Vibration analyzing in horizontal pumping aggregate by soft computing

Miloš Milovančević, Vlastimir Nikolić, Dalibor Petkovic, Ljubomir Vracar, Emil Veg, Natalija Tomic, Srđan Jović

PII: S0263-2241(18)30381-6
DOI: https://doi.org/10.1016/j.measurement.2018.04.100
Reference: MEASUR 5501

To appear in: *Measurement*

Received Date: 11 February 2018
Revised Date: 29 April 2018
Accepted Date: 30 April 2018

Vibration analyzing in horizontal pumping aggregate by soft computing

Miloš Milovančević[1], Vlastimir Nikolić[1], Dalibor Petkovic[2]*, Ljubomir Vracar[3], Emil Veg[1], Natalija Tomic[1], Srđan Jović[4]

[1]University of Nis, Faculty of Mechanical Engineering, Aleksandra Medvedeva 14, 18000 Nis, Serbia
[2]University of Niš, Pedagogical Faculty in Vranje, Partizanska 14, 17500 Vranje, Serbia
[3]University of Nis, Faculty of Electronic Engineering, Aleksandra Medvedeva 14, 18000 Nis, Serbia
[4]Faculty of Technical Sciences, Kneza Miloša 7, 38220 Kosovska Mitrovica, Serbia

*Correspondent author: Email address: dalibortc@gmail.com

Abstract

The main goal of the study was to analyze vibration of pumping aggregate. There are fourth position which could be very harmful for the total working operation of the pumping aggregate. The pumping aggregated should have smooth continuous operations without any mistake. Vibration could affect different parts or segments of the pumping aggregate and therefore it is need to analyze the vibrating. Analyzing of the vibration could be highly nonlinear task since many different parameters are involved in the model. To avoid the analytical model in this article soft computing approach was used since the soft computing approach does not require internal knowledge of the vibration model. For the soft computing model there is enough to collect the input output data pairs through experimental measurement procedure. Based on the input/output data pairs the model will be created. The approach should rank the influence of the measuring positions vibration on the pumping aggregate. Finally three different soft computing methods were compared and results were reported.

Keywords: soft computing; vibration; pumping aggregate.

1. Introduction

The development of non-invasive methods of monitoring of the machine conditions are important in order to predict maintenance of the machines. There are various indicators for machine condition; however, the method of use vibration monitoring for determination of machine operating conditions was proved the most important.

Vibration monitoring is one among many methods of technical diagnostics which has been continuously monitoring a technical state of a device by observing the level of a mechanical oscillation in a real time [1]. The mechanical oscillation is the manifestation of a device during its operation [2]. Certain parts become vibration exciters, others, depending on excitation, react specifically [3]. Therefore the vibration monitoring is one of the most important methods used in technical diagnostics for identifying a technical state [4]. With the use of vibration diagnostics we are able to detect an incipient failure, locate the place of an incipient failure and predict the length of time during which a device is going to work before a failure occurs or a preventive action is performed [5-8]. For example in article [9] the vibration behavior of microscale beams and plates was studied based on micropolar theory (MPT). Presented in paperr [10, 11] was a size-dependent analysis of the surface stress and nonlocal influences on the free vibration characteristics of rectangular and circular nanoplates.

Maintenance and repair of pumping units requires a lot of high material costs and time. Therefore, control of vibration and parametric characteristics of pumping units in real time allows to identify defect of pumping units at an early stage [12]. The condition monitoring of a rotating machine is efficient, but often it is difficult and labour intensive task for maintenance crew to troubleshoot the machine and vibration analysis is a method used for condition monitoring of the machine [13]. Measured signals are usually fed into filters or signal decomposers to extract useful features to assist making identification in state monitoring or fault diagnosis. But what is routinely ignored is that an experienced expert can realize what is happening just by watching the signals presented on the oscilloscope even without the analyzing report [14]. Vibration-based condition monitoring is an important approach to ensure the reliability of industrial machines [15]. Semi-supervised vibration-based classification and condition monitoring of the reciprocating compressors installed in refrigeration appliances was proposed in paper [16]. The use of wireless sensor networks (WSN) for monitoring of rotating machinery is constantly growing [17]. A process monitoring system which is integrated with virtual machining for a more accurate diagnosis of machining operation without the need for test machining was proposed in article [18]. The effort in article [19] was to reduce the number of sensors per bearing pedestals by enhancing the computational effort in vibration signal processing. On-shaft vibration (OSV) measurement has been proposed in study [20] using a tiny Micro Electro Mechanical Systems (MEMS) accelerometer with a wireless node for the data transmission to the computer and the approach was expected to reduce the number of sensors used currently and may also contain enriched vibration information about the shaft which may ease the fault diagnosis process. Paper [21] presented an approach for machine vibration analysis and health monitoring combining blind source separation (BSS) and change detection in source signals where the problem is transferred from the original space of the measurements to the space of independent sources, which leads to the reduced number of components is going to simplify the monitoring problem while the change detection methods are going to be applied for scalar signals. A large vibration data set makes the diagnosis process complex generally for a large rotating machine supported through a number of bearing pedestals [22]. The Doppler-frequency shift of a laser beam was used in article [23] to monitor flexural and torsional vibration of the main axle in a numerically controlled machining tool. Development of a system for machine condition monitoring system requires reliable machining data that can reflect machining processes [24]. In paper [25] was presented an automatic feature construction method which can reveal the inherent relationship between the input vibration signals and the output machining states, including idling moving, stable cutting and chatter, using a reasonable and mathematical way.

Since the analyzing of the vibration signals could be highly tedious and nonlinear task in the article soft computing method (ANFIS – Adaptive Neuro-Fuzzy Inference System) is applied [26]. The soft computing methodology is based on the acquired input/output data pairs [27-29]. Therefore there is no need to know internal knowledge of the system behavior. The basic design idea is to create a measurement and data collection system for vibration monitoring in which the data analyses and decision-making are based on soft computing method.

2. Methodology

2.1. Device description for vibration monitoring

Devise for vibration monitoring is developed on the basis of Microchip PIC16F877A (20MHz) microcontroller for RS232 version or on the basis of PIC18F4550 if USB variant is needed. Additional plate is 12-bit A/D converter with 4 channels, based on MCP3204 A/D converter. The following characteristics are used:

- Device is connected to PC computer via USB or RS232 (serial) port
- There are 8 analogue input channels (range 0 to 5V and 0 to 200mV, with other ranges possible, all safe until 250V)
- Digital temperature sensor (-55°C to +125˚C, with 0,1 ˚C resolution)
- Liquid conductivity sensor
- High sensibility acceleration sensor
- Accelerometer and inclination sensor by 2 axes with ±2g range [30, 31, 32].

2.2 Software for data processing

Software for data processing is written in Visual Basic 6. It is possible to enlarge certain areas on the graph for detailed analyses, to save the data into picture format and to perform FFT analysis of measured signal. Microcontroller program is written in Micro Basic. Device is tested at Electronic Faculty, University of Niš, using TEKTRONIX AFG3102 signal generator by inputting the 100Hz sinusoidal signal into the device itself. After performed FFT analysis of the signal at PC platform, the program showed perfect match with generator input signal [30, 31, 32].

2.3 Pumping aggregate vibration parameters

It is necessary to take safety measures to assure the precision of turbo pumps operating conditions. It is considered that a basis of supervision is the control of vibrations and their measuring via electric means. The primary objective of all safety measures is timely recognition of critical operating conditions. Operation of centrifugal pumps is accompanied by two undesirable side effects: vibrations and noise. The intensity level of vibrations and noise characterize the perfection of pump operation, its construction and pump condition during exploitation period, as well as cavitation phenomenon in the pump. More about all these effects to the emitted noise as a side effect of centrifugal pumps is given in [33, 34, 35].

The sources of vibrations in centrifugal pumps are mechanical, hydraulic and electrical processes caused by the pump construction, operating regime, exploitation and manufacturing technologies used. Due to the blade passage frequency (BPF) with frequency $f_z = z\omega/2\pi = zn$, where z is the number of impeller blades and n is the rotational speed in rps. Disbalance of rotational masses of rotor is caused by oscillation with frequency $f_1 = \frac{\omega}{2\pi}$.

Vibrations caused by the collisions of parts in the contact are produced in bearings, gear box, couplings and connected shafts of the pump and the driver. Rolling bearings may produce vibration with frequency often lower than 30 kHz [36].
Disturbance force is generated by connecting a pump and a driver shaft with the geared coupling, with the frequency $f_2 = z_s \frac{\omega}{2\pi}$, ($z_s$- number of coupling teeth). Electromotor vibrations are caused by disturbance forces generated from variations of electromagnetic field, with frequency for this case: $f_E = \frac{\omega}{2\pi} z_w$, ($z_w$- number of motor poles).

Mechanical vibrations of pumps were the subject of numerous researches [37]. Result analysis draws the conclusion that the level of vibration can be lowered with respect to the certain instructions and recommendations in balancing of rotational masses, selection of bearings, couplings, eccentricity between the shaft axis of pump and driver, etc.

Hydrostatic vibrations of centrifugal pumps are the result of vortex arisen in liquid stream, flow heterogeneousness, turbulent pulsation of speed and pressure, and cavitation phenomenon [33, 34, 35]. Vortexes are generated during the liquid run through circulation channels because of stream segregation from channel surface, hydrodynamic trail and liquid loss through gaps and sealants. Unstable flows with relative high gradation of pressure are noticed at a point where vortexes segregate from streamed object's surface. Intensity of vibrations, caused by vortex sources, is proportional to the sixth grade of stream line peripheral speed [26]. In numerous cases at centrifugal pumps turbulent pulsations are also generated together with vortexes. Their mutual activity causes vibrations of pump walls. Field of speed and pressure of liquid flow after the stream line is heterogeneous and non-stationary, causing the pulsation of flow hydrodynamic force on impeller and volute tongue. There are also pulsations of flow hydrodynamic force because of flow heterogeneousness after entry directional apparatus.

Vibrations generated flow heterogeneousness can by proper selection of radial gap between impeller blade and volute tongue. At centrifugal pumps the flow heterogeneousness produces the highest level of vibrations after the impeller, with its frequency equal to the BPF. The intensity of these vibrations is proportional to the sixth grade of stream line peripheral speed and does not depend on a pump and casing construction [38].

Various measurements were performed at pumping aggregates with centrifugal pumps for water supply in municipality of Nis and its surroundings. Two types of pumps were tested: multistage horizontal and well pumps, using the microcontroller device.

2.4 Vibration monitoring at centrifugal pumps

Horizontal pumps have a significant role in water transportation. This role of horizontal pumps defines also the importance of providing the flawless work (Figure 1). Electro motors of horizontal pumps are extremely burdened from the aspect of continuous exploitation for maintaining the permanent operation. Adequate choice of measuring point at a pump aggregate of a horizontal pump can indicate the operating condition for electromotor bearings and rotor, the pumping aggregate bearings and coupling, and complete aggregate construction likewise.

Figure 1: Horizontal pump aggregate

Influence of the four vibration points are analyzed on the fifth output point. The following measuring points are chosen according to the Figures 2-3:

- The first measuring point is chosen for the operational condition diagnosis of the first bearing at electromotor.
- The second measuring point is defined to diagnose the condition of driving electromotor second bearing

- The third measuring point is determined in such a manner that it is possible to diagnose both the condition of pump first bearing and elastic coupling.
- The fourth measuring point is defined to diagnose the condition of pump second bearing.

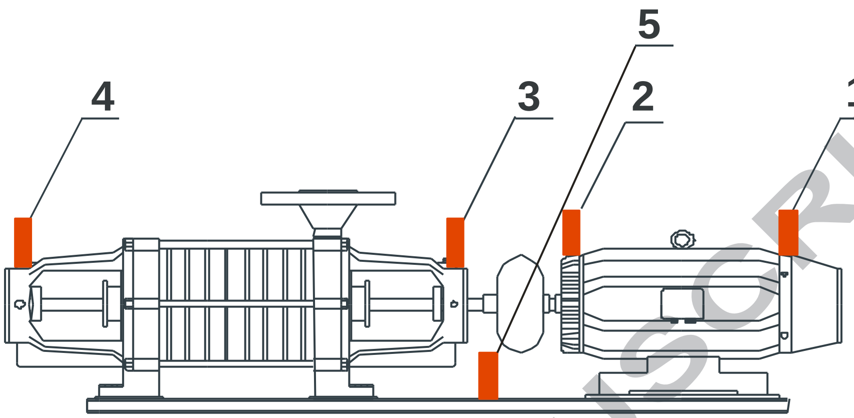


Figure 2: Measuring point at horizontal pump aggregate

(a)

(b)

(c)

(d)

(e)

Figure 3: Measuring point at horizontal pump aggregate: (a) first measuring point, (b) second measuring point, (d) third measuring point, (e) fourth measuring point and (f) fifth measuring point

Vibrations of aggregate are controlled according to standard ISO 10816-7 for acceleration of rotational machines [39], for following parameters of operating regime:

- Pressure at pump suction 1,93 bar
- Pressure at pump discharge 91,4 bar
- Pump power 539 kW
- Flow rate $Q = 150\ m^3/h$
- Pumping height 934 m
- Speed 2989 rpm
- Temperature 305,55 K

2.5 Analytical model of vibration

Vibrations occur as a result of rotating or straight-line moving bodies. The course of vibrations is influenced mainly by a technical state of single machine components such as shafts, gear boxes, crank mechanisms, cam mechanisms, antifriction bearings, and also by the imbalances of rotating parts, backlash in friction bearings, wear, material fatigue, occurring cracks, corrosion and other parameters affecting a smooth machine run. The vibration itself is defined then as a dynamic phenomenon when particles or solid bodies move around a zero equilibrium position. They are given by a combination of six movements, namely by a shift in an orthogonal coordinate system x, y, z and a rotation about these axes. Vibrations can describe by amplitude and a phase at a certain period of time. Depending on the time variations of values, the vibrations are of a periodical, non-periodical or random character. As for periodical vibrations, a time course of vibration measured values repeats. A harmonic vibration which has a sinusoidal waveform is based on these vibrations. For harmonic vibrations we need to set only one determining value and the other ones can be calculated.

The basic way of describing oscillations is to determine their displacement x, velocity v, acceleration a, maximum amplitude X_{max}, a root of mean square X_{RMS}, and an absolute value X_{ave} (Figure 4). The measurement of displacement x is convenient for low-frequency events such as measuring backlashes, etc. which might be calculated the following way

$$x = X_{\max} \sin \omega t \quad (1)$$

$$\omega = 2\pi f \quad (2)$$

where X_{max} - maximum amplitude (maximum displacement), ω - angular frequency, f - frequency (oscillation), t - time.

Velocity can be expressed as the characteristics of motion which informs us about the way of changing the position of a body (particle) in time. Velocity is a vector physical value, because it defines both the change magnitude and its direction. Velocity might be determined as the time derivation of trajectory (displacement) using the equation below

$$v = \frac{dx}{dt} = X_{max}\omega\cos\omega t \tag{3}$$

Acceleration can be expressed as the characteristics of motion which shows the way the velocity of a body (particle) changes in time. The acceleration is a vector physical value, since it gives both the change magnitude and its direction. It is possible to calculate momentary acceleration and average acceleration. The acceleration might be also determined as the time derivation of velocity using the formula below

$$a = \frac{dv}{dt} = -X_{max}\omega^2\sin\omega t = X_{max}\omega^2\sin(\omega t + \pi) \tag{4}$$

If the acceleration is in counter-motion, it is called deceleration and has a minus sign.

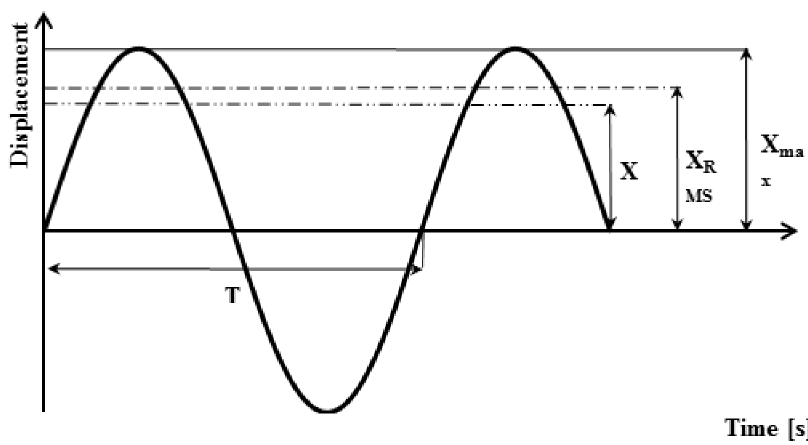


Figure 4: Harmonic oscillation with the illustration of maximum amplitude X_{max}, a root of mean square X_{RMS}, and an absolute value X_{ave}

The mean absolute value X_{ave} can be expressed as follows:

$$x_{ave} = \frac{1}{T}\int_0^T |x| dt \qquad (5)$$

where T – a period expressed by the formula.
The root of mean square can be calculated by the equation below:

$$x_{RMS} = \sqrt{\frac{1}{T}\int_0^T x^2 dt} = \frac{1}{\sqrt{2}} X_{\max} \qquad (6)$$

In order to interpret the measured values correctly, it is advisable to transform the oscillation time course into a frequency domain, i.e. vibrations are to be replaced by a sequence of its oscillation components. It can be said that a time signal contains the information about when a certain event occurred, but a frequency spectrum contains the information about how often the same event occurs in an observed signal. The procedure during which complex signals are subdivided into their frequency components is called a frequency analysis which applies either selective band-pass filters or more often a Fast Fourier transformation (FFT). Along with the FFT also a wavelet, cosine or Walsh-Hadamard transform can be used for expressing a signal by orthogonal basis functions. In the paper we have applied a Fast Fourier transformation; therefore we introduce the formula expressing its transformation which is as follows:

$$F(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} dt \qquad (7)$$

where f – frequency, j – imaginary unit, x(t) – continuous signal.

2.6 Soft computing methodology

In this study ANFIS network is used for vibration data processing. The ANFIS network could perform the ranking of the inputs based on their influence on the vibration signal. Figure 1 shows ANFIS structure with five layers. Each layer has specific task during data processing. The most important layer is layer 2 since this layer defined the membership functions for data fuzzyfication. The membership functions are defined by trial and error procedure. In this study bell shaped membership functions are used since this type of functions are the most suitable for large data sets with high nonlinearity.

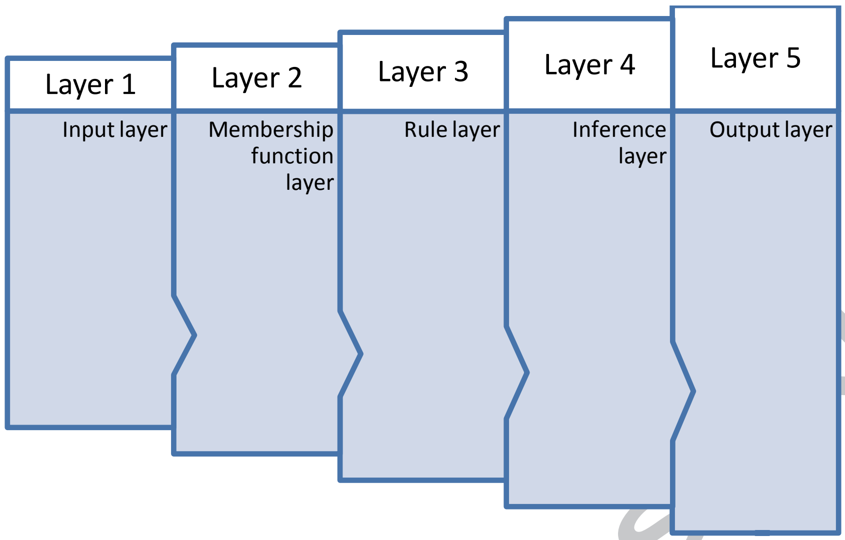


Figure 5: ANFIS layers

The Bell-shaped membership functios is defined as follows:

$$\mu(x) = bell(x; a_i, b_i, c_i) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \quad (8)$$

where $\{a_i, b_i, c_i, d_i\}$ is the parameters set and x is input.

The third layer is the rule layer where all signals from the second layer are normalized. The fourth layer provides the inference of the rules. The final layer sumarized the all signals and provied the output value. As accuracy indices root mean square error (RMSE) and coefficient of determiniation (R^2) are used.

2.7 Inputs and output vibration indicators

Table 1 shows input and output indicators which are used. The main aim is to analyze the influence on inputs at positions 1-4 on the output position 5.

Table 1: Input and output indicators

Inputs	Parameters description	Rotational speed
input 1	Vibration at position 1	(1490 rpm.)
input 2	Vibration at position 2	(1980 rpm.)
input 3	Vibration at position 3	(2470 rpm.)

input 4	Vibration at position 4	(2989 rpm.)
output	Vibration at position 5	

3 Results

3.1 Experimental results

Figure 6 shows the first measuring position and acceleration diagram at the point. Here the vertical acceleration goes above 4 g. The limit acceleration at the point is 2.5 g so one can conclude there is damage condition at the first bearing at electromotor. The limit acceleration of 2.5 g is determined according to standard ISO 10816-7 for acceleration of rotational machines [39]. This standard is a measure for determination of maximal acceleration for rotational machines. Analysis of resonance phenomenon is not need since the whole procedure is based on the standard procedure for the maximal allowed acceleration.

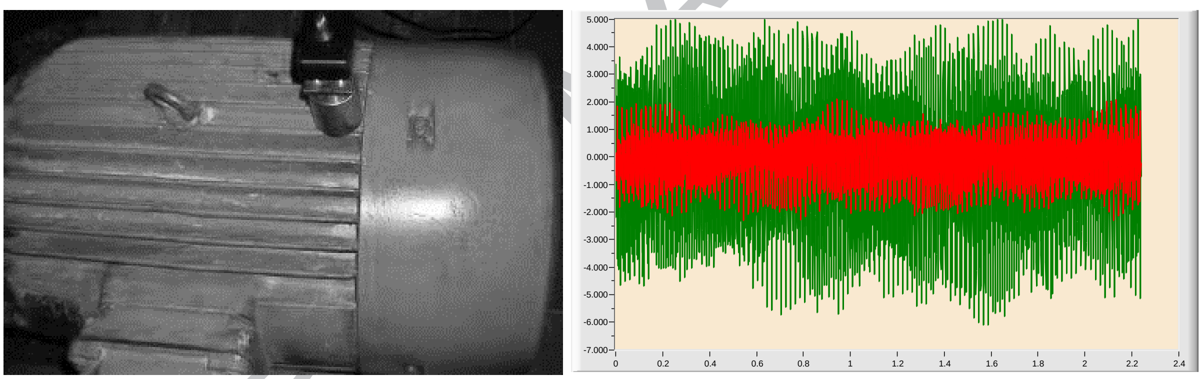


Figure 6: The first measuring position and acceleration

Figure 7 shows the second measuring position and acceleration diagram at the point. Here the vertical acceleration goes above 3 g. The limit acceleration at the point is 2.5 g so one can conclude there is damage condition at the driving electromotor second bearing.

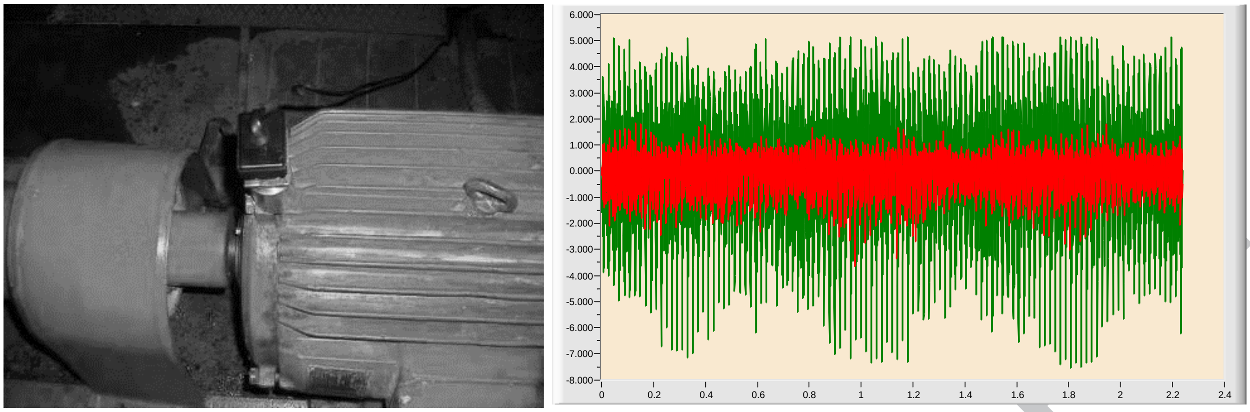


Figure 7: The second measuring position and acceleration

Figure 8 shows the third measuring position and acceleration diagram at the point. Here the vertical acceleration goes around 3 g which is highlight under limitation so one can conclude there is high damage condition at the pump first bearing and elastic coupling.

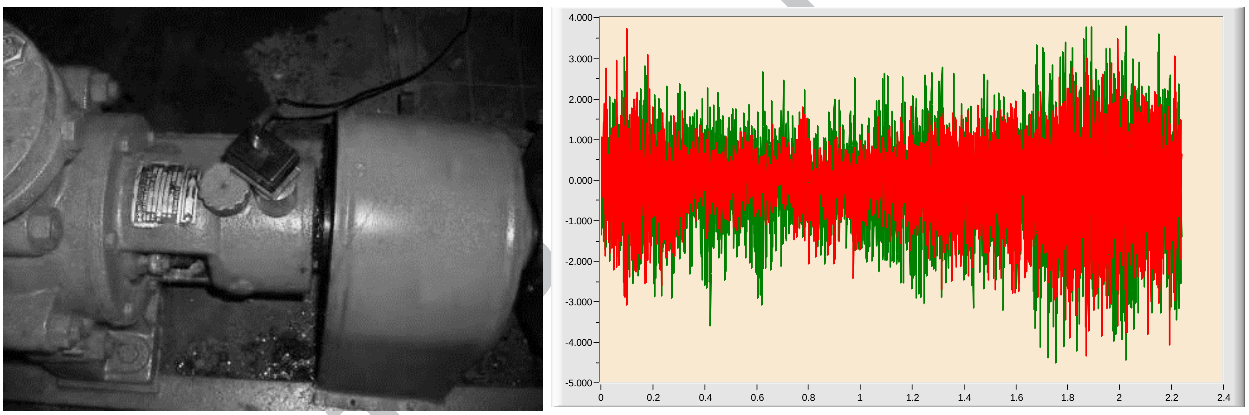


Figure 8: The third measuring position and acceleration

Figure 9 shows the fourth measuring position and acceleration diagram at the point. Here the vertical acceleration goes above 4 g. The limit acceleration at the point is 2.5 g so one can conclude there is damage condition of pump second bearing.

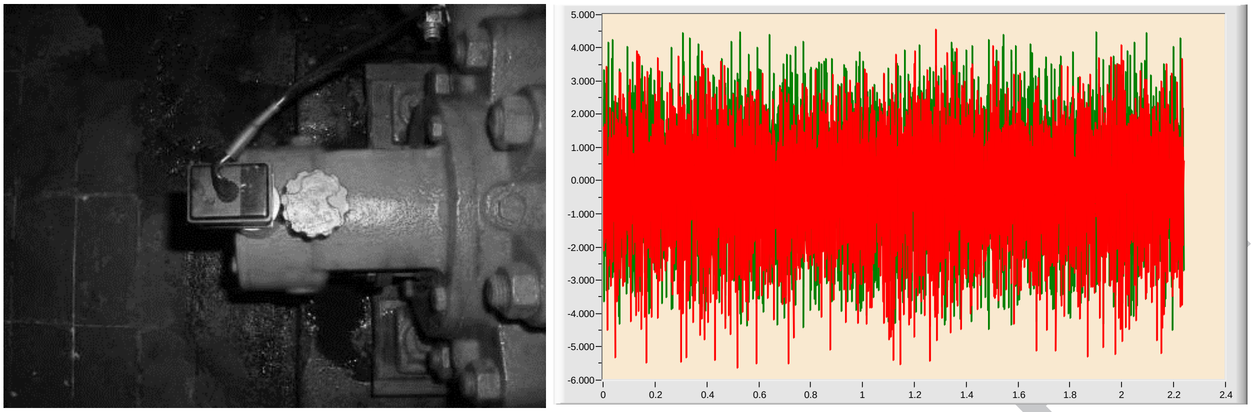


Figure 9: The fourth measuring position and acceleration

Figure 10 shows the fifth (output) measuring position and acceleration diagram at the point. Here one can note high vibration also so it mean there is to analyze which input position has the highest influence on the pump support vibration.

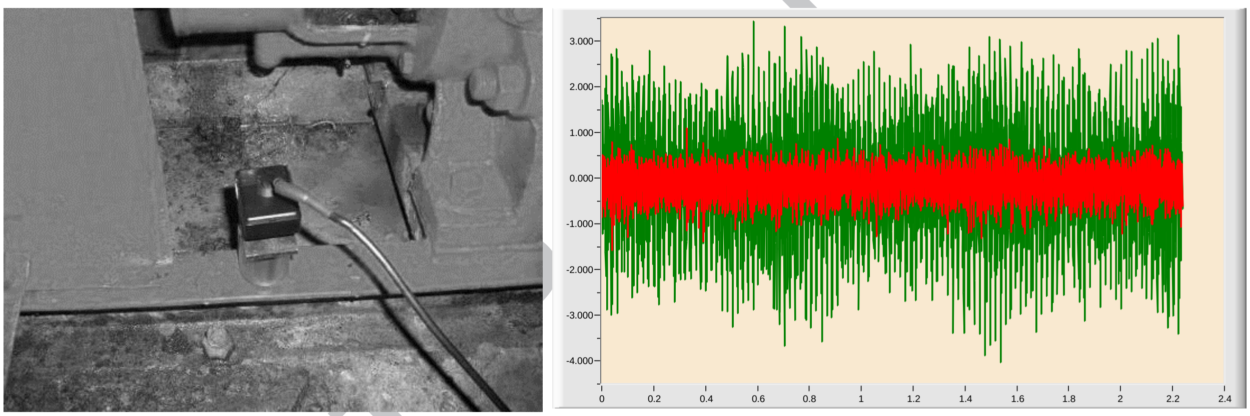


Figure 10: The fifth measuring position and acceleration

The result of several years of research and development of vibration monitoring to determine the operating condition for most of the pump aggregates used in industry is presented. The diagrams presented in above diagrams points to the following facts: in electro motor, it is possible to determine a bearing malfunction as well as other mechanical defects such as incorrect coupling operating condition. The diagrams present pump bearing malfunction but also a high frequency range, which is appearing as a result of hydro-dynamic processes in a pump.

3.2 Measuring points sensitivity analysis

The input measurement positions are ranked based on their influence on the fifth or output position. ANFIS is trained for one epoch for each input separately in order to rank the inputs.

Figure 11 shows the RMSE errors of the all inputs for vibration in X direction. Based on the training RMSE one can conclude that the measuring position 4 has the highest impact on the pumping aggregate support in X direction. On the contrary measuring position 4 has the smallest impact on the pumping support vibration in X direction. The checking errors show there is not overfitting between training and checking data.

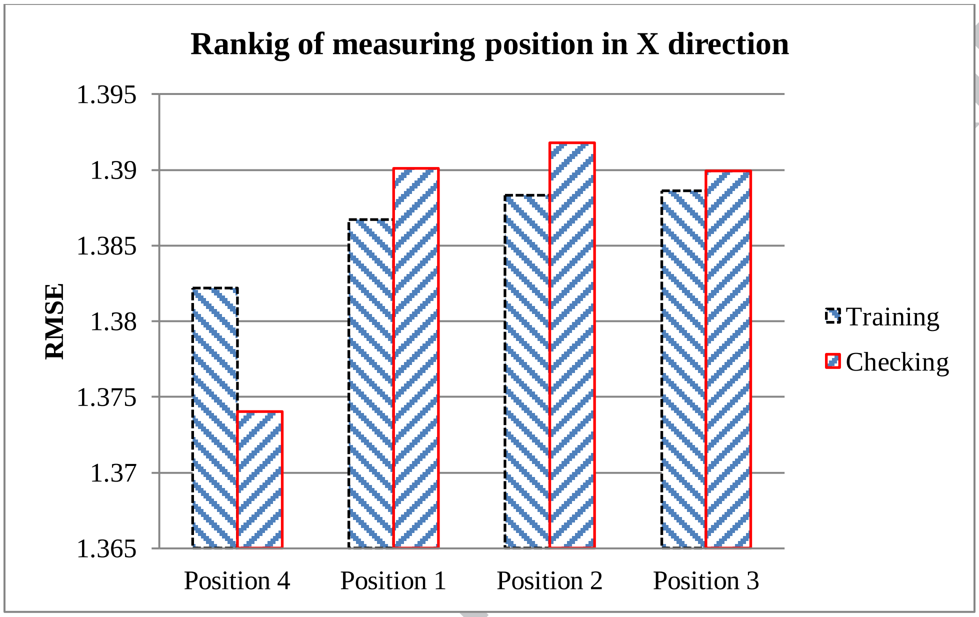


Figure 11: Ranking of input measurement points vibration based on their influence on the fifth point in X direction

Figure 12 shows the RMSE errors of the all inputs for vibration in Y direction. Based on the training RMSE one can conclude that the measuring position 3 has the highest impact on the pumping aggregate support vibration in Y direction. On the contrary measuring position 2 has the smallest impact on the pumping support vibration in Y direction. The checking errors show there is not overfitting between training and checking data.

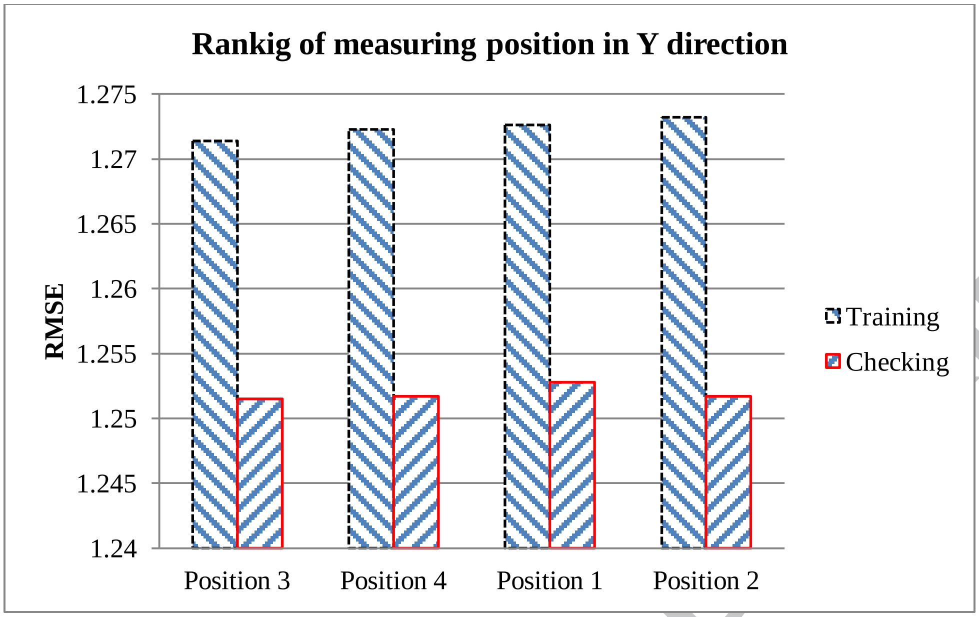
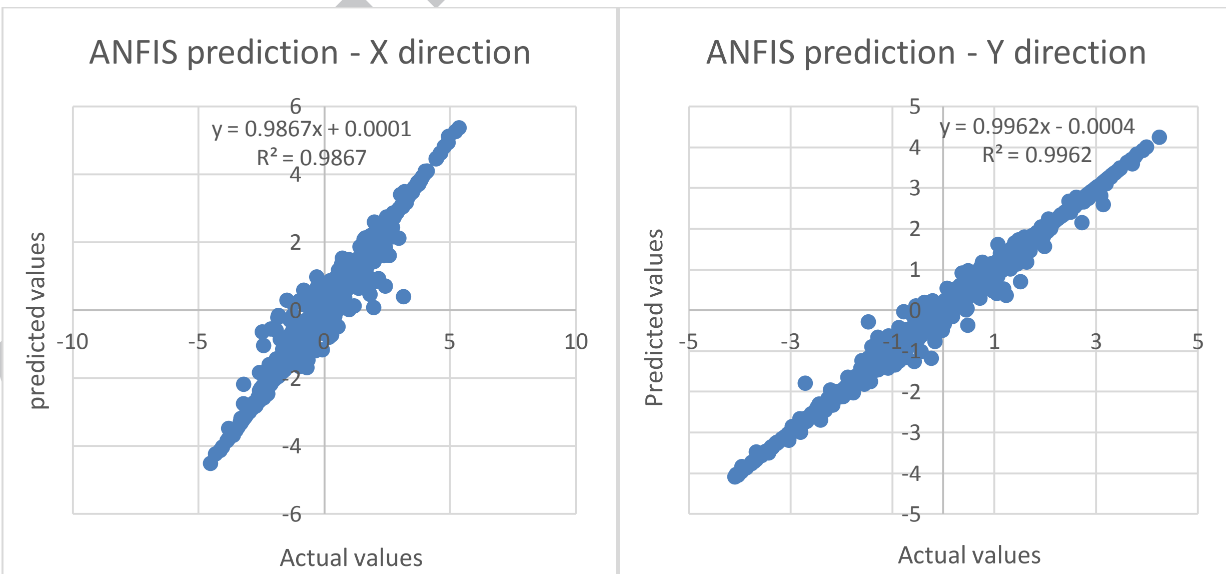


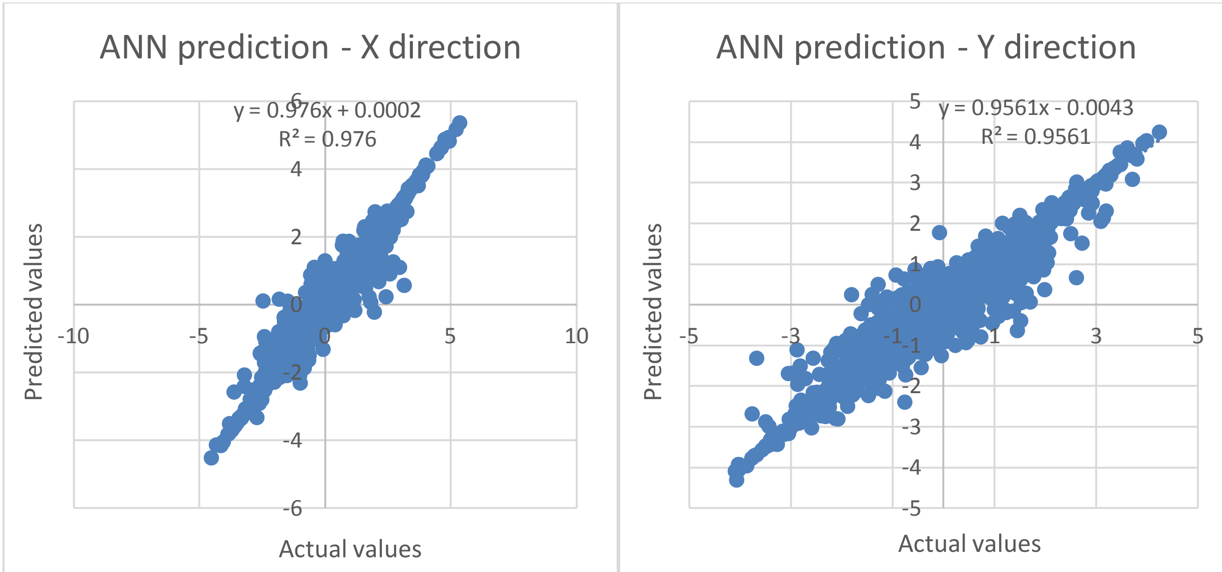
Figure 12: Ranking of input measurement points vibration based on their influence on the fifth point in Y direction

3.3 Comparative study

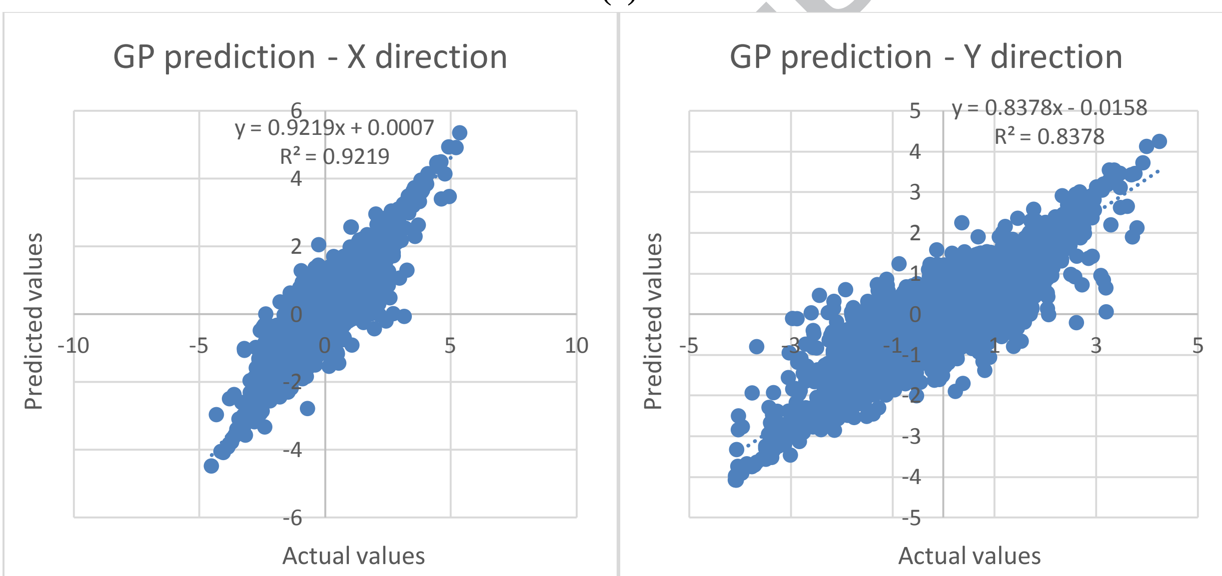
Figure 13 shows the prediction results of the vibration of pumping aggregate by the three approaches. As the benchmark models for comparison artificial neural network (ANN) [41] and genetic programming (GP) [41] models are used. Based on the analyzing one can note the highest prediction accuracy for ANFIS methodology. Table 2 shows the numerical results for the three methods.



(a)



(b)



(c)

Figure 13: Prediction of vibration of the pumping aggregate by: (a) ANFIS, (b) ANN and (c) GP methodology

Table 2: Performances of three approaches for the vibration prediction of pumping aggregate

		ANFIS	ANN	GP
X direction	R^2	0.9867	0.976	0.9219
	RMSE	0.1601	0.2153	0.3884
Y direction	R^2	0.9962	0.9561	0.8378
	RMSE	0.0783	0.2647	0.5085

Table 3 shows the ANFIS comparative study for vibration monitoring for the pumping aggregates and planetary power transmissions in pellet mills. One can note better vibration prediction for pumping aggregate.

Table 3: ANFIS vibration prediction for two different machines

		ANFIS – pumping aggregate	ANFIS - planetary power transmissions in pellet mills [42]
X direction	R^2	0.9867	0.258
	RMSE	0.1601	0.747936
Y direction	R^2	0.9962	0.366
	RMSE	0.0783	1.298971

4 Conclusion

Vibration could affect different parts or segments of the pumping aggregate and therefore it is need to analyze the vibrating. In order to avoid highly nonlinear analytical solution in this article soft computing approach was used since the model does not require internal knowledge of the vibration model. It is enough to collect the experimental input/output data pairs and to train the soft computing model. In this study the measuring points were ranked based on their influence on the pumping aggregate.

Examination of pumps vibration phenomenon provides the data about the vibration magnitude and its frequency components as well as their change with respect to the operating parameters. Hydraulic vibrations are hard or almost impossible to avoid. Hydraulic processes which happen in pumps are complex and non-stationary by the rule. For description of such processes it is possible to form mathematical models, whose evaluation is performed after very comprehensive, expensive and long-lasting researches.

An approach was carried to determine the most influential parameters for the vibration forecasting by the ANFIS methodology. By this way one can eliminate the unnecessary inputs for further investigation. ANFIS prediction results of the vibration is highly precise according to coefficient of determination (in X direction $R^2 = 0.9867$ and in Y direction $R^2 = 0.9962$).

The presented results in the study points out that in electro motor, it is possible to determine a bearing malfunction as well as other mechanical defects such as incorrect coupling operating condition.

For future research directions there is need to analyses other parts of the system which could have potential harmful effect on the bearing malfunction. Artificial intelligence approaches could be implemented as embedded system for tracking of the bearing malfunction of the pumps which could be also potential future direction of investigation.

References

[1] Yang, D., Li, H., Hu, Y., Zhao, J., Xiao, H., & Lan, Y. (2016). Vibration condition monitoring system for wind turbine bearings based on noise suppression with multi-point data fusion. *Renewable Energy*, *92*, 104-116.

[2] Ruiz-Cárcel, C., Jaramillo, V. H., Mba, D., Ottewill, J. R., & Cao, Y. (2016). Combination of process and vibration data for improved condition monitoring of industrial systems working under variable operating conditions. *Mechanical Systems and Signal Processing*, *66*, 699-714.

[3] Rolek, P., Bruni, S., & Carboni, M. (2016). Condition monitoring of railway axles based on low frequency vibrations. *International Journal of Fatigue*, *86*, 88-97.

[4] Hu, W. H., Thöns, S., Rohrmann, R. G., Said, S., & Rücker, W. (2015). Vibration-based structural health monitoring of a wind turbine system. Part I: Resonance phenomenon. *Engineering Structures*, *89*, 260-272.

[5] Nguyen, T., Chan, T. H., Thambiratnam, D. P., & King, L. (2015). Development of a cost-effective and flexible vibration DAQ system for long-term continuous structural health monitoring. *Mechanical Systems and Signal Processing*, *64*, 313-324.

[6] Shan, B., Zheng, S., & Ou, J. (2015). Free vibration monitoring experiment of a stayed-cable model based on stereovision. *Measurement*, *76*, 228-239.

[7] Rainieri, C., & Fabbrocino, G. (2015). Development and validation of an automated operational modal analysis algorithm for vibration-based monitoring and tensile load estimation. *Mechanical Systems and Signal Processing*, *60*, 512-534.

[8] Huang, Q., Tang, B., & Deng, L. (2015). Development of high synchronous acquisition accuracy wireless sensor network for machine vibration monitoring. *Measurement*, *66*, 35-44.

[9] Ansari, R., Norouzzadeh, A., Shakouri, A. H., Bazdid-Vahdati, M., & Rouhi, H. (2018). Finite element analysis of vibrating micro-beams and-plates using a three-dimensional micropolar element. *Thin-Walled Structures*, *124*, 489-500.

[10] Norouzzadeh, A., & Ansari, R. (2018). Isogeometric vibration analysis of functionally graded nanoplates with the consideration of nonlocal and surface effects. *Thin-Walled Structures*, *127*, 354-372.

[11] Norouzzadeh, A., & Ansari, R. (2018). Nonlinear dynamic behavior of small-scale shell-type structures considering surface stress effects: An isogeometric analysis. *International Journal of Non-Linear Mechanics*, *101*, 174-186.

[12] Oscar, S., & Anvar, V. (2017). The monitoring system of an actual technical condition for pumping units with frequency analysis. *Procedia Engineering*, *176*, 144-149.

[13] Vishwakarma, M., Purohit, R., Harshlata, V., & Rajput, P. (2017). Vibration Analysis & Condition Monitoring for Rotating Machines: A Review. *Materials Today: Proceedings*, *4*(2), 2659-2664.

[14] Fu, Y., Zhang, Y., Gao, Y., Gao, H., Mao, T., Zhou, H., & Li, D. (2017). Machining vibration states monitoring based on image representation using convolutional neural networks. *Engineering Applications of Artificial Intelligence*, *65*, 240-251.

[15] Huang, Q., Tang, B., & Deng, L. (2015). Development of high synchronous acquisition accuracy wireless sensor network for machine vibration monitoring. *Measurement*, *66*, 35-44.

[16] Potočnik, P., & Govekar, E. (2017). Semi-supervised vibration-based classification and condition monitoring of compressors. *Mechanical Systems and Signal Processing*, *93*, 51-65.

[17] Bengherbia, B., Zmirli, M. O., Toubal, A., & Guessoum, A. (2017). FPGA-based wireless sensor nodes for vibration monitoring system and fault diagnosis. *Measurement*, *101*, 81-92.

[18] Heo, E. Y., Lee, H., Lee, C. S., Kim, D. W., & Lee, D. Y. (2017). Process Monitoring Technology Based on Virtual Machining. *Procedia Manufacturing*, *11*, 982-988.

[19] Sinha, J. K., & Elbhbah, K. (2013). A future possibility of vibration based condition monitoring of rotating machines. *Mechanical Systems and Signal Processing*, *34*(1-2), 231-240.

[20] Elnady, M. E., Sinha, J. K., & Oyadiji, S. O. (2012, September). Condition monitoring of rotating machines using on-shaft vibration measurement. In *IMechE, 9th international conference on vibrations in rotating machinery. Springer, London, UK* (pp. 11-13).

[21] Popescu, T. D. (2010). Blind separation of vibration signals and source change detection–Application to machine monitoring. *Applied Mathematical Modelling*, *34*(11), 3408-3421.

[22] Elbhbah, K., & Sinha, J. K. (2013). Vibration-based condition monitoring of rotating machines using a machine composite spectrum. *Journal of Sound and Vibration*, *332*(11), 2831-2845.

[23] Xiu-kun, Y., Xiao-qi, T., & Guo-lu, M. A. (2017). Real-time monitoring of the flexural and torsional vibration of the main axle of a numerically-controlled machine tool. *Journal of Optics*, *46*(3), 352-357.

[24] Zhang, J. Z., & Chen, J. C. (2008). Tool condition monitoring in an end-milling operation based on the vibration signal collected through a microcontroller-based data acquisition system. *The International Journal of Advanced Manufacturing Technology*, *39*(1-2), 118-128.

[25] Fu, Y., Zhang, Y., Gao, H., Mao, T., Zhou, H., Sun, R., & Li, D. (2017). Automatic feature constructing from vibration signals for machining state monitoring. *Journal of Intelligent Manufacturing*, 1-14.

[26] Jang, J. S. (1993). ANFIS: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics*, *23*(3), 665-685.

[27] Ai, W., Li, K., & Li, K. (2017). An effective hot topic detection method for microblog on spark. *Applied Soft Computing*.

[28] Pan, G., Li, K., Ouyang, A., & Li, K. (2016). Hybrid immune algorithm based on greedy algorithm and delete-cross operator for solving TSP. *Soft Computing*, *20*(2), 555-566.

[29] Xiao, Z., Tong, Z., Li, K., & Li, K. (2017). Learning non-cooperative game for load balancing under self-interested distributed environment. *Applied Soft Computing*, *52*, 376-386.

[30] Milovančević, M., Veg, A., Makedonski, A., & Marinović, J. S. (2014). Embedded systems for vibration monitoring. *Facta Universitatis, series: Mechanical Engineering*, *12*(2), 171-181.

[31] Milovančević, M., & Cvetković, M. (2009). Application of new microcontroller generation for pump aggregate working condition analyses. *Journal of Applied Engineering Science*, *7*(23-24), 35-40.

[32] MILOVANČEVIĆ, M., Miltenović, Đ., & Banić, M. (2008). Spectral analysis of the working order conditions for the engines on pumping power units. *MONOGRAPH MACHINE DESIGN*, 1960-2008.

[33] Čdina, M. (2003). Detection of cavitation phenomenon in a centrifugal pump using audible sound. *Mechanical systems and signal processing*, *17*(6), 1335-1347.

[34] Čudina, M., & Prezelj, J. (2008). Use of audible sound for safe operation of kinetic pumps. *International Journal of Mechanical Sciences*, *50*(9), 1335-1343.

[35] Čudina, M., & Prezelj, J. (2009). Detection of cavitation in operation of kinetic pumps. Use of discrete frequency tone in audible spectra. *Applied Acoustics*, *70*(4), 540-546.

[36] Milovančević, M., Milenković, D., & Troha, S. (2009). THE OPTIMIZATION OF THE VIBRODIAGNOSTIC METHOD APPLIED ON TURBO MACHINES. *Transactions of FAMENA*, *33*(3).

[37] Grjanko, L. P., & Papir, A. N. (1975). Lopastine nososi. *Mašinostroine Leningrad*.
[38] D. Cvetković, D. Milenković, Vibrations of centrifugal pump agregates, Proceedings Mechanical system and elements research and development, Istraživanje i razvoj mašinskih sistema i elemenata, IRMES 1995, str. 168-172
[39] Standard, I. S. O. (1996). Mechanical Vibration-Evaluation of Machine Vibration by Measurements on Non-Rotating Parts. *ISO/IS*, *10816*
[40] Wang, S. C. (2003). Artificial neural network. In *Interdisciplinary computing in java programming*(pp. 81-100). Springer, Boston, MA.
[41] Koza, J. R. (1994). Genetic programming as a means for programming computers by natural selection. *Statistics and computing*, *4*(2), 87-112.
[42] Milovančević, M., Nikolić, V., & Anđelković, B. (2017). Analyses of the most influential factors for vibration monitoring of planetary power transmissions in pellet mills by adaptive neuro-fuzzy technique. *Mechanical Systems and Signal Processing*, *82*, 356-375.