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SPECTRAL ANALYSIS OF TAPERED ROLLER BEARING VIBRATION USING INDUCTIVE MODELING

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Abstract

This paper deals with a case of vibroacoustic testing of tapered roller bearings. Tapered roller bearings are often used at the mechanical designs where higher requirements on rigidity and accuracy of a shaft roller placing are asserted. This is especially the case of metal cutting machine shafts or automotive gearboxes. Even a small clearance must be excluded in both mentioned designs and thus used tapered roller bearings are axially mechanically preloaded. The vibrations of the tapered roller bearings were measured at the tapered roller bearings stand which was designed for this purpose. The testing stand consisted of a shaft placing fitted with two tapered roller bearings. Influence of a bearing axial mechanical preload on the vibration level was evaluated. On the basis of that evaluation the optimal value of the axial mechanical preload forcing on a tapered roller bearing was estimated. The measured vibration was evaluated using methods of spectral analysis. The fact that bearing defects can be often detected and localized by their characteristic frequencies was taken into consideration. The axial preload should affect the levels of vibration at the bands where these frequencies occur. The bands were determined in two ways. Firstly, they were calculated from bearing dimensions and the shaft revolution rate. Secondly, they were estimated directly from the measured data using Inductive Modeling. Inductive modeling methods enable us to recognize those bands which are most affected by the preload and hence those bands might be important for the evaluation of the influence of the axial preload on the tapered roller bearing vibration level. In particular, the Group Method of Data Handling and the Group of Adaptive Models Evolution were used.

1. INTRODUCTION

Requirements to ensure a longer lifetime and less noisy running of modern rotating machinery lead to necessity to set all used components so that they can operate at their optimal states in general. Some mechanical designs require high demands on accuracy and rigidity of the shaft placing. Elimination of even a small clearance is particularly vital to pinion gears included in automotive gearboxes or metal cutting machine shafts. Mechanically preloaded tapered roller bearings are often used for this purpose presently. The mechanical axial preload which is forced on a tapered roller bearing improves the shaft placing accuracy, enhance the bearing

rigidity, and decrease a level of produced noise [1].

The bearing rigidity c is defined as a quotient of power F forcing on the bearing and elastic deformation δl inside the bearing, see equation (1).

$$c = \frac{F}{\delta l} \tag{1}$$

The elastic deformation caused by the bearing operational load is lower in case of the preloaded bearing than the non-preloaded bearing.

The noise level produced during the machinery operation depends on the bearing axial preload too. The noise level is reduced especially because of the lower clearance in the bearing. The bearing roller elements lead better when the bearing load is lower. Hence the bearing working is quieter and operational loaded shaft doesn't show so much deflection though the bearing. For instance, usage of axially preloaded bearings for construction of automotive gearboxes causes that the gearbox operation is quiet and can be characterized by the long working life.

The axial preload affects the bearing vibration and temperature, because of the bearing axial preload causes the bearing roller elements lead with higher pressure to the surface of the inner and outer ring. The bearing temperature increases along with the preload value. The temperature should be kept as low as possible because of heat loss minimizing. There is also proven the fact that too high axial preload causes the extensive shortening of the bearing working life. These two different requirements are satisfied by looking for a compromise where the optimal value of the bearing axial preload is set. The axial preload optimal value assessment for the bearing ZVL 32010AXA was the main objective in our approach. The optimal value was assessed via measurement of bearing vibration and temperature [2]. Analysis of the vibration used for this purpose is described in this paper.

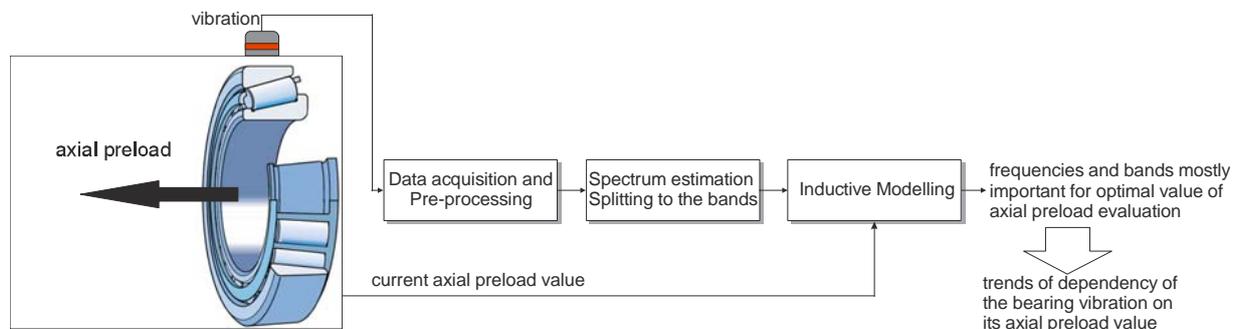


Figure 1. Inspection of the bearing vibration dependency on its axial preload value.

The bearing was tested at a stand which was designed specially for this purpose. Spectral analysis was used for data processing due to its simplicity and general availability of software libraries implementing spectral analysis methods partially for LabVIEW software which was used to control the test procedure. Although all considerable quantities were measured and controlled during the tests, e.g. keeping a constant value of the shaft revolution rate and monitoring of torsion oscillations of the shaft, evaluation of the axial preload influence on the bearing vibration cannot easily be done by visual comparison of measured spectra or the influence was hidden because of huge amount of peaks from different parts of the stand in the power spectra. Therefore there were applied methods which could make analysis of the spectrum easier and could also provide partial automation of this procedure. The objective of these methods used for spectral analysis was automated localization of frequencies or bands which provide valuable information about the axial preload influence on

the bearing vibration. The optimal value of the bearing axial preload could be assessed subsequently via trends evaluation of vibration levels at the few selected frequencies during all tested axial preloads applied to the tapered roller bearing, the procedure shown in Fig. 1.

2. BEARING FAULT RECOGNITION

The classical approach to the spectral analysis of bearing vibration which is still widely used in the industry puts to use the bearing characteristic defect frequencies. This approach models a failure of a bearing as a localized defect [3] and assumes that the failure begins when a small piece of contact surface in bearing is cracked or dislodged and that causes beats if a roller passes through this crack. This effect generally results in simply periodic bursts of acoustic emission and sequentially vibration. The bearing vibrates at its own resonant frequencies, and so the bearing vibration signal appears as an envelope on a high frequency signal given by these resonant frequencies. This takes effect in frequency spectrum of gearbox vibration by increase in corresponding repetitive frequencies which are characteristic for each bearing type. Defects at different locations of a bearing as inner race, roller and outer race can be characterized by different own characteristic defect frequency. Assuming pure rolling contact and negligible elastic deformation of bearing component, characteristic defect frequencies can be calculated from the geometry and speed of a bearing using the equations:

$$f_o = \frac{n}{2} f_s \left(1 - \frac{RD}{PD} \cos \beta \right); \quad f_i = \frac{n}{2} f_s \left(1 + \frac{RD}{PD} \cos \beta \right); \quad f_r = \frac{PD}{2RD} f_s \left(1 - \left(\frac{RD}{PD} \cos \beta \right)^2 \right), \quad (2)$$

where f_o , f_i and f_r are characteristic frequencies of outer race defect, inner race defect and defect on a roller. RD is a roller diameter, PD is a bearing pitch diameter, f_s is rotating speed, β is a contact angle between race and roller, n is a number of rollers.

The equations are mentioned in most catalogues of the biggest bearing producers, e.g. SKF, and even some producers provide a tool which calculates the frequencies after typing the bearing type number.

Among other disadvantages, which especially consist in imperfect bearing failure modeling and neglecting possible appearances of quasi-periodicity via speed fluctuations, this approach vitally requires keeping constant value of shaft revolution rate during each measurement. Nowadays there are other techniques which could describe the bearing failure in a better way, e.g. cyclostationarity analysis described in [4]. On the other hand the main advantage of this technique using the bearing characteristic frequencies is simplicity and easy implementation in software.

3. PRELOAD INFLUENCE ESTIMATION

There were expected that impact of axial preload applied to the bearing which causes the lead of rollers with higher pressure to the surface of the inner and outer ring could result in bearing imperfections appearance. These imperfections result in behaviour similar to fault behaviour.

In accordance with equations (2), the bearing faults can be described at the bearing characteristic defect frequencies and also at their higher harmonics. In practice, many bearing components contain natural repetitive frequencies and their significant harmonics almost in the range up to approximately hundred times the revolution rate, e.g. 2500 Hz for the revolution rate at 1500 rpm. The analysis could be focused on this band to reduce influence of high-frequency noise.

Because we are mainly interested in energy of vibration at each frequency, Power

Spectral Density (PSD) was employed for vibration spectral analysis. Welch's method for Power Spectral Density determination [5] was used to estimate spectrum of the measured vibration.

Whole spectrum of measured vibration was split to the equidistant spread bands with constant bandwidths. The levels of vibration in these bands were expressed by a total power value of vibration within each band. This representation of measured vibration was used in order to reduce the dimensionality of the feature vectors characterizing the bearing state and make a state description containing all considerable information.

We applied the classical approach using the bearing characteristic defect frequencies, but there is no surety that the influence of axial preload couldn't show itself at another part of spectra, so it is important to find appropriate frequencies at which a level of vibration depends on the value of axial preload forced on the bearing in whole spectrum. These frequencies or more precisely bands were estimated directly from the measured data using Inductive Modeling. The basic idea takes into consideration that the application of a value of the axial preload on the tapered roller bearing affects or changes mainly a level of vibration produced by the bearing itself, and so there could be found correlation (or dependency) between the vibration level at corresponding affected bands and an actual value of the axial preload.

4. INDUCTIVE MODELING

Modeling methods used in our research constitutes an approach for automatic black-box model generation. Deductive modeling, e.g. classical neural networks as back-propagation neural networks, requires domain expertise to conclude math models of a system. That model is subsequently fitted via training by measured data. Some neural networks are also very sensitive to the presence of irrelevant features in a data set. On the other hand, Inductive modeling uses machine learning techniques to derive models including the model structure automatically from the measured data using just data describing the modelled system. The inductive models are designed to deal with irrelevant features (by ignoring them). Some features can be relevant just in a small subspace of the state space of all input features. This is necessary for our approach because we have a large set of bands with a small bandwidth.

Inductive modeling methods are based on genetic algorithms. They use a network of forwardly interconnected units representing the model. This network is evolved in very sophisticated way, using the process of induction. Beyond the initial number of units and number of surviving units, the kind of basic units is only needed to know.

We use Multilayered Interactive algorithm (MIA GMDH) and Group of Adaptive Models Evolution (GAME). In our case the input to the modeling process were formed by a set of vectors of vibration power in split bands. The expected output of modeling (target variable) was formed by the corresponding set of axial preload forcing on the tapered roller bearing.

4.1 Group Method of Data Handling

Group Method of Data Handling is a set of several methods for inductive models construction for different problems solution [6]. This inductive approach is based on sorting-out of gradually complicated models and selection of the best solution by minimum of external criterion. This leads into selection the features witch are able to describe the real problem in the best way.

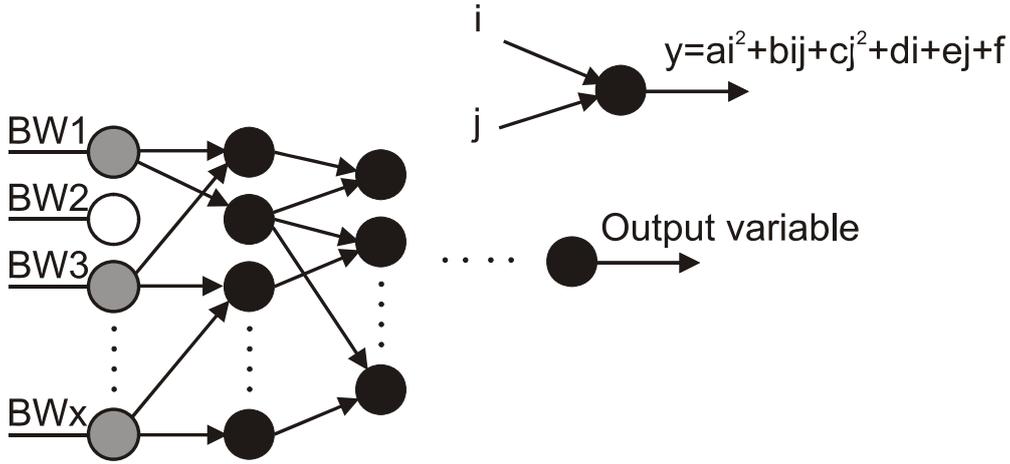


Figure 2. Multilayered Iterative Algorithm GMDH neural network
(BWx denotes split bands, BW2 denoted a disconnected input)

The GMDH engine presented in this contribution was formed by the Multilayered Iterative Algorithm (MIA GMDH). It uses a data set to construct a model of a complex system. The model is represented by a network shown in Fig. 3. Layers of units transfer input signals to the output of the network. The coefficients of units transfer functions are estimated using the data set describing the modelled system. Networks are constructed layer by layer during the learning stage.

The original MIA algorithm works as follows. First initial population of units with given the polynomial transfer function is generated (Figure 2). Units have two inputs and therefore all pair-wise combinations of input variables are employed. Then coefficients of unit transfer functions are estimated using stepwise regression or any other optimization method. Units are sorted by their error of output variable modeling. Few of the best performing units are selected and function as inputs for next layer. Next layers are generated identically until the error of modeling decreases. Which units are performing best results and therefore should survive in a layer is decided using an external criterion of regularity (CR). There are several possible criteria applicable.

The most popular is the criterion of regularity based on the validation using an external data set [6]:

$$V(A, B) = \frac{1}{N_B} \sum_{i=1}^{N_B} (y_i(A) - d_i)^2 \rightarrow \min, \quad (3)$$

where the $y_i(A)$ is the reaction of a GMDH model trained on the A data set on the sample from the B data set, d_i is the target variable value (included in B), N_B denotes a size of the data set. Additional criterion to discriminate units that will be deleted is the variation accuracy criterion (VAC) [6]:

$$\delta^2 = \frac{\sum_{i=1}^N (y_i - d_i)^2}{\sum_{i=1}^N (d_i - \bar{d})^2} \rightarrow \min, \quad (4)$$

where the y_i is the output of a GMDH model, d_i is the target variable and \bar{d} is the mean of the target variable. With $\delta^2 < 0.5$ the model is good, and if $\delta^2 > 1$, the modeling failed and the output unit should be deleted.

The fitted MIA GMDH neural network describes the solved problem via polynomial equations, shown in Fig. 3.

4.2 Group of Adaptive Models Evolution

The Group of Adaptive Models Evolution (GAME) method [7] is derived from the GMDH theory. It improves the Multilayer Iterative Algorithm (MIA GMDH). The GAME method uses niching genetic algorithm [7] to build inductive networks with neurons and connections proper to the data set. The connecting can be more complex than MAI GMDH provides and there are possible several types of neurons.

GAME also contains a technique how to verify the created models. A selected number of models are created during training phase whereas the inner structures of all models are compared and possible correlations in inner structure are penalized (danger of possible creation of similar models). Subsequently the models reached during the training phase are compared altogether and to the known right values (answers). This results to selection of a few best models and simultaneously the credibility of models for each value of known parameter is determined.

It is proven that the GAME networks are able to solve certain type of complex problems which cannot be solved using MIA GMDH [8]. The main disadvantage of using GAME is the high computing severity.

5. EXPERIMENTAL SETUP

The tapered roller bearings type ZVL 32010AXA is being tested. The first bearing was tested and vibration was measured using the Brüel & Kjær PULSE system. The axial preload values from 0 to 3000 N with step 500 N were applied during the test and the revolution rate was kept constant at 1480 Hz. The data analysis of the obtained data is shown in this paper. Another bearing should be tested using software written in LabVIEW which was used to control the test.

The measurement stand consists mainly of two bearing housing, a robust shaft and driving engine. The tapered roller bearing housing is placed on a rigid base. The stand also contains a mechanism that enables to set the axial preload value for the tested bearing. The driving engine is formed by an asynchronous electric motor. The testing stand is fitted with working state diagnostics, as a revolution rate sensor and feed-back control. For bearing features monitoring, the stand is equipped with a gyroscopic moment sensor, axial power measurement and bearing temperature measurement. PULSE 7537 analyser fitted with calibrated accelerometers 4507 B was used to measure vibration of the bearing in axial direction. The accelerometer was placed on the bearing housing.

The digitalized vibration signals were filtered by low-pass filter in order to reduce noise and disturbances. We use low-pass Butterworth filter order 6 with stop-band frequency at 1200 Hz. Welch's Power Spectral Density estimation was calculated from the filtered signal. The Hanning window in time was applied. The Welch's segment length was selected as one hundredth of the whole signal length, the overlap value was 25 %.

The frequency range up to 1200 Hz was selected. The PSD spectrum of measured vibration was divided into the equidistant spread bands with constant bandwidths at 20 Hz. Vibration in each band was represented by the total power value. Each measurement of the data set was represented by a feature vector of 60 real numbers. The target variable was formed by the appropriate axial preload value. MIA GMDH network contained 3 layers. Each layer was initiated with 30 units, from that 5 units survived. GAME was formed from 10

models build during the training stage. Each model contained 3 layers, initiated with 30 units, from that max. 5 units survived. We used neuron types: Linear, Polynomial, Perceptron [7]. The network was trained by the Quasi Newton method. The result that we are interested is a set of inputs to which were connected survived units of the network. The tools we used can estimate quality rating of each input [7].

6. EXPERIMENTAL RESULTS

The characteristic defect frequencies for the bearing ZVL 32010AXA is shown in Table 1. The most rated bands selected via Inductive modeling are shown in Table 2 and Table 3.

Table 1. Characteristic defect frequencies for ZVL 32010AXA.

Inner ring	Outer ring	Roller
341 Hz	276 Hz	225 Hz

Table 2. Frequencies selected via MIA GMDH (mean values from 5 models, most rated inputs).

Band	80 to 100Hz	140 to 160 Hz	240 to 260 Hz	260 to 280 Hz	340 to 360 Hz	820 to 840 Hz
Rating	14 %	9 %	23 %	15 %	13 %	23 %

Table 3. Frequencies selected via GAME (10 models, most rated inputs).

Band	80 to 100Hz	140 to 160 Hz	240 to 260 Hz	260 to 280 Hz	680 to 700 Hz	820 to 840 Hz
Rating	12 %	9 %	14 %	10 %	17 %	16 %

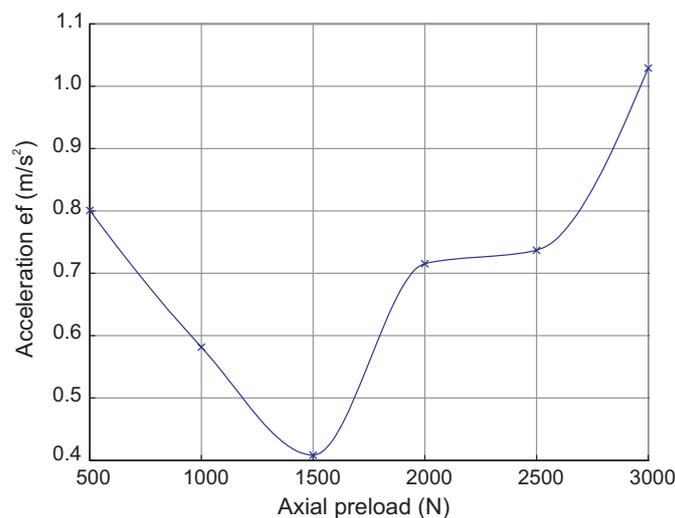


Figure 3. Dependency of sum of vibration at characteristic defect frequencies for inner ring, outer ring and roller on the bearing axial preload.

Because both MIA GMDH and GAME assessed bands that contain the bearing characteristic frequencies or their higher harmonic, the influence of axial preload on the bearing vibration was evaluated via its characteristic defect frequencies, shown in Figure 3. The optimal value of the axial preload was estimated at 1500 N.

7. CONCLUSIONS

This paper has outlined usage of inductive modeling methods for analysis of the influence of axial preload on the tapered roller bearing vibration. Group Method of Data Handling and Group of Adaptive Models Evolution were used. The inductive modeling enables to recognize frequencies where a level of vibration depends on an axial preload value applied for the bearing by automated way. More precisely the inductive modeling selects frequencies that match vibration of parts being impressed with the axial preload value, therefore other knowledge about the solved problem is useful to utilize.

The methods were applied for a project that aims to estimate the optimal value of the bearing axial preload for the bearing type ZVL 32010AXA. Both inductive modeling methods gave very similar results in this project. Using of Group of Adaptive Models Evolution seems to be convenient especially for more complicated tasks. The optimal value of the axial preload of the tapered roller bearing ZVL 32010AXA was estimated at the 1500 N.

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REFERENCES

- [1] V. Dynybyl, P. Mossóczy, Z. Češpíro, "Experimental Assessment of Bevel Gearboxes", *Proceedings of 22nd Danubia-Adria Symposium on Experimental Methods in Solid Mechanics*, Parma, University of Parma, 2005, s. 296-297.
- [2] V. Dynybyl, P. Mossóczy, "Temperature Field of Tapered Bearings", *Proceeding of 47. mezinárodní konference kateder částí a mechanismů strojů*, Praha, Česká zemědělská univerzita, Technická fakulta, 2006, p. 67-70. ISBN 80-213-1523-7. (in Czech).
- [3] M. Kreidl et al, *Diagnostic Systems*, Czech Technical University Publishing House, Prague, 2001, 352 p. ISBN 80-01-02349-4. (in Czech).
- [4] R. B. Randall, J. Antoni, S. Chobsaard, "The Relationship between Spectral Correlation and Envelope Analysis in the Diagnostics of Bearing Faults and Other Cyclostationary Machine Signals", *Mechanical Systems and Signal Processing* **15(5)**, p. 945 – 962, 2001.
- [5] H. Schröder, H. Blume, *One- and Multidimensional Signal Processing*, John Wiley & Sons, Ltd., New York, 2000.
- [6] A. G. Ivakhnenko, G. Ivakhnenko, and J. Muller, „Self-organization of neural networks with active neurons”, *Pattern Recognition and Image Analysis* **4(2)**, p.185 - 196, 1997.
- [7] P. Kordík, M. Šnorek, "Progress in inductive modelling", *Proceedings of EUROSIM Congress 2004*, Paris, 2004.
- [8] P. Kordík, J. Saidl, M. Snorek, "Evolutionary Search for Interesting Behavior of Neural Network Ensembles", *Proceedings of 2006 IEEE Congress on Evolutionary Computation*, p. 235-238, Los Alamitos, IEEE Computer Society, 2006. ISBN 0-7803-9489-5.