A R C H I V E S O F M E T A L L U R G Y A N D M A T E R I A L S
Volume 58 2013 Issue 3
DOI: 10.2478/amm-2013-0080

J. KOWAL*, J. DAŃKO**, J. STOJEK*

QUANTITATIVE AND QUALITATIVE METHODS FOR EVALUATION OF MEASUREMENT SIGNALS ON THE EXAMPLE OF VIBRATION SIGNALS ANALYSIS FROM THE CORPS OF PROTOTYPE RECLAIMER REGMAS

ILOŚCIOWE I JAKOŚCIOWE METODY OCENY SYGNAŁÓW POMIAROWYCH NA PRZYKŁADZIE ANALIZY SYGNAŁÓW WIBRACJI PROTOTYPOWEGO REGENERATORA MAS FORMIERSKICH REGMAS

The article presents examples of vibration signals analysis derived from the research of prototype reclaimer REGMAS. After the division of the time-frequency analysis methods of measuring signals, their non-parametric and parametric models were estimated. At the end of the article the summary and conclusions were set.
Keywords: mould sand reclaimer, vibration signals, signal analysis, parametric and non-parametric models, time series

W artykule zaprezentowano przykłady analizy sygnałów wibracji uzyskanych z badan prototypowego regeneratora mas formierskich REGMAS. Po dokonaniu podziału czasowo-częstotliwościowych metod analizy sygnałów pomiarowych, wyznaczono ich modele parametryczne i nieparametryczne. Na końcu zawarto podsumowanie oraz wnioski końcowe dotyczące przedstawionych analiz.

1. Introduction

The effective source of information about the phenomena occurring during the operation of machinery are appropriately selected and correctly applied numerical methods of signal analysis. Properly prepared and analyzed measuring signals can be use to control device, monitoring the performance of the device or use to their wider diagnosis. In this article the analysis of existing methods of measuring signals and the examples of vibration signals analysis which were obtained during operation of reclaimer prototype Regmas [1, 2, 3] is presented.

2. Classification of measurement signals

Occurring in the natural phenomena signals which are energy and information carriers can be divided into deterministic and random signals [5]. The deterministic signals are signals whose properties are described using the strict mathematical dependencies. Physical phenomena which are not determined (cannot be described by strict linear differential equations or nonlinear differential equations) are represented by the averaging static characteristics of their signals. Such signals are called random. The classification of the nature of the signal (deterministic or random) mainly concerns the possibility of its repeated plays with measurement uncertainty (provided that identical conditions are assured to carry out experiments). The deterministic signals respectively are periodic and non-periodic signals. In turn, the random signals are divided into stationary signals and transient signals. Measured vibrations signals of the molding sand reclaimer Regmas were qualified as stationary random signals with additional assumption of their ergodicity [5].

3. Time-frequency signals analysis methods

Currently the most used tools in the analysis of the measuring signal are frequency and time-frequency signal analysis methods. The popularity of these methods results from periodicity of many physical phenomena occurring during the operation of machinery and equipment, as well as the traceability of the variability phenomena which periodicaly evolves in time [8]. The simplified scheme of time-frequency signal representation resulting from estimation methods (parametric or non-parametric) and structures equations (linear and non-linear) are presented in figure 1. In the next part of this article the parametric models and spectrograms used by the authors to describe vibration signals (obtained from working reclaimer) will be discussed in more details.

3.1. Parametric methods

Parametric models describing the phenomena occurring during the operation of the machinery must meet the crite-

* AGH UNIVERSITY OF SCIENCE AND TECHNOLOGY, FACULTY OF MECHANICAL ENGINEERING AND ROBOTICS, AL. A. MICKIEWICZA 30, 30-059 KRAKÓW, POLAND
** AGH UNIVERSITY OF SCIENCE AND TECHNOLOGY, FACULTY OF FOUNDRY ENGINEERING, REYMONTA ST. 23, 30-059 KRAKÓW, POLAND

rion of the optimal fit to the actual observation of physical phenomena.

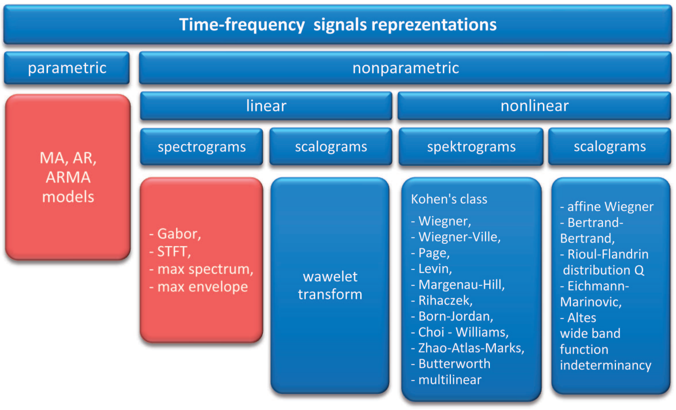

Fig. 1. The division of time-frequency signal analysis methods [8]

Assuming that there is no known reason for the evoke of the activation of phenomena (or it is not available to measure the signals on the entrances of the device), one can advance a hypothesis that recorded the stationary random signal $x(t)$ is a response of a linear dynamic system activated by white noise $\varepsilon(t)$ (Fig. 2).

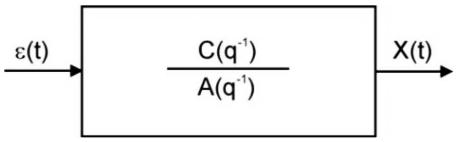

Fig. 2. The model of the linear dynamic system temporarily activated by white noise

The general equation of the time series model which is the autoregressive with moving average ARMA model is expressed as follows:

$$x\,(t) = \frac{C(q^{-1})}{A(q^{-1})} \cdot \varepsilon(t) \tag{1}$$

where:

$x(t)$ – the linear and stationary time series,

$\varepsilon(t)$ – white noise,

$A(q^{-1}), C(q^{-1})$–the polynomials of na, nc order. The rational functions, with delay operator q^{-1}, are expressed as follows:

$$A\left(q^{-1}\right) = 1 + a_1 \cdot q^{-1} + a_2 \cdot q^{-2} + \cdots + a_{na} \cdot q^{-na}$$

$$C\left(q^{-1}\right) = 1 + c_1 \cdot q^{-1} + c_2 \cdot q^{-2} + \cdots + c_{nc} \cdot q^{-nc}$$

In this model, the current value of the process is a finite linear combination of the values of this process in earlier moments of time and previous values of white noise signal. Given in equation (1) $nc = 0$, the ARMA model simplifies to the autoregressive model AR (2). The parameters of this model are entirely linear combination of the previous values of the process caused the white noise signal $\varepsilon(t)$:

$$x\,(t) = \frac{1}{A(q^{-1})} \cdot \varepsilon(t) \tag{2}$$

The model in which the current value of the process is a finite linear combination of the previous value of the stationary random process $\varepsilon(t)$ with zero mean and constant variance is called the model of the finite moving average process MA and is expressed as follows:

$$x\,(t) = C(q^{-1}) \cdot \varepsilon(t) \tag{3}$$

The MA model has not found wider spectral analysis applications and it is mainly used in econometric studies.

3.2. Non parametric methods

Applied to the measured vibration signals non-parametric analysis methods included their analysis in the frequency domain as well as in the field of time and frequency domain. Frequency analysis of test signals was performed as the first and their spectral power densities (PSD) were calculated. Then using the short-time Fourier transform (STFT) the time-frequency analysis has been carried out. Power spectral density (PSD) is a popular tool in the theory of signal analysis. It determinates how the energy of examined signal distribute in his band. Mathematical write of the power spectral density is the Fourier transform of the autocorrelation function of the test signal and is given by the formula:

$$S_{xx}(f) = 2\int_{-\infty}^{+\infty} r_{xx}\,(\tau)\,e^{-j2\pi f\tau}d\tau \tag{4}$$

where:

$$\mathrm{r_{xx}}\,(\tau) = \mathrm{E}\,[\mathrm{x}\,(\mathrm{t})\,\mathrm{x}(\mathrm{t}-\tau)]$$

$r_{xx}(\tau)$ – the autocorrelation function of the signal $x(t)$.

As compared with power spectral density PSD, which allow analysis signal of frequency domain only, the short-time Fourier transform STFT (commonly used in analysis of non-stationary signals), allows three-dimensional representation of the signal (its amplitude) in time and frequency domain. In analysis of non-stationary signals, STFT is expressed as [6]:

$$X\,(t, f) = \int_{-\infty}^{+\infty} x(t) \cdot w\,(t-\tau)e^{-j2\pi f\tau}d\tau \tag{5}$$

where:

$x(t)$ – tested time signal of physical quantity,

$w\,(t-\tau)$ – time window of constant width τ.

In this analysis, frequency analysis of successive fragments of measured signal $x(t)$ is executed by multiplication it with window function $w\,(t-\tau)$ of constant width. Next fragments tested independently, combining spectrum components with time.

4. Laboratory tests

Laboratory tests of the developed reclaimer prototype included among other things, the vibration measurements made on its corps in three given directions (Fig. 3). Registered waveforms of vibration have been analyzed numerically. The main purpose of the analysis was to determine the amplitude of movement corps of the reclaimer, in each of the established measurement directions. In addition to the carried out analysis the basic parameters of the elemental sand mass motion trajectory in the reclaimer guides were calculated (the results of this part of the research were published in [4]). The experiment was carried out for the three assigned positions of unbalanced masses mounted on two electrovibrators which represented the reclaimer drive. The value of supply voltage frequency of the electrovibrators motors has been changing from 40 to 60 Hz. This resulted in a change of their shafts speed. During the tests a variable load of used sand on reclaimer corps was applied (ranging from a lack of load to the load of its construction of 100 and 300 kilograms of mass sand). Due to the large number of the obtained results from the laboratory tests the authors decided the later part of the article, concern only to analysis of the waveforms obtained for one measurement direction (X direction only).

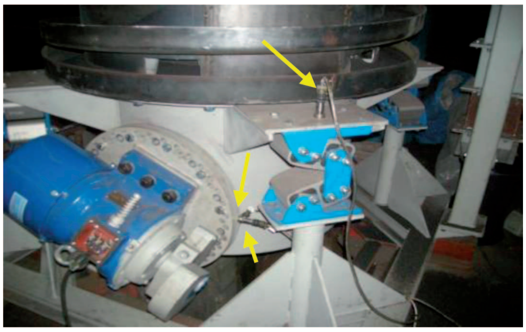

Fig. 3. The view of measurement transducers location on reclaimer corps

5. Analysis of measurement signals

At the beginning of the analysis the probability density functions $p(x)$ of the measured signals were calculated. Obtained waveforms of density distribution (Fig. 4) indicate that the measured signals can be assigned to a group of harmonic signals with additive noise. The waveforms also provide the information about noise content in a useful signals. In measured signals the maximum noise value occurs at the direction Z.

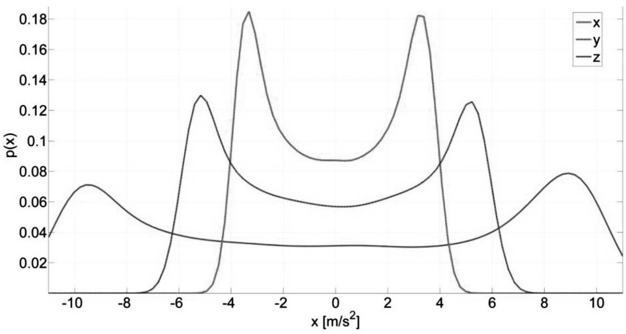

Fig. 4. Examples of the probability density distributions $p(x)$ runs obtained from vibration signals measured in X, Y and Z direction

The next step in the analysis was to verify the stationarity of registered time series by examining the autocorrelation function run for each of them (Fig. 5).

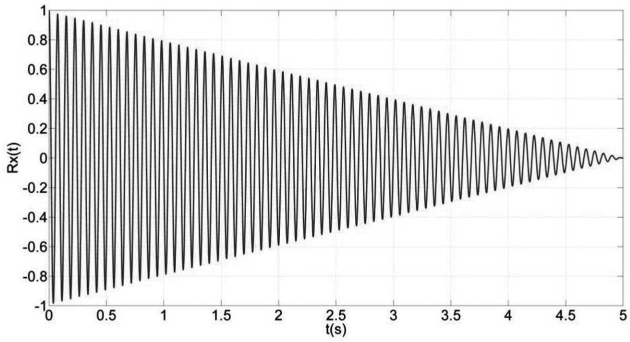

Fig. 5. The run of the autocorrelation function of vibration signal in the X direction obtained for electrovibrators supply voltage frequency f = 40 Hz

Because each of the measured time series are stationary (Fig. 5) and ergodic [5] thus assumed their parametric models ARMA and AR are stable. Before the identification of characteristic parameters of AR model polynomial, the order of the polynomial was specified so as to reached the assumed value of matching error between polynomial and time series. Minimizing the final prediction error criterion (loss function V) [8] optimal order for autoregression AR model was estimated for n_a =10. At that order the maximum value of the matching error model was $\delta \leqslant 0.0021$. Graphical representation of changes in the value of the loss function V (matching error δ) with the increase in the order of polynomial model is shown in Figure 6.

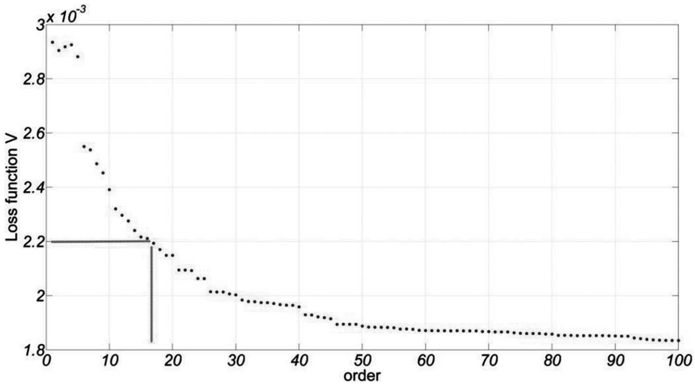

Fig. 6. The loss function V changing with the increase of autoregressive model AR order

As in the case described above (presented in the selection of AR model order estimation), before the identification of the characteristic polynomials of the autoregressive with the moving average ARMA model, the orders of characteristic polynomials were estimated. Gradually increasing the order of characteristic polynomial it was observed the reduction in loss function V (matching error δ) to the assumed minimum value after which the matching error has not significantly reduced with further increases in the order of the equation. Based on the established matching error δ ($\delta \leqslant 0.0021$) the order of a polynomial $A(q^{-1})$ was set. Established accuracy of the fit was achieved for row $n_a = 4$. Minimizing the mean-square error, the parameters (a_1, ...,a_{10}) of autoregressive AR model and the characteristic parameters of the polynomials ($A(q^{-1})$) and ($C(q^{-1})$) of the ARMAX model were estimated. Evaluated parameters of the AR and ARMAX models with final value of matching errors (models to time series) were put in Tables 1 and 2.

TABLE 1

Autoregressive AR model parameters for time series measured in X direction and set electrovibrators supply voltage frequency

40 Hz	a_0	a_1	a_2	a_3	a_4	a_5	a_6
	1	- 0.9741	0.03945	- 0.02822	- 0.04752	- 0.3073	0.2265
	a_7	a_8	$a9$	a_{10}	δ = 0.002		
	-0.07372	0.05173	-0.03382	0.1476			
50 Hz	a_0	a_1	a_2	a_3	a_4	a_5	a_6
	1	- 1.049	0.5238	- 0.158	- 0.1381	- 0.03124	0.0622
	a_7	a_8	a_9	a_{10}	δ = 0.0021		
	- 0.1234	0.08106	- 0.255	0.08923			
60 Hz	a_0	a_1	a_2	a_3	a_4	a_5	a_6
	1	- 1.183	0.4869	- 0.0887	- 0.1717	- 0.03555	0.06812
	a_7	a_8	a_9	a_{10}	δ = 0.00191		
	- 0.05215	0.05482	- 0.2713	0.194			

TABLE 2

Autoregressive with moving average ARMAX model parameters for time series measured in X direction and set electrovibrators supply voltage frequency

40 Hz	a_0	a_1	a_2	a_3	a_4
	1	- 2.84	3.094	- 1.669	0.4146
	c_0	c_1	c_2	c_3	δ = 0.0019
	1	- 2.004	- 2.004	- 0.3378	
50 H	a_0	a_1	a_2	a_3	a_4
	1	- 1.62	1.241	- 0.7454	0.1253
	c_0	c_1	c_2	c_3	δ = 0.0021
	1	- 0.5548	0.1269	- 0.1763	
60 Hz	a_0	a_1	a_2	a_3	a_4
	1	- 1.872	1.716	- 1.141	0.2979
	c_0	c_1	c_2	c_3	δ = 0.0021
	1	- 0.694	0.4238	- 0.2501	

Applying the test of the white-hot forecast errors (residua error test) consistency of the estimated parameters of AR and ARMA models were checked.

Application of non-parametric methods for the analysis of the measured signals included determination of their power spectral densities PSD and the representation of the short time Fourier transforms STFT. Function of constant Hemming's window of time range τ = 25 ms, which were shifted superimposing consequent windows with 75% solidity, was used for time-frequency distributions. Obtained frequency representations PSD and time-frequency representations STFT for vibration runs measured in X direction are gathered in diagrams shown below separately, for each supply voltage frequency of elecrovibrators.

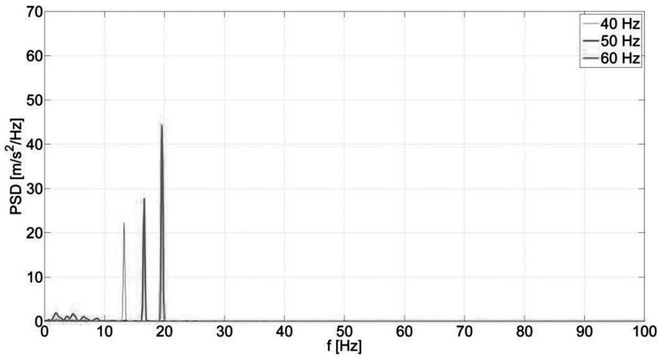

Fig. 7. Power spectral density PSD runs of vibration signals measured along the X axis for electrovibrators supply voltage frequency 40, 50 and 60 Hz

Analysis of time-frequency representations prepared in form of bit maps (Fig. 8) can be based on both quantitative and qualitative analysis. Qualitative assessment is reduced to verbal description of examined representations. In case of used quantitative measure another option is observed, which as a rule determines numerical measure of chosen parameter. Quantitative assessment of the influence of supply voltage frequency changes on vibration level was made in order to facilitate the analysis of obtained time-frequency STFT representations. The root mean square was taken as a measure of changes of spectrum amplitude factors of the STFT, calculated from whole signal time range t, with targeted frequency f_i:

$$rmsX\,(t, f_i) =$$

- $\sum_{j=0}^{N} X(t_j, f_i)^2 N$(6)where:

$X(t_j, f_i)-$ spectrum amplitude factor of the STFT,

N – length of time course corresponding to one second of vibration measurement.

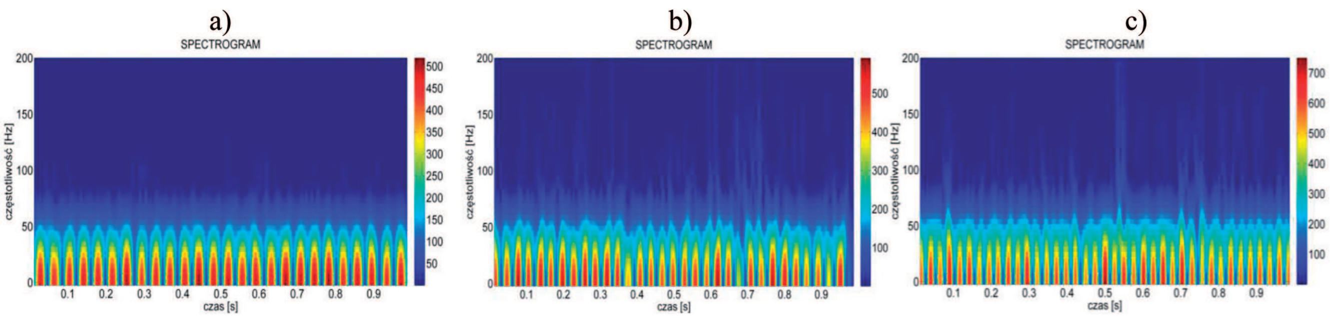

Fig. 8. Time-frequency representation STFT of signals measured along the X axis for electrovibrators supply voltage frequency: a) 40Hz, b) 50Hz, c) 60 Hz

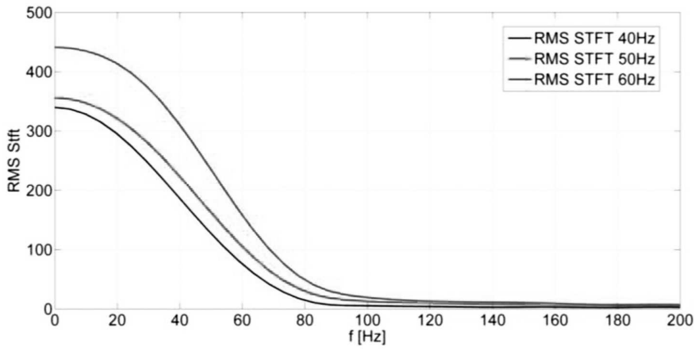

Fig. 9. The root mean square of the amplitude spectra factors of the STFT for different supply voltage frequency

from the analysis of vibration signals provide information about reclaimer operation using as a gauge of this information frequency (PSD) and time-frequency (STFT) qualitative data distributions. Application of quantitative assessment of time – frequency distributions (the root mean square values of the STFT coefficients) helps them interpret and may be useful for tracking the wear of the main elements of the reclaimer. Assuming for selected items (e.g. those the most heavily loaded) limited values of their wear, it is possible to develop (based on the $rmsX = F(\mathrm{f})$ curves runs) routine repair plans of the reclaimer and to predict the earlier exchange of its most wear parts so as to minimize economical losses due to unplanned stoppages of the device.

6. Summary and conclusions

Presented in this article selected numerical methods of vibration signals analysis allow use of their results in the later operating of the reclaimer. Obtained parametric models of the vibration signals can be used (in order to rise efficiency of used sand regeneration process) to maintain (control) the desired nature of vibrations on the reclaimer corps as well as for monitoring and diagnosis of its operational state. At this time, it should be noted that autoregressive AR models of the time series due to its high rows may not be used in the process control. The high rows of the AR models usually bring time delays in process control. For this purpose models of the lower orders should be used e.g. autoregressive with moving average ARMA models. Non-parametric models which were received

REFERENCES

[1] R. D a ń k o, Metalurgija **50**, 93-96 (2011).
[2] R. D a ń k o, Int J Cast Metal Res **23**, 92-96 (2010).
[3] R. D a ń k o, M. H o l t z e r, Arch Metall Mater. **55**(3), 787-794 (2010).
[4] R. D a ń k o, J. S t o j e k, J. K u ź m i n, Archives of Foundry Engineering **12**, 27-32 (2012).
[5] K. M a ń c z a k, Z. N a h o r s k i, Komputerowa identyfikacja obiektów dynamicznych. PWN, Warszawa (1983).
[6] R.G. L y o n s, Wprowadzenie do cyfrowego przetwarzania sygnałów. WKŁ, Warszawa (2006).
[7] P. W e l c h, IEE Transactions on audio and electroacustics, June (1967).
[8] T. Z i e l i ń s k i, Od teorii do cyfrowego przetwarzania sygnałów. WKiŁ, Warszawa (2009).

This article was first presented at the VI International Conference "DEVELOPMENT TRENDS IN MECHANIZATION OF FOUNDRY PROCESSES", Inwałd, 5-7.09.2013

Received: 20 January 2013.