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ANALYSIS OF THE LONGWALL CONVEYOR CHAIN BASED ON A HARMONIC ANALYSIS

ANALIZA PRACY ŁAŃCUCHA PRZENOŚNIKA ŚCIANOWEGO W OPARCIU O ANALIZĘ HARMONICZNĄ*

This paper describes the use of harmonic analysis in the analysis of a longwall conveyor chain. Correct and stable operation of the chain is connected both with the safety of the work and the economic performance of the transportation process. The aim of the study was to show the ability to detect changes in conveyor work related to damage or improperly conducted procedure of chain length changing. Observation of the conveyor chain work was to monitor the power consumption of the three motors driving the conveyor. The analysis included nearly 26 000 startups have been reported within 20 months of the conveyor work. This paper describes the initial stage of raw measurement data analysis, and analysis of data transformed by the Fourier transform. As a result of the data analysis, diagnostic procedures allowing to signal deviations from the conveyor normal conditions were proposed.

Keywords: *device diagnostics, harmonic analysis, longwall conveyor.*

Artykuł opisuje zastosowanie analizy harmonicznej do analizy stanu łańcucha przenośnika ścianowego. Poprawna i stabilna praca łańcucha wiąże się zarówno z bezpieczeństwem prowadzenia prac jak i ekonomiczną wydajnością procesu. Celem przeprowadzonych badań było wskazanie możliwości wykrywania zmian pracy przenośnika związanych z uszkodzeniem bądź przeprowadzoną w sposób nieprawidłowy procedurą zmiany długości łańcucha. Obserwacja pracy łańcucha przenośnika polegała na monitorowaniu poboru prądu przez trzy silniki napędzające przenośnik. Analizie poddano blisko 26 000 uruchomień, jakie odnotowano w okresie 20 miesięcy pracy przenośnika. W pracy opisano etap wstępnej analizy surowych danych pomiarowych, a także analizy danych przekształcony transformacją Fouriera. W rezultacie analizy danych zaproponowano procedury diagnostyczne pozwalające sygnalizować odstępstwa od normalnych warunków pracy przenośnika.

Słowa kluczowe: *diagnostyka urządzeń, analiza harmoniczna, przenośnik ścianowy*

1. Introduction

In the industry, including coal mining, there is observed significant increase in the importance of information derived from the monitoring systems. The main task of the monitoring system is to visualize the current state of the devices (e.g. power consumption, temperature, fluid pressure and levels (cooling, hydraulic) etc.).

It can be assumed that at the present time functionality of monitoring systems provides full monitoring and visualization of any industrial process (production, machines and equipment work, natural hazards, etc.). The data collected by these systems are mainly used for the current visualization and reporting.

At the moment, more and more software developers and users of monitoring systems indicate the need for analysis of the data collected in their repositories. In particular, the purpose of this analysis may be defining the diagnostic models of monitored devices [2, 7, 15]. Identification of diagnostic model may be done through the planned experiments or analysis of data collected during device operation. In this paper we concentrate on the second approach. Based on data collected by SMOK [13], the longwall monitoring system, we present how the application of the Fourier transform can be used to detect changes in longwall conveyor chain (in particular by joining the chains with different parameters).

This paper is organized as follows: the next section provides a short overview of the work related to diagnostics of mining machines, in particular longwall conveyor. The following part describes the stages of initial data processing and a substantial processing of the recorded signals. This is followed by diagnostic models, based on an analysis of the value described here in the paper as a *basic period*.

2. Analysis of longwall conveyor

The problem of monitoring and diagnosing the condition of machines used in the mining industry was raised in [2, 4, 5, 6, 10, 11, 15]. It has also been reviewed extensively in [2, 5, 15]. Papers [2, 15] also present new methods of extracting and processing of diagnostic features to discover diagnostic relations. In particular, a part of the work [2] was devoted to the diagnosis of belt conveyors, used as the main transport device in the mining industry. In [11] power consumption and temperature of a coal combine cutting heads were monitored. Therefore, three operating states of the coal combine were defined. Two of the identified states describe different but correct conditions of mining. This work has identified a parameter describing the efficiency of the coal combine cooling system.

Diagnosis of longwall conveyor was the subject of such works as [4, 6, 10]. The work [4] presents a method for detecting defects on a conveyor chute of the bottom side of the conveyor. Based on the analysis of power consumption of longwall conveyor driving motors during one repair shift, the damage was localized with an accuracy of one section. In [6] a comprehensive management system of the conveyor belt components was proposed. The system allows generating both summary statements and, operational and analytical reports. These reports allow for evaluation of the conveyors monitored in the system.

(*) Tekst artykułu w polskiej wersji językowej dostępny w elektronicznym wydaniu kwartalnika na stronie ***www.ein.org.pl***

In [10] power consumption of motor driving the conveyor is analyzed. The result of the study is to propose summary reports of motor operation including the level of exceeded values of the rated current as well as the duration of the exceedances. In addition there was proposed rule-based description of the operating parameters of the motor, based on association rules [1].

3. Acquisition of measurement data

The results presented in the latter part of the paper were obtained due to the analysis of power consumption of each of the motors driving the conveyor transport system. We analyzed data from two periods of operation of the conveyor. Later in the paper, the time interval between the turning on and turning off the conveyor will be called *startups*. In the first period (called P) lasting more than 19 months, there were more than 24 500 *startups* of the conveyor, in the second period (called NP) more than 1 200 startups were reported. The most important, from the point of view of data analysis, was that in the second period a part of the chain was replaced with another one. Unfortunately, information about the difference in the construction of both chains was not available, therefore, it could not be assumed that replaced part of the chain was composed of links of different size or scrapers were placed in the other intervals.

Observation of work consisted in measuring the power consumption by each of the three motors of the conveyor within one second intervals. Motors identified as M1 and M2, served as a “pulling”, the task of the motor denoted as M3 was pulling the chain from under the conveyor (turning back). The analyzed conveyor was equipped with two-speed starter.

3.1. Initial processing of data

The aim of the analysis was to evaluate the work of conveyor in a steady state. In the measurement data concerning each startup the first two phases were omitted: work at low speed and switching the motor from low to high speed. Duration of speed shifting phase and consequent increase in the values of current was based on observations at 20 seconds from the moment of switching on high speed.

In the next step of data processing all startups were discarded from the analysis, the duration of which is less than 80 seconds, since assuming the conveyor moving speed is about 1.5 m/s in this time conveyor path was shorter than the length of the longwall (it was more than 110m).

The last stage of pre-processing was the data smoothing. The smoothing process consisted of averaging the value of power consumption based on n preceding and n subsequent values (moving average).

Taking as $x(i)$, unsmoothed value of current at the time i, the smoothed value at the moment i is given by formula (1):

$$x'(i) = \frac{\sum_{j=i-n}^{i+n} x(j)}{2n+1} \tag{1}$$

where: $x'(i)$ represents a new smoothed value, n is a smoothing parameter, whose value equaled 5 (which corresponds to averaging nine consecutive values). This value allows to compromise between filtering fast-changing current intensity components and keeping the nature of the course. This value was determined by observing smoothed courses of 30 randomly chosen long (more than 120 s) startups. For the first four and last four measurements averaging were not performed. Sample comparison of the original and smoothed course is shown in Fig. 1.

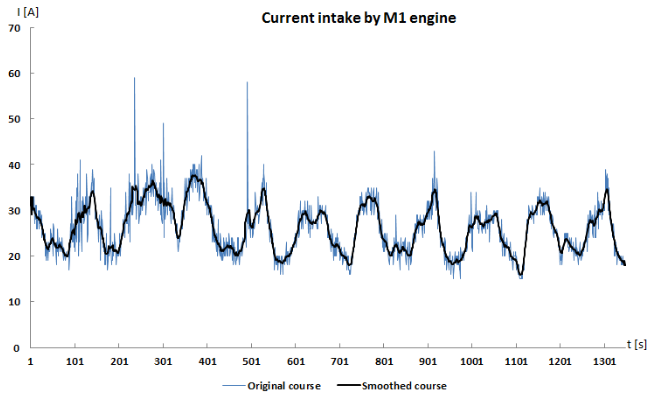


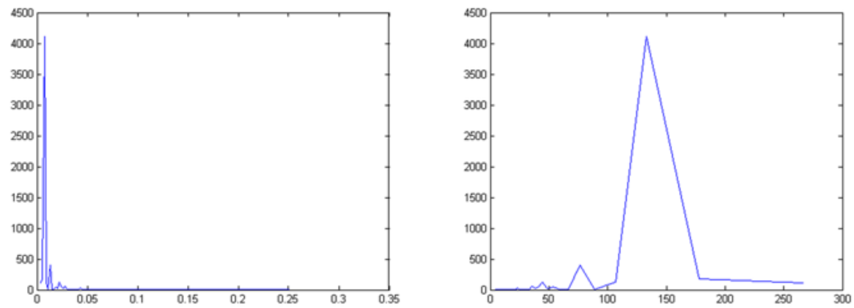
Fig. 1. Comparison of unsmoothed and smoothed courses describing the current consumption of one of the motors.

3.2. Data transformation into the frequency domain

Diagnosis of a chain in conveyor means studying periodicity of rolling the chain through the conveyor. The aim is to check whether during conveyor operation, periodicity of the conveyor work can be registered and whether changes of periodicity can be associated with damage or improperly conducted “repairs” of the chain.

It should be noted that it is impossible to diagnose individual links in the chain, this happens due to the sampling frequency of measurement data. Sampling time in the monitoring system is one second, the conveyor during its work moves at a speed of about 1.5 m / s (± 10%). As a result, between two consecutive samples the conveyor travels generally longer than the length of a single link.

For the collected measurement data the Fourier transform was used. For each of the motors the changes frequency spectrum of current was obtained. After analyzing the spectra for many motors of many startups, it was observed that the initial values of the spectrum (corresponding to the lowest frequencies) obtain disproportionately high values (especially for the first argument, corresponding to the constant component of signal), thereby distorting the spectrum of motors work. Therefore, it was concluded that the domain of spectrum should be reduced of the initial arguments. Finally, it was found that the first two arguments obtained in the distribution will be excluded.



M3 motor current spectrum for the startup marked as 1192.
The X-axis unit is 1 Hz

Periodogram of M3 motor startup marked as 1192. The X-axis unit is 1 second

Fig. 2. Illustration of spectrum transform into periodogram

Due to the fact that distribution values showed the highest significance in the initial (the lowest) frequency domain (fractional hertz) it was decided to consider time domain instead of frequency domain. Further analysis was based on the periodogram observation that showed how input course of current intensity change is distributed into sinusoidal changes in a specified period of time. Comparison of the spectrum and the periodogram for a selected startup is illustrated in Fig. 2.

In the example, for each single startup and at the same time for each of the three motors, were obtained graphs showing changes in the current intensity depending on the period of these changes. Further analysis of the data focused on local maxima in received periodograms. For each of the motors five periods with the greatest local maxima in periodogram were taken into account, sorting them from the most significant. These periods are marked: M11, M12, …, M15 and analogically M21, M22, …, M25 and M31, M32, …, M35.

4. Analysis of longwall conveyor motors

After analyzing periodograms, in such a way as described in the previous section, each conveyor startup was characterized by a vector of 15 features. Analysis of the resulting data set has demonstrated that it is impossible to determine the relationship between the *basic period* (the *basic period T* means the time in which the chain travels equal to twice the length of the conveyor), and one (for example, the largest) value in periodogram.

The first attempt to identify the basic period was based on the calculation of arithmetic mean values of M11, M21 and M31, separately for startups recognized as correct (startups of period P) and incorrect startups (startups of period NP). Mean values of M11, M21, M31 for correct startups marked γ_i, $i\in\{1,2,3\}$. Mean values of M11, M21, M31 for incorrect startups were marked β_i, $i\in\{1,2,3\}$. Then, for each startup there was calculated distance between γ_i, and M11, M21 and M31, as well as for β_i, and M11, M21 and M31. On this basis startups were being classified as correct or incorrect. The highest accuracy was achieved for means γ_3 and β_3. However, the results were not satisfactory, because the variance of the variable M31 for correct and incorrect startups was very high. As a result, algorithm reflecting presented way of classification was characterized by low sensitivity and specificity (i.e. a large number of correct startups was recognized as incorrect and vice versa).

It was necessary to take actions leading to a situation in which the variance of the strongest period, derived from the analysis of periodograms of motors M3, M2, M1 would be as small as possible. Therefore such a filter is defined to minimize the variance for correct startups, ignoring the incorrect, with assumption that in case of incorrect starts the basic period should change.

Therefore the following actions were taken:

1) Startups of less than 4 minutes were removed. For startups shorter than 4 minutes in most cases the strongest period was less than 70 seconds, it was then considered that the length of the chain is longer than 110 meters, so these periods were found to be incorrect;
2) In order to determine the basic period that allows distinguishing between correct and incorrect start the following logic rule was fixed (*RL*):

```
IF M31=M21=M11 THEN T=M31
 ELSE
 IF ((M31=M22=M12) OR (M31=M23=M13) OR (M31=M24=M14) OR
     (M31=M25=M15)) THEN T=M31
     ELSE
     IF ((M31<M22) AND (M22=M12) AND (Time>300)) THEN T=M22
       ELSE T=M31
```

In the formula above it can be observed that it was necessary to extend the duration of the startup to 5 minutes (300 seconds), the remaining part of the formula is somehow responsible for negotiating the length of the basic period, which can be identified in periodogram.

Using the methodology outlined above, there was obtained the mean value for the basic period for the correct startups equal to $\gamma=117$ s,

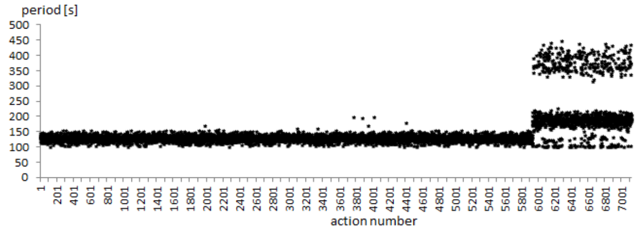


Fig. 3. The chart of the basic period of each startup after the final data filtration.

with a standard deviation $\sigma=36.28$ s. For incorrect startups these values were $\beta = 158.43$ s, $\sigma=105.66$ s. In order to further reduce the variance of the basic period for correct startups, all startups of which the basic period $T<100$ s were removed. Finally, there were achieved 7125 startups, among which for correct startups the mean of the basic period was $\gamma=128.45$ s, and the standard deviation $\sigma=8.63$ s (Fig. 3).

Presented way of filtration and identification of the basic period does not allow for the diagnostics of the conveyor after each startup, as these shorter than 5 minutes will not be the subject of evaluation, however, we obtain the possibility of diagnosing on average of every second startup. Average daily number of startups was 25, while the average daily number of startups, for which performing the diagnostic procedure is possible, is 12.

Now it is possible to perform diagnostic procedure using the parameters γ and β. However, this will be a diagnostic procedure for a specific type of change in working conditions of conveyor (lengthening the chain by combining different chains). In order to diagnose unknown types of error it is necessary to monitor whether the basic period and its standard deviation change.

Distribution of the basic period for correct startups was a normal distribution (Shapiro-Wilk W test was performed), ninety-five percent of startups should therefore lie in the interval $[\gamma-1.95996\sigma, \gamma+1.95996\sigma]$. It appears that it can be assumed that the distribution of the basic period is a normal distribution, with various values of the mean (γ) and the standard deviation σ. If, however, it turned out differently, it is always under the Chebyshev inequality holds. It says that for any $k>1$ probability that a randomly selected feature value differs from the expected value by more than $\pm k\sigma$ is at most $1/k^2$, which is outside the range $[\gamma-2\sigma, \gamma+2\sigma]$ is at most 25% of the feature value.

This information can be used in the following way: as an incorrect startup (or rather: different from the pattern found to be diagnostically correct) will be considered such a strartup, the basic period of which will

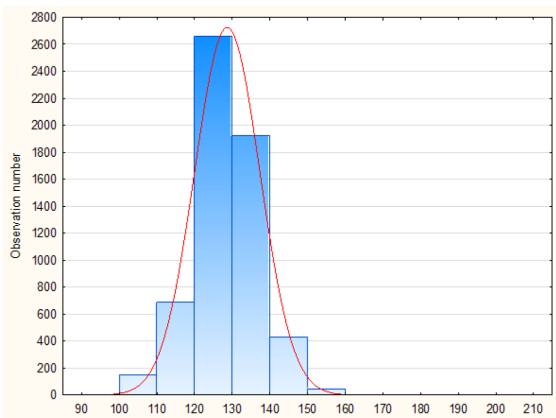


Fig. 4. Distribution of the basic period for correct startups.

not lie in the mentioned intervals. In such a case, the user would have the ability to view courses of current on all three motors and browse periodograms. As a result, one would qualify startups as actually incorrect, or could change the value of the basic period, when it would clearly result from the periodogram, thus, from the actual reconstruction of the conveyor. The second option would include the phase of updating parameters used in diagnostic procedures. Information about the reconstruction of the structure of the monitored device or its location is often registered into diagnostic or monitoring systems with a delay.

To further reduce the number of the user interventions, incorrect startups may be only these for which the basic period will be an outlier. For the filtered the basic periods, median M and the first and third quartiles (*Q1 and Q3*, respectively) can be calculated, then the interquartile range IQR is expressed by the formula (2)

$$IQR = Q_3 - Q_1 \qquad (2)$$

Values lying in the ranges (Q_3+1.5IQR, Q_3+3IQR] and [Q_1−3IQR, Q_1−1.5IQR) are considered outliers. Values grater than Q_3+3IQR and less than Q_1−3IQR are considered extreme outliers. In the case of diagnosis referred to in this paper, the user would observe all startups for which outliers in the basic period were registered.

Information about specificity and sensitivity of diagnostic procedure described above is presented in Table 1. Diagnostic procedures verification was performed on the data set used for defining the Table.

Table 1. Information about the number of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) for different diagnostic methods.

Method	TP	FP	TN	FN
Normal distribution (2σ)	5713	212	123	1077
Normal distribution (1σ)	5119	806	316	884
Outliers	5718	207	1146	54
Distance from the means γ, β	5921	4	923	277

Taking all the analyses into consideration, the following diagnostics scheme can be proposed:

1. Select a group of startups reflecting correct operation of the conveyor.
2. Select a group of startups reflecting incorrect operation of the motor (if there are startups describing different types of failure, for each failure type create a separate group). Point 2 can be omitted if you have examples only of correct startups.

(the following points concern of all three motors, these actions apply only to startups selected in step 2)

3. For all the startups perform the processes of deleting low speed and switching into high speed.
4. For all startups perform data smoothing process.
5. For all startups perform the process of determining the Fourier transform, skip the first two components and determine the reciprocal of arguments in frequency domain.
6. For all startups find the first five maximum values in periodogram and determine their equivalent arguments.
7. For each startup specify a value of the basic period according to the rule RL (section 3.3).
8. Determine the arithmetic means and standard deviations, as well as quartiles and interquartile range for correct startups group.
9. Determine the arithmetic means and standard deviations for all identified groups of incorrect startups.
10. Determine limits for outliers (formula (2)).
11. For each new startup begin the diagnostic procedure, checking whether startup parameters qualify it as correct or incorrect.

Block diagram of the procedure is shown in Fig. 5.

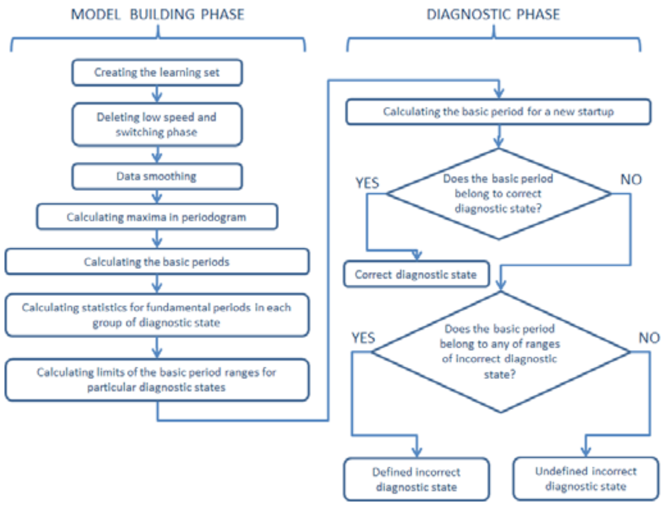


Fig. 5. Block diagram of the diagnostic procedure.

The diagnostic procedure presented above includes some inconvenience. The most important one is the need to define the rule (RL) identifying the basic period. Such methodology is not appropriate if the ultimate goal is automation of the diagnosis process. As it is known, in order to define the diagnostic model of the device, machine learning also can be applied [7, 15]. As sets of correct (Period A) and incorrect (Period B) startups of conveyor were available, rule induction algorithm PART was used [3, 14]. Calculations were carried out in Weka environment [14]. Detailed description of PART algorithm can be found in [3].

In the data set submitted to the algorithm, each startup was characterized by already mentioned in section 3.2 vector of 15 features (local maxima in periodograms), also used to identify the rule RL. The results are presented in Table 2. The first line of Table 2 presents the results obtained by using 10-fold cross validation. The second line presents the result of the analysis of whole available set of examples (i.e. without isolating a test set).

Table 2. Information about the number of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) for the basic period identification based on rule induction

Metod	TP	FP	TN	FN
PART (10CV)	5875	51	1138	60
PART	5896	30	1173	25

As it can be observed, the results obtained by PART and the diagnostic method based on the distance from the means γ, β (the last line of Table 1) are satisfactory. The best sensitivity and specificity lies in the method applying the PART algorithm to recognize correct and incorrect startups. Therefore, in the diagnostic scheme (points 1-11), points 8 and 9 can be replaced by training the classifier and including it into the diagnostic process.

The fact is, that presented methods of identification the correct values of the basic period (including the method based on rule induction) need a set of positive examples (correct startups) and negative examples (incorrect startups). This diagnostic method can be used only after a certain period of conveyor work. In the initial period of operation, we may assume that the conveyor is working properly, and the Fourier analysis (in particular analysis of the values classified as outliers in terms of the basic period) allows for identification of potentially incorrect startups. After collecting sufficient number of negative examples based on the Fourier analysis (based on the characteristics resulting from the analysis), the classifier is determined and then it is used for fully automatic diagnostics.

Note also that the set of negative examples can be created based on startups considered as incorrect for various reasons (reflecting various types of damage). In this situation we may deal with so-called *concept drift*, resulting in the need to re-train classifier on the extended set of negative examples, in order to improve its sensitivity and specificity. However, this process can be automated.

The procedure suggested here including: acquisition of a set of positive and negative examples, monitoring the classifier quality and (if necessary) re-training it, has successfully been applied to predict the total energy of seismic events that were recorded in a given period of time in coal mines [8] and to predict the concentration of methane [9].

Certainly, acquisition of diagnostic knowledge (correct and incorrect startups) can be carried out also by the planned experiment [7]. However, it is definitely more complicated in underground conditions of conveyor work.

5. Summary

This paper presents the diagnostic procedure, which allows monitoring work of a longwall conveyor, with particular emphasis on the diagnostics of "transporting" chain. Diagnostic procedure is based on harmonic analysis, power analysis, monitoring of outliers, as well as the induction of classification rules. The work presents all the necessary steps to allow the implementation of the presented diagnostic procedure. The results are satisfactory, developed diagnostic procedure can with high precision indicate correct and incorrect startups. The procedure generates a small number of so-called false alarms which is especially important for the dispatcher monitoring more devices working. It is planned to implement presented diagnostic procedure into the monitoring system DEMKop [12] (the successor of the SMoK system).

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