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# MONITORING AND MAINTENANCE OF A GANTRY BASED ON A WIRELESS SYSTEM FOR MEASUREMENT AND ANALYSIS OF THE VIBRATION LEVEL

# MONITOROWANIE I UTRZYMANIE SUWNICY BRAMOWEJ NA PODSTAWIE BEZPRZEWODOWEGO SYSTEMU POMIARU I ANALIZY POZIOMU DRGAŃ*

*The paper describes a system for monitoring and diagnosing a gantry. The main goal of the system is to acquire, visualize and monitor vibration levels of the gantry crucial elements. The system is also equipped with a computing and analytical part which enables predictive maintenance related to the vibration level assessment. The system architecture can be used in other applications too, i.e. those which require a wireless network of vibration sensors to carry out diagnostic tasks.*

**Keywords**: *vibration sensor, monitoring system, maintenance, gantry, predictive maintenance, data mining, trend analysis.*

*W artykule przedstawiono system monitorowania i diagnostyki suwnicy bramowej. Głównym zadaniem systemu jest akwizycja, wizualizacja i monitorowanie poziomu drgań newralgicznych elementów suwnicy. System wyposażony jest również w część obliczeniowo-analityczną, umożliwiającą realizację zadań predykcyjnego utrzymania ruchu (ang. predictive maintenance) związanych z oceną poziomu drgań. Architektura systemu umożliwia wykorzystanie go również do innych zastosowań, w których dla realizacji zadania diagnostyki wymagana jest bezprzewodowa sieć czujników drgań.*

**Słowa kluczowe**: *czujnik drgań, system monitorowania, utrzymanie, suwnica, utrzymanie predykcyjne, eksploracja danych, analiza trendu.*

## 1. Introduction

Today's IT systems for monitoring and diagnosing industrial facilities offer extensive data storing and processing possibilities. For several years, in accordance with the ISA95 standard [11], a distinct specialization has been forming which allows for distinguishing the following systems: measurement data acquisition systems, online monitoring and process visualization systems (HMI – Human Machine Interface; SCADA – Supervisory Control and Data Acquisition), process execution systems (MES – Manufacturing Execution System), and ERP (Enterprise Resource Planning) systems which ensure comprehensive support of enterprise management.

Data analysis is a dynamically developing area of IT systems application. New analysis-based functionalities support suppliers and manufacturers in gaining competitive advantage on the market. There are two groups of applications related to the analysis of data collected by SCADA and MES systems: CMMS (Computerized Maintenance Management Systems) and DAP (Data Analytics Platforms). In the ISA95 architecture, these applications should be placed between MES and ERP. DAP applications provide tools and methods to build diagnostic models of devices or to analyze the collected data with a view to improving manufacturing processes.

Modern organizations have been increasingly more aware of the necessity to employ data scientists who develop and maintain diagnostic modes used, for example, in Predictive Maintenance (PdM) [18].

The paper presents a gantry monitoring and diagnosing system. The diagnosed gantry is an element of a raw material transportation line for a converter steel plant in a foundry. The gantry is one of the key elements of the production line, therefore it is necessary to monitor its operations and to identify, at least with some approximation, a moment in time when the gantry operation starts to be dangerous or impossible.

The source of data involves a wireless network of vibration sensors. The data are processed by a dedicated SCADA system, while the analytical part is based on R analytical environment [21].

Section 2 of the paper features examples of related works about systems dedicated to machine diagnosing based on historical data analysis, particularly that of the vibration level. Section 3 presents the monitored object and the issue of its diagnostics. Section 4 includes a description of the hardware and software parts of the monitoring system. Section 5 features the data analysis process and the resulting diagnostic procedure whose practical application is presented in section 6. Section 7 includes conclusions and a system development concept.

## 2. Related works

Computer systems dedicated to defining, monitoring and predicting diagnostic states of machines can be categorized from different points of view. One of them is the division into frameworks [13] and

(*) Tekst artykułu w polskiej wersji językowej dostępny w elektronicznym wydaniu kwartalnika na stronie ***www.ein.org.pl*** systems dedicated to a specific solution or a group of solutions (e.g. [17]). Methodologies for performing diagnostic tasks, maintaining machines and devices [29], predictive maintenance [14,26], or diagnosing damages [20,25,10] allow for an increasingly more efficient use of equipment owned by the organization.

In the literature one can find many publications about diagnostics. Depending on the degree of machine complexity, its structure, intended use, and operation mode, the diagnosing process is carried out using diverse research methods. For example, the diagnostics of combustion engines in terms of their wear is very often performed based on the spectrometric analysis of the composition of oil taken from these engines [12]. Some works apply an analytical approach to the modelling of the oil combustion process in pistons in order to describe the relation between the content of pollutants and the passed time [16].This example illustrates two main approaches to the construction of diagnostic models: one is based on the analysis of the collected measurement data or other data related to the machine work monitoring (e.g. thermal images [9]), the other – on modelling/simulation of the diagnosed object operations.

Due to the topic of the paper, it is particularly important to refer to works in which the vibrations generated by a working machine are the input signal being the basis for the diagnosis. In the work [6] the authors monitored the behavior of a plunger pump in a truck crane through the acquisition of its vibrations in three dimensions. The spectra of the machine operations in a correct state were known, along with its operations spectra in five incorrect diagnostic states. The classification of the pump's current state was conducted by means of Bayesian reasoning whose parameters were tuned with the use of the particle swarm optimization algorithm. In the work [8] the authors described the use of advanced features extraction from the vibration signals describing the work of a commutator motor in the range of frequency.

In order to analyze data from vibration sensors, the wavelet transform is used. The works [19,27] feature a review of this methodology application for machine diagnosing. The method was used particularly to detect failures of an induction engine rotor [28], failures in transmission networks [23] or damages of bearings [15].

The vibration amplitude waves are usually not stationary. For this reason, their analysis is often performed with the use of the so called spectral kurtosis [1]. The method has been used to detect failures in wind turbines drives [7] or to assess the condition of bearings [5].

Samuel's work [22] presents a comprehensive approach to the issue of building diagnostic models on the basis of the vibrations analysis. The work features many variants of using vibrations measurement (from simple statistical indicators of time and frequency, through wavelet transform, use of neural networks, to mathematical modeling) to construct diagnostic models of machines.

In works [2, 3] Bartelmus and others point out that, while analyzing the vibrations, it is necessary to take into account the load under which the machine (e.g. conveyor or wheel excavator) works at a given moment. The component of vibrations induced by the changing load of the machines is isolated and deducted from the originally observed series of vibrations. This allows, in special cases, to obtain proper input data for the diagnostic process.

## 3. Object and goal of monitoring

The monitored object involves two gantries, each with a lifting capacity of 500 tons, working in a steel plant. The gantries are elements of a raw material transportation line in a converter plant. Each gantry takes full ladles of crude steel from transportation trolleys, transports them towards the converter mouth, pours the crude steel inside by tilting the ladle and, eventually, puts the empty ladles back onto the trolleys.

Figure 1 features a diagram of a drive system responsible for lifting and lowering the ladle. The system is the place where vibration sensors are located. Each gantry has two drives – left (L) and right (R). The drives are connected by rollers with toothed gears which reduce the rotary speed of the roller in the main lifting mechanism. In addition, the figure presents the location of vibration sensors which are placed on the rollers (1, 6), pinion bearings (2, 5) and on the supporting beam. Sensors 3 and 4 are, in fact, auxiliary ones and their task is to monitor the vibration level of the background. They may serve as reference points for other sensors. For the diagnostic system (particularly for the data preparation phase) it is important to note that for different gantries (even gantries of the same type) it is very difficult to locate vibration sensors exactly in the same place.

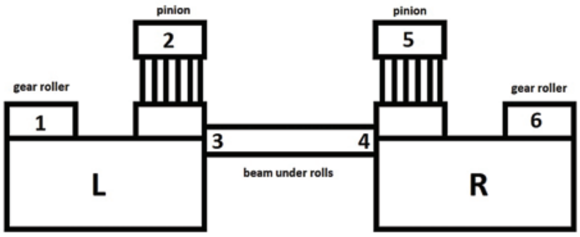


*Fig. 1. Drive system of a gantry with vibration sensors locations*

Accurate operation of the gantries is one of key elements to maintain steel production continuity. Their damage results in the failure to supply raw steel from the blast furnace to the converters. This, in turn, prevents the supply of raw material to the successive production stages (continuous casting and rolling) and, in extreme cases, leads to the necessity to extinguish the furnace.

The gantry works in difficult environmental conditions, in a production hall (Figure 2). The gear mechanism operates in the presence of penetrating metal oxide dust. The impact of dust can be observed by the rising vibration level of the whole gantry, as the gear vibrations are transmitted into other elements, including the structural elements of the hall. In an extreme situation, the work of the gantry becomes impossible or the operators are forced to reduce the engine gears, which has an unfavorable impact on the production efficiency. In such situations the gear needs a major renovation.

The key diagnostic issue is to analyze the vibration level and to determine, on this basis, whether further normal operation will be possible within the next several days. The diagnostic procedure should make it easier for the maintenance personnel to make decisions about

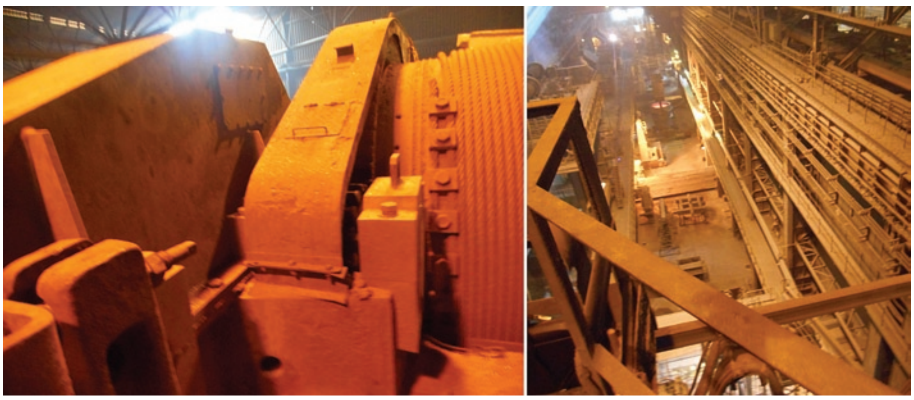

*Fig. 2. Part of the housing of the gantry drive and the view of the production hall from the operator's stand*

renovations or interim maintenance works that were not included in the renovation plan, such as oil change in the gear or control of capstan teeth.

From the practical point of view, the diagnostic procedure should be parameterizable as the impossibility to install vibration sensors in the same places each time leads to a situation in which vibration levels that are non-acceptable in certain operating conditions could prove acceptable in others. In the analysis in section 5, it is important to note the crucial role of information from the so called event log where all maintenance and renovation works performed on a given object are recorded. This information was used to develop the presented method and to assess its efficiency. Thanks to this, it was possible to refer the vibration level to the performed renovations and, in particular, to not treat sudden drops of the vibration level as data errors.

## 4. Monitoring system

The main goal of the monitoring system is to acquire, monitor and analyze the level of vibrations registered by sensors. Apart from ongoing visualization, tracking the level and the changing dynamics of the vibrations allows one to determine the moment of warning and alarm levels of vibrations.

The main source of data for the presented system involves vibration sensors installed in crucial points of the monitored objects. The practice shows that these points are often located in places with difficult access. Movable parts of machines are often monitored as well.

These conditions determined the following main features of the described system:

- the sensors are installed permanently in measurement points,
- the sensors are wireless (supplied by batteries),
- the sensors are resistant to so-called temperature surges as they may be periodically exposed to flames,
- the sensors are dustproof which makes them protected against metal dust,
- communication with the sensor network is provided via radio, with the use of a network of transceivers,
- the IT part of the system is created in the client-server architecture:
  - the server records, stores and gives access to measurements collected in the database,
  - the SCADA client application enables defining managers' panels and cockpits (allowing for visualizing device operations, including the registered vibration level) and generating summary reports,
- the analytical server, which makes use of the R environment [21], is an integral part of the system; the server is used for launching diagnostic procedures related to data analysis and provides information about the current state of the device.

Figure 3 depicts the architecture of the system dedicated to the gantry monitoring. The Server computer features a communication software (for data acquisition), a database server (PostgreSQL) and the R analytical environment. The Maintenance station computer represents the client's application (there may be many of such applications). In addition, the server can provide access to data to other applications, e.g. MES or ERP systems.

Further part of this section contains a brief description of the vibration sensor selected to monitor the gantry, as well as of the selected elements of the client application.

### 4.1. Vibration sensor

Vibrations are understood as oscillations of physical bodies of a certain weight in an assumed reference system. Vibrations can be described by one of the following three parameters: dislocation, velocity or acceleration. To diagnose vibrations it is enough to measure one of the three parameters – the remaining ones can be obtained based on the known physical relations. The easiest way to measure the level of higher-frequency vibrations is to measure acceleration, because the amplitude of this size is measureable within a wide range of the vibration spectrum.

From the point of view of diagnostic requirements, the sensor should have the best possible measurement accuracy and resolution, a considerable bandwidth and measurement linearity in this band.

Table 1 features a list of sample sensors which are analyzed for use as sources of measurement data (the first sensor is manufactured by Banner Engineering, the second – by KCF Technologies, the third – by Swift Sensors, the fourth – by EMAG-Serwis, and the fifth – by Somar).

The SD-VSN-2 sensor was one of two considered for use. However, due to communication problems encountered during the system implementation in the production hall, eventually the other sensor was selected: WS-VT1 created by Somar S.A. As seen in Table 1, the selected sensor has all the features required for the considered application. In particular, its communication band is sufficient for accurate data transmission in the production hall. Additionally, the sensor has been integrated with a radio transmitter.

WS-VT1 allows for measuring acceleration in three axes, in the ±2g/±4g/±8g/±16g ranges, and in the band up to 2.5 kHz. In addition, the sensor allows one to measure ambient temperature, which is performed by a digital temperature converter. The converter makes measurements with a 12-bit resolution and accuracy of 1°C within the range of –55÷+85°C. Both converters can be put in sleep mode in order to save energy. The measurements are managed by an energy-saving, 16-bit micro-controller equipped with a radio transceiver working in the 860 MHz band. The whole

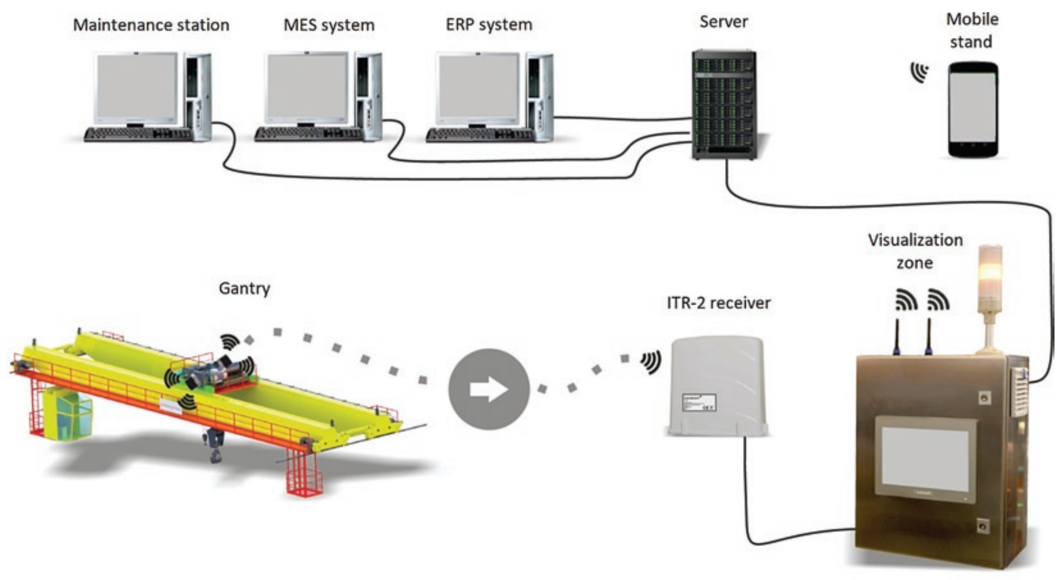


*Figure 3. System for monitoring vibrations and diagnosing machines with the use of wireless vibration sensors*

*Table 1. List of sensors enabling acceleration measurement*

| Sensor type | QM42VT1 | SD-VSN-2 | 201R | Pantera | WS-VT1 |
|---|---|---|---|---|---|
| Resistance to difficult environmental conditions (humidity, dustiness, temperature surges) | - | + | - | - | + |
| Ability to work in atmospheres with gas and dust explosion hazards | - | - | - | - | + |
| Communication band | 2.4GHz | 2.4GHz | 860MHz | None | 860MHz |
| Time of work with battery backup | + | + | + | - | + |

element is supplied by a lithium-ion ½ AA battery with a 1.2 Ah capacity.

In its basic working mode the sensor is periodically woken up from the sleeping mode so that the acceleration, temperature and battery charge level could be measured. The sensor sends the following information via radio:

- its identification number,
- RMS and maximal value of vibrations,
- temperature value,
- battery charge level.

Putting the sensor to sleep and then waking it up, performed periodically, is not the only way to carry out the measurements. The developed embedded software allows for changing the frequency of the measurements' acquisition, depending on the observed vibration level. This solution allows one to save energy during machine downtimes (lack of or low level of vibrations) and to raise the frequency of data acquisition when the registered vibrations are above the user-predefined boundary value. Theoretically, the sensor can be specially programmed to raise the frequency of measurements while crossing the successive, increasingly higher, vibration levels.

### 4.2. Maintenance station

The sensors and transmitters are data sources for the application which monitors the state of the device. Data from the sensors are collected with the use of radio transceivers. The transceivers work in Ethernet, in a 10Base-T or 100Base-Tx standard. Their basic task is to receive measurement data from the sensors which are within their range. These data are supplemented with the indication of the receiver signal strength and stored in suitable database tables.

The database server collects the measurement data and grants access to them to the maintenance station application, being a SCADA

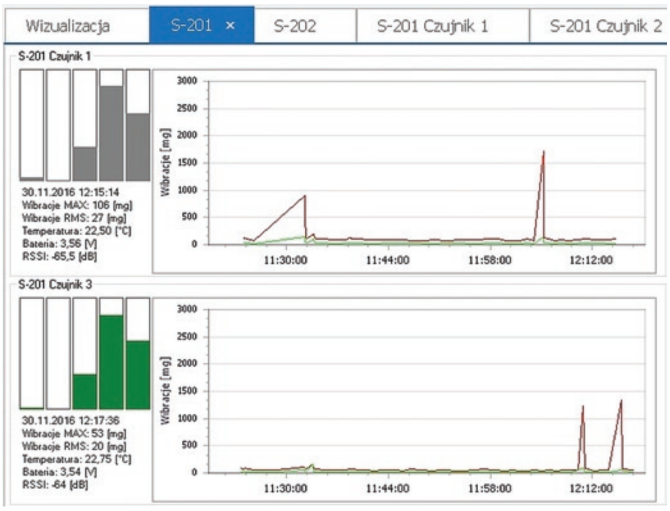


*Fig. 4. Visualization of measurements for a group of sensors – current measurements are visible (bar diagram), along with historical measurements (in the figure these are measurements from the last hour)*

program, and to the R environment server where the data analysis is performed.

The maintenance station application enables the following:

- to present current values of vibrations, temperature and battery charge level,
- to configure and set accurate, warning and alarm vibration levels (in general, the parameters of a diagnostic procedure) as well as the levels of temperature and battery charge,
- to present current and legacy data on diagrams (Figure 4. Visualization of measurements for a group of sensors – current measurements are visible (bar diagram), along with historical measurements (in the figure these are measurements from the last hour)),
- to present selected results of data analyses performed by the analytical part of the system,
- to generate periodic reports (shift-, day- and long-term reports).
- In addition, the application makes it possible to prepare a log of failures, renovations and maintenance works. As it was mentioned before, this is a very important feature of the system which enables to use information from the log during data analysis. In particular, the information about replacing an element of the gantry results in resetting the information about non-failure working time of this element.

## 5. Diagnostic procedure

### 5.1. Data preprocessing

Two gantries were monitored, each via a set of six sensors. The analysis used information about the registered vibration values – maximum (VibrMAX) and effective (VibrRMS) value.

The first stage of data processing was based on the preparation of two data sets (one for each gantry) in which each successive line included information about the maximum and effective level of vibrations registered by each of the six sensors in successive seconds (Table 2).

In a situation in which no measurements were recorded from a given sensor during a given second and the gap in data transfer was shorter than 30 seconds, the lacking data were supplemented with the last registered value. The period of 30 seconds resulted from the transmission configuration which forced the transfer of data from the sensors at least every 30 seconds. Gaps longer than 120 seconds were treated as missing data.

The diagnostic procedure is based on the analysis of the variables vector which describes a single work cycle of the gantry. The work cycle should reflect the operations of the gantry, i.e. lifting an element, transferring it to another place and putting it down. As there was no information available about the work of elements which are responsible for lifting and moving, the cycle was defined as a period of time during which the sensors registered increased levels of vibrations. In addition, the following additional assumptions were adopted to identify work cycles:

*Table 2. Set of basic data describing the operations of each gantry*

| Date/time | VibrRMS1 | ... | VibrRMS12 | VibrMAX1 | ... | VibrMAX12 |
|---|---|---|---|---|---|---|
| 2017-05-05 15:12:00 | 28 | ... | 29 | 71 | ... | 74 |
| 2017-05-05 15:12:01 | 28 | ... | 30 | 70 | ... | 72 |

- the basis for cycle identification included measurements for which the registered value of effective vibrations level exceeded 150 mg, lower values were treated as a temporary stoppage of the gantry,
- identified cycles shorter than 70 seconds were not taken into account,
- if the stoppage was shorter than 60 seconds, two successive cycles were combined.

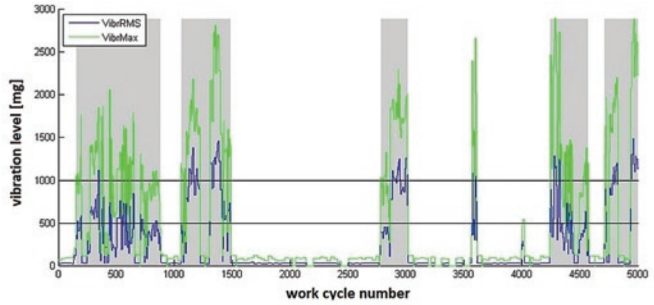


*Fig. 5. Sample identification of the gantry work cycles – gray areas depict identified work cycles*

For each of the identified work cycles a number of parameters were calculated. The parameters describe the course characteristics of VibrMAX and VibrRMS variables. The calculations were performed along the entire range of the registered values and for filtered values of these features in the ranges 2,000-2,500 mg, 2,500-3,000 mg, and 3,000-3,500 mg. For VibrMAX and VibrRMS, the following were determined:

- minimal value,
- average value and its 5th(P5) and 95th (P95) percentile,
- the number of measurements above 3,500mg,
- harmonic analysis results of the signal of the effective vibrations value: the frequency of the first 10 harmonics (including the constant) and their amplitude,
- harmonic analysis results of the signal of the vibrations maximal value: the frequency of the first 10 harmonics (including the constant) and their amplitude,
- 1st quartile (Q1),
- median (Q2),
- 3rd quartile (Q3),
- maximal value,
- interquartile range (Q3-Q1),
- percentile range (P95-P5),
- mode of registered values.

For each sensor the final effect of the conducted analysis was a vector of 115 features characterizing each work cycle of the gantry.

The first analysis dealt with checking whether, on the basis of the above parameters, it is possible to clearly recognize the work cycles in which the gantry is loaded by a full ladle. The tests were conducted with a very limited testing set containing 48 runs of the gantry of which the personnel qualified 24 as "full runs" and 24 as "empty runs." On the basis of the available sample runs and with the use of the RPART algorithm [24] a decision tree was generated (see: Figure 6).

The features based on Fourier's analysis allowed for obtaining a tree with the following classification ability: 0.792 accuracy of the empty class and 0.958 accuracy of the full class. Unfortunately, after launching the classifier on the data that had been collected for a long time, it was observed that most samples (5,467 out of 6,439) were classified as empty. In spite of the fact that the samples did not have class labels, such a classification result was recognized as bad, because according to the specification of the gantry operations the distribution of samples should be close to the regular one. Eventually, during a further analysis of the gantry work cycles no differentiation was introduced between empty and full runs.

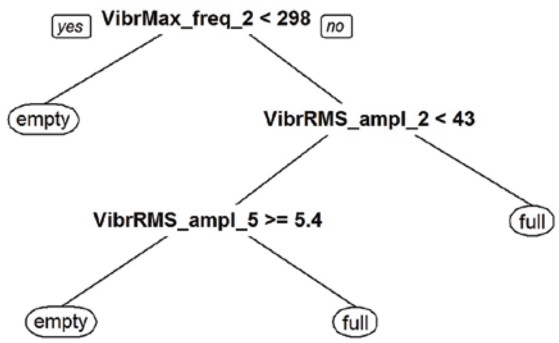


*Fig. 6. Decision tree to identify full and empty gantry runs*

In the next phase of testing, the diagnostic procedure was determined using data from one gantry. The data from the other gantry were used to verify the conducted tests.

In order to identify the features with the highest diagnostic significance, a feature selection method was used. The method is based on ranking the features of a classifier made with the use of the random forest methodology [4]. The vector of successive cycles from the period of 4 months of the gantry operations (a total of 11,818 cycles) was labelled so that the cycles registered in the period up to two weeks directly before the failure received a 0 label (operational gantry), while the cycles registered within the period of two weeks before the failure up to the failure point were labelled 1 (pre-failure gantry state). This way, a data set was obtained in which 9,275 samples pointed to class 0 and 2,543 indicated class 1. On a data set prepared for each vibration sensor separately, a classifier created of 1,000 decision trees was trained. The main criterion of the node assessment involved the Gini index [4]]. The following quality of classification was obtained for the successive sensors:

- sensor 1 – specificity 0.984, sensitivity 0.898,
- sensor 2– specificity 0.991, sensitivity 0.722,
- sensor 3 – specificity 0.986, sensitivity 0.828.

Based on the analysis of trees creating the random forest, the relevance of each feature was assessed from the point of view of its importance in the developed classifier. Based on the random forest, the importance of feature $X$ was determined according to the following formula:

$$Imp(X)=\frac{1}{M}\sum_T \sum_{t\in T:v(t)=X}\frac{N_t}{N}\cdot\left\{G(t)-\left[\frac{N_{t_L}}{N_t}G(t_L)+\frac{N_{t_R}}{N_t}G(t_R)\right]\right\} \quad (1)$$

where:

$M$ – the number of all $T$ trees in the random forest (in this case 1,000),

$t$ – the node of tree $T$,

$t_L, t_R$ – left and right child of node $t$,

$v(t)$ – a feature occurring in the condition of node $t$,

$N$ – the number of all observations in the training set (in this case 11,818),

$N_t$ – the number of observations in node $t$,

$G(t)$ – the Gini index for node $t$; $G(t) = 1 - \left(\frac{N_t^+}{N_t}\right)^2 - \left(\frac{N_t^-}{N_t}\right)^{-2}$, where $N_t^+$ and $N_t^-$ are, respectively, the number of positive samples (class 1) and the number of negative samples (class 0) in node $t$.

The higher the value of the measure (1), the better the recognition is of diagnostic states by the feature describing the gantry work cycle. This way, it is more eligible as a diagnostic feature. If the feature did not occur in any trees of the random forest, its importance was 0.

The features were ranked according to measure (1) for each sensor separately. This way, three feature ranks were obtained. The final rank of a given feature was an arithmetic average of the positions the feature held in each rank.

The first five features in the rank were used for further work on the diagnostic procedure. These included the following:

- VibrMax2000_Q3 – the value of the 3rd quartile of the VibrMAX feature; only VibrMAX>2000 values were taken into account in the calculations,
- VibrMax3000_Q3 – as above,
- VibrMax2500_Q3 – as above,
- VibrMax_P95 – the value of the 95th centile of the VibrMAX feature;
- VibrMax2000_P95 – the value of the 95th centile of the VibrMAX feature; only VibrMAX>2000 values were taken into account in the calculations.

## 5.2. Trend analysis

The basis of the diagnostic procedure is the trend analysis of changes of the features values (let us call them diagnostic variables) identified as the key ones in the previous subsection. The trend analysis is conducted on the basis of historical data, simultaneously for the *h1, h2, h3* work cycles of the gantry. Here *h1* describes a short period of time while *h2=2h1, h3=3h1*. This allows for identifying dynamic (though maybe short-term) and stable change trends in the analyzed time series.

The procedure considers the following parameters as well:

- smoothing degree (*sm*) – due to a very big variance of diagnostic variable values, before the trend analysis the values are smoothed by a moving average which takes into account 100 previous values (100 work cycles of the gantry),
- boundary level of a diagnostic variable value (*cvl*) – a reference level which allows for estimating the number of work cycles of the gantry remaining until the level is exceeded; in the case of testing the increase of the diagnostic variable value, this level does not have to be identified with the gantry failure.

The trend extrapolation allows for estimating the number of work cycles remaining until the *cvl* level is exceeded. Instead of the number of cycles, it is possible to use the number of days after which the *cvl* level is exceeded. For this purpose, it is assumed that the average daily number of cycles (*awc*) is arbitrarily set or calculated (based on historical data) and it is an equivalent of one day of the gantry operation. This value can be modified as the information about the operation of a given gantry is being collected.

Let *S* denote a time series of consecutive values of the diagnostic variable in the range of work cycles. Let $S_{sm}$ denote a time series of value *S* smoothed by means of the moving average from the last sm of value *S*. The analysis of a linear trend in the $S_{sm}$ series, in which the estimation of parameters $hi\left(i \in \{1,2,3\}\right)$ of the last values of the $S_{sm}$ series were used, leads to the following model:

$$\hat{S}_{sm,h}(i) = Ai + B \tag{2}$$

where: *i* is the number of the gantry work cycle, *A* and *B* are parameters of the model estimated on the basis of $h$ of the last values of the $S_{sm}$ series.

If $\hat{S}_{sm,h}(i)$ is the current value of the model (2), the number of work cycles remaining until the boundary value *cvl* is exceeded can be calculated according to the following formula:

$$\Delta i = \begin{cases} \dfrac{cvl - \hat{S}_{sm,h}(i) - B}{A} & A \neq 0 \\ \infty & A = 0 \end{cases} \tag{3}$$

Assuming that the daily average number of gantry work cycles is *awc*, it is possible to determine the number of gantry workdays after which the value of the considered diagnostic variable will exceed the *cvl* level. The values of indicator (3) can be grouped so that their interpretation could be better understood by the end user. This way, we will obtain a meta-indicator marked as $\Delta i_+$ whose values are interpreted as follows:

- $\Delta i_+ = 0$ if and only if $\Delta i$<0 or $\Delta i_+ = \infty$ – this refers to a situation in which we have a downward or lateral trend,
- $\Delta i_+ = 1$ if and only if $\Delta i_+ \in [0,1]$ – this refers to a situation in whih the *cvl* level is exceeded or will be exceeded in less than *awc* work cycles of the gantry,
- $\Delta i_+ = \left(\frac{1}{awc}\right)\Delta_i$ in all other cases.

Due to the way it is defined, the $\Delta_{i+}$ indicator does not reflect the drop of the diagnostic variable value. To put it more precisely, in the case of a constant or downward trend $\Delta i_+ = 0$, particularly when the values of the considered variable get stabilized on a certain level (including a the level of >*cvl*).

The $\Delta i_-$ meta-indicator allows for indicating time ranges in which the trend of the monitored value is downward. The threshold value for this indicator was set as 0. An=other solution is to set this value as an average vibration level during the period for which we are sure that the gantry was operational. The interpretation of $\Delta i_-$ – after modifying the formula (3) by replacing the *cvl* value with the *nvl* value – is as follows:

- $\Delta i_- = 0$ if and only if $\Delta i$<0 or $\Delta i_- = \infty$ –this refers to a situation in which we have an upward or a lateral trend,
- $\Delta i_- = 1$ if and only if $\Delta i_- \in [0,1]$ – this refers to a situation in which the 0 level is exceeded or will be exceeded in less than *awc* work cycles of the gantry,
- $\Delta i_- = \left(\frac{1}{awc}\right)\Delta i$ in all other cases.

The values of $\Delta i$+ and $\Delta i_-$ can be visualized on a diagram. Coming back to the analyzed data set: in the first half of February we can observe two moments of a significantly worse diagnostic condition of the device (the analysis was conducted for *h1*=7 days, *awc*=40, *cvl*=4000). From the $\Delta i_+$ diagram we can see that the first moment is in its maximum at a time of less than 7 days remaining to the time when the admissible level of the diagnostic variable value is exceeded, while for the second moment it is 10 days.This can be clearly seen on diagrams of trends built on the basis of the analysis of the last 3 (black) and 7 (red) days of the gantry operations. The diagram of $\Delta i_-$ diagram, in turn, does not demonstrate any significant improvement

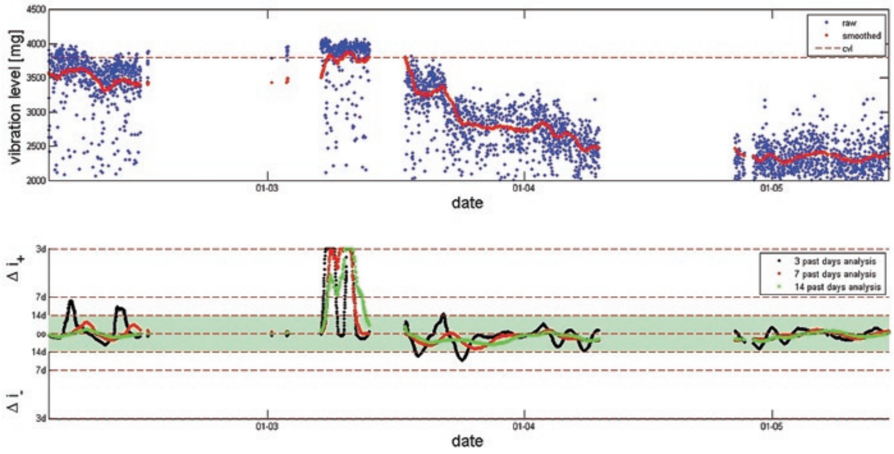


*Fig. 7. Diagram of monitoring the value of VibrMax2000_Q3 – gantry 1. Upper diagram: original values (blue), smoothed values (red) and the cvl level. Lower diagram: values of the Δi indicator generated on the basis of a trend analysis conducted based on 3, 7 and 14 past days of the gantry operations*

in the diagnostic state between these two periods, though the analysis of the smoothed course of the diagnostic variable (Figure 7, upper diagram) shows a small temporary drop of the diagnostic variable value.

For legibility reasons, the Y axis of in the lower diagram of Fig. 7 was cut to a value corresponding to 3 days after exceeding the *cvl* level. In addition, the value of *nvl* was set as 0, which lowers the warning and alarm thresholds and, at the same time, ramps up the values placed in the report.

In the considered period, the report log did not contain any information about repairs; however, it was noted that the operator recorded an increased vibration level. A break in the measurement data resulted from a break in the gantry operations. Then, around the 10th of March, the gantry was operating again but, as it could be seen from the beginning of its operations in fact, the $\Delta i_+$ indicator reached the boundary value very quickly. This was confirmed by an increasing vibration level which followed the values of $\Delta i_+$. Next, the gantry was under renovation for a few days, after which it was put back in operation. The renovation period was reflected by a decreasing value of $\Delta i_+$ and a rising value of $\Delta i_-$, followed by stabilized trends of 7- and 14-day values of the $\Delta i_+$ indicator.

The interpretation of changes in the $\Delta i_+$ and $\Delta i_-$ values, as well as the value of the diagnostic variable based on which these indicators are calculated, can be placed in the report. Table 1 features a sample report.

The values in the report are determined according to the following rules:

- OK! if the $\Delta i_+$ indicator is equal to 0 and the values of the diagnostic variable are below *cvl* 0.7; additionally, if the trend is upward, then the number of "days" is given after which the *cvl* level will be exceeded, provided that this number is below 35;
- W if $\Delta i_+$ is equal to 0 and the values of the diagnostic variable are within the range (*cvl* 0.7, *cvl* 0.8]; additionally, if the trend is upward, then the number of "days" is given after which the *cvl* level will be exceeded, provided that this number is below 28; if the number is above 28, only the information about the trend direction is given,
- A if the values of the diagnostic variable are above cvl 0.8; additionally, if the trend is upward, then the number of "days" is given after which the *cvl* level will be exceeded, provided that this number is below 21; if the number is above 21, only the information about the trend direction is given.

Please note that 1 "day" is the average number of gantry activations during the day. This value can be set arbitrarily or calculated based on the history of the gantry work cycles.

The far right column contains the number of the same decisions for trend analyses conducted on the basis of the last 3, 7 and 14 "days". This column allows for tracking the stability of changes in the diagnostic variable values.

Depending on the user's needs, the report may refer to one or more sensors as well as to a bigger number of diagnostic variables.

The report does not give any suggestions about the time in which a failure will occur or the gantry will have to be renovated. Still, it allows one to observe, in an organized manner, the trends in the changes of a variable (or variables) identified as diagnostic variables.

### 5.3. Application phase

A practical application of the presented method requires the following:

- distributing sensors on the monitored gantry;
- identifying the gantry work cycles in accordance with the method presented at the beginning of section 5.2;
- calculating the value of VibrMax2000_Q3 for each sensor and, possibly, successive features from the rank included in section 5.2;
- determining the values of *cvl*, *awc*;
- calculating the values of the $\Delta i_+$, $\Delta i_-$ indicators regularly, once a day; during the calculation of these values, the values of the sm and h1 parameters are set at 100 and 7 *awc*, respectively;
- generating the diagrams of $\Delta i_+$, $\Delta i_-$ values and a report presented in Table 3.

From the practical point of view, it is also necessary to specify the principles of operation during renovation works (whether the history of the diagnostic variable value must be reset) and when the gantry works in the so-called start-up mode. There are frequent situations when the gantry is operated in the start-up mode despite the fact that it should not be operated at all – in such instances the vibration level is considerably lower.

*Table 3. Diagnostic report with trends of the values of the diagnostic variable describing vibration levels in particular work cycles of the gantry (gantry 1)*

| Gantry 1 trends in changes of $\Delta i+$ values | | | | |
|---|---|---|---|---|
| Diagnostic variable Vibr_Max2000_Q3 | Trend analysis based on the last: | | | |
| Date | 3 days | 7 days | 14 days | Compatible decisions |
| 2017-02-04 | A (8) | A(↑) | A (↑) | 3 |
| 2017-02-05 | A (10) | A(↑) | A(↑) | 3 |
| ... | ... | ... | ... | |
| 2017-02-08 | A(↓) | A(↑) | A(↑) | 2 |
| ... | ... | ... | ... | ... |
| 2017-03-24 | W(↓) | W(↓) | W(↓) | 3 |
| ... | ... | ... | ... | |
| 2017-05-09 | OK! | OK! | OK! | 3 |

## 6. Verification tests

Verification tests were conducted on a second identical gantry used in the same foundry. The renovations log claimed that the gantry was renovated in the period of 16-18.08.2017. Still, it was not done properly and another renovation was necessary in a short time (in October). The latter renovation included the replacement of a pinion. From the beginning of September to the time of the second renovation, the gantry was working much less frequently than when it was fully operable.

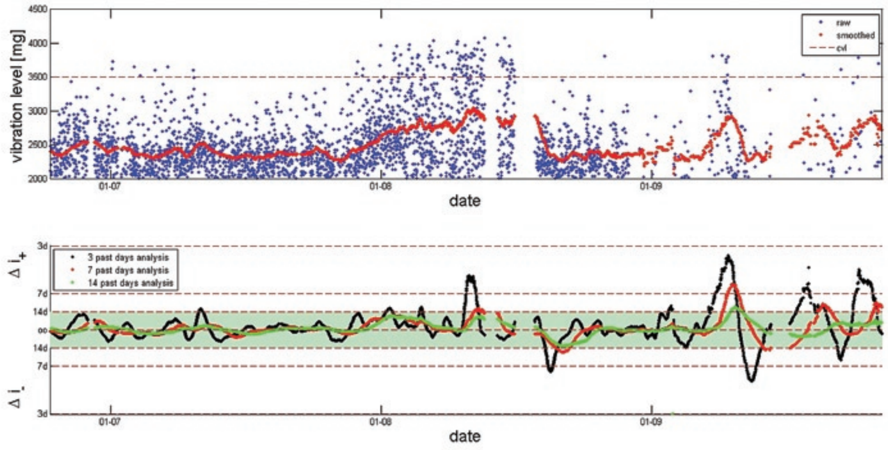


*Fig. 8. Diagram of monitoring value of VibrMax2000_Q3 – gantry 2. Upper diagram: original values (blue), smoothed values (red) and the cvl level. Lower diagram: values of the Δi indicator generated on the basis of a trend analysis conducted based on 3, 7 and 14 past days of the gantry operations*

*Table 4. Diagnostic report with trends of the values of the diagnostic variable describing vibration levels in particular work cycles of the gantry (gantry 2)*

| Gantry 1 trends in changes of Δ$i$+ values | | | | |
|---|---|---|---|---|
| Diagnostic variable Vibr_Max2000_Q3 | Trend analysis based on the last: | | | |
| Date | 3 days | Date | 3 days | Compatible decisions |
| 2017-07-25 | OK! | OK! | OK! | 3 |
| ... | ... | ... | ... | ... |
| 2017-08-07 | W (↓) | W(↑) | W(↑) | 2 |
| ... | ... | ... | ... | |
| 2017-08-11 | A(5) | A(20) | A(↑) | 3 |

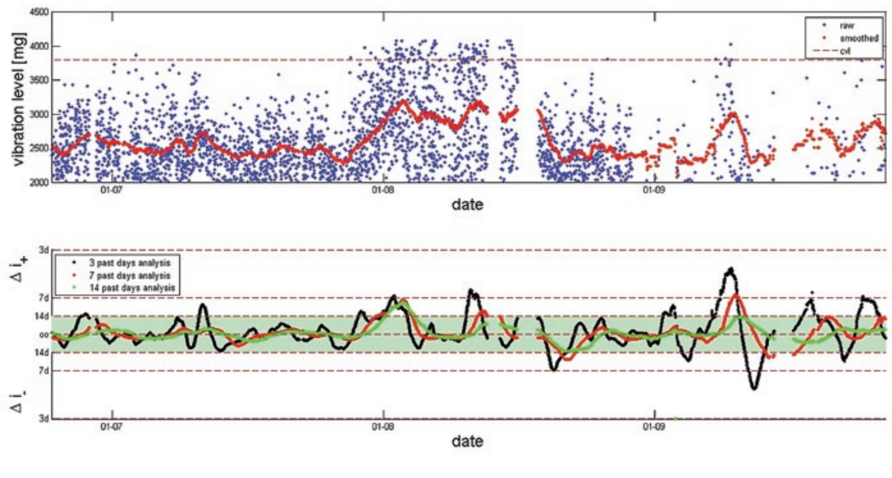


*Fig. 9. Diagram of monitoring value of VibrMax2000_P95 – gantry 2. Upper diagram: original values (blue), smoothed values (red) and the cvl level. Lower diagram: values of the Δi– indicator generated on the basis of a trend analysis conducted based on 3, 7 and 14 past days of the gantry operations*

Figure 8 presents original and smoothed values of the VibrMAx_Q3 diagnostic variable, along with the values of the Δ$i$+ and Δ$i$– indicators. Table 4 features a report for the first few days of August. It is important to note that before the renovation the gantry worked in the start-up mode only, which slightly weakened the dynamics of the vibration level increase. This can be seen on the diagram of the VibrMax2000_Q3 diagnostic variable value.

Figure 9 also features a diagram of the VibrMax2000_P95 diagnostic variable. This is the last of the relevant variables identified in subsection 5.2.

This variable shows the process of the gantry deterioration very well as clear upward trends are observed at the beginning of August when the gantry was still working in normal conditions (in the working mode, not start-up mode). Then, in spite of lowering the course of operations, the moment for performing necessary renovation is predicted properly. After the improper renovation, irregularities in the machine work are signalled as well.

This example shows how important it is to generate diagrams and diagnostic reports for all five diagnostic variables identified in section 5.2, for all monitored sensors. From the practical point of view, the analysis and interpretation of such a big number of diagrams and reports is impossible for the operator to carry out. Therefore, a data analyst should prepare recommendations as to which diagnostic variable and which vibration levels *cvl* and *nvl* should be applied as the basis for generating the report. Such work is increasingly more often conducted as a maintenance service for a decision-support system by data science departments of companies which supply these types of systems.

## 7. Summary and conclusions

Monitoring and diagnostics of technical devices is not an easy task as each time it requires an individual approach to the analyzed object.

The paper presents a system for monitoring vibrations which makes use of a wireless network of sensors. In addition, it features the use of measurements collected by sensors which monitor the diagnostic state of gantries.

In the second part of the paper the authors presented a method which allows for analyzing trends in the changes of the vibration level and for associating this level with the deteriorating condition of the gantry. Additionally, they listed the requirements regarding the practical use of the method. As it was not possible to simulate different kinds of damages and failures, the diagnostic methodology is relatively simple – it is based on the assumption that the deteriorating condition of the gantry is demonstrated by an increasing vibration level (which is in accordance with the gantry operators' intuition). The key issues of the diagnostic procedures include: the process of identifying work cycles, identification of statistics which most reflect the impact of the vibration level on the machine state, as well as short- and medium-term trends of changes in the statistics values. The paper features solutions to these issues. Moreover, the authors proposed a structure of a diagnostic report generated for the maintenance operator.

The presented measurement system was implemented in a foundry in Upper Silesia, Poland.

Further works will focus on the system application for monitoring and diagnosing other devices – it is planned to monitor the vibrations of rollers on which a conveyor belt moves. In order to implement the system, it will be necessary to develop a new diagnostic procedure dedicated to this type of task. The remaining parts of the system (hardware and software – monitoring part) are ready to use on any object.

The developed system is, to a large extent, in compliance with the architecture of data driven frameworks for decision support. In such systems the diagnostic models are made to meet the users' specific needs on the basis of historical data analyses, while the modules for data acquisition, storage and visualization are ready to use.

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