# An Adaptive Radiometric Meter with Variable Measurement Time for Monitoring of Coal Jigs Operation

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**Abstract:** The authors discuss the problem of how to monitor the coal/water pulsating bed in a jig with the use of a radiation density meter. The dynamic measurement error of changes in density depends on the time of measurement; its optimal value can be found for a given shape of density changes. An alternative method of the signal filtration is proposed using variable time of measurement during a cycle of pulsations as a function of the time derivative of the density changes. The shape of the density changes during one cycle varies slowly from a cycle to a cycle. This is why the time derivative of the density determined during one cycle can be used in the subsequent cycle to adapt periodically the algorithm generating the variable times of measurement during each cycle. The above time derivative can be calculated from the polynomial fit of stochastic data measured during the previous cycle. In this case, the dynamic error of the measurement *MSE* can be reduced significantly compared to the optimal constant time of the measurement. This methodology of signal filtration was applied in the simulation model and the results of simulation were compared with field measurements taken with the use of a conventional radiometric density meter.

***Keywords:*** density monitoring, radiometric measurements, dynamic errors, optimal filtration, coal preparation

## 1. INTRODUCTION

Radiometric density meters have been widely used in the industry to monitor various technological processes such as mineral processing or coal beneficiation in heavy media systems or jigs. The application of these instruments to monitor coal separation processes in jigs was discussed in detail by Lyman (1991), Loveday & Jonkers (2002) and more recently by Cierpisz & Joostberens (2016a). Most radiometric density meters use gamma-ray absorption where the mean intensity of detected radiation depends on the density of the monitored media.

Various types of detectors used in such systems were reviewed by Knoll (2000). The output signal from the detector $s(t)$, in on line monitors, is usually a non-stationary series of pulses of Poisson distribution (Knoll, 2000, Cierpisz & Joostberens, 2016a). The mean value $n(t)$ of pulses counted over time $\tau_s$ is a function of the measured media density modulating the intensity $I$ of the detected radiation beam (Fig. 3). Generally, the longer the time of measurement $\tau_s$, the higher the accuracy of the monitor when the measured density is constant over time. However, when density varies, the dynamic error of measurement increases the longer is the time of measurement $\tau_s$. This applies to coal separation jig machines in which stratification of coal grains takes place in a pulsating coal/water bed. This problem was discussed by Cierpisz & Joostberens (2016a). The measured parameter (e.i. density) can be generally a stochastic process. Output signal $s(t)$ in such a case called "doubly nonstationary Poisson process" was discussed in details by many authors such as Snyder & Miller (1991), Picinbono (2014), Leveille & Hamel (2018). General problems of filtration of discrete non homogenous Poisson processes was discussed by many authors such as Centanni et. al. (2011) and Korbel (2011). Few articles were devoted to on-line monitoring systems in which filtration of non-stationary signals was an essential problem. Adaptive analogue filters of output signals from radiation detectors in on-line monitors (density measurements) were analysed by Cierpisz & Joostberens (2016b). Application of fuzzy logic in signal filtration in ash content monitors was discussed by Cierpisz & Heyduk (2003). The aim of this paper is to present and discuss a new method of signal filtration using an adaptive discrete filter with a variable time of measurement.

## 2. TECHNOLOGICAL OBJECTIVE

Raw coal is often beneficiated in gravitational processes, where coal grains are stratified according to their densities in a pulsating coal/water medium in jigs. This problem was discussed in many papers by Jonkers et al. (2000), King (2001). Lyman (1992) and Cierpisz & Joostberens (2018). Separation of stratified material is based on a chosen separation density which is the density of the layer reporting in half to the upper product (concentrate) and in half to the discharged lower product (refuse). The refuse is removed through the discharge gate and the concentrate overflows the splitting gate. The quality of products is determined by the density of the separation layer. Its position should be monitored on-line and kept at the splitting-gate level regardless of the changes in the tonnage of the feed or changes in the washability characteristics of the raw coal. It is usually measured by a metal float of a required shape and density.

The desired position of a float is stabilised through controlling the amount of the lower product discharged through the bottom gate. Float is not accurate in indicating the chosen density layer, especially with changes in the amount of the feed and varying composition of grains. In new experimental systems, floats are being replaced by more accurate radiometric density meters which can monitor the process of material loosening/compressing during each cycle of coal/water pulsations. The output signal from a radiometric meter can be used for two purposes: (a) to stabilise the shape of dynamic changes in the density and (b) to stabilise the separation density measured when material is compressed at the end of the cycle.

The typical dynamic change in coal/water density in a single cycle of the separation process is shown in Fig. 1.

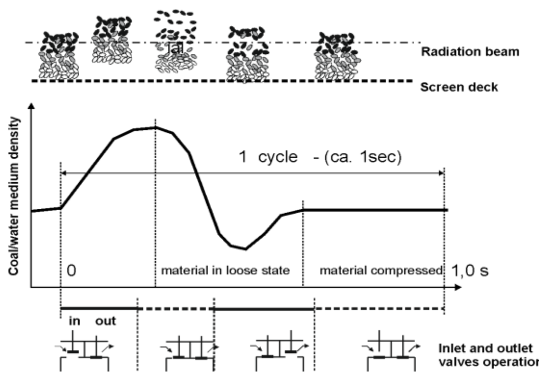


Fig. 1. Changes in medium density over a single cycle of pulsations (the density measured by the radiometric density meter at the level of the upper product gate – dotted line) - (Cierpisz & Joostberens, 2016a).

At first, while the inlet air valve is opened, the material is lifted upwards without loosening the upper part of the coal bed. Then the material gradually separates, the inlet valve is closed and grains sink again to be consolidated at the end of the cycle. The outlet air valve is opened to speed-up the sinking. Then the outlet valve is closed to ensure the same hydraulic conditions for the next cycle. The shape of changes in density at the level where the concentrate overflows the upper discharge gate varies due to variations in the feed tonnage, density composition of the grains and fluctuations in air pressure in the air collector. To achieve the best conditions for coal separation, i.e. the optimal stratification of grains according to their density and constant separation density in the jig, the shape of changes in density during each cycle of pulsations should be stabilised. The radiometric density monitor should reproduce changes in medium density with minimum error to achieve the best monitoring and control results.

The range of the density change is ca. +0,2 g/cm$^3$ to -0,1 g/cm$^3$ around its steady value (1,2–1,7 g/cm$^3$). It is in the first part (50-70%) of the cycle that the conditions of separation should be stabilised over feed variations, as this phase is characterised by significant variations in the density of the bed. However, the separation density measured when the material is compressed also varies due to feed fluctuations and operation of the refuse discharge gate. Predictably, these two processes have contrasting dynamics as it is presented in Fig. 2 which shows density changes in 10 cycles typical for the whole process registered during a shift. Industrial tests of the monitoring system were performed in the "Rydultowy" mine (Joostberens, 2019). The density $\rho(t)$ was measured by the radiometric density meter with constant time of measurement $\tau_s$ = 50 ms. The real density $\rho(t)$ is not known exactly and can be only modeled by the output signal from the meter $y(t)$. The stochastic process $y(t)$ during each *j-th* cycle was modeled by the equation (1) (Joostberens, 2019).

$$\rho(t) \approx y(t) = A_j \cdot e^{-\alpha_j \cdot t} \cdot sin\, sin\left(\omega_j \cdot t - \psi_j\right) + \varphi_{uj} \qquad (1)$$

where:

$A_j$, $\alpha_j$, $w_j$, $\Psi_j$, $\varphi_{uj}$ – parameters of equation (1) for *j-th* cycle

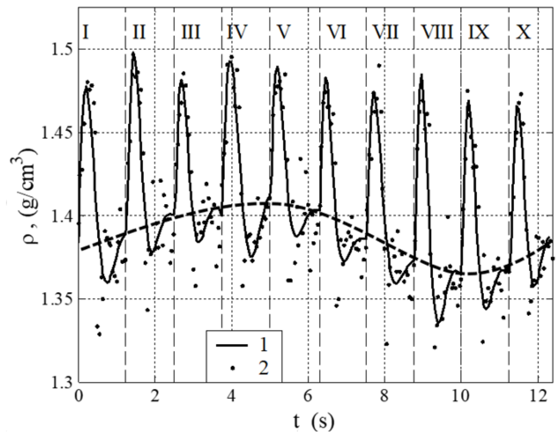


Fig. 2. Changes in the medium density over a longer period of time (10 cycles), 1 – model eq. (1), 2 – measurement data dashed line – separation density

The slope of the function for the dynamic density change over a single pulsation cycle is ca. 1,0-2,0 g/(cm$^3$ s), whereas for the separation density (dotted line)) it is (0,1 ÷ 0,5)·10$^{-2}$ g/(cm$^3$ s). This suggests that the density change identified in a single pulsation cycle could be used to estimate the optimal filter parameters for the next cycle. This concept will be analysed in more details in the later part of the paper.

## 3. THE METHOD OF SIGNAL FILTERING FROM THE DIGITAL RADIOMETRIC METER

The proposed methodology of the signal $s(t)$ filtration to measure rapid changes in the density in each cycle, basing on the relatively slow change in the shape of $\rho(t)$ in subsequent cycles, is as follows:

a) the proposed filter (counter of pulses) adapts the time of measurement $\tau_s$ to the time derivative of $\rho(t)$ – the higher value of $d\rho(t)/dt$, the shorter time of measurement $\tau_s$,

b) the time derivative $d\rho(t)/dt$ in the measured cycle will be estimated on the basis of the polynomial fit of $\rho(t)$ changes in the previous (or earlier) cycle or on the basis of averaged changes of few (in our case - 10) cycles,

c) the limit values of the measurement time $\tau_{s(min)}$ and $\tau_{s(max)}$ will be determined using the criterion minimising the error of $\rho(t)$ measurement.

This methodology will be discussed in details below.

The output signal $s(t)$ from the scintillation detector can be processed in an analogue integrator or as a moving average number of pulses $y_c(t)$ counted during the time of measurement $\tau_s$ as it is shown in Fig. 3. The relation between the measured medium density $\rho(t)$ and the mean intensity of registered pulses $\lambda(t)$ is theoretically exponential and can be described by following equations:

$$\rho(t) = a_0 - a_1 \cdot ln(\lambda(t)) \tag{2a}$$

$$a_0 = \frac{\ln(\lambda_0)}{\mu \cdot x},\ a_1 = \frac{1}{\mu \cdot x} \tag{2b}$$

$\lambda$ – mean number of pulses in time $\tau_s$,
$\lambda_0$ – number of pulses for the reference density (e.g. air),
$\mu$ – mass absorption coefficient,
$x$ – thickness of the absorbent,
$\rho$ – density of the absorbent.

The parameters of the calibration characteristics of the tested density meter were: $\lambda_0 = 4.7 \cdot 10^5$ 1/s, $\mu = 0.083$ cm$^2$/g for the radiation source $^{137}$Cs and coal/water bed (Knoll, 2000), $x = 30$ cm (the distance between the radiation source and the detector).

In the simulation analysis of the industrial monitoring system presented in this paper the following values of parameters have been accepted: $a_0 = 5.250$, $a_1 = 0.402$. These values were derived from the practical parameters of the radiometric density meter tested in one of mines (Joostberens, 2019).

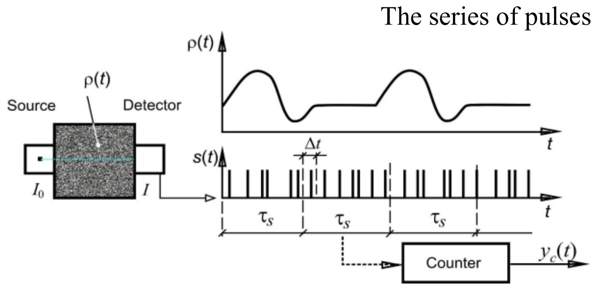


Fig. 3. Digital filtration of a stochastic signal from the detector (Cierpisz & Joostberens, 2016a).

The measurement time $\tau_s$ is constant in typical industrial radiometric monitoring systems. Extending the measurement time $\tau_s$ reduces the statistical error of the measurement but at the same time deteriorates the dynamic properties of the density meter. On the other hand, the short measurement times improve the dynamic properties of the meter, but increase stochastic fluctuations in the signal $y_c(t)$. The optimal $\tau_s$ value for a known change of the media density $\rho(t)$, can be determined from the minimum value of the mean square error (*MSE*):

$$MSE_c = \frac{1}{N_i} \sum_{m=1}^{N_i} (y_c[i] - \rho[i])^2 \tag{3}$$

where: $N_i$ – number of data used for computation of $\tau_s$.

The proposed method of the discrete counter design for the radiometric monitoring system of the coal bed pulsations in a jig is based on the analysis of variations in the density profile as a function of time. Changes in the density profile over a longer period of time are relatively slower in comparison to changes taking place in a single coal/water pulsation cycle (Fig. 3). The amplitude and slope of the density as a function of time differs from one cycle to another by no more than 10%. However, during the $n$-th cycle those changes can be significant when compared to the first cycle. Therefore a valid solution to this problem would be to examine the progression of density changes in one cycle (using for instance eq.1)) and to use this information to optimise the time of measurement $\tau_s$ in the following cycles. The time derivative of the identified model (1) can be used to change on-line times of measurement $\tau_s$ during each cycle. This method of a counter design is a combination of two methods discussed by Cierpisz & Joostberens (2016a, 2016b). At first, let us consider the method of determination the constant time of measurement $\tau_s$ for the *j-th* cycle on the basis of information gained during the measured data in (*j*–1)-*th* cycle.

### *3.1. The radiometric meter with the constant time of measurement during a cycle*

The principle of operation of the meter with the constant time of measurement $\tau_s$ is shown in simplified form in Fig. 4. The time $\tau_s$ is constant during the *j-th* cycle and is set on the basis of information gained during the previous (*j*–1)-*th* cycle.

The $s[i]$ signal processing system consists of the main counter producing the output signal $y_c[i]$, the counter 1 with a short measurement time $\tau_{s(id)}$ converting the series of pulses $s[i]$ into the signal $y(t)$. Then the signal $y(t)$ polynomial approximation $y_{ref}(t)$ is performed. The signal $s[i]$ is registered also in the data recording block to process data from previous cycles. The counter 2 performs the simulation procedure of finding the optimal time of measurement $\tau_s$ minimising the mean square error between $y_{ref}(t)$ and $y_c(t)$. The signal $y_c(t)$, registered during field measurements, for 10 cycles of pulsations (equation (1)) is used in off-line simulation to estimate the dynamics of the real density signal $\rho(t)$ and to find the optimum time $\tau_{s(id)}$ of identification of $y(t)$. For the simulation analysis the generator of the Poisson discrete series of pulses (GSDP) was used.

Let us accept a polynomial $y_{ref}[i]$ for identification of the changes in the output signal from the detector $s[i]$:

$$y_{ref}[i] = \sum_{q=0}^{q=P} g_q \cdot i^q \tag{4}$$

This approximation makes calculations faster than equation (1). The optimum parameters of the equation (4) can be found minimising the criterion (5):

$$J_P = \sum_{i=1}^{N} \left( y[i] - \sum_{q=0}^{P} g_q \cdot i^q \right)^2 \tag{5}$$

where: $N$ – the number measured raw data.

In this way we can find optimum parameters $g_0, g_1, g_2, \ldots g_P$ of the polynomial (4) filtering the signal $y[i]$ at the output of the counter 1.

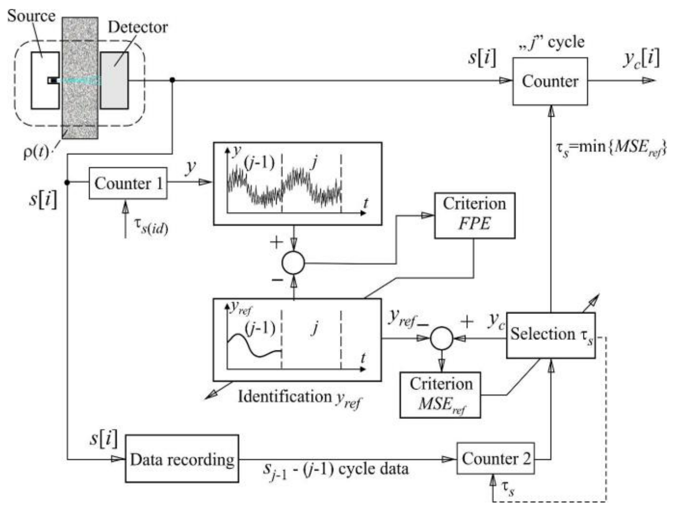


Fig. 4. The method of selection of the optimum constant measurement time $\tau_s$ based on the reference signal $y_{ref}$

The degree of the polynomial ($P$ = 5) was found using the criterion (*FPE*) of *Final Prediction Error* (Akaike, 1974). The time of measurement $\tau_{s(id)}$ used in this identification should be preferably short but properly selected. Time $\tau_{s(id)}$ is constant and not changed during a long period of the density meter operation (e.g. a shift) and can be determined minimising the criterion (6):

$$J_s(\tau_{s(id)}) = \sqrt{\frac{\sum_{i=0}^{Nj}\left(y_{ref}[i]-\rho[i]\right)^2}{\sum_{i=0}^{Nj}(\rho[i])^2}} \tag{6}$$

To minimise the criterion (6) we used off-line the GDSP generator and 5 series of the density changes during 10 pulsation cycles (equation (1)). The optimal time of identification was ca. $\tau_{s(id)}$ = 20 ms.

The simulation analysis of the system presented in Fig. 4 was performed using Matlab software. The radiometric density meter was modeled as a generator of a discrete Poisson series of pulses (GDSP) with modulated mean intensity value, described by the equation (1). The generator was based on the method presented by Li (2011).

The mean value of $\tau_s$ for 10 cycles can be calculated (Larminat & Thomas, 1983) from the equation (7) and is shown in Fig. 5:

$$J_c = \sqrt{\frac{\sum_{i=0}^{Nj}(yc[i]-\rho[i])^2}{\sum_{i=0}^{Nj}(\rho[i])^2}} \tag{7}$$

$N_i$ – number of data used for calculation of $\tau_s$.

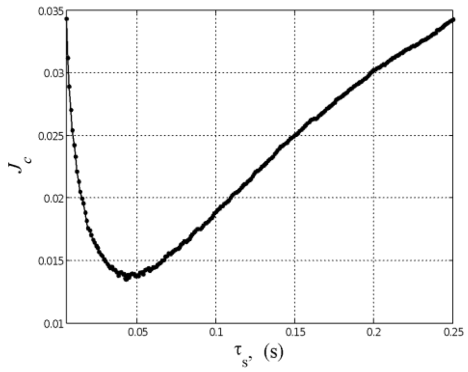


Fig. 5. The $J_c$ (eq.4) as a function of the time of measurement $\tau_s$ for 10 cycles of pulsations

The optimum time of measurement for 10 cycles is $\tau_{s(min)}$ = 43ms and the minimum $MSE_c = 0.361 \cdot 10^{-3}$. The $MSE_c$ for constant $\tau_s$ during each *j-th* cycle determined from data in (*j*-1)-*th* cycle is $0.387 \cdot 10^{-3}$. The example of changes in the density and the output signal from the counter is shown in Fig. 6.

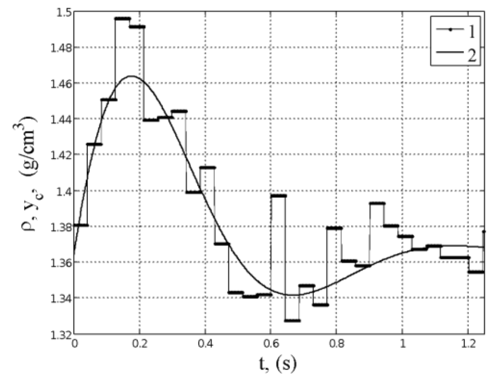


Fig. 6. Change in the density in the VIII cycle (filtered from measured data using eq. (1)) and the output signal from the counter (2) at the $\tau_s$ = 43 ms (Fig. 4)

### *3.2. The radiometric meter with the variable time of measurement during each cycle*

The principle of operation of the meter with the variable time of measurement $\tau_s$ during each cycle is shown in Fig. 7. This method is based on the time derivative of the signal $y_{ref} \approx \rho(t)$ which is used to adjust the proper times $\tau_s$ during a pulsation cycle:

$$\tau_s = f\left(\frac{d\rho(t)}{dt}\right) \tag{8}$$

For $y_{ref}$ approximated by a polynomial (5) we have:

$$\frac{d\rho}{dt} = \frac{dy_{ref}}{dt} = \sum_{q=1}^{P} q \cdot g_q \cdot i^{q-1} \tag{9}$$

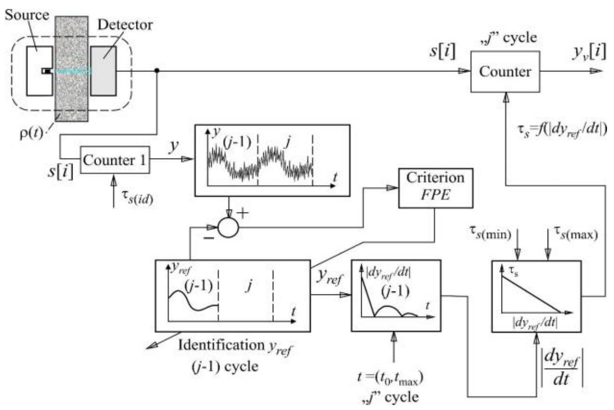


Fig. 7. The method of selection of the variable time of measurement $\tau_s$ during each cycle of pulsation

Let us normalize the time $t$ and the density in the range [0, 1]:

$$t_N = \frac{t - t_0}{t_{max} - t_0} \tag{10}$$

$$\left(\frac{d\rho}{dt}\right)_N = \frac{\frac{d\rho(t)}{dt} - \left(\frac{d\rho}{dt}\right)_{min}}{\left(\frac{d\rho}{dt}\right)_{max} - \left(\frac{d\rho}{dt}\right)_{min}} \tag{11}$$

where:

$t_N$ – normalized time [0, 1],

$t_0$ – the beginning of the pulsation cycle,

$t_{\max}$ – the end of the pulsation cycle,

$(d\rho/dt)_N$ – normalized derivative $d\rho/dt$,

$(d\rho/dt)_{\min(\max)}$ – expected (minimum/maximum) value of $d\rho/dt$ during the pulsation cycle.

The time of measurement $\tau_s$ should depend on the value of the derivative $d\rho/dt$ and not on its sign. Hence the equation (8) should be rewritten as follows:

$$\tau_{sN} = f\left(\left|\left(\frac{d\rho}{dt}\right)\right|_N\right) \tag{12}$$

To establish a proper relation between the time of measurement and the time derivative of the density, the following relations were tested: exponential, quadratic and linear (Cierpisz & Joostberens, 2018). The linear relation (13) appeared to be one of the best and also the simplest:

$$\tau_{sN} = -\left|\left(\frac{d\rho}{dt}\right)\right|_N + 1 \tag{13}$$

Values of the time of measurement $\tau_s$ can be calculated from normalized values as follows:

$$\tau_s = (\tau_{s(max)} - \tau_{s(min)}) \cdot \tau_{sN} + \tau_{s(min)} \tag{14}$$

Values of the mean square error $MSE_{v(j)}$ can be determined minimising the criterion (Joostberens, 2019):

$$MSE_{v(j)}(j) = \frac{1}{N}\sum_{i=1}^{Nj}\left(y_{v(j)}[i] - \rho_{(j)}[i]\right)^2 \tag{15}$$

where:

$y_{v(j)}$ - the output signal from the density meter at the variable time of measurement for the *j-th* cycle of pulsations,

$N_j$ - the number of data during the *j-th* cycle.

Values of $\tau_{s(min)}$ and $\tau_{s(max)}$ can be found from the criterion (16) and their optimum values minimise this criterion.

$$J_v(\tau_{s(min)} or\ \tau_{s(max)}) = \sqrt{\frac{\sum_{i=0}^{Nj}(y_v[i] - \rho[i])^2}{\sum_{i=0}^{Nj}(\rho[i])^2}} \tag{16}$$

$N_j$ - the number of data for $J$ cycles.

Mean values of the criterion (16) as functions of $\tau_{s(min)}$ and $\tau_{s(max)}$ are shown in Fig. 8 and Fig. 9.

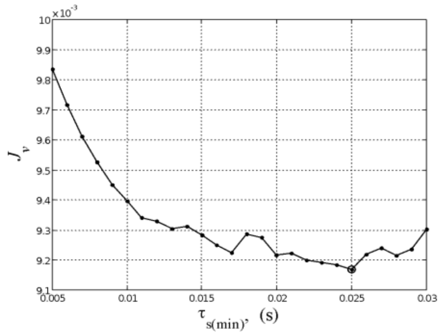


Fig. 8. The criterion $J_v$ as a function of $\tau_{s(min)}$

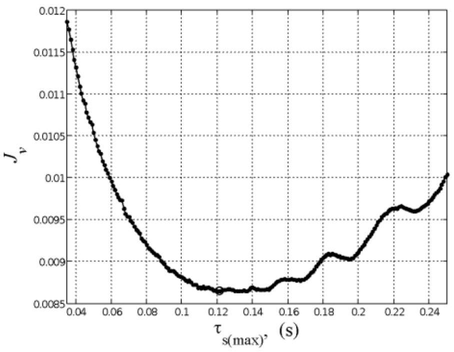


Fig. 9. The criterion $J_v$ as a function of $\tau_{s(max)}$

The mean optimal values are: $\tau_{s(min)opt} = 25$ ms and $\tau_{s(max)opt} = 122$ ms. The $MSE_v$ for variable mean $\tau_s$ for all averaged 10 pulsation cycles (eq. (1)) is $0.206 \cdot 10^{-3}$. An example of the output signal $y_v[i]$ as a function of time for the variable time of measurement $\tau_s$ is presented in Fig. 10.

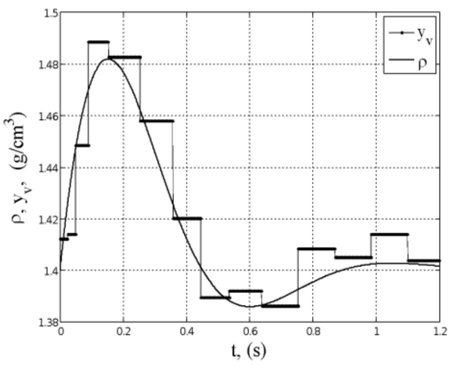


Fig. 10. Change in the density in the VIII cycle ($\rho$) and the output signal from the counter ($y_v$) for variable $\tau_s$.

$MSE_v$ for variable $\tau_s$ during each *j-th* cycle determined from data in (*j*–1)-*th* cycle is $0.182 \cdot 10^{-3}$. Detailed information on $MSE_v$ values for each of all 10 cycles is presented in Table 1.

**Table 1. Values of $MSE_{vj}$ (x$10^{-3}$) for variable time of measurement $\tau_s$ computed on the basis of time derivative in the previous (*j*-1) cycle (5 series of simulations using eq.(1))**

| Cycle | Series | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| II | 0.195 | 0.206 | 0.220 | 0.220 | 0.227 |
| III | 0.273 | 0.152 | 0.150 | 0.163 | 0.124 |
| IV | 0.372 | 0.203 | 0.151 | 0.136 | 0.193 |
| V | 0.171 | 0.201 | 0.209 | 0.214 | 0.177 |
| VI | 0.137 | 0.238 | 0.318 | 0.266 | 0.412 |
| VII | 0.214 | 0.128 | 0.118 | 0.091 | 0.191 |
| VIII | 0.290 | 0.265 | 0.211 | 0.238 | 0.257 |
| IX | 0.184 | 0.187 | 0.177 | 0.175 | 0.185 |
| X | 0.281 | 0.262 | 0.279 | 0.235 | 0.226 |
| II – IX | 0.203 | 0.175 | 0.172 | 0.166 | 0.195 |
| II - IX | 0.182 | | | | |

The summary of mean square error values of the density measurement is presented in the Table 2.

**Table 2. The summary of $MSE$ (x$10^{-3}$) values for analysed methods of $\tau_s$ determination**

| | |
|---|---|
| a) Constant time of measurement $\tau_s$ for all 10 pulsation cycles ($\tau_s$ = 43 ms) | $MSE_c = 0.363 \cdot 10^{-3}$ |
| b) Constant $\tau_s$ during each *j-th* cycle determined from data in (*j*–1)-*th* cycle | $MSE_c = 0.387 \cdot 10^{-3}$ |
| c) Variable mean $\tau_s$ for all 10 pulsation cycles | $MSE_v = 0.206 \cdot 10^{-3}$ |
| d) Variable $\tau_s$ during each *j-th* cycle determined from data in (*j*–1)-*th* cycle | $MSE_v = 0.182 \cdot 10^{-3}$ |

## 4. CONCLUSIONS

The signal from the radiometric density meter is a non-stationary series of pulses which mean intensity is a function of measured density. In case of the pulsating coal/water bed in a jig, adaptive filters of the signal should be applied to measure rapid changes in the density. The time of measurement should adapt to the time derivative of the variable density; it should decrease with the increase of the speed of the density changes. The shape of rapid cyclic variations in the bed density changes relatively slowly in subsequent cycles so the time derivative of the density in measured cycle can be estimated from data measured during the previous cycle. This method of measurement gives much smaller dynamic errors of measurement than conventional counters of pulses with constant time of measurement.

The best results ($MSE_v = 0.182 \cdot 10^{-3}$ $(g/cm^3)^2$) have been achieved for the filter with the variable time of measurement $\tau_s$ computed on the basis of values of the time derivative computed from the polynomial fit of measured values during the previous bed pulsation cycle.

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## REFERENCES

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, Vol. AC-19, No.6, p. 716-723.

Centanni, S., Minozzo, M., Tardelli, P. (2011). Continuous Time Filtering for a Class of Marked Doubly Stochastic Poisson Processes. Working Paper Series. Department of Economics, University of Verona. ISSN: 2036 – 4679.

Cierpisz, S., Joostberens J. (2016a). Monitoring of a coal separation in a jig using a radiometric density meter. *Measurement*. Vol.80, 2016.

Cierpisz S., Joostberens J. (2016b). Optimization of a Radiometric Density Meter for Monitoring of a Coal Separation Process in a Jig. *IFAC MMM Conference*, Vienna 2016.

Cierpisz S., Joostberens J. (2018). Monitoring of coal jig operation using a radiometric meter with a variable time of measurement. *Mineral Engineering Conference MEC* Zawiercie, Poland 2018.

Joostberens, J. (2019). *Optimisation of dynamic properties of a radiometric meter in control system of a coal jig*. Monograph no.791, Silesian University of Technology, Gliwice (in Polish).

King, R.P. (2001). *Modeling & Simulation of Mineral Processing Systems.* Butterworth-Heinemann Linacre House, Oxford.

Knoll, G. F. (2000). *Radiation Detection and Measurement*. John Wiley & Sons.

Korbel, K. (2011). Noise, Signal and Filtration in Nuclear Spectrometry. AGH University of Science and Technology. Cracow, Poland, (in Polish).

Larminat P., Thomas. Y. (1983). *Automation – linear systems*. Vol 2, Identification. WNT, Warsaw. (in Polish).

Leveille, E., Hamel, P. (2018). Conditional, Non Homogeneous and Doubly Stochastic Poisson Processes with Stochastic Discounted Claims. *Methodology and Computing in Applied Probability* vol.20, pp.353-368.

Li, Z. (2011). The stability of delays BAM neural networks with variable-time and Poisson arrival impulses. *Proc. of the Fourth International Workshop on Advanced Computational Intelligence IWACI (Wuhan, China)*

Lyman, G. J. (1992). Review of jigging principles and Control. *Coal Preparation*, 11, 41-72.

Loveday, G., Jonkers, A. (2002). The Apic jig and the ScanJig controller take the guess-work out of jigging. *Proceedings of the 14th ICPC*. Johannesburg, RSA, 247-251.

Picinbono, B. (2014). Simulation of Some Doubly Stochastic Poisson Point Process *Communications in Statistics - Simulation and Computation* vol. 43, issue 7.

Snyder, D. R, Miller, M. (1991). *Random Point Process in Time and Space* (New York: Springer – Verlag).