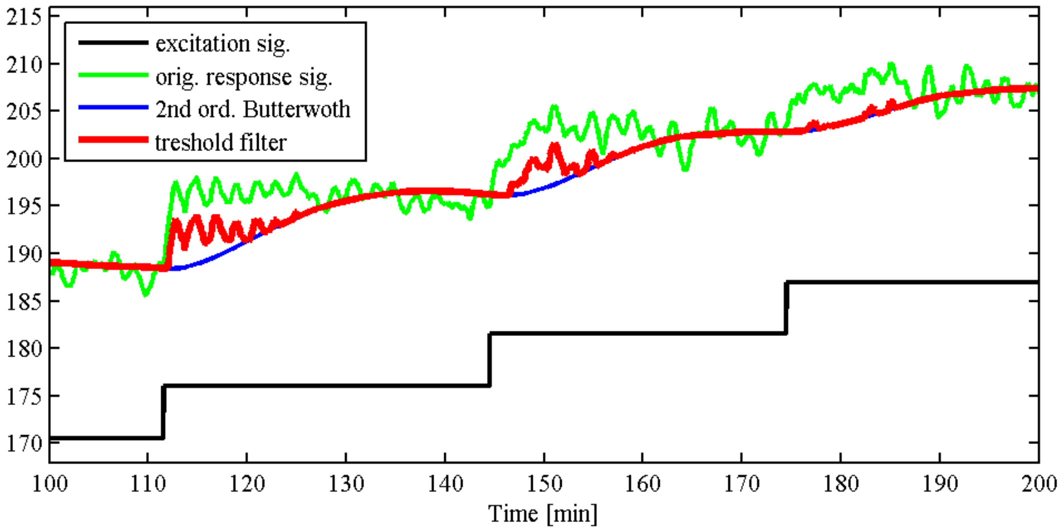

Fig. 7. – Detail of the filtered response using Threshold filter.

In Fig. 7 is shown the result of applying the Threshold filter on the response data with Butterworth filter used for signal filtering before the threshold element. The filter is able to switch between our two demands. When the source signal is "near" the filtered signal (noise level is inside threshold interval, that is) the filtered signal is perfectly smoothed by Butterworth filter. During fast transitions, when original signal moves away from the filtered signal (when the deviation from the signal is not considered as a noise anymore but as a transition) the Threshold filter bypass the Butterworth filter and passes the unfiltered signal to the output. A Drawback of the Threshold filter is that during fast transitions, the signal is not filtered at all.

The filter introduced in this paper is Gaussian weighted average filter published in [BORŽÍKOVÁ et. al. 2012]. The weighted average is computed using the standard equation:

$$y_i = \frac{w_1 x_1 + w_2 x_2 + \ldots + w_k x_k}{w_1 + w_2 + \ldots + w_k}$$

where: x means source sample,
w means Gaussian weight of the sample,
k means size of running average window and
y means filtered sample.

But the weights are computed using simplified Gaussian formula:

$$w_i = e^{\frac{-(x_i-\mu)}{2\sigma^2}},$$

where μ means mean value (taken from previous filtered sample) and
σ determines sensitivity of the weights computing function.

In Fig. 8 is the comparison of common running average with 1000 seconds wide running window, with Gauss-weighted running average with 500 seconds wide running window. It can be seen that the smoothing ability of Gauss-weighted running average with half size wide running window is comparable with common running average. It allows for using narrower running window for the Gauss-weighted running average for same smoothing but much faster filter response.

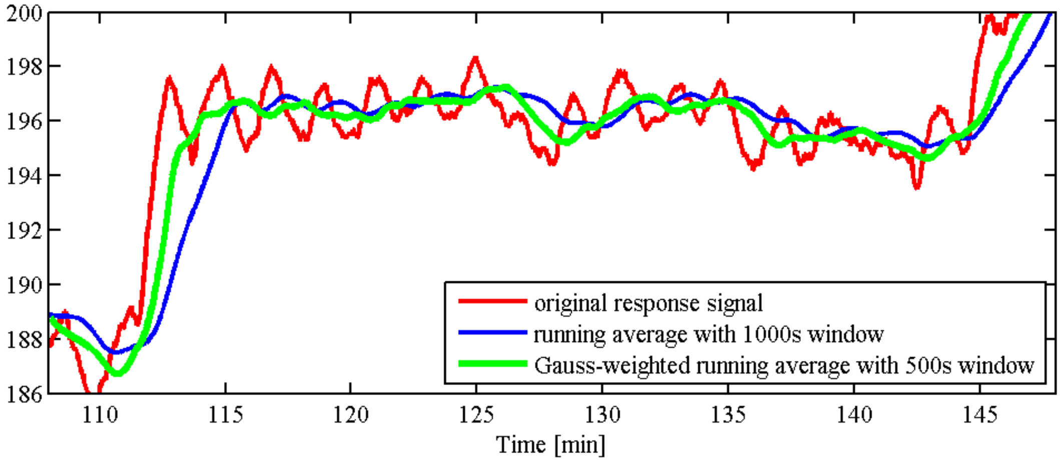

Fig. 8. Detail of the filtered response using Gaussian-weighted moving average

4 CONCLUSIONS

Three common linear filters and two less common non-linear filters were tested. The filters were used for smoothing a set of data measured during experiments on small-scale biomass boiler. It was shown that linear filters are able to smooth measured signal but weight the time rows with additional dynamic delay that may spoil proper system identification.

The Threshold filter is quite easy to implement and able to smooth signal sufficiently and at the same time show fast transients almost without dynamic delay. However, during fast transients the signal is not filtered at all.

The Gaussian-weighted running average filter adds smoothing ability to common running average filter. It is then possible get smoothing results similar as with running average with wide running window but with response as fast as with narrow running window.

This work has been supported by the Ministry of Education of the Czech Republic under the project No. MSM68400770035 “Development of environmentally friendly decentralized power systems”, which is gratefully acknowledged.

The work of Ph.D. students has been supported by Doctoral Grant Support of the Czech Technical University in Prague, grant No. SGS10/252/OHK2/3T/12.

The master studies of Mr. Emmanuel Placier in the Czech Technical University in Prague are sponsored by the National Council of Science and Technology of Mexico (CONACYT).

REFERENCES

PLAČEK, V., et. al. 2011. Investigation in Control of Small-scale Biomass Boilers. In *Proceedings of the 2011 12th International Carpathian Control Conference (ICCC)*, 312–315, Velké Karlovice, IEEE - Systems, Man, and Cybernetics Society, 2011

HAAPA-AHO J., et. al. 2011. Continuous Control Issues Concerning Operation Improvement of Small-Scale Biomass Boilers. In: *18th IFAC World Congress, 2011*.

BORŽÍKOVÁ, J., et. al. 2012. Využitie kľzavého váženého priemeru na filtrovanie meraných údajov. In: *ARTEP 2012*. Stará Lesná.