VIBRATION DIAGNOSTICS OF ROLLING BEARINGS USING THE TIME SERIES ANALYSIS

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Rolling bearings are an important part of most machines with rotating parts. Therefore, their technical diagnostics is an essential condition for ensuring the safe operation of the machine. This article focuses on the assessment of the condition of bearings using one of the methods of technical diagnostics - **vibration diagnostics**. In our case it is determination of the value of diagnostic variables of rolling bearings with a subsequent prediction of their condition based on the evaluation of time series analysis. Theoretical knowledge and practices are verified based on measurement data obtained from single-row ball bearings of type 3208A in the manufacturer test room.

KEYWORDS
rolling bearing, vibration diagnostics, time series, decomposition model.

1 INTRODUCTION

Development of vibration diagnostics starts as early as in the sixties of the twentieth century. It is closely connected with the development of measurement techniques, sensors and information technology. Only with the help of modern computer technology it was possible to fully utilize the previously described methods requiring the processing of large amounts of data.

Generally, vibrations can be considered to be a signal, i.e. the time-dependent function or the time series including random effects. For the analysis we can use statistical tools and methods, the results of which provide valuable information not only about the signal itself, but also about its source. Based on the analysis of waveforms of the individual variables, it is possible to predict their subsequent development, thus determining the probability of fault condition in the upcoming time slot.

1.1 Measured variables of vibrations

Motion in mechanics can be described by trajectory (in the case of harmonic motion it is **amplitude**), **velocity** or **acceleration**. These variables are interrelated, as shown in detail in Fig. 1:

- speed is a deviation derivative with respect of time,
- acceleration is a velocity derivative with respect of time.

Acceleration is then often expressed as converted into gravitational acceleration *g*.

Theoretically it is therefore possible to measure only one variable. In practice, where the maximum signal to noise ratio is required, the optimum value is selected depending on the measured frequency. Thus, for frequencies from 10 to 1000 Hz, the measurement of velocity is used, while for lower frequencies it is the measurement of displacement, and vice versa for higher frequencies, it is acceleration. [Bilos 2012]

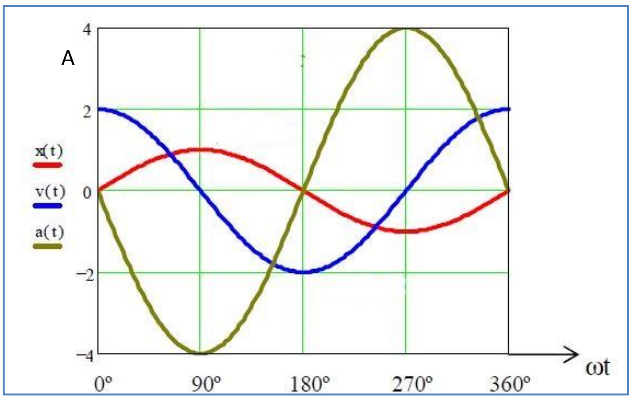

Figure 1. Waveforms of amplitude, velocity and acceleration of signal x=sin(ωt)

1.2 Function and design of rolling bearings

The main function of rolling bearings is to allow a free rotation of the shaft and transfer of load from the rotating part to the stationary one. To ensure this function, three basic components are necessary. These are the following: inner ring, outer ring and rolling elements - Fig. 2. In addition, a cage is used to maintain the same distance between the individual elements, which facilitates a uniform load distribution. Other applications include sealing elements to keep the lubricant inside the bearing and to prevent dirt from entering inside. [SKF 1994]

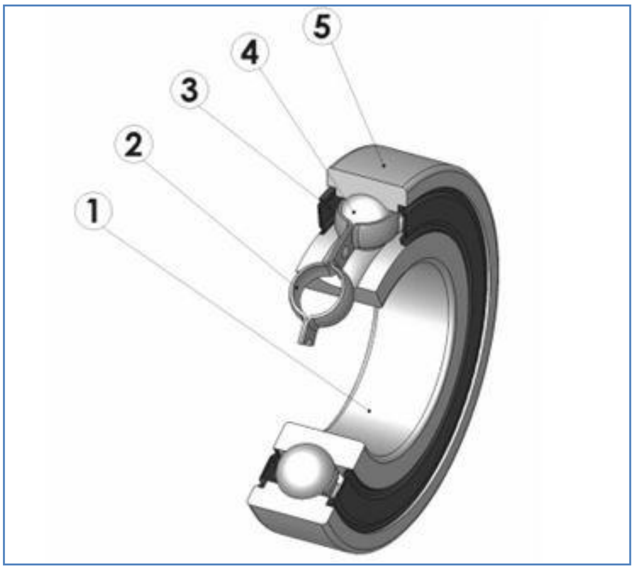

Figure 2. Radial ball bearing: 1 inner ring, 2 cage, 3 sealing, 4 rolling element, 5 outer ring

According to the primary direction of the force vector acting on the bearing, these are classified as of radial and axial design. Another classification is made based on the shape of rolling elements; ball bearings, cylindrical roller bearings, tapered roller bearings, spherical roller bearings, needle roller bearings and toric bearings.

2 METHODS OF VIBRATION DIAGNOSTICS FOR ROLLING BEARINGS

Technical practice uses a number of methods and indicators using the analysis in the time and frequency spectrum of vibrations of rolling bearings. Generally, these methods can be divided into:

– Basic methods: use mathematical / statistical evaluation of signal. This is a calculation of effective value, statistical moments, crest factor, etc., details will follow.

– Advanced methods - focused on specific parts of the signal at given frequencies, it is e.g. an envelope method, etc. Again, details are given in the following section of this article.

2.1 *Effective value (RSM)*

The effective value indicates the mean square signal level and represents the vibration energy of the system. It serves as a basic method for determining the condition of machinery and bearings throughout their lifetime. The effective value can detect the occurrence of equipment failure, but cannot be used for determination of the cause of vibrations. RMS is used in the assessment of machines according to ČSN ISO 10816-1; it is given by the following equation (1).

$$RMS = \sqrt{\frac{\sum X_i^2}{N}} \tag{1}$$

2.2 *Crest factor (CF)*

The value of CF ranks among the basic diagnostic quantities of rolling bearings. This method is based on calculating the ratio between the effective value and the peak value of vibration - the relationship (2).

$$CF = \frac{PEAK}{RMS} \tag{2}$$

The main advantage of this method is that it is independent of the type and dimensions of the bearing. CF is a very sensitive parameter capable of recognizing mechanical bearing damage at an early stage. A disadvantage is that, despite increasing damage, the value decreases to the CF level of faultless bearing. Further, it is also a suitable auxiliary indicator of lubrication failures.

2.3 *Statistic factor of kurtosis (K)*

This method is based on a statistical calculation of kurtosis factor. It is the ratio of the fourth and the second central moment, see the relation (3).

$$K = \frac{m_4}{\sigma^4} \tag{3}$$

It is investigated in the respective frequency bands:

– K_1: 2,5 – 5 kHz
– K_2: 5 – 10 kHz
– K_3: 10 – 20 kHz
– K_4: 20 – 40 kHz
– K_5: 40 – 80 kHz

A higher value indicates the occurrence of values exceeding the normal level for faultless bearing. Depending on the result, the bearing condition is evaluated:

– K = 3 – 4 … good condition
– K = 5 – 8 … initial damage
– K = 9 – 12 … serious damage
– K > 13 … risk of accident

A disadvantage of this parameter is the possibility of a downward trend for seriously damaged bearings, where vibrations can be high, but at the same level.

2.4 *Envelope method*

The envelope method uses large amplitudes of defects around the resonant frequency. The envelope method is very sensitive to initial damage. The individual steps are shown in Figure 3.
The main advantage is the accurate identification and visual display of error frequencies. A disadvantage of this method is higher computational complexity in signal filtering and transformation.

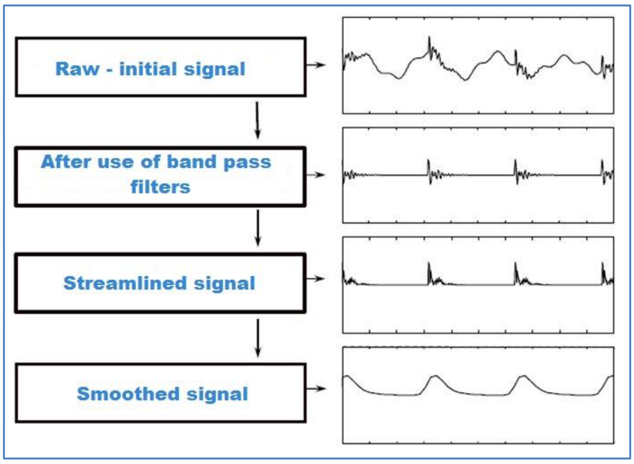

Figure 3. Individual steps of envelope method (Envelope)

In the first stage of the analysis of bearing condition, it is appropriate to use statistical methods. In the case of indication of possible damage, it is recommended to further switch to more accurate, but more demanding methods.
[Hochmann 2005]

3 ANALYSIS OF TIME SERIES

For the analysis of time series of measured and calculated diagnostic variables, we will apply the additive decomposition model (ADM) [Brockwell2002], which is characterized by the following relations (4).

$$\begin{aligned} X_t &= Tr_t + Sz_t + C_t + E_t \\ D_t &= Tr_t + Sz_t + C_t \\ P_t &= Sz_t + C_t \end{aligned} \tag{4}$$

where:
X_t … random stochastic process
D_t … deterministic component
P_t … overall periodic component
Tr_t …trend
Sz_t …seasonal component
C_t … cyclic component
E_t … random component

3.1 *Stabilization of variance (ADM)*

ADM can only be used in the case of constant variance of X values for all times t. If this condition is not satisfied, the time series needs to be transformed in an appropriate manner. This transformation is then denoted as the variance stabilization.
The exponential model assumes a dependence of standard deviation on the mean value according to the following equations (5).

$$\sigma_X(t) = \sigma_0 \mu_X(t)^{\theta} \tag{5}$$

According to the value of parameter θ, the type of transformation is then selected. For the series $X_t > 0$, it is possible to choose a power or logarithmic transformation. If $\lambda = 1 - \theta$, then

$$Y_t = \begin{cases} X_t^{\lambda} & pro \quad \lambda \neq 0, \\ \ln(X_t) & pro \quad \lambda = 0. \end{cases} \tag{6}$$

3.2 *Identification of periodic components*

A periodic component of the stochastic process according to the relation (4) is composed of seasonal and cyclic parts. However, in practice, it is very difficult to distinguish between them; therefore the identification is performed based on decomposition of T-periodic function x (t) into its Fourier series:

$$x(t) = \sum_{k=-\infty}^{\infty} c_k e^{\frac{i2\pi kt}{T}} = \frac{a_0}{2} + \sum_{k=1}^{\infty} A_k \cos\left(\frac{2\pi kt}{T} - \varphi_k\right),$$
$$A_k = 2|c_k|.$$

The objective is to identify the most energy-intensive harmonic components.

3.3 *Estimation of trend component*

The next step in the construction of decomposition model (ADM) is to determine the trend component characterizing the long-term development of time series. Generally, a variety of methods can be used [Hammer 2011].

For example:

- **method of small trend (LT):** assumes a constant trend in each period, which is estimated using the average,
- **linear regression model (LR)** based on the method of least squares,
- **robust regression (RR)** using weighted method of least squares
- **kernel smoothing (KS)** using the Gaussian kernel.

3.4 *Assessment of faulty component*

In the final stage, it is necessary to assess the quality of the obtained decomposition model. For this purpose, tests of randomness are used, to which the random component of the analysed process is subjected.

- Sign test (SGN)
- Test of growth and fall (RPN) risk priority number
- Test of Kendal coefficients (KND)
- Test of Spearman coefficients (SP)
- Median test (MED)

The model created and validated in this way is further exploited for the analysis and prediction of diagnostic variables to be examined.

4 DIAGNOSTICS OF SINGLE-ROW BALL BEARINGS OF TYPE 3208 A

In the test room of manufacturer, testing of bearings of type 3208A was carried out. Data were scanned by an accelerometer via subscription card with a maximum sampling frequency of 51.2 kHz. The length of scanned recording was set to 2s, and measurement was performed automatically every 30 minutes.

4.1 *Statistics of obtained set*

For individual measurements, basic statistical variables and indicators were calculated. Their waveforms throughout the test were monitored and subsequently evaluated. Kolmogorov-Smirnov one-sample test came out positive for all measurements. It was also used in estimating the mean value and variance using the sample mean and sample variance. This was first done for the initial, and then for the streamlined signal. Theoretically, the mean value should be zero. In the case of real measurements it was shifted to the value of -33.01 ± 1.06. This shift is stable throughout the test and it can be concluded that it was caused by setting of the measuring system. Examples of waveforms of mean value and variance are given in Figure 4.

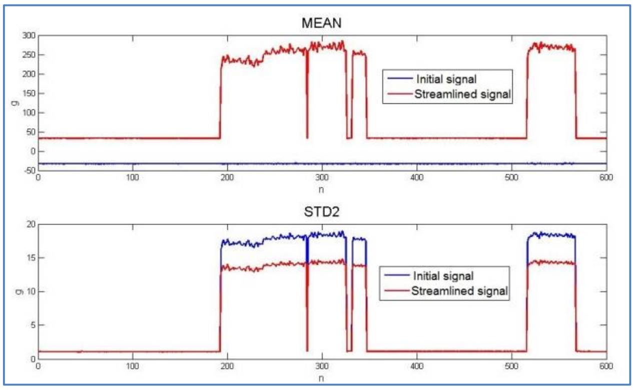

Figure 4. Waveform of mean value and variance

4.2 *Effective value (RMS)*

The graph in Figure 5 shows a waveform of RMS throughout the entire text.

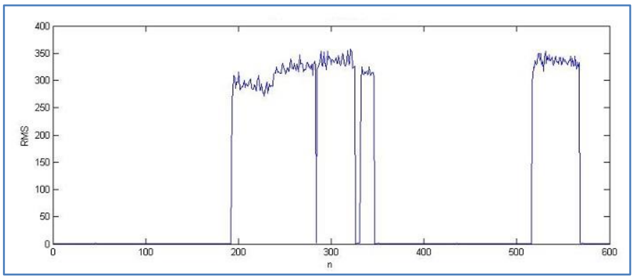

Figure 5. RMS waveform throughout the entire text

In the first stage, the results are close to zero. This was caused by improper mounting of the sensor. Furthermore, the relevant data follow. The next stage, the measuring system stopped working. This is again followed by a portion of the investigated data and the test is completed.

For further analysis, the data with non-zero effective value will be used.

4.3 *Crest factor (KF)*

The CF values of measured bearing ranged in 97% of cases between 7.5 and 10. This indicates a steady state with a possible initiation of failure.

4.4 *Factor of kurtosis (K)*

This was particularly investigated in four frequency bands.

- K_1: 2.5 – 5 kHz
- K_2: 5 – 10 kHz
- K_3: 10 – 25 kHz
- K_4: 20 – 50 kHz

The waveforms of individual factors are shown in Figure 6. The maximum and average kurtosis factor in comparison with the reference value K = 3, corresponding to the normal probability distribution, is shown in the graph (Fig. 7).

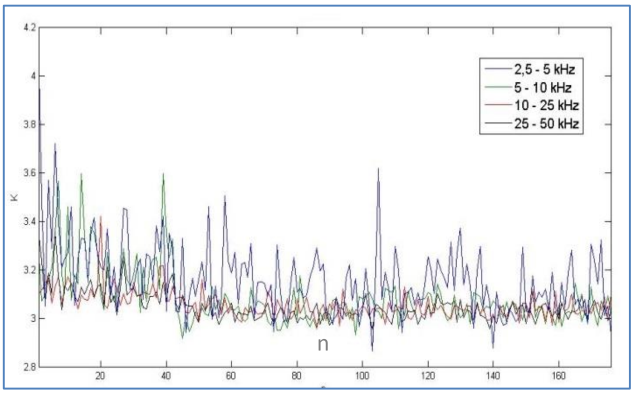

Figure 6. Waveform of kurtosis factor for the individual frequency bands.

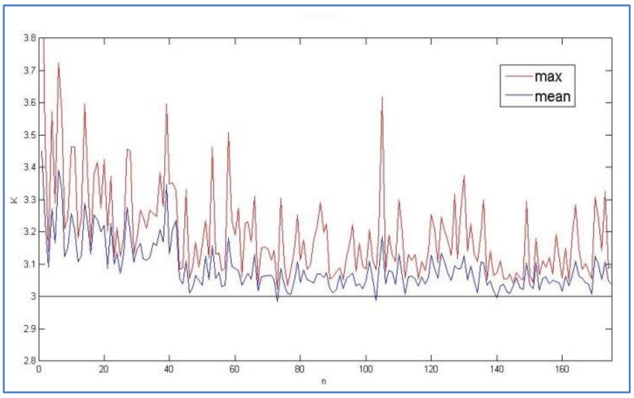

Figure 7. Waveform of **m**aximal and average K factor

4.5 *Envelope method*

In the first stage, the initial signal is processed by a band pass filters. Subsequently, it was streamlined. In the last step, the signal envelope was created along with its frequency spectrum. The results are shown in Figures 8,9,10.

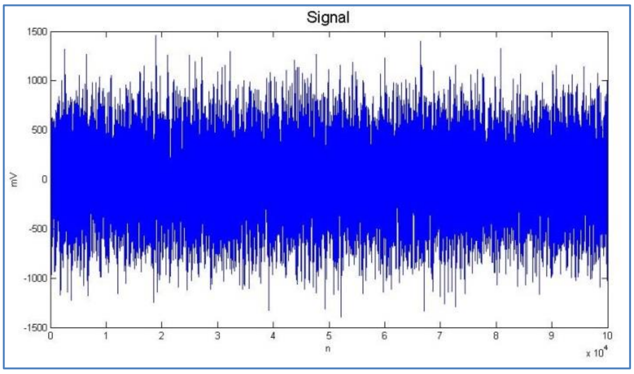

Figure 8. Initial signal

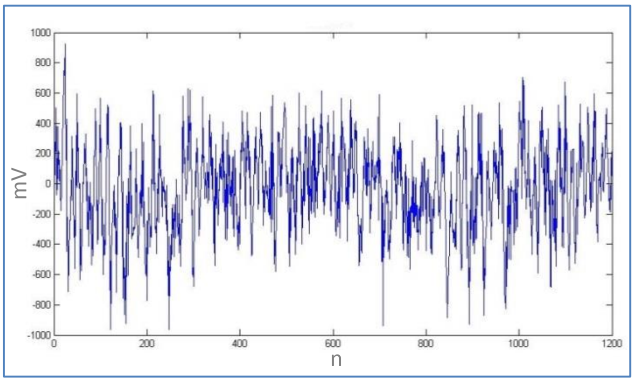

Figure 9. Filtered **s**ignal

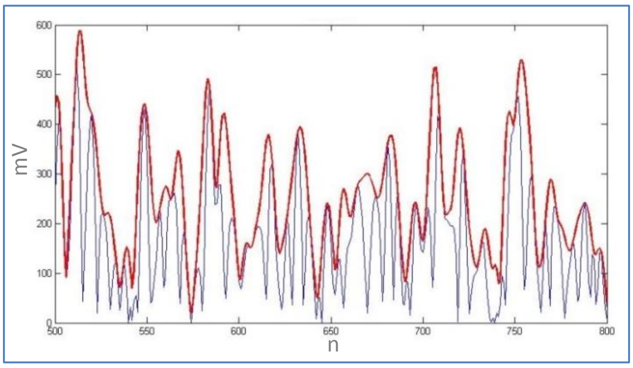

Figure 10. Envelope of streamlined signal

In the graph of frequency spectrum of the signal, to which a bandpass filter with a pass-range of 0.5 - 10 kHz was applied, the frequency values of 1.2 and 2.1 kHz are significant. In the case of low pass filter, where the frequencies above 1000 Hz were suppressed, the frequency of 25 Hz and its harmonic frequencies are significant. These correspond to the frequency of rolling element and indicate the possibility of damage initiation of this particular part of measured bearing.

A three-dimensional graph in Figure 11 shows a record of the time course of frequency spectra.

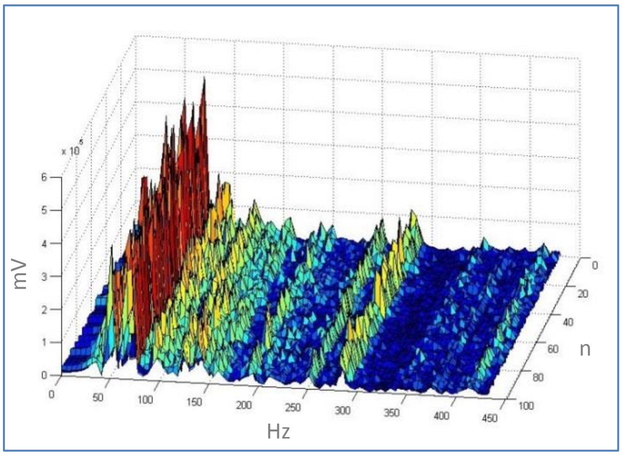

Figure 11. Development of frequency spectrum throughout the test

4.6 *Decomposition model (ADM)*

The use of time series analysis will be demonstrated on the example of the effective value of acceleration.

The hypothesis of constant variance was not rejected by the test; therefore the step of variance stabilization is not necessary.

It is followed by identification of periodic components. For this purpose, a periodogram (graphical representation of a sequence of estimates of energy values) - Fig. 12.

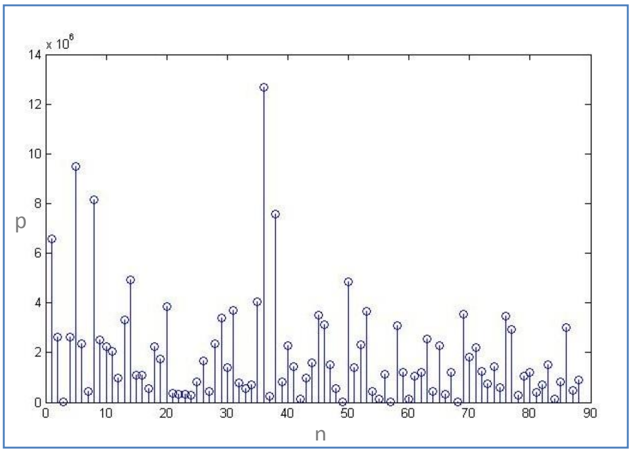

Figure 12. Periodogram

None of the values is statistically significant. The entire decomposition model is thus composed solely of the trend and random component.

The graph in Figure 13 shows the estimates of RMS trend using the individual methods described in Section 3.3. The part remaining after deduction of the trend was further subjected to tests of randomness, listed in Section 3.4, to verify the quality of the used methods.

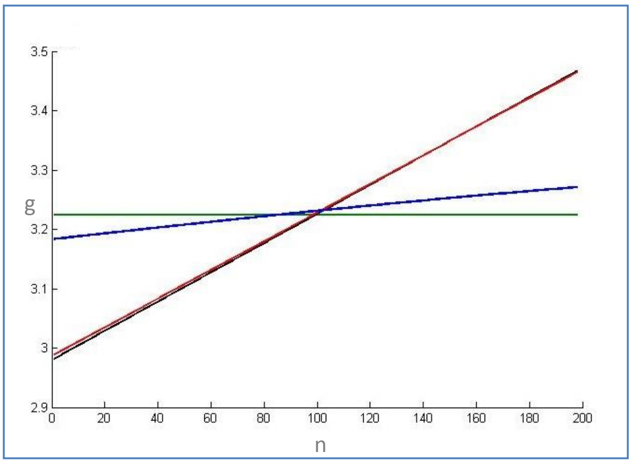

Figure 13. LT – green, LR – red, RR – Black, KS - blue

Test of randomness	SGN	RPN	KND	SP	MED
Small trend	1	1	1	0	1
Linear regression	1	1	1	1	1
Robust regression	1	1	1	1	1
Kernel smoothing	1	1	1	1	1

Table 1. Results of randomness tests

The final step of the analysis was to predict a trend for a segment of five consequent measurements. The entire analysis was performed for each diagnostic variable. A point estimate with confidence interval of 95% based on the method of linear regression is shown in Fig. 14.

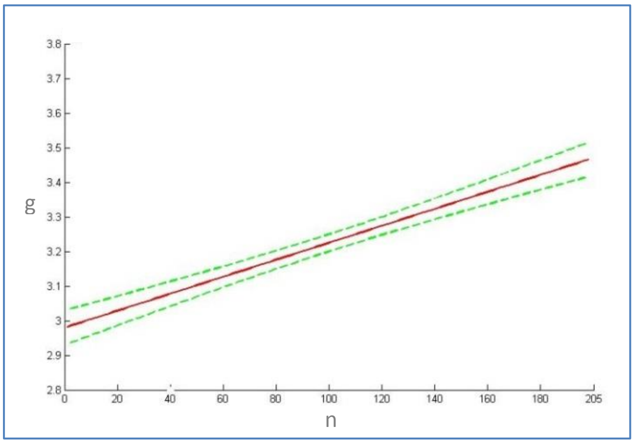

Figure 14. 95% confidence interval

5 CONCLUSIONS

Theoretical knowledge obtained from diagnostics of rolling bearings and time series analysis were interconnected and applied to the particular problem from technical practice. Data obtained by measuring the bearings of type 3208A were subjected to a thorough analysis, the results of which were published in this article. The applied decomposition model was, having rejected the existence of periodic components, simplified as the sum of trend and random component. Using a trend prediction and determination of the confidence interval for the respective estimate, it is possible to quantify the probability of increase in monitored diagnostic variables, thus predicting the change of operating condition of the bearing.

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