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ADOPTING ARTIFICIAL NEURAL NETWORK FOR WEAR INVESTIGATION OF BALL BEARING MATERIALS UNDER PURE SLIDING CONDITION

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Abstract:
In the industry, ball bearings are the most widely used machine element. The ball materials may differ in various bearing applications. Wear of the ball and recess after a period of use is the most common cause of ball bearing failure. The present study aims to develop the artificial neural network model for assessing the wear of different ball bearing materials. A wear test method has been followed as suggested by the ASTM-G99 standard. The pin on disc apparatus was selected to conduct numerous trials. L9 array was considered to design the experiments. The factors considered for this study were load, time, and sliding speed. Based on the results obtained, ANN code was proposed to evaluate wear using numerous test parameters. The results obtained from the proposed model are nearly similar to experimental results, which would be evidence for the correctness of the model. The proposed neural network model can be used in numerous applications with given parameters.

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1. INTRODUCTION

The rapid advancement in science and technology has affected the original design and construction of bearings with high accuracy and peak performance in the most demanding working conditions [1,2]. The bearing is a supporting tool for relative positioning and rotation when transferring a load among two machine elements [3]. Loads operating on the bearing might be axial, radial or angular depending on the bearing specified requirements. Although ball in addition to roller bearings seem to be simple mechanisms, their internal processes are somewhat complicated. Bearing service life is measured in terms of time or the total number of revolutions before failures in the outer ring, inner ring or rolling element (ball or roller) occurs as a result of rolling fatigue caused by repetitive stress. The rated life of a ball bearing is defined as the time it takes for an item of equipment or a machine element to fail under the manufacturer's specified conditions of usage [4]. Metals, polymers, ceramics, and composites are among the materials used in bearings. Chrome steel, often known as 52100 chrome alloy steel, is the most common material used to make balls for ball bearings. The rolling contact bearing material customarily used is AISI52100 alloy steel. It has elevated compressive strength, inexpensive, superior wear resistance, and has admirable corrosion resistance in oxidation and acidic environments; however, Silicon Nitride and Alumina Oxide materials are also used for higher load applications [5,6].

Wear life is a critical property of deep groove ball bearings. Wear and Frictions are the critical processes especially in case of ball bearings. Bearing wear alters their form and surface condition, resulting in lubrication pollution. When lubrication pollution reaches a particular level, the bearing's lubrication efficacy deteriorates and finally disappears, leading the bearing to lose

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rotational precision and even basic operating capabilities. Adhesive wear is the term for this occurrence. The defect diagnostic procedure is divided into two stages: the first comprises signal processing, which includes feature extraction in addition to noise reduction, and the second is signal classification, which is based on the features collected in the previous stage. Many times noise signals collected from ball bearings are considered as the indicators for knowing the bearing health.

2. RELATED WORK

Many researchers are now working on ball bearings in order to improve the usage of neural network predictors on bearing systems and to investigate the accurate neural model of a ball bearing system [7]. Some researchers used feed forward neural network to develop a model which can be employed practically. Further, Patel and Upadhyay predicted and analysed the bearing defects using artificial intelligence algorithms. Experiments on rolling bearings with localised flaws on various bearing components were carried out across a wide range of speeds, and vibration signals were recorded [8]. A critical overview on Failure Diagnosis of Element Bearings using Artificial Neural Networks has been presented. When a bearing fails, precise, dependable, and proactive diagnosis is essential to restoring it to service as soon as possible, efficiently, and cost-effectively. Every factor of bearing performance must be regularly examined, diagnosed, and forecasted utilising the most advanced technologies available. [9]. The wear rate of nanocomposites with A356 aluminium alloy matrix and silicon carbide nanoparticle reinforcement was optimised by examining the primary influences: wt percent of reinforcement, normal load, and sliding speed. The primary goal of the carried out the experiment was to identify the most significant components or combinations of factors that have the greatest impact on wear rate, so that the wear rate could be optimised [10,11]. The compocasting technique effectively produced the hybrid aluminium composite, A356 aluminium alloy reinforced with SiC (10 wt. percent) and Gr (1 wt. percent and 5 wt. percent) particle [11].

Some studies investigated the dependability of ball bearings on the crankshafts of piston compressors. The findings of the study on the tested ball bearings reveal that the size of the axial clearance corresponds to the sizes and temperatures before the time of noticing that condition and is a good indication of the technical system's dependability [12]. Furthermore, Reliability model of bearing assembly on an agricultural cardan shaft was exhaustively studied by researchers with the major goal of the suggested and conducted research within the provided work was to diagnose bearing assembly at cardan shaft joints in order to define the overall reliability of shafts [13]. Few researchers focussed on tribological behaviour of A356/10SiC/3Gr hybrid composite in dry-sliding conditions [14].

Vibration, wear, and lubrication processes, fluid dynamics and lubricant rheology, material characteristics, and contact mechanics all have an impact on rolling bearing function [15]. Palmgren proposed the fatigue limit approach in 1924 [16]. Lundberg and Palmgren presented their rolling bearing life theory in the years 1947–1952, and it was used as the equation for the fundamental rating life of rolling bearings, L_{10}, in millions of rotations.

The lifespan of a rolling bearing is currently often evaluated using the modified rating life *Lnm* formula rather than the standard rating life:

$$Lnm=a_1 X\, a_{ISO} X\, L_{10} \quad (1)$$

Where:

a_1 - modification factor for reliability other than 90 per cent and

a_{ISO} - represents parameters such as load, speed, oil viscosity, material fatigue limit, and content of contamination particles in the oil.

Although rated life detection methods are available; however, very few wear detection models are available in past literature, therefore, authors primary intention is to introduce artificial neural network model for wear investigation of ball bearing under pure sliding context.

2.1 Taguchi Method

Taguchi techniques begin with the idea that we are creating an engineering system, such as a machine that will perform a certain function or a manufacturing process that will produce a specific product or item. Taguchi techniques also recognise that there are factors that are under our control and ones that are not. These are referred to as Control Factors and Noise Factors, respectively, in Taguchi nomenclature.

The Taguchi Method is applied in four steps:

1) Consider the critical quality attributes and design factors for the product/process;
2) Design of experiments and conduct trials as per selected array;
3) Analyze the findings to find the optimum solutions;
4) Confirm your findings with a follow-up test under ideal conditions.

The Taguchi design is used to investigate the effect of graphite reinforcement, load, and sliding speed with constant sliding distance on the tribological behaviour of A356 aluminium matrix composites reinforced with 10% silicon carbide and graphite [17].

2.2 Artificial Neural Networks

An ANN is composed of a network of connected units or nodes called artificial neurons, which are often modelled after biological neurons. Each link, like synapses in a biological brain, has the ability to send a signal to other neurons. Back propagation is a technique for adjusting connection weights to compensate for errors discovered during learning as shown in Fig. 1. The quantity of error is efficiently distributed among the connections. Back prop calculates the gradient (the derivative) of the cost function associated with a particular state in relation to the weights.

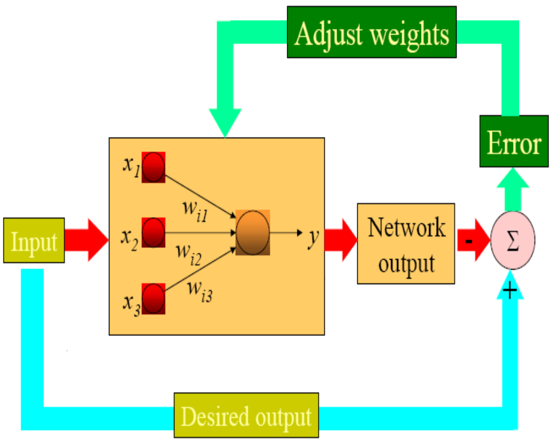

Fig. 1. Back propogation model in ANN

Reinforcement learning, supervised learning, and unsupervised learning are the three primary learning paradigms. A collection of paired inputs and intended outputs is used in supervised learning. The goal of learning is to create the desired outcome for each input. In unsupervised learning, input data is supplied together with the cost function, a function of the data X, and the output of the network. The goal of reinforcement learning is to weight the network (create a policy) to do actions that have the lowest long-term (expected cumulative) cost. Therefore, it was planned to use supervised learning neural network model for ball bearing wear analysis with three parameters such as time, sliding speed and load under sliding condition of various ball materials.

3. EXPERIMENTAL WORK

This test was carried out in accordance with ASTM G99. Metallographic abrasive sheets (C-400) and (C-600) were used to polish chrome steel discs. The diameter of the ball rotation under the sliding conditions on the disc was adjusted according to the sliding speed track diameter of a steel disc revolving at a given speed. This pre-rubbing technique guaranteed that the ball and disc surfaces made complete contact. Disc specimens had a surface roughness of 0.09–0.11 µm. All of the specimens were cleaned manually in petrol and completely dried.

3.1 Design of Experiments

"Sir R. A. Fisher proposed the approach of putting out the conditions (designs) of experiments involving several parameters in the 1920s" [18]. Factorial design of experiments is the name given to this procedure. For a given set of components, a complete factorial design discovers all feasible combinations. Because most industrial trials contain a huge number of variables, the findings of a complete factorial design may need a large number of experiments. The tests are carried out in accordance with the Taguchi technique. The appropriate L9 orthogonal array is chosen based on the number of parameters and levels. The trials were carried out using the typical orthogonal array. The purpose of selecting an L9 orthogonal array is to reduce number of trials and optimize the results. load, sliding speed and time were three parameters as well as three levels were employed for creating L9 array.

3.2 Pin on Disc Apparatus

The friction and wear tests are carried out in an environment at room temperature (28^{0}C) as shown in Fig. 2. The applied loads ranged from 10 N to 120 N, while the rotation rates of the discs ranged from 7m/s to 14m/s. The period ranged from 30 to 90 minutes, and the sliding distance was adjusted appropriately as shown in Fig. 3. During the wet test, Servo engine oil (20W40) was applied to the rubbing surfaces using an oil lubrication system at a flow rate of 50 ml/min. During the wet test, it was ensured that lubrication would be continuous between the Pin and the counter face.

Fig. 2. Wear test rig setup

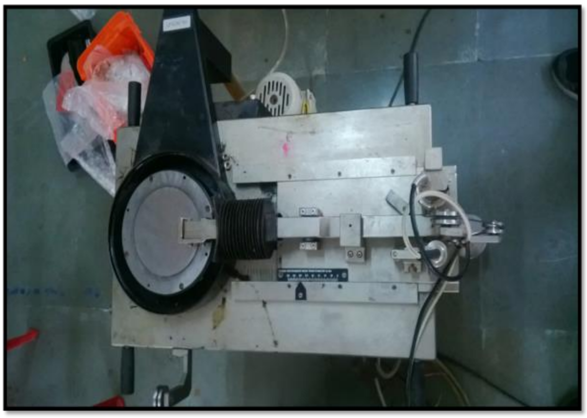

Fig. 3. Track diameter selection

3.3 Experimental trials

All of the specimens were cleaned by hand in petrol and then dried properly. The applied weights ranged from 10 N to 120 N, with disc rotation speeds ranging from 7 to 14 m/s, duration ranging from 30 to 90 minutes, and sliding distance varying appropriately. During the wet test, Servo engine oil (20W40) is applied to the rubbing surfaces at a flow rate of 50 ml/min utilizing an oil lubrication system. L9 array was chosen as shown in Table 1 below for trials

Table 1. Control Factors with different levels

Control factors	Units	Level I	Level II	Level III
(A) Load	N	10	60	120
(B) Sliding speed	m/s	7	14	21
(C) Time	min	30	60	90

After performing numerous trials, the coding for artificial neural network was employed to evaluate the correctness of trials with their results.

3.4 Neural Network Model

The code for given neural network has been implemented on neural network model by using Matlab 2020. The coding of the programming was achieved with multilayer consideration as shown in Fig. 4. The following ANN program was used for machine learning.

```
I=[7 7 7 10 10 10 14 14 14;10 60 120 10 60 120 10 60 120;30 60 90 60 90 30 90 30 60];
O=[0.001 0.005 0.018 0.002 0.009 0.016 0.003 0.004 0.010];
net = newff(I,O,[1 1],{'tansig','purelin'});
net=train(net,I,O);
net.trainParam.epochs = 1;
net.trainParam.goal = 0.01;
a =sim(net,I);
y1=sim(net,[7 7 7 10 10 10 14 14 14;10 60 120 10 60 120 10 60 120;30 60 90 60 90 30 90 30 60]);
plot(a,y1,'--rs');
```

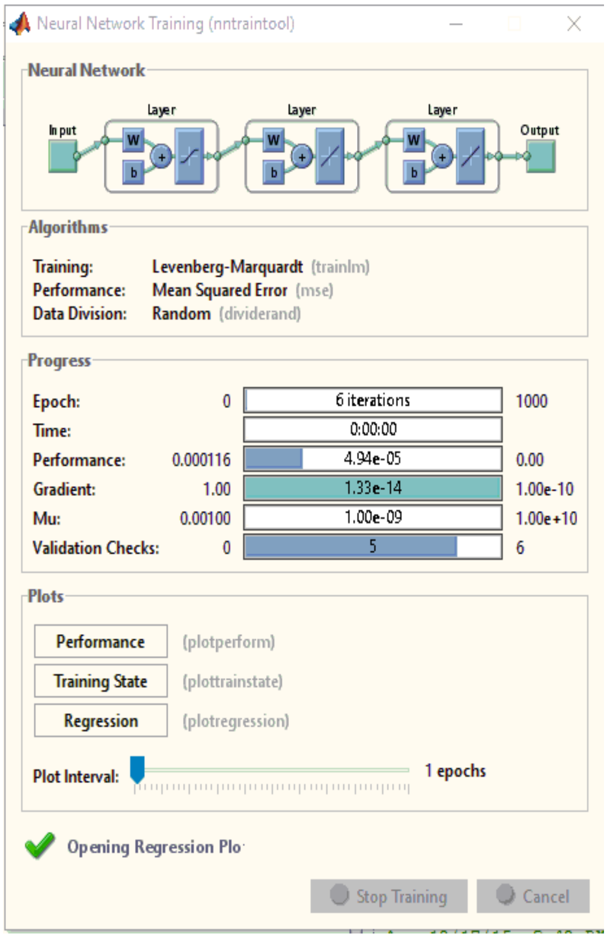

Fig. 4. Neural Network Training

4. RESULTS AND DISCUSSION

The following results were obtained from the dry and wet conditions trials are shown in Table 2 and Table 3 respectively.

Fig. 5 highlights the neural network training state for possible ANN model. Furthermore, results obtained from this test were nearly matching with the experimental results.

Table 2. ANN Results for dry conditions

Sr. No.	Sliding speed (m/s)	Load (N)	Time (min)	Chrome Steel		Si3N4		Al2O3	
				Wear of Ball by ANN (gm)	Wear of Ball by Expt. (gm)	Wear of Ball by ANN (gm)	Wear of Ball by Expt. (gm)	Wear of Ball by ANN (gm)	Wear of Ball by Expt. (gm)
1	7	10	30	0.044836	0.042	0.016435	0.001	0.002768	0.002
2	7	60	60	0.112694	0.112	0.019538	0.021	0.076430	0.032
3	7	120	90	0.151347	0.151	0.02875	0.031	0.089009	0.089
4	10	10	60	0.05425	0.067	0.017753	0.002	0.002768	0.003
5	10	60	90	0.127998	0.127	0.026999	0.030	0.072090	0.072
6	10	120	30	0.150532	0.157	0.023273	0.024	0.089009	0.032
7	14	10	90	0.071075	0.063	0.025276	0.003	0.002768	0.004
8	14	60	30	0.123332	0.123	0.020004	0.021	0.030333	0.029
9	14	120	60	0.152093	0.225	0.028874	0.030	0.089009	0.096

Table 3. ANN Results for wet conditions

Sr. No.	Sliding speed (m/s)	Load (N)	Time (min)	Chrome Steel		Si3N4		Al2O3	
				Wear of Ball by ANN (gm)	Wear of Ball by Expt. (gm)	Wear of Ball by ANN (gm)	Wear of Ball by Expt. (gm)	Wear of Ball by ANN (gm)	Wear of Ball by Expt. (gm)
1	7	10	30	0.00216	0.007966	0.008	0.000488	0.00100	0.001
2	7	60	60	0.01771	0.009356	0.009	0.002848	0.00200	0.002
3	7	120	90	0.03547	0.037787	0.038	0.005578	0.00600	0.006
4	10	10	60	0.00981	0.008406	0.009	0.000863	0.00124	0.001
5	10	60	90	0.02536	0.024977	0.027	0.003223	0.00492	0.003
6	10	120	30	0.02962	0.028954	0.029	0.004423	0.00400	0.004
7	14	10	90	0.01851	0.019854	0.018	0.001193	0.00338	0.001
8	14	60	30	0.02056	0.018991	0.019	0.002023	0.00200	0.002
9	14	120	60	0.03832	0.007966	0.040	0.004753	0.00600	0.005

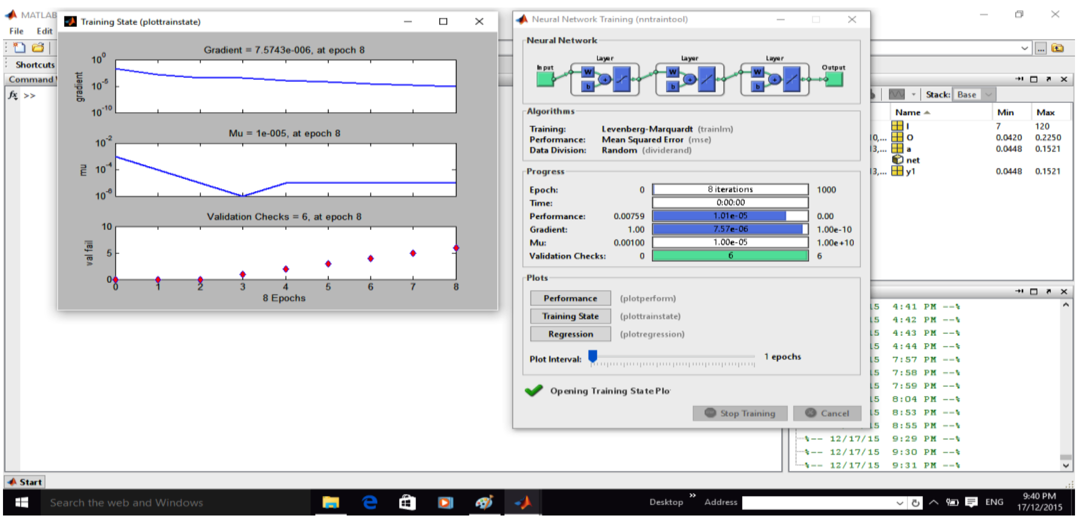

Fig. 5. Neural Network Training State

After successful completion of experimental test and software analysis, the confirmation test had been carried out and results are as given in Table 4.

Table 4. ANN Results for dry conditions

Material	Sliding speed (m/s)	Load (N)	Time (min)	Wear by Experimental (gm)	Wear by ANN (Software Analysis)
Chrome Steel	7	10	30	0.044	0.05802
Aluminium Oxide	10	60	90	0.072	0.07209
Silicon Nitride	14	60	30	0.020	0.01998

Confirmation tests have been completed satisfactorily in both dry and wet situations. The regression equation's prediction of wear for various materials has been verified to be in good agreement with experimental data. In terms of experimental outcomes, the Artificial Neural Network constructed in MATLAB is likewise doing well. Wear of balls is higher in dry circumstances, whereas wear of balls is lower in wet situations for the corresponding materials. Silicon Nitride material demonstrates good wear resistance under high load situations and may be best suited for aviation engines.

The artificial neural network is one of the most extensively used computer models (ANN). The capacity to be employed as an arbitrary function approximation method that 'learns' from observed data is its biggest benefit. A neural model including recurrent neural network structure is given and assessed in this research. Real-time data is employed in artificial intelligence modelling. Previously, wear damage was examined by few researchers [19,20]. To represent the damage (wear) induced by dry fretting and to characterise the dynamical frictional behaviour of the contact, an approach based on artificial neural networks was adopted [21,22] whereas in our research the wear analysis was carried out. The results obtained were nearly matching with previous results with minor variation and that could be likely because of instruments error and material’s physical properties [3,23].

Ball bearing is the most important component of any machine. The failure of ball bearing can be studied with different approach [1,9,13,24] such as reliability analysis of ball bearing, wear depth analysis, failure diagnosis of ball bearing, wear analysis and many more. In our case, the results show the predictable damage of ball bearing which may be useful while selecting bearing for specific applications. Wear scars of ball materials of ball bearings are presented Fig. 6. The Al_2O_3 balls shows less wear and less area of contact while compared with chrome steel.

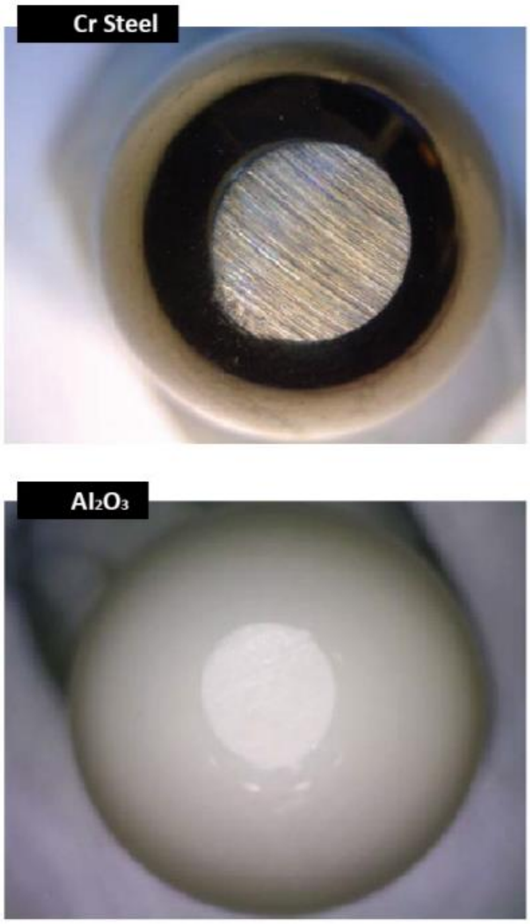

Fig. 6. Wear Scars of chrome steel ball and Al2O3 ball

An additive also helps to reduce wear [25], however; it is not possible to maintain the flow of lubricant in real working situations. Ball material adhesion was discovered to be the predominant wear process in both uncoated and coated raceways [26] which is as similar to present research on Al_2O_3 ball materials. Previous investigations have shown that the addition of a chemically active ingredient in the oil can cause faster fatigue of rolling contacts, even when there is little sliding, however The addition most likely lowers fatigue life by increasing the number of possible surface nuclei for pits throughout its chemical (re)activity [25]. The impacts of angular misalignment variability on wear of angular contact ball bearing in the spindle system were studied. An increased spindle speed increases wear depth but reduces wear depth dispersion [24], therefore wear analysis were carried out in the present research which gives initial prediction of wear.

5. CONCLUSION

The artificial neural network model for measuring the wear of different ball bearing materials was created in this study to analyse the wear of different ball bearing materials. A supervised learning neural network model was developed for ball bearing wear analysis with three parameters such as time, sliding speed and load under sliding condition of three ball material. Following a series of tests, the built artificial neural network was used to assess the accuracy of trials based on their outcomes. Confirmation tests have been completed satisfactorily in both dry and wet situations. Wear of balls is higher in dry circumstances, whereas wear of balls is lower in wet situations for the corresponding materials.

REFERENCES

[1] F. Lu, R. Zhu, Q. Fu, Wear depth calculation and influence factor analysis for groove ball bearing. *MATEC Web Conf.*, Vol.211, 2018: 08002. https://doi.org/10.1051/matecconf/201821108002

[2] L. Patil, A.V. Patil, R.B. Barjibhe, A Wear Analysis of Composite Ball Materials using Tribometer, *Int. Journal of Engineering Research and Applications*, 6 (1), 2016: 79-78.

[3] L.N. Patil, A.V. Patil, Wear Prediction Model for Composite Bearing Balls under Pure Sliding Contact Condition, *International Journal of Engineering Research & Technology,* 4 (12), 2015: 547-550. http://dx.doi.org/10.17577/IJERTV4IS120620

[4] R. K. Upadhyay, L. A. Kumaraswamidhas, Md. S. Azam, Rolling element bearing failure analysis: A case study. *Case Studies in Engineering Failure Analysis*, 1 (1), 2013: 15-17. https://doi.org/10.1016/j.csefa.2012.11.003

[5] L. Wang, R. W. Snidle, L. Gu, Rolling contact silicon nitride bearing technology: a review of recent research. *Wear*, 246 (1–2),2000: 159-173. https://doi.org/10.1016/S0043-1648(00)00504-4

[6] C. Piconi, S. G. Condo, T. Kosmač, Alumina - and Zirconia-based Ceramics for Load - bearing Applications. in *Advanced Ceramics for Dentistry, Chapter 11,* J.Z. Shen and T. Kosmač. *Butterworth-Heinemann*, 2014: 219-253.

[7] H. Taplak, İ. Uzmay, Ş. Yıldırım, An artificial neural network application to fault detection of a rotor bearing system. *Industrial Lubrication and Tribology*, 58 (1), 2006: 32-44. https://doi.org/10.1108/00368790610640082

[8] J.P. Patel, S.H. Upadhyay, Comparison between Artificial Neural Network and Support Vector Method for a Fault Diagnostics in Rolling Element Bearings. *Procedia Engineering*, 144, 2016: 390-397. https://doi.org/10.1016/j.proeng.2016.05.148

[9] B.K.N. Rao, P.S. Pai, T.N. Nagabhushana, Failure Diagnosis and Prognosis of Rolling - Element Bearings using Artificial Neural Networks: A Critical Overview. *J. Phys.: Conf. Ser.*, 364, 2012: 012023. http://doi: 10.1088/1742-6596/364/1/012023

[10] S. Veličković, B. Stojanović, M. Babić, A.Vencl, I. Bobić, G. Vadászné Bognár, F. Vučetić, Parametric optimization of the aluminium nanocomposites wear rate. *J Braz. Soc. Mech. Sci. Eng.*, 41(1), 2019: 19. https://doi.org/10.1007/s40430-018-1531-8

[11] B. Stojanovic, J. Blagojevic, M. Babic, S. Velickovic, and S. Miladinovic, Optimization of hybrid aluminum composites wear using Taguchi method and artificial neural network. *Industrial Lubrication and Tribology*, 69 (6), 2017: 1005-1015. https://doi: 10.1108/ILT-02-2017-0043

[12] D. Mikic, E. Desnica, A. Asonja, B. Stojanovic, and V. Epifanic-Pajic, Reliability Analysis of Ball Bearing on The Crankshaft of Piston Compressors. *Journal of the Balkan Tribological Association*, 22 (4), 2016: 5060-5070.

[13] E. Desnica, A. Asonja, D. Mikic, B. Stojanovic, Reliability Model of Bearing Assembly on An Agricultural Cardan Shaft. *Journal of the Balkan Tribological Association*, 21 (1), 2015: 38-48.

[14] B. Stojanovic, M. Babic, N. Miloradovic, S. Mitrovic, Tribological Behaviour of A356/10SiC/3Gr Hybrid Composite In Dry-Sliding Conditions. *Materials and Technologies*, 49 (1), 2015: 117-121.

[15] J. Halme P. Andersson, Rolling contact fatigue and wear fundamentals for rolling bearing diagnostics - state of the art, *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology*, 224 (4), 2010: 377-393.

[16] E. V. Zaretsky, A Basics of Bearing Life Prediction. *Lewis Research Center Cleveland*, Ohio, 1997: p.12.
[17] S. Veličković, B. Stojanović, M. Babić, I. Bobić, Optimization of tribological properties of aluminum hybrid composites using Taguchi design. *Journal of Composite Materials*, 51 (17), 2017: 2505-2515. https://doi:10.1177/0021998316672294
[18] R K. Roy, *A primer on the Taguchi method*, 2. ed. Dearborn, *Society of Manufacturing Engineers*, 2010.
[19] T. Zhaoping, S. Jianping, The Contact Analysis for Deep Groove Ball Bearing Based on ANSYS. *Procedia Engineering*, 23, 2011: 423-428. https://doi:10.1016/j.proeng.2011.11.2524
[20] V.G. Pavlov, Wear calculations for radial ball bearings. *Russ. Engin. Res.* 28 (7), 2008: 643-650. https://doi.org/10.3103/S1068798X08070058
[21] T. Kolodziejczyk, R. Toscano, S. Fouvry, G. Morales-Espejel, Artificial intelligence as efficient technique for ball bearing fretting wear damage prediction. *Wear*, 268 (1-2), 2010: 309-315. https://doi:10.1016/j.wear.2009.08.016
[22] X. Zhang, H. Xu, W. Chang, H.Xi, S. Pei, W. Meng, H. Li, S. Xu, A dynamic contact wear model of ball bearings without or with distributed defects. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 234 (24), 2020:4827-4843. https://doi: 10.1177/0954406220931544
[23] H. Li, H. Li, Y. Liu, H. Liu, Dynamic characteristics of ball bearing with flexible cage lintel and wear. *Engineering Failure Analysis*, 117, 2020: 104956. https://doi:10.1016/j.engfailanal.2020.104956
[24] Z. Yang, Y. Zhang, K. Zhang, S. Li, Wear Analysis of Angular Contact Ball Bearing in Multiple-Bearing Spindle System Subjected to Uncertain Initial Angular Misalignment. *Journal of Tribology*, 143 (9), 2021: 091703. https://doi:10.1115/1.4049258
[25] A.A. Torrance, J.E. Morgan, G.T Y. Wan, An additive's influence on the pitting and wear of ball bearing steel. *Wear*, 192 (1-2), 1996: 66-73. https://doi: 10.1016/0043-1648(95)06751-5
[26] B. Hanrahan, S. Misra, C.M. Waits, R. Ghodssi, Wear mechanisms in microfabricated ball bearing systems. *Wear*, 326-327, 2015: 1-9. https://doi:10.1016/j.wear.2014.12.032