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OPTIMISATION OF DYNAMICS OF ON - LINE ASH MONITORS

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Abstract: On-line nuclear meters have been in use in the coal industry for many years. They have been utilised for coal quality monitoring, in the control systems for coal blending, or for separating coals in the heavy media separation process. Their operation is based on the scattering or the absorption of incident gamma radiation, and the derived density or ash value is the result of a time-averaged measurement. In this paper, dynamic models of ash monitors have been presented and discussed. The analysis of monitors with constant time of measurement shows that it is possible to determine the optimal time for which the dynamic error is the smallest. The analysis also shows that the monitors in which the time of measurement is variable and adapts to changes of the input signal give better result. A fuzzy logic decision table has been applied to control the time of measurement according to variations of the input signal. The simulation of the system operation has been performed with the use of the Matlab (Simulink) program package.

Keywords: fuzzy monitoring systems, ash content monitors.

1 INTRODUCTION

On-line nuclear meters such as heavy media and coal slurry densitometers or ash content in coals monitors have been in use in the coal industry for many years. They have been utilised for coal quality monitoring, in the control systems for coal blending, or for separating coals in the heavy media separation process. Their operation is based on the scattering or the absorption of incident gamma radiation, and the derived density or ash value is the result of a time-averaged measurement over a period of tens of seconds or even a few minutes. Such monitors cannot produce an exact dynamic record of the rapid variations in the parameter to be measured.

A general scheme of an on-line ash monitor is shown in the Figure 1. Signal processing is similar in all the three measuring methods (back-scattering, absorption, natural radiation). The only difference is the mean intensity of output pulses from the detector and the amount of pulses per second corresponding to the 1% of ash content change. The series of pulses from the detector (scintillation counter) are counted in a counter.

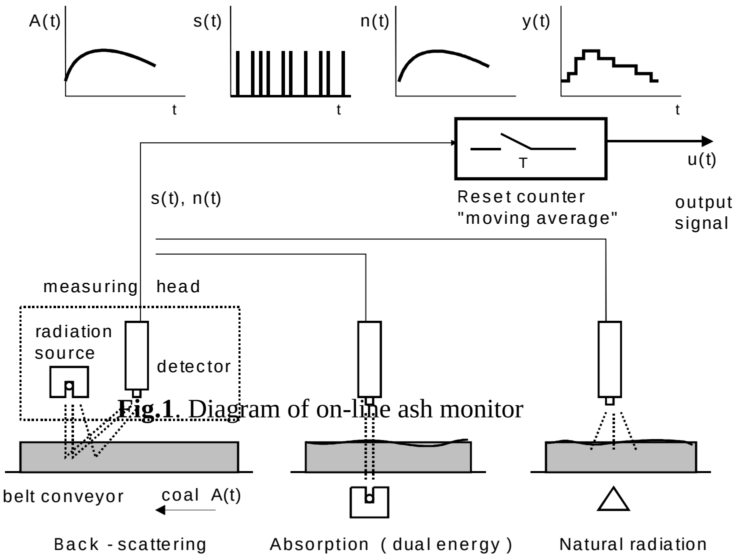


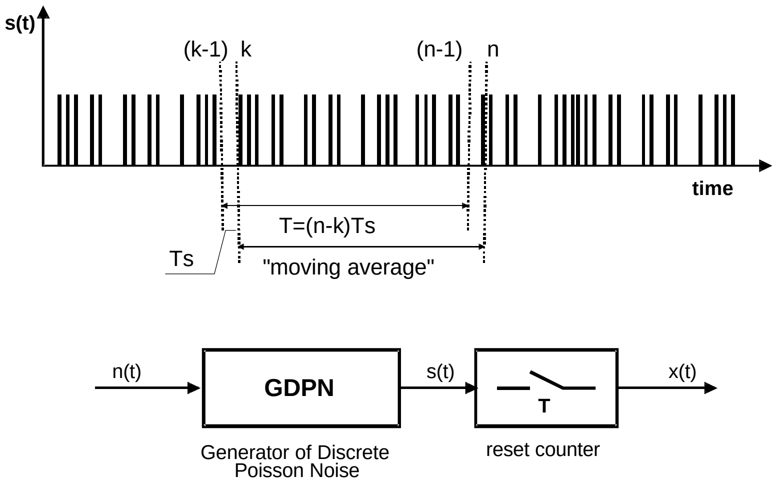
Figure 1. A general scheme of an on-line radiometric ash monitor.

The output signal from the detector is always a stochastic signal, regardless of the character of the input signal (i.e. ash content) modulating the intensity of the detected radiation beam. The longer the averaging time the higher the statistical (static) accuracy of the monitor. At the same time, if the input signal varies, the dynamic error of the measurement is higher. This suggests that for a given shape of the input signal and a given structure of the monitor circuit, one can find an optimal averaging time of input pulses, which gives the minimum dynamic error according to the accepted criteria. Furthermore, this leads to the application of a circuit with an adapting time constant. If the input signal is, for example, a step function and the ash monitor is to reproduce this change, the time of measurement should be small at the beginning of the measurement to speed-up the reaction of the meter and then it should become greater to read-out accurately the new value of the ash content.

The concept of an ash monitor with a time of measurement adapting to variations of the input signal (ash content) has been analysed. Such a system allows to speed-up the reaction of the instrument to rapid variations of ash content and at the same time to achieve better statistical accuracy for a longer period of time. This is particularly important in closed loop control systems or in splitting of a coal stream to different products.

2 DYNAMIC PROPERTIES OF ON-LINE ASH MONITOR

A detailed description of the operation of the ash monitor can be found in [3,4,5]. Let us assume that one wishes to measure accurately a step change of the ash content A(t) controlled by the monitor with the digital counter of pulses shown in the Figure 1. That means that the shape of the output signal u(t) should closely resemble the input step function so as to minimise the distance between A(t) and the output signal u(t).



Figure

2. Output signal from the detector s(t) and the model of the detector

For small changes of ash content A(t) in coal let us assume a linear relation with the mean intensity n(t) of
pulses s(t):

$$n(t) = n_o + \Delta n(t) = k_d * (A_o + \Delta A(t)) = k_d * A(t) \tag{1}$$

The mean intensity of pulses n(t) is determined in the counter with the “moving average”, counting at each elementary step T_σ (for instance nT_σ =1 sec) pulses from last “n-k” steps, as it is shown in Figure 2.

The output stochastic signal y(t) can be calculated from the equation:

$$y(nT_s) = \sum_{i=n-k}^{i=n} N_i \tag{2}$$

where N_i is the number of pulses which appeared in the interval of time T_s.

The mean value $M_y(nT_s)$ and the variance $D_y(nT_s)$ of the output signal y(t) can be calculated [5] from the equations:

$$M_y(nT_s) = \int_{(n-k)T_s}^{nT_s} n(t)dt \qquad D_y(nT_s) = \int_{(n-k)T_s}^{nT_s} n(t)dt \tag{3}$$

The "distance" L_k^2 between the input signal A(t) and the output signal u(t) and the mean value L^2 of L_k^2 are often defined [5] for k-th realisation of the stochastic process as follows:

$$L_k^2 = \int_o^{To} [kd * A(t) - u(t)]^2 dt \qquad L^2 = \lim_{k \to \infty} \frac{1}{k} \sum_{k=1}^{k} L_k^2 \tag{4}$$

The relation between *L* and the time of measurement T for a monitor with constant T is shown in Figure 3. Parameters of the monitor were as follows: k_d=100 %s^{-1}, n_o=10^4 s^{-1}. For short T the error of measurement L increases due to the poor filtration of the stochastic noise, for the optimum T reaches minimum, and for a long T the error L also increases due to the slow reaction of the monitor for the step-wise change of n(t).

The equations (4) can give an analytical solution for optimal parameters of the monitor for linear systems with constant parameters [4,5]. For non-linear adaptive circuits the computer simulation analysis can be used for optimisation of the monitor operation.

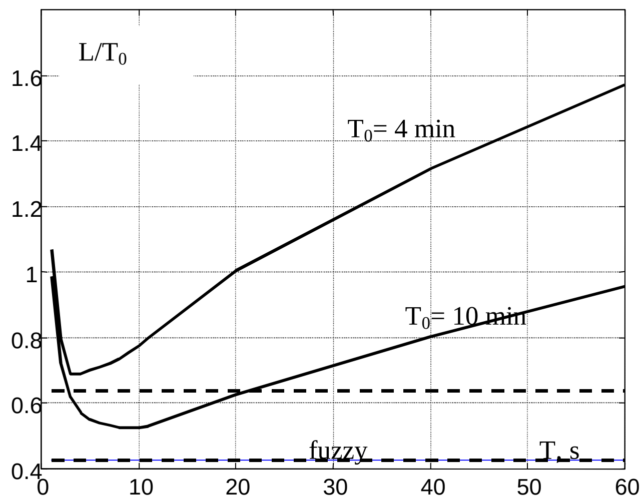


Figure 3. Dynamic error L/T_o as the function of constant time of measurement T (for T_o= 4 min and T_o=10 min)

3 FUZZY CONTROL OF MONITOR OPERATION

The model of an on-line ash monitor in which the concept of the adaptive time of measurement T has been applied, is shown in Figure 4. The monitoring system consists of (a) three low band discrete filters (FLT,FMT,FST) with weights set by (b) the fuzzy controller and (c) the differential filter (DF) which reacts to changes of the input signal.

3.1 Discrete filters

The basic elements of the fuzzy monitor are three discrete filters with long (FLT), medium (FMT) and short (FST) time of measurement. Each filter can be described by the equation (7):

$$y_{i(n)} = (1 - \acute{a}_i) \cdot y_{i(n-1)} + \acute{a}_i \cdot x_{(n)} \tag{5}$$

where: y_i - the output signal from the i-th filter,
x - the input signal to the filters,
σ_i - the coefficient forming dynamics of the filter ($0<\sigma<1$).

For the three filters with feedback from the output signal (sum of outputs from each filter) as is shown in Figure 4, the output signal $y_{(n)}$ can be described by equation (8):

$$y_{(n)} = y_{(n-1)} \left(1 - \sum_{i=1}^{N_f} w_i a_i \right) + \sum_{i=1}^{N_f} w_i a_i x_{(n)} \tag{6}$$

where: N_f - the number of filters,
w_i - the weight coefficient.

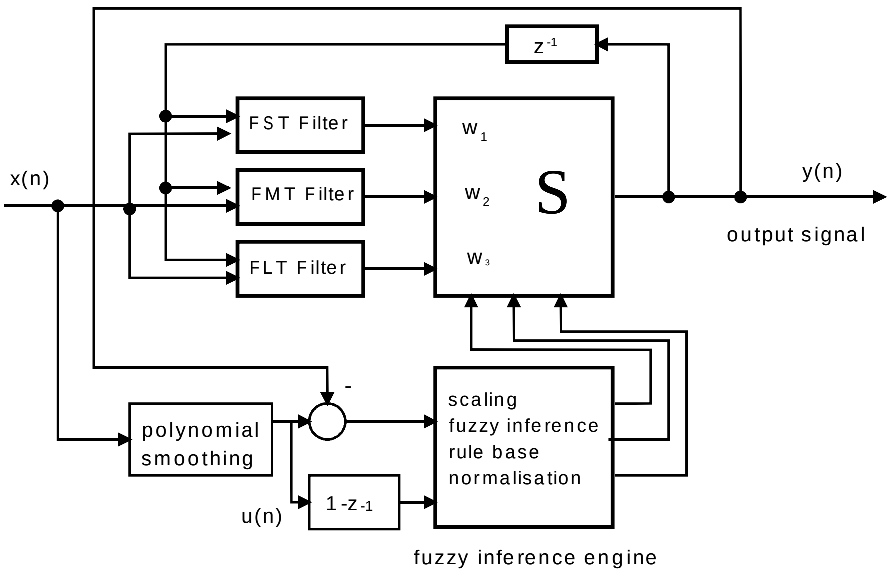


Figure 4. Model of the on-line ash monitor with the fuzzy controller

The feedback signal for the three filters eliminates step-wise changes of the output signal $y_{(n)}$ during filters switching. The proper choice of the weight coefficients w_i enables one to minimise the dynamic error of measurement and to shape the way in which the time of measurement adapts to changes of the input signal (in our case σ_1=0.03 (FLT), σ_2=0.2 (FMT), σ_3=0.7 (FST)).

3.2. Discrete differential filter (DF)

The weight coefficients w_i are chosen on the basis of the evaluation of the the input signal $x_{(n)}$ derivative. The input signal $x_{(n)}$ is strongly a stochastic signal due to the short time T_s of pulses s(t) counting . For this reason the signal $x_{(n)}$ is initially filtered with the use of 3^{rd} -order polynomial approximation of the last five samples $x_{(n)}$, $x_{(n-1)}$, ...,$x_{(n-4)}$. The difference $u_{(n-2)} – u_{(n-3)}$ (Fig.4) has been accepted as a measure of the derivative of the x(t). The time delay introduced by this way of derivative calculation is negligible in comparison to the dynamics of the input signal and the dynamics of the whole monitoring system.

3.3. Fuzzy controller

The derivative v_1 of the input signal x(t) and the difference v_2 between the output signal $y_{(n)}$ and $u_{(n)}$ (polynomial approximation of the last 5 samples of x) are accepted as input signals for the fuzzy controller which generates weight coefficients w_i for output signals from FST,FMT,FLT filters. Both signals are normalised (scaled) with the reference $N_{ref} = 3\, x_{(n)}^{1/2}$ (three standard deviations of the x(t) having Poisson distribution [1]). Due to this scaling, the rule bases for the fuzzy inference can be defined within the standard range <0...1>. This range has been divided to three categories described by corresponding fuzzy sets: QS -quasi-stable signals,
SV- slow changing signals, FV - fast changing signals.

Membership functions corresponding to these fuzzy sets have been shown in Figure 5. The fuzzy controller operates according to the linguistic formula:

if $\mathbf{v_1}$ is $\mathbf{A_i}$ and $\mathbf{v_2}$ is $\mathbf{A_j}$ then **w** is $\mathbf{B_{ij}}$

where: v_1 - normalised derivative of the input signal x(t),
v_2 - normalised difference between the output signal $y_{(n)}$ and $u_{(n)}$ (filtered x(t)),
A_i,A_j(QS,SV,FV) – fuzzy sets of three categories of input signals,
w - weight coefficient of a given filter,
B_{ij} - singleton of a value of *w* corresponding to the combination (A_i, A_j).

Singletons B_{ij} for different combinations of (A_i, A_j) are given in the Table 1.

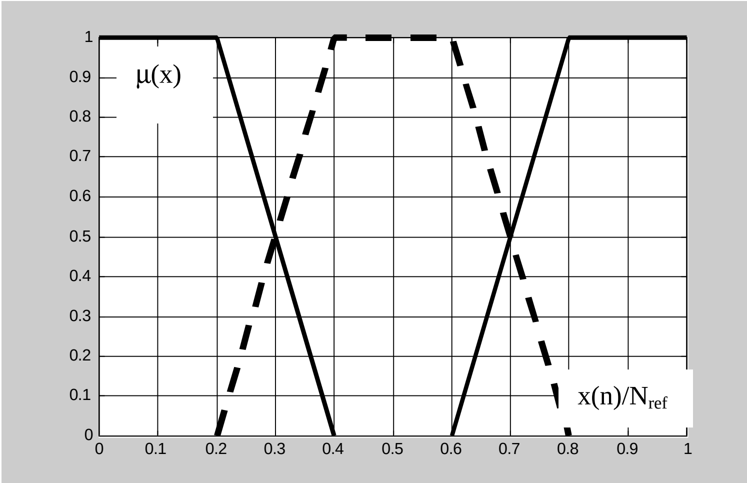


Figure 5. Membership functions

Table 1. The rule base of the fuzzy controller

difference v_2	value of derivative v_1								
	filter FST			filter FMT			filter FLT		
	QS	**SV**	**FV**	**QS**	**SV**	**FV**	**QS**	**SV**	**FV**
QS	1	0	1	0	1	0	1	0	0
SV	0	0	0	1	1	1	0	0	0
FV	1	1	1	0	0	0	0	0	0

The output signal from the fuzzy controller (weight coefficient *w*) is calculated as the sum of signals generated by all rules in the base for a given filter:

$$w_k = \sum_{i,j=1}^{N_i \times N_j} m_{ij} \cdot B_{ij} \qquad (7)$$

where: $k \in \{TST, FMT, FLT\}$
N_i - the number of rules for a given filter,
$\mu_{ij} = \min\{A_i(v_1), A_j(v_2)\}$.

The output signal from filters is calculated from the equation:

$$y(n) = \sum_{i=1}^{N_F} w_{iN} \cdot y_i(n) \qquad (8)$$

where:
$y(n)$ - output signals from the filters,
$y_i(n)$ - output signal from i-th filter,
w_{iN} - normalised weight coefficient w_i,
N_F - the number of filters applied.

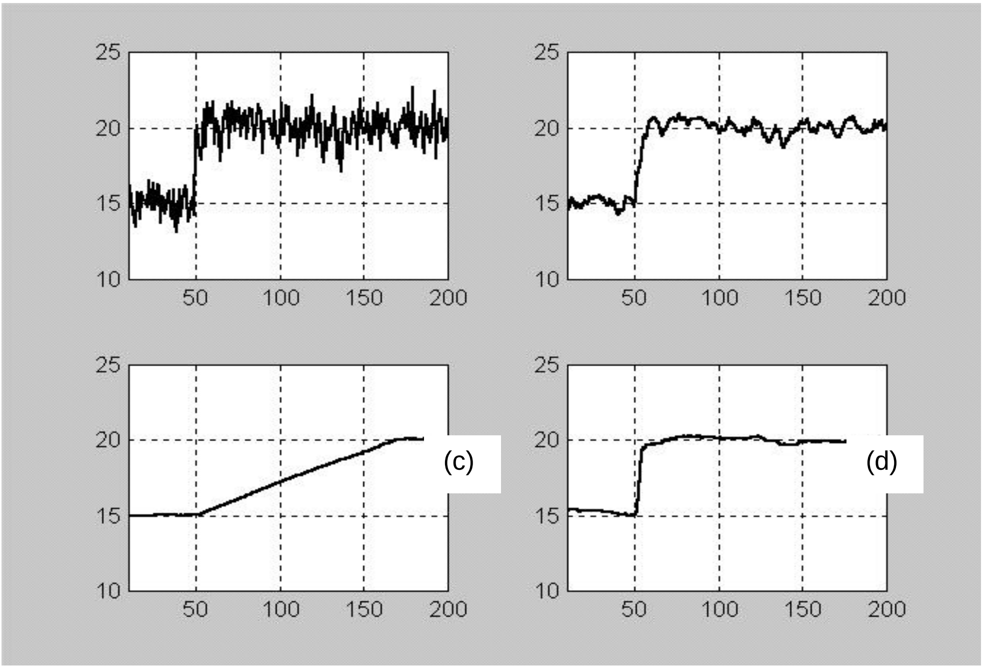


Figure 6. The response of the ash monitor (fig.4) to the step change of the ash content
time of measurement T : a) 1s, b) 5 s, c) 50 s, d) fuzzy

The on-line y(t) onitor with the fuzzy controll y(t) n in Figure 4 has been tested with use of Simulink (Matlab) program package. The response of the system is shown in Figure 5. The fuzzy control of the monitor operation (adaptive time of measurement) gives much better results than the operation with the constant time of measurement (Figure 3). The minimum dynamic error L_{min}/T_o = (0.53) for T_{opt} and for fuzzy system (a) (b)
L_{fuzzy}/T_o= (0.41).

4 CONCLUSIONS

One can consider the electronic circuit of an on-line ash monitor to be a generator of Poisson discrete noi y(t) he mean intensity of pulses c y(t) by the measured signal (ash content).

The analysis of the circuit dynamics shows that it is possible to determine the optimal time of measurement, which gives the minimum dynamic error of the measurement.

Dynamic properties of an on-line ash monitor can be upgraded in circuits in which the time of measurement adapts to changes of the input signal. Such a circuit can be designed with the use of fuzzy controller influencing the time of r (c) ement according to the conclusi (d) om the analysis of the output signal from the detector.

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