Acta Montanistica Slovaca
ISSN 1335-1788
actamont.tuke.sk

Weibull distribution as a criterion of emergency levels

Witold BIAŁY[1], *Dariusz PROSTAŃSKI*[1], *Tomasz KORBIEL*[2] *and* *Ivan KURIC*[3]

Authors' affiliations and addresses:
[1] KOMAG Institute of Mining Technology, Gliwice, Poland
e-mail: wbialy@komag.eu
e-mail: dprostanski@komag.eu

[2] AGH University of Krakow
Mickiewicza 30, 30-059 Krakow, Poland
e-mail: tkorbiel@agh.edu.pl

[3] Faculty of Mechanical Engineering and Computer Science, University of Bielsko-Biala, ul. Willowa 2, 43-309 Bielsko-Biala, Poland
e-mail: kuric.ivan@gmail.com

***Correspondence:**
Witold Biały, 41-101 Gliwice, Pszczyńska 27, Poland
e-mail: wbialy@komag.eu

Acknowledgement:
The contribution is sponsored by the project VEGA project Nr. 1/0470/23: Research of implementation methods and means of artificial intelligence in systems of automated quality control of products with volatile quality parameters.

How to cite this article:
Biały, W., Prostański, D., Korbiel, T. and Kuric, I. (2024). Weibull distribution as a criterion of emergency levels. *Acta Monstanistica Slovaca,* Volume 29 (1), 216-226

DOI:
https://doi.org/10.46544/AMS.v29i1.19

Abstract
In the exploitation of machinery and equipment, one of the most important parameters is the dynamic state of the object. Observing residual processes is the most popular method of assessing the dynamic state. In particular, dynamic residual processes are a carrier of diagnostic information. Measuring the vibrations and noise of working mini-mining machines provides knowledge about the dynamics of the assessed machinery. Many years of knowledge and experience have allowed for the creation of diagnostic procedures. Within most machines used in the industry, the procedures considered standard allow for an effective diagnostic assessment and optimal management of mini-mining machine exploitation. The applicability of these standards is quite wide. However, there are machines with parameters that prevent the application of said standards. Mini-mining machines used in subterranean mining are one of these machines. In the case of diagnostic assessment of continuous miners, chain conveyors, as well as other machinery used in the technological chain, the usage of assessment brackets consistent with adopted standards is incorrect. In the diagnostic assessment of these types of mini-mining machines, an analysis of long-term trends is often used. The determination of acceptable vibration levels is obtained heuristically through observations of the damage up to the state of emergency. In the article, methods of mini mining machines state assessment using models of machine degradation, using Weibull distribution, are presented. The presented method has been used in real results of vibration measurement of underground machinery used in a coal mine. The analyses showed a large effectiveness of the presented method.

Keywords
technical diagnostics, Weibull distribution, machine condition assessment, trend analysis, mini mining machines.

Introduction

In the exploitation of machinery and equipment, one of the most important pieces of information is the dynamic state of the object. The most popular method of assessing the dynamic state is the observation of residual processes (Kosicka et al., 2015; Małysa et al., 2023). The dynamic residual processes are especially carriers of diagnostic information (Rojek et al., 2021).

The measurement of vibrations and noise of working machinery provides knowledge about the dynamics of the assessed machine. It allows for a diagnosis, that is, an assessment of the actual dynamic state and the genesis and cause of the current state. It is also based on experience and knowledge that prognoses, an assessment of the actual dynamic state, can be made. Many years of knowledge and experience have allowed for the creation of diagnostic procedures.

Within most machines used in industry, procedures specified by standards (Polak, 2010; Biały, 2017) allow for effective diagnostics and optimal management of machine operation (Kovanič et al., 2023; Kovanič et al., 2020). The applicability of these standards is quite wide, however there are machines with parameters that prevent the application of said standards. Mini-mining machines used in subterranean mining are one of these machines.

In the diagnostic assessment of mining combines, scraper conveyors and other machines in the technological process, the use of assessment brackets in accordance with the (ISO 10816-3, 2014) and (ISO 20816-3, 2022) standards is incorrect.

Performing diagnostic assessments for this type of mini-mining machine, which remains idle, does not reveal states of emergency. That is caused by the changing grounding of the machine, the technological environment, and many other factors that occur underground (Krenicky, 2022). The strain on the machinery can happen only as a result of a technological process (Olejarova, 2021). This process is characterized by large dynamics and significant instability (Kovanič et al., 2021). By analyzing the values of the average quadratic velocity of vibrations, the results are significantly higher than in the assessment brackets shown in the adopted standards. This is connected with the applied technical solutions of machine drive systems. An analysis of long-term trends is often used in the diagnostic assessment of these types of machines.

Such an approach requires regular measurements of machine vibrations in strictly defined points of measurement and at operating conditions (Polak, 2010; Chmielowiec, 2020; Biały et al., 2023). Effective alert thresholds are determined heuristically through observations of the damage up to the state of emergency. If wanting to lower exploitation costs, one must exclude states of emergency.

Pre-emergency states should be detected, allowing for a planned shutdown of the machinery and carrying out necessary repair work. Observing the dynamic state from the beginning of exploitation through a couple of repair cycles, it is possible to define the deadline levels of vibration, hinting at a pre-emergency state (Biały, 2010; Ding et al., 2016; Chmielowiec, 2020). Such an approach results in good results after a couple of years of observation and result analysis.

Weibull distribution in the assessment of machinery reliability

For machines in motion without known origin, the long-term trend analysis method cannot be applied. In such cases, the model of damage development can be used. An exponential distribution is a simple model that describes basic phenomena connected with damage development, emergency-proneness, and reliability of technical systems (Kuric et al., 2016).

This distribution has been used in the norm of "Reliability in technics" (PN-77/N-04021 1979). In this norm, a plan for analyzing the object has been shown. In model studies, the object is observed throughout its entire technical life. In real-life studies, this approach is considered too time-consuming. Usage of the PN-77/N-04021 norm allows to reduce time spent on studies to 1% of the proper work. This, however, requires an appropriate number of the studied objects. These operations are justified under the assumption that the lifetime of the object can be described through an exponential distribution. In practice, however, some differences are noticed: for new objects, greater unreliability and emergency-proneness are observed, as well as for objects nearing the end of their technical lifetimes. These phenomena have been described using the bathtub curve, the curve of a failure rate graph. The Weibull distribution is a generalization of the exponential distribution, taking both the beginning and the end of exploitation into account (Weibull 1939).

In the assessment of machine reliability, a recognized statistical model is the Weibull distribution. Exponential distribution models the reliability of a constant damage intensity. A general model has been proposed by (Weibull, 1951), having analyzed the durability of the product. A discrete equivalent of the exponential distribution is geometric distribution. The Weibull distribution is a generalization of the exponential distribution. This distribution can be used when the intensity of damage is a variable with a monotonic course. This distribution is used to describe the fatigue strength of materials and mechanical constructions. (Vasko et al., 2020; Barnik et al., 2018)

The intensity of damages can be determined with the formula:

$$\lambda(t) = \alpha\beta t^{(\alpha-1)} \tag{1}$$

where:
α, β > 0 = const – constant number,
α – parameter of shape,
β – parameter of scale.

The parameters of shape (α) and scale (β) allow referencing of the machine's lifetime curve or risk curve. This curve describes the intensity of damages or risk of emergencies over time. The intensity of vibrations is connected with the intensity of damages, which allows for the reference of the machine's lifetime curve over the exploitation time. Used often in practice, the lifetime curve describes the average quadratic of vibrations over exploitation time. It is similar to the function of machine damage probability. Over the first exploitation time period, the intensity of vibration increases.

This phenomenon is connected with friction between working elements, stabilizing assembly errors and processes of machine adaptation to work conditions. In this time period, the failure risk is higher. However, it decreases over time, and the shape parameter in the Weibull distribution is less than 1 (α < 1). The middle period called the period of normal exploitation, is characterized by a slow increase in vibration intensity. In this time period, the failure risk slowly increases as well, and the shape parameter in the Weibull distribution is approximately equal to one. In the pre-emergency state, the intensity of vibrations and probability of damage rapidly increases over time, and in the Weibull distribution, the shape parameter is greatly larger than one.

Reliability function:

$$R(t) = e^{(-\beta t^{\alpha})}, t \geq 0 \tag{2}$$

Unreliability function (distributor):

$$Q(t) = F(t) = 1 - e^{(-\beta t^{\alpha})} \tag{3}$$

Probability density function:

$$f(t) = \alpha\beta t^{(\alpha-1)} e^{(-\beta t^{\alpha})} \tag{4}$$

Analysis of the probability density function $f(t)$ shows that for shape parameter α = 1, the distribution is exponential, but for shape parameter α > 1, the distribution is normal – Gaussian distribution. Using the rule of mutuality, it can be indicated that if the estimated emergency probability distribution is an exponential distribution, then the object is in the state of regular exploitation. The probability of emergency increases over time of usage. However, suppose the estimated probability distribution is a normal distribution. In that case, that suggests a state of pre-emergency, during which the probability of damage is going to increase rapidly over time of exploitation.

For multiple objects for which the state takes two values – good or bad, the rules described above allow for an assessment of their reliability in given conditions. The studies carried out over rolling element bearings have shown that the probability of damage is proportional to time spent working in given exploitation conditions. As exploitation time nears face value, the emergency-proneness of the bearing shows a normal distribution, with the expected value as nominal durability (Łazarz et al., 2008; Ebner, Henze, 2020; Grynchenko, Alfyorov, 2020). These studies have also shown the crucial connection between the reliability of bearings and parameters of vibration signals, especially with an effective value of vibration speed in given frequency bands. This correlation has been used to describe norms of acceptable vibrations in rolling element bearings.

The correlation between the level of vibrations and the probability of emergencies is known, and the simplest model describing the impact of vibrations on the technical state of the machine is the energy dissipation model (Henze, Visagie 2019; Lai et al., 2006). In this model, the dynamic residual phenomena impact the object, introducing destructive energy. This energy accumulates within the object in the form of fatigue changes in chemical, thermal, or other types of degradation, causing intensified residual processes. Therefore, dynamic residual phenomena in the form of vibrations and quasistatic, such as temperature gradients, will describe the dynamic state of the object and be correlated with the reliability function of the given object. This dependence has been confirmed through extensive studies of systems such as gas turbine drives, gears, and many others (Tiryakioglu et al., 2010; Mori et al., 2021; Mykhailiuk, 2024).

The following works are devoted to modern research in the field of machine diagnostics (Božek et al., 2021; Kuric et al., 2021; Lekomtsev et al., 2021; Nikitin et al., 2022; Nikitin et al., 2022; Nikitin, 2020a; Nikitin, 2020b; Nikitin et al., 2020; Peterka et al., 2020; Stepanov et al., 2021; Trefilov et al., 2021; Kovanič, 2013).

Assuming the correlation of vibration energy with the reliability of complex objects, within which the dominant destructive phenomena are connected with material fatigue, the probability density of failure will be proportional to vibration intensity.

Numerical model

The assumption of a correlation between the levels of vibration and the function of reliability leads to the conclusion that, during the exploitation of the machine, the estimated distribution of vibration energy over time can also be described using the Weibull distribution. Therefore, parameter α will show the state of the machine, as it is in the reliability analysis. For $\alpha < 1$, the set will find itself starting up; for $1 < \alpha < 2$, it will be in the state of regular exploitation; and for $\alpha > 2$, a state of pre-emergency can be indicated.

A lack of correlation with the time of exploitation characterizes the above method. That is a trait of Weibull distribution, in relation to which it is possible to observe any time period resulting from observation of the object.

A verification of the above assumptions can be found in the numerical analysis using the machine's energetic model. Assuming the time of observation T = 1500 units, over the time period of t (0, 100), the machine runs in, but during the end of the time period, the machine will reach a state of pre-emergency. Therefore, a signal defined by the below formula has been generated:

$$x(t) = \left(A \cdot t \cdot \frac{t^{\gamma}}{T^{\gamma}} + B\right)^{A \cdot \frac{t^{\gamma}}{T^{\gamma}} - 1} \tag{5}$$

where:
$x(t)$ – value of the average quadratic vibration level
T – time of observation
A, B, γ – parameters

The function flow is shown in Figure 1. During the beginning of the observation time period, there is a decrease in the vibration levels. After stabilization of the level, during regular exploitation, a slow increase is observed up until the moment of a pre-emergency state. During the pre-emergency state, one can observe a dynamic increase in the vibration levels.

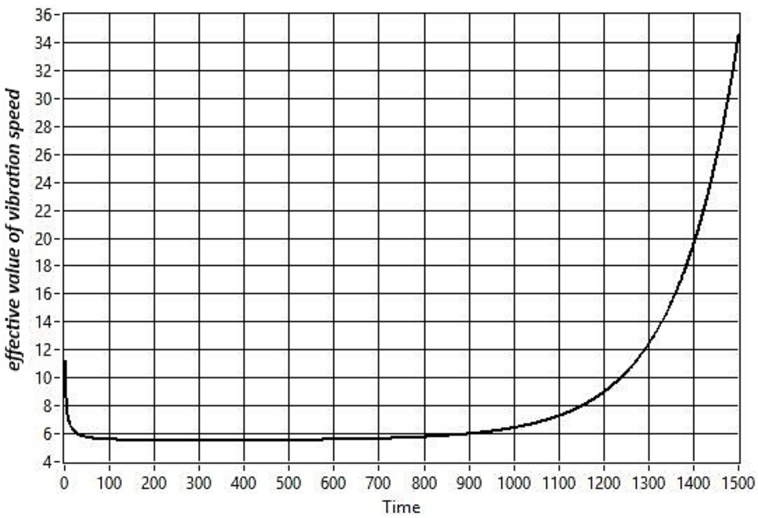


Fig. 1 A simulated flow of the rms value of the vibration velocity during a full exploitation cycle

For the given range of observation τ, a two-sided approximation of the function $x(t)$ has been carried out.

The approximation has been carried out through the Gauss and exponential functions.

The approximation of the exponential function has been carried out using an interactive method of the smallest possible squares, as well as the Levenberg-Marquardt method (Gavin 2022). The missing value is best fitted to the data of the exponential function, as shown:

$$f = ax^{b} + c \tag{6}$$

where:
x – is the sequence of entry data X,
a – amplitude,
b – exponent,
c – shift.

The applied algorithm defines the function while minimizing the sum of squares of differences between the observation data and the missing function.

$$y[i] = a(x[i])^b + c \tag{7}$$

An approximation of the Gauss function has also been produced using the interactive method of the smallest square as well as the Levenberg-Marquardt method. This algorithm matches the data to the Gauss curve in accordance with the equation:

$$f = A \cdot e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)} \cdot C \tag{8}$$

where:
x – sequence of entry data X,
A – amplitude,
μ – expected value,
σ – standard deviation,
c – shift.

This algorithm determines values a, μ, and c, which best fit observations (x, y). The equation of the Gauss curve is described by the Gauss function resulting from an algorithm:

$$Y[i] = A \cdot e^{\left(-\frac{(x[i]-\mu)^2}{2\sigma^2}\right)} \cdot C \tag{9}$$

Analysis of numerical simulation results

Therefore, for function $x(t)$, describing the effective value of the machine's vibration at time $t = (0,T)$, we choose the observation $\tau(t_N)$, which is a certain interval of the function $x(t)$. On the basis of this observation, the technical state of an object can be estimated by examining the approximating Gaussian function and the approximating exponential function. The numerical experiment consists of shifting a rectangular observation window of length N along the function $x(t)$. We obtain the family of functions $\tau_i(t_N)$ where $i = (0;T\text{-}N)$, $t_N = (t_i;t_i+N)$. For each of the obtained segments, approximations of the Gaussian function were made to obtain A_i, μ_i, and C_i. The most interesting result is related to the expected value of μ_i. This value is directly proportional to the exploitation time of the device, assuming fatigue phenomena as the main destructive factor. For the signal simulated function (5) and its waveform, the functions $\mu_i(i)$ are obtained as in Figure 2.

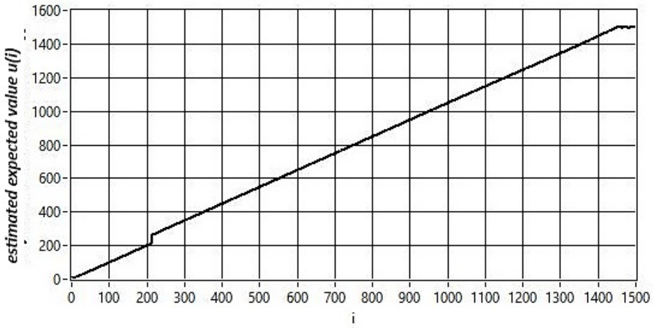


Fig. 2 The expected value for an approximating Gauss function for N = 50

Another interesting course is the standard deviation in the function i (Figure 3). Up to a certain point, this value increases, but after a given time, it starts to decrease. The analysis of function (1) shows that this is the moment ending the arrival period and the transition to normal exploitation.

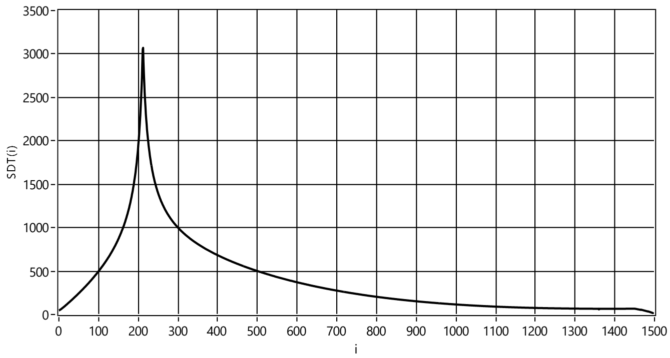


Fig. 3 Standard deviation for an approximating Gauss function for N = 50

For the approximating exponential function, the power exponent *b* (6) may also be an indicator of the machine's state. For the correct exploitation condition, it is close to zero. When this condition worsens, the *b* index starts to rise (Figure 4).

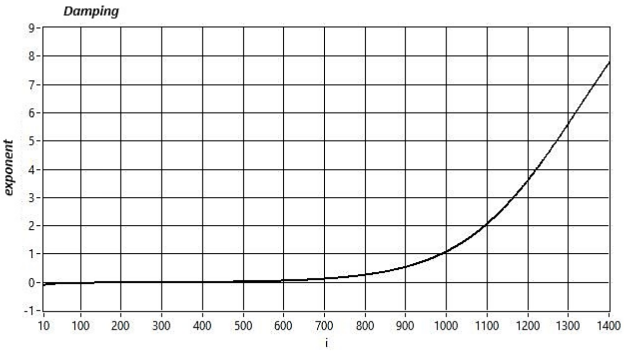


Fig. 4 Power exponent for an approximating exponential function for N = 50

The particular usefulness of this index lies in its dynamics. The slope of this curve increases as a result of machine degradation. From the relationship (1), it follows an important conclusion that for $b > 2$, it is possible to indicate a pre-emergency state. In the given case, for the time $t = 1100$, the system goes into a pre-emergency state, in which there is a significant increase in the dynamics of the vibration level and, thus, a decrease in reliability. Analysis of the amplitude of the approximating exponential function provides some diagnostic information. However, further studies have shown a lack of usefulness of this information (Figure 5).

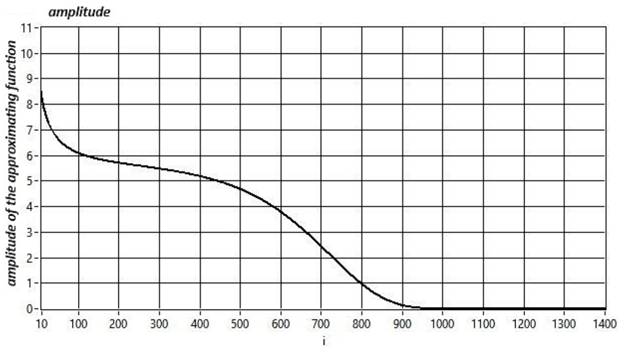


Fig. 5 Exponential amplitude of an approximating function

The presented selected statistical parameters were based on a representative synthetic signal. In practice, vibration level measurements are burdened with considerable dispersion. This phenomenon can be modeled by including the perturbing function in the equation (5):

$$x(t) = \left(A \cdot t \cdot \frac{t^{\gamma}}{T^{\gamma}} + B\right)^{A\frac{t^{\gamma}}{T^{\gamma}} - 1} + \varepsilon(t) \qquad [10]$$

where:

$\varepsilon(t)$ – is the interfering signal;

A synthetic signal analogous to Fig. 1 was generated, taking into account an interfering signal of uniform distribution and amplitude $A_{p\text{-}p} = 5$. The simulated curve is shown below (Figure 6).

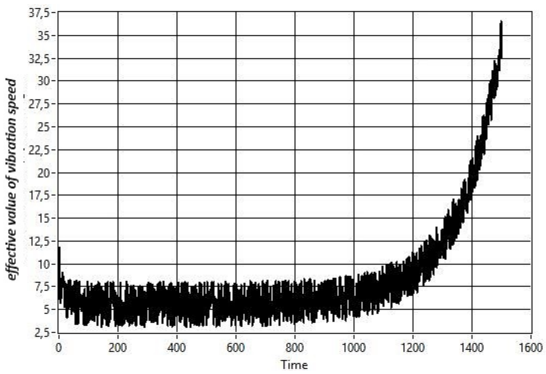


Fig. 6 A Simulated curve of the rms value over the full operating cycle with the jamming signal

Analyses analogous to the previous example resulted in an estimated expected value of the interpolating Gaussian function, similar to the previous result (Figure 7).

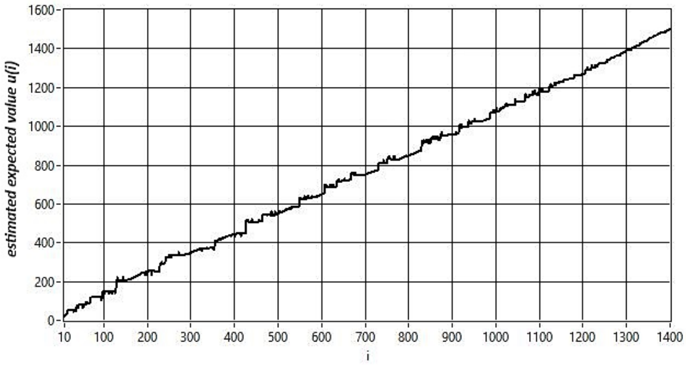


Fig. 7 Expected value for an approximating Gauss function N = 100

A feature of the expected value is the centralization of a random variable with a symmetric distribution. For an interpolating function, this value will be related to the slope of the interpolated waveform or, more specifically, its dynamics. If, in a time window containing N observations of the process, the given process is characterized by some dynamics, then the interpolating Gaussian curve function registers a change in the values of these observations. If symmetrically distributed disturbances are applied to the observations, the approximation process will be slightly disturbed. Thus, the estimated expected value of the Gaussian interpolation function is an indicator of the change dynamics of the observed process.

A significant influence of disturbances can be observed for the exponential value of the approximating exponential function (Figure 8). However, this indicator may also be an estimator of the technical condition.

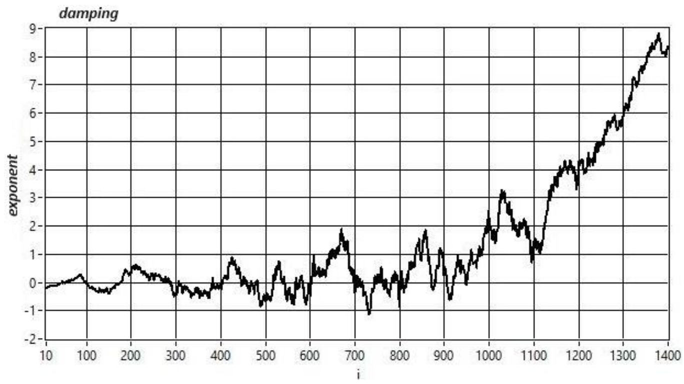


Fig. 8 Power exponent of an approximating exponential function for N = 100

If we enter the absolute time of selected observations, we get a family of functions approximating the signal $\tau_i(t_N)$ where $i = t(0;T\text{-}N)$, $t_N = (0;N)$. The power exponent of the exponential approximation function will be linearly proportional to the slope of the characteristic $x(t)$. Its value will depend on the width of the observation window N (Figures 9, 10).

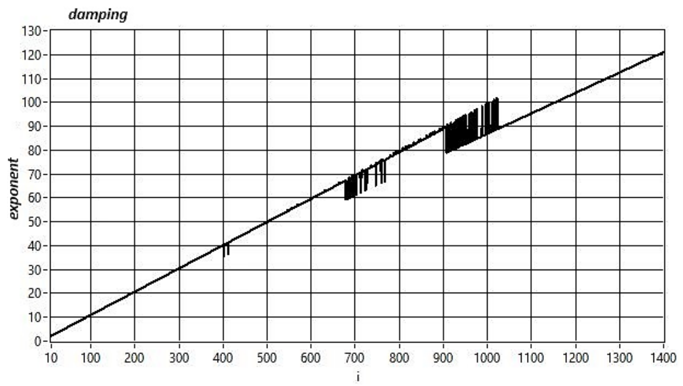


Fig. 9 Power exponent of an approximating exponential function for N = 20 εpp = 5

The analyses showed the effectiveness of the proposed algorithm in detecting the state of pre-emergency. In general, it can be pointed out that if the value of the power exponent of the approximating exponential function exceeds $b > 2$ (7), then we are dealing with a state of pre-emergency.

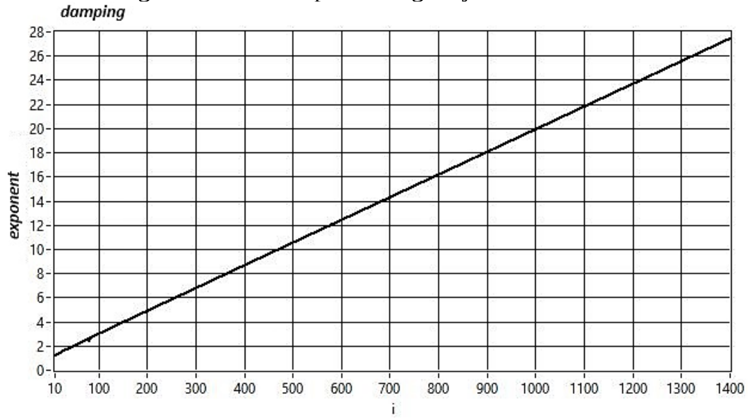


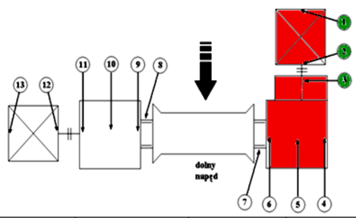
Fig. 10 Power exponent of an approximating exponential function for N = 100 εpp = 5

Method verification in industrial conditions

The proposed algorithm has been implemented in the Company Diagnostic System in a coal mine. An observation of the underground mining machinery's technical state has been conducted based on, among other measurements, periodic measurements of vibration parameters at the given points of the machine. The measurements were collected using a pen vibrometer (Figure 11).

Fig. 11 A PEN plus CMVP 50 pen vibrometer of SKF production

A sample measuring card was used to monitor the technical state. The measuring card contains information with the measurement point numbers reflected on the device. The presented methodology was used to determine the maximum levels of the mean vibration velocity, referred to as the pre-emergency level. An example part of the measuring card and the arrangement of measuring points for the bottom drive of the R-850 RYFAMA wall scraper conveyor are shown below (Figure 12).



Another Measurement	Orientation Measurements	Measuring Point Number			Another Measurement	Orientation Measurements	Measuring Point Number		
		1	2	3			1	2	3
1	↓	3.1	2.0	2.3	6	↓	3.7	4.1	7.5
	→	3.1	1.7	2.2		→	3.2	4.0	7.3
	⊗	2.2	-	-		⊗	3.0	-	-
	↑	**1.51**	**0.46**	**2.00**		↑	**3.4**	**15.20**	**34.20**
2	↓	3.2	2.3	2.4	7	↓	3.9	4.3	44.5
	→	3.1	2.2	2.4		→	3.5	4.1	37.0
	⊗	2.5	-	-		⊗	3.5	-	-
	↑	**1.60**	**1.82**	**6.00**		↑	**5.8**	**19.70**	**37.40**
3	↓	3.0	2.1	2.3	8	↓	3.9		
	→	2.7	2.0	2.3		→	3.5		
	⊗	2.3	-	-		⊗	3.5		
	↑	**1.76**	**1.84**	**4.90**		↑	**7.8**	**19.70**	**37.40**
4	↓	3.1	2.1	2.4	9	↓	3.8		
	→	2.7	2.2	2.3		→	3.3		
	⊗	2.3	-	-		⊗	3.7		
	↑	**1.85**	**1.92**	**5.90**		↑	10.4		
5	↓	3.7	4.1	7.5	10	↓	4.1		
	→	3.2	4.0	7.3		→	3.7		
	⊗	3.2	4.0	7.3		⊗	3.9		
	↑	**3.30**	**5.00**	**9.10**		↑	**15.5**		

Fig. 12 A piece of the measuring card. as well as the arrangement of measuring points for the lower drive of the wall scraper conveyor

For the collected data, a graph of changes in the value of the effective vibration velocity has been created (marked in the above table ↑) This diagram corresponds to the assumptions of fatigue degradation of the machine (Figure 13).

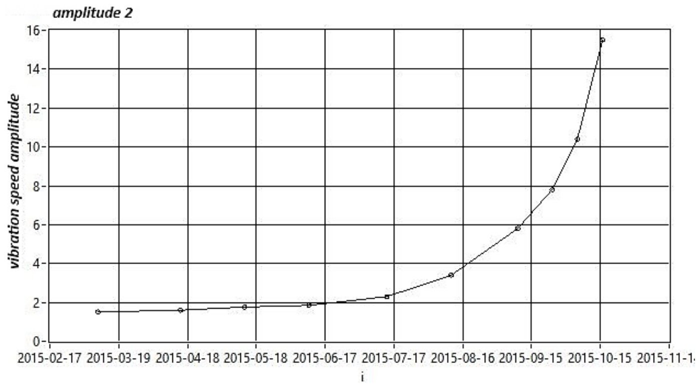


Fig. 13 Average vibration velocity for 1 measuring point

The analysis was carried out by taking 3 and 4 historical measurements into account. In this case. the measurements were $N = 4$ or $N = 5$. The value of the power exponent and the expected value are shown in Figure 14a,b.

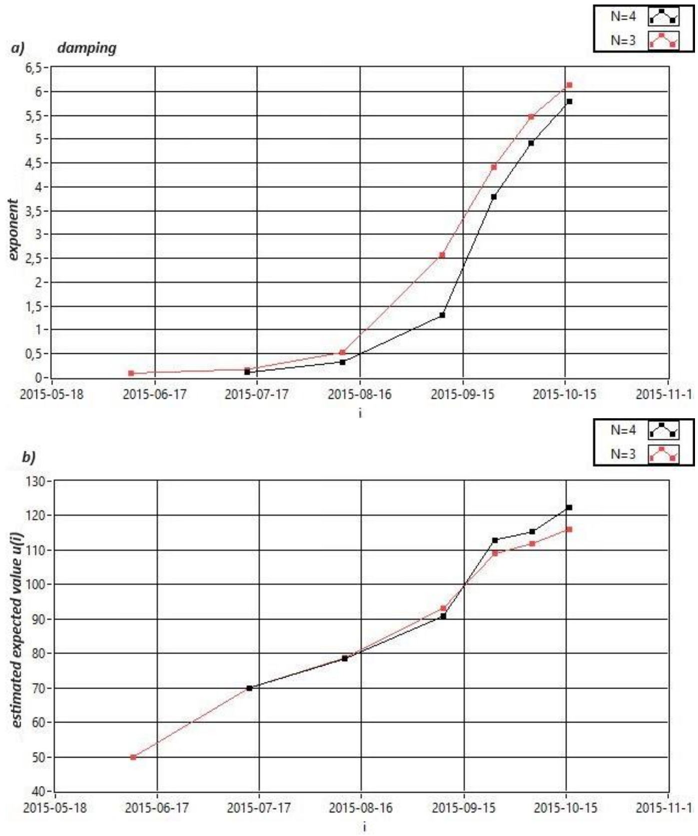


Fig. 14 The value of power exponent and expected value

From the conducted sample analyses, one can deduce that the measurement was carried out on 9 September, for which the rms of the vibration velocity was 5.9 mm/s. The power factor slightly exceeded the value of 1. Another measurement carried out on 24 September caused the power factor to exceed 3.5, indicating that the pre-emergency phase had begun. The expected value also rose sharply, confirming the hypothesis. This information indicated the pre-emergency condition of the conveyor drive. This resulted in increased control of its technical condition and technological preparation for its repair. The conveyor remained in this condition for two more weeks, after which it was decommissioned. Its repair unequivocally confirmed the observed damage.

Summary

The Weibull distribution, known in reliability theory, models the phenomena of degradation of technical systems. The dynamic state is a reflection of the degradation of the object and can be assessed on the basis of observation of residual processes, especially vibrations. Therefore, vibration parameters are connected to the machinery's reliability level. As such, an attempt has been made to assess the state of degradation of the mini-mining machines on the basis of vibration level trend analysis and the Weibull distribution model. Simulations confirming the possibility of applying this theory have been executed. A valuable correctness of the algorithm has been found, based on averaging of disturbances in measurement and independence from time. The algorithm has been applied to real measurement data from underground mining machinery. Long-term measurements and the presented methodology have allowed us to assess the acceptable levels of vibration for given mini-mining machines, as well as the option to assess the state of machine degradation in the case of an incomplete working cycle.

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