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# Analysis of the Impact of Lubrication on the Dynamic Behavior of Ball Bearings Using Artificial Neural Networks

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*Abstract:* - Ball bearings can be found in all machines with rotary movement. Dynamic behavior analysis of ball bearings is a phenomenon that has been studied for many years. Previous studies on the dynamic behavior of ball bearings are based on describing the state of ball bearings using mathematical models. In addition to mathematical description, computers simulations based on finite element methods are also applied. This paper presents study of the dynamic behavior of ball bearings using artificial neural networks. Artificial neural network models are able to predict the amplitude of vibration that will generate the analyzed bearings depending on the lubrication. In this way, by the application of artificial neural networks bearing dynamic behavior can be predicted depending on the geometric parameters and lubrication.

*Keywords:* - ball bearing, artificial neural network, lubrication, amplitude of vibration speed.

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## 1. INTRODUCTION

Ball bearings are machine elements whose function is to allow the relative movement of the rotating parts while simultaneously transferring the load between them and provide the accuracy of their position. They are primarily used as shaft supports, where they allow the shaft to rotate relative to the fixed support while carrying the load. The vibrations generated by the ball bearing depend on a number of influencing factors, which according to [1] can be divided into the following categories: design, technological and exploitative.

One way to control the quality of ball bearings is to measure the vibration that the bearing generates after assembling. The measurement conditions and procedure are prescribed by standard ISO 15242-1. Based on the knowledge of vibration amplitudes and the frequencies at which they occur, it is possible to

determine the cause on fault of the ball bearing elements.

The amplitudes of vibration generated by the ball bearing depends on various factors. Influencing factors may be the geometry of the bearing parts, deviations from the accuracy of the shape, the external load, the amount of lubrication, the contamination of the lubricant and others. In this paper, the effect of the amount of lubrication on the vibration amplitudes generated by the ball bearing will be analyzed. The influence of the amount of lubrication on the dynamic behavior of the ball bearings was experimentally confirmed. An artificial neural network (ANN) was applied to analyze the experimental results and to determine the relationship between vibration amplitudes and the amount of lubrication.

Lubrication of the ball bearing is the most commonly performed using grease. Lubrication of the

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ball bearings, the amount of lubrication and the selection of the proper lubricant characteristics have a significant impact on the bearing life. In this paper, the effect of the amount of lubrication on the vibration generated by the ball bearing will be considered.

According to [2] there are hydrodynamic, elastohydrodynamic and boundary lubrication at the contact point of the ball and the raceways. Which type of lubrication will be present at the contact point depends on the type of lubricant, the thickness of the oil film and the surface roughness of the balls and raceways. The initial amount of grease in the ball bearing after assembling, in addition to other factors, affects the vibration amplitudes.

## 2. APPLICATION OF ANN IN BEARING ANALYSIS

ANNs are computer systems that operate on the principle of the human brain. ANNs are tools that are applied in various fields of human activity, such as finance, medicine, engineering, chemistry, physics and others. Very good results of ANNs are recorded in the field of image processing and recognition, pattern recognition that apply to large databases, etc. According to [3] in the field of rolling bearings, ANNs are being applied to identify bearing failure. They are also used to identify failure on pumps, gears, fans, and other systems with rotary motion.

According to [4] ANNs can be used to identify failures in the operation of rotary machines by processing the measured signal by statistical methods and using the results as input parameters. In addition to neural networks, support vector machines (SVMs) can be used for the same purpose. The paper shows that there is an opportunity to optimize both techniques for checking the condition of rotary machines.

According to [5], feed forward neural network and self organizing maps (SOM) were used to determine major faults such as bearing faults, stator winding fault, unbalanced rotor and broken rotor bars are considered. The results show that the ANN produces better results. Different types of ANNs have been used to detect the causes of bearing fault in operating conditions.

Hong and Yin [6] presented the application of an ANN to predict the remaining bearing life. They used wavelet packet energy feature to extract input parameters for the ANN from the measured signal. Least Squares Support Vector Machine (LS-SVM) was used to control the operation of the ANN. The results show that the ANN can be used to predict the remaining bearing life.

In [7], Kankar et al presented the application of artificial intelligence methods such as neural

networks and support vector machine (SVM) to identify ball bearing fault. A high speed bearing tester was used to measure vibrations and obtain data. The test bearings had fault on the outer ring in the form of a crack, then the bearing had fault in the form of a rough surface on the raceway on the inner ring and the last bearing had fault to the ball in the form of pitting and corrosion. The characteristic signal parameters in the time domain are extracted by statistical techniques. The results showed that the SVM has the ability to determine the bearing condition somewhat better. In the case of bearings with fault on the raceway of the inner ring or a fault ball, or a combination thereof, stochastic vibration signals are obtained, which are difficult to predict for the applied methods.

Convolution Neural Networks have been used successfully for image recognition and classification. According to [8], the quality of ANN performance in recognizing and classifying ball bearing failure depends on the manner and quality of signal processing. This paper presents the application of deep convolution neural network (DCNN), which does not require vibration signal processing and extraction of characteristic signal parameters. Here the recorded signal is divided into segments and images are formed for each of them. The pictures are a two-dimensional representation of the vibrating signal. Four load cases were considered and a data set containing 2424 vibration signal images created for each of them. A network with two convolution layers was applied, and the output layer contained a number of neurons equal to the number of failures considered. The results show that accuracy ranges from 96,75 to 100%. Satisfactory results are obtained when changing the data set or using the data network for a new load.

## 3. PROBLEM FORMULATION

At the end of the ball bearing manufacturing process, quality control can be performed by measuring the vibration amplitudes. The vibration amplitudes that the bearing will generate depend on the design parameters. Technological parameters, which are the result of the accuracy of machining of balls and raceway, have a significant influence. In addition to these parameters, the external load applied during the measurement and the amount of lubrication has a significant influence. Experimental investigations have been conducted to determine the influence of the aforementioned parameterizes on vibration amplitudes. The results of the experimental research have been applied to the training and testing of ANNs whose task is to predict the vibration amplitudes of the tested bearing in characteristic

bands. ANN trained on a given data set is able to predict the vibration amplitudes of the ball bearing depending on the amount of lubrication.

### 3.1. Experiment description

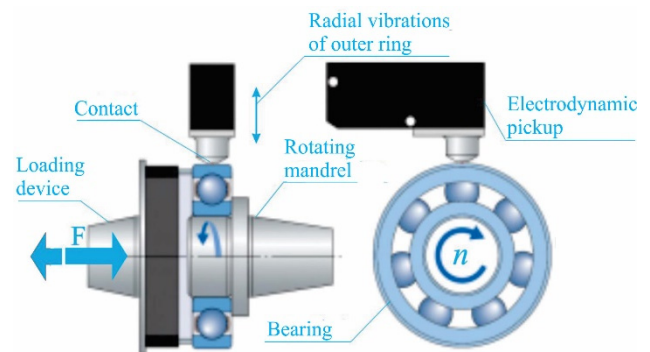
Experimental measurement was carried out on the device for measuring the bearing vibration level, Figure 1. Bearing vibration measurement is a technique used to determine the quality class of the bearing, and can be used to determine the working ability of the system with rolling bearings, or to determine the causes of potential failure of the system.



**Figure 1.** Measuring device for control of vibration of ball bearings

The vibration measurement and control system is installed on a measuring instrument for testing, analyzing and diagnosing rolling bearings and is based on vibration measurement of rolling bearings using an electrodynamic speed encoder (pickup). Measuring - control device is used for diagnostics of deviation in micro and macro geometry of bearings, as well as for detection of fault of bearings elements during production or assembly of bearings. The bearing is mounted over the inner ring to the spindle, which is supported by hydrodynamic bearings. The spindle speed is constant during the measurement ( $n = 1800$  RPM). The outer ring is stationary and loaded with axial force over the pneumatic cylinder. The basic element in the vibration measurement chain is the velocity sensor (electrodynamics pickup), Figure 2, which generates a voltage at its output whose amplitude and frequency is proportional to the vibration level generated by the observed rolling bearing. Since the amplitude of the signal obtained from the used velocity sensor is small for digital processing and the displaying, signal is amplified by an amplifier. Block diagram of the measurement-

control system for testing rolling bearing vibrations is shown in Figure 3.



**Figure 2.** Schematic view of measuring principle of electrodynamic pickup [9]

Elements which task is analog signal processing are an amplifier and a filter bandwidth. The amplifier has the task of increasing the signal level from the velocity sensor to a level that is suitable for digital processing and display. An amplifier with an amplification of 1500 was used, which provides sufficient signal amplitude for digital processing. The frequency range of the signal which is of interest for testing vibrations of rolling bearings is from 20 Hz to 10 kHz. The filter has the task of limiting the spectrum of the signal received from the amplifier to the given range. The projected filter introduces a relatively small attenuation of wave oscillations in one or more frequency bands and a relatively large attenuation for oscillations of other frequencies (below 20 Hz and above 10 kHz) according to standard ISO 15242-1 (Rolling bearings - Measuring methods for vibration - Part 1: Fundamentals). The bandwidth of the filters is also defined based on the above standard. Digitalization of the signal is done using the NI DAQ USB-6009 measuring system. The sampling frequency is 48 kHz, while the resolution of the internal A/D converter is 13 bit. In this way, the quality preparation of the signal obtained by applying the velocity sensor and its digitalization for further computer processing is provided.

The experimental study was conducted on 30 ball bearings of designation 6006. For each bearing, the radial clearance ( $G_r$ ), waviness of the raceway of the outer ring ( $W_{te\ max}$ ) and waviness of the raceway of the inner ring ( $W_{ti\ max}$ ), the surface roughness of the raceways ( $R_{ae}$  and  $R_{ai}$ ), the radius of the raceways of both rings ( $R_e$  and  $R_i$ ) are known. During measurements variables are axial load ( $F$ ) and the amount of lubricant in the bearing. A total of 4050 vibration spectra were recorded. The axial load is variable from 200 to 1000N in 100N increments and the lubrication amount from 0 to 2.8g in 0.7g increments.

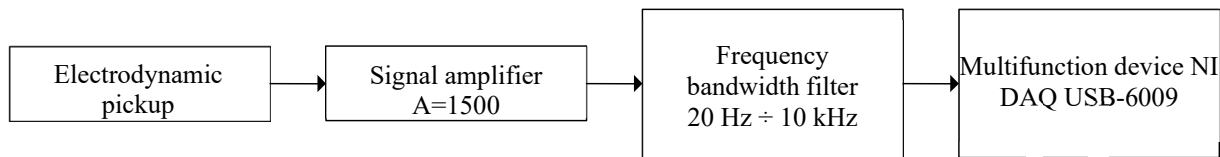


Figure 3. Block diagram of measuring device

#### 4. PROBLEM SOLUTION

The ANN has 9 input parameters and 3 output parameters. A feed forward network was applied, with a back propagation training algorithm. The neurons in the hidden layers have a sigmoid and the neurons in the output layer have a linear activation function. The number of hidden layers is three, with 15 neurons in each layer. An example of the input parameters is shown in Table 1. The values of the input parameters for each bearing were measured in an accredited laboratory of the manufacturer of the tested rolling bearings.

Table 1. Example of input parameters

Bearing designation	11	12	13	14
$W_{te\ max}$ [ $\mu\text{m}$ ]	0.79	0.45	0.66	0.79
$R_{ae}$ [ $\mu\text{m}$ ]	0.112	0.125	0.168	0.14
$R_e$ [mm]	3.834	3.832	3.834	3.829
$W_{ii\ max}$ [ $\mu\text{m}$ ]	0.39	0.26	0.26	0.3
$R_{ai}$ [ $\mu\text{m}$ ]	0.398	0.271	0.279	0.245
$R_i$ [mm]	3.67	3.68	3.706	3.693
$G_r$ [ $\mu\text{m}$ ]	6	10	10	7
$F$ [N]	200	200	200	200
Grease quantity [g]	0	0	0	0

The output parameters represent the measured RMS (Root mean square) values of the vibration velocity amplitude in the characteristic bands. Part of the output parameter matrix is shown in Table 2. The first characteristic band covers frequencies of 50 from 300 Hz, the second from 300 to 1800 Hz and the third from 1800 to 10000 Hz. ISO 15242-4 prescribe low,

medium and high frequencies band. RMS vibration velocity values for each measurement were obtained by analyzing the vibration spectrum recorded during the measurement. Measurements recorded the velocities of vibrations in the time domain, which were transformed into the frequency domain by the application of Fast Fourier Transformation (FFT).

Table 2. Example of output parameters

Bearing designation	21	21	21	21	21
Axial Force [N]	200	300	400	500	600
Grease quantity [g]	0	0.7	1.4	2.1	2.8
RMS 50–300 Hz [ $\mu\text{m/s}$ ]	79.60	86.17	118.9	174.4	171.3
RMS 300–1800 Hz [ $\mu\text{m/s}$ ]	62.0	73.38	71.48	95.21	98.26
RMS 1800–10000 Hz [ $\mu\text{m/s}$ ]	120.8	82.52	94.52	94.75	89.44

From a sample of experimental results 10% of samples was extracted for network testing and was not used for training of ANN.

The remaining 90% of the experimental results was prepared for ANN training and divided into training (70%), validation (15%) and testing (15%). The training data are divided according to the random principle. Bayesian Regularization training algorithm was selected for training function.

The architecture of the artificial neural network is shown in Figure 4.

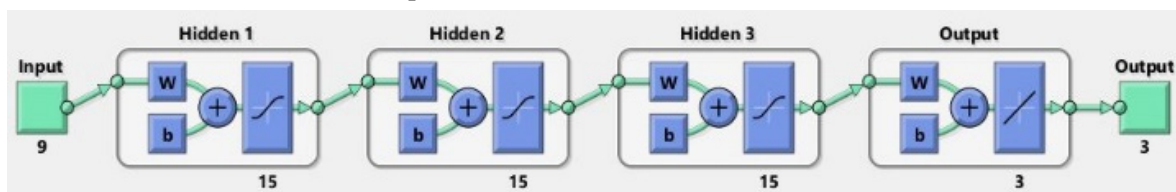


Figure 4. Architecture of neural network

#### 5. RESULTS

The prediction error of ANN in the characteristic bands is shown in Table 3. The test sample contains 405 measurements. The mean value of the prediction

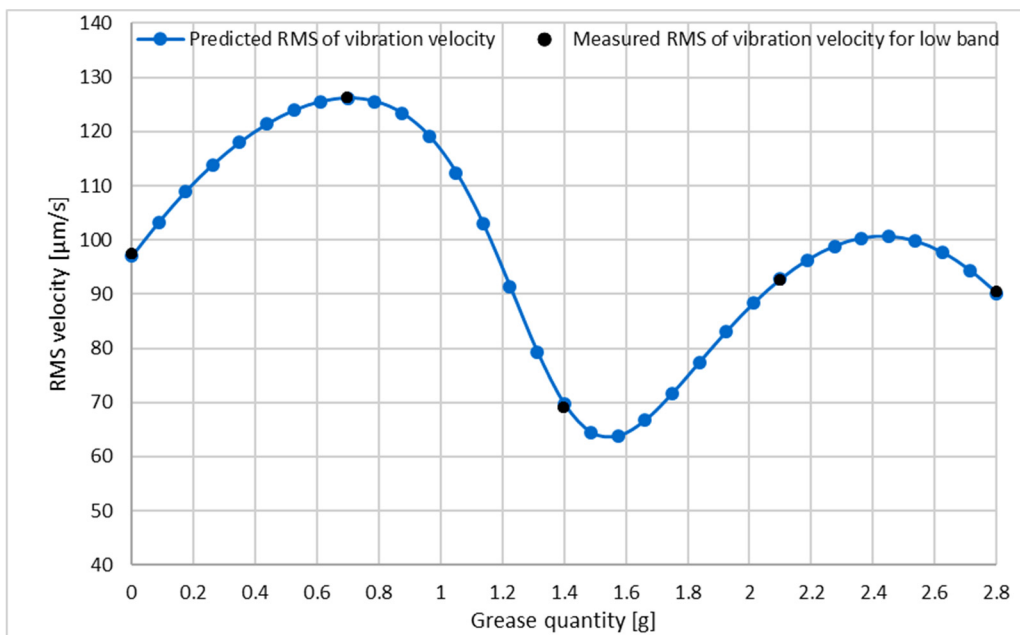
error in all three bands is close to zero. For this reason, the standard deviation of the error is calculated. The results show that the prediction error is the smallest in the first band. The biggest prediction error is in the high band, which is due to the largest

width of this band. The standard deviation of the prediction error in percentage has the highest error in the high band and is 8.7%. The prediction error is acceptable because the measurement equipment error due to a large number of influencing factors is approximately equal to the magnitude of the prediction error.

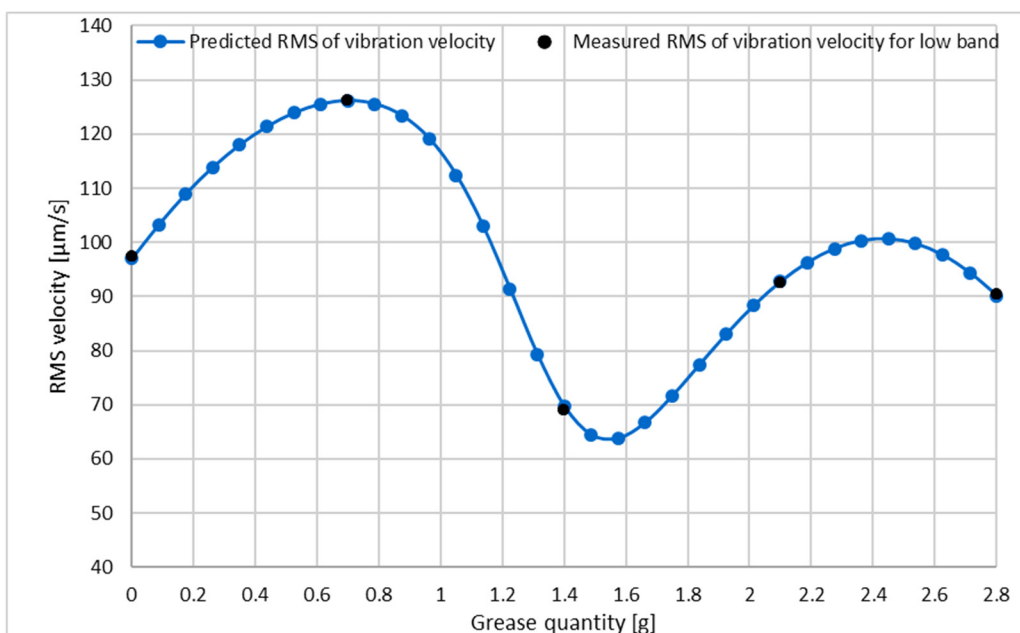
For the purpose of further testing of ANN prediction, a test matrix is conducted in which the amount of lubrication is variable from the minimum to the maximum amount for one bearing. In the test matrix, the amount of lubricant changes in 0.0875 g increment. In this way, the network was tested at 33 characteristic points. The prediction results are shown in Figure 5 to Figure 7.

**Table 3.** ANN prediction error

Bands	Average error [ $\mu\text{m/s}$ ]	Standard deviation [ $\mu\text{m/s}$ ]	Standard deviation [%]
RMS 50 – 300 Hz	0.10	5.4	4.6
RMS 300 – 1800 Hz	-0.24	8.6	8.4
RMS 1800 – 10000 Hz	-0.01	11.7	8.7



**Figure 5.** Predicted and measured RMS of vibration velocity for low band frequencies – bearing 12



**Figure 6.** Predicted and measured RMS of vibration velocity for medium band frequencies – bearing 12

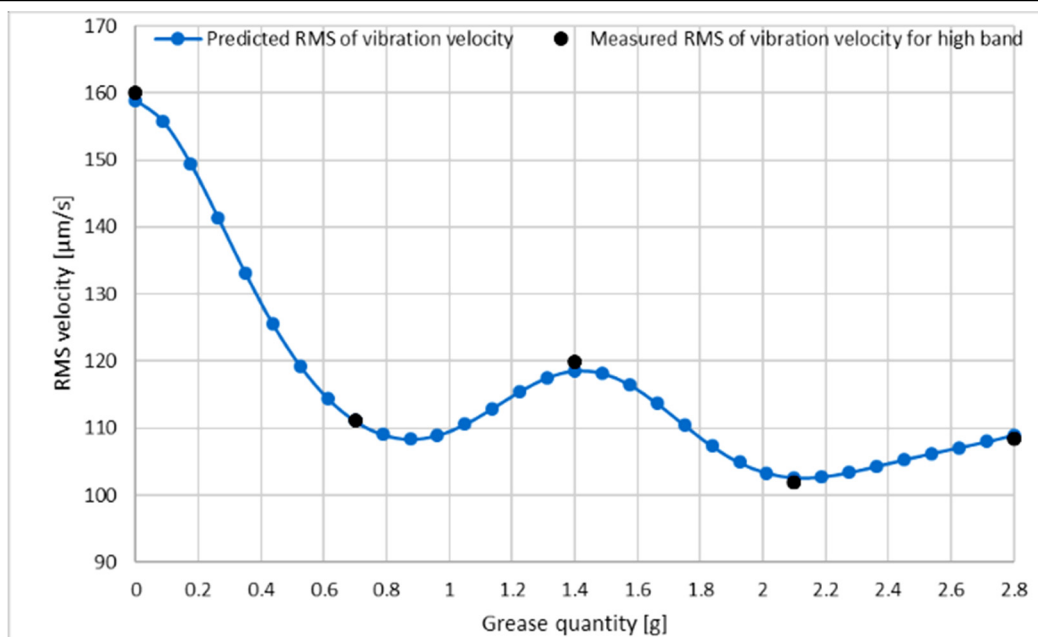


Figure 7. Predicted and measured RMS of vibration velocity for high band frequencies – bearing 12

According to the results shown in Figures 5-7, one can observe the dependence of the change in the vibration amplitude in all characteristic according to the amount of lubrication. Experimentally, vibration amplitudes were obtained for lubrication quantities 0; 0.7g; 1.4 g; 2.1 g and 2.8g. The vibration velocity amplitudes predicted for the quantities between are accompanied by changes in the vibration amplitudes with a small deviation from measured.

## 6. CONCLUSIONS

According to the results presented, it can be concluded that ANNs can be used to predict the vibration amplitudes of ball bearings. Shallow neural network with 3 layers and 15 neurons in each layer and Bayesian Regularization training algorithm were applied. Training time is approximately a few minutes.

The results of the study show that the accuracy of the prediction of vibration amplitudes is high, with a prediction error of 4.6% in the low 8.4% in the medium and 8.7% in the high frequency range. It has been shown experimentally and using a neural network that vibration amplitudes change with the change of the amount of lubrication in the bearing and that the minimum occurs with the amount of 1.4g of grease. This quantity corresponds to the amount of lubricant used by the manufacturer of the tested bearings to fill the bearings of the 6006 designation.

The presented results are the part of preliminary research of implementation of ANNs for prediction of vibration amplitudes of ball bearing.

## ACKNOWLEDGMENTS

This research was supported by the Ministry of Education, Science and Technological Development, Republic of Serbia, project TR 35025 and TR35036.

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