Ensuring Vibration Reliability of Turbopump Units Using Artificial Neural Networks

Ivan Pavlenko[1(✉)], Vitalii Ivanov[1], Ivan Kuric[2], Oleksandr Gusak[1], and Oleksandr Liaposhchenko[1]

[1] Sumy State University, 2 Rymskogo-Korsakova Street, Sumy 40007, Ukraine
i.pavlenko@omdm.sumdu.edu.ua
[2] University of Zilina, 8215/1 Univerzitna Street, 010 26 Zilina, Slovakia

Abstract. This paper is devoted to developing the scientific approach of using artificial neural networks for solving a significant problem of vibration reliability of rotary machines that is urgently needed to improve the quality of their diagnosis and manufacturing. The proposed methodology integrates analytical dependencies, recent techniques of numerical simulations and artificial neural networks. The design schemes for realizing the related approach are presented on the example of the turbopump unit for liquid rocket engine. The main advantage of this approach in comparison with the traditional regression analysis and other existing techniques is absence of necessity for setting trial imbalances and carrying out additional initial starts of the turbopump unit. The mathematical model for identification nonlinear parameters of the dependence between bearing stiffness, deflection of the rotary axis, and rotor speed is presented. The proposed methodology is proved by the research of rotor dynamics on the example of turbopump units for liquid rocket engines and allows refining parameters of the nonlinear mathematical models describing forced oscillations of the rotor as a complicated mechanical system with nonlinearities. The results of the research can be used for carrying out the virtual balancing procedure for identification the system of imbalances by the reliable model of forced oscillation of the system “rotor – bearing supports”.

Keywords: Reliability · Bearing support · Stiffness · Nonlinear characteristics · Artificial neural network

1 Introduction

Rotary machines take the significant role in the up-to-date production. Especially, recent turbopump units for aerospace industry are permanently designed for providing their reliable work in overestimated parameters and high precision quality requirements for their manufacture. Primarily, ensuring the vibration reliability of the rotary machines is an urgent problem for identification of the vibration characteristics in the conditions of designing for extremely increased parameters and operation in real conditions.

Recently, a lot of research works are devoted to investigation of the stated problem of ensuring vibration reliability of rotors. Particularly, the research work [1] is aimed at

J. Trojanowska et al. (Eds.): *Advances in Manufacturing II* - Volume 1, LNME, pp. 165–175, 2019.
https://doi.org/10.1007/978-3-030-18715-6_14

developing the condition-based maintenance approach for providing maintenance decisions based on the condition monitoring dataset. It consists of several substeps including data acquisition, processing and decision-making. The main aspects in application of this program (diagnostics and prognostics) are indicated. Recent techniques in diagnostics of mechanical systems are summarized, as well as the proposed maintenance approach, its models and algorithms for data processing and decision-making are implemented.

In the paper [2], the approach of the fault diagnosis for rotary machines is investigated using empirical mode decomposition as a comparatively new method of time-frequency analyzing for nonstationary nonlinear signals. However, this research shows that sometimes this approach does not allow revealing the signal characteristics due to the huge impact of external noises. For solving this problem, the combined mode function is proposed for increasing accuracy of the identification of fault characteristics of the rotating machine.

The previous research [3] was aimed at investigating rotor dynamics of the multistage centrifugal oil pump with ball bearings using the proposed computer programs, which realize the mathematical models of free and forced oscillations of the rotor analytically using finite element method (FEM) considering the dependence of bearing stiffness on rotor speed defined previously by the experimental results. In addition, in the papers [4, 5] the theoretical foundations and practical approaches are proposed for providing static and dynamic analysis of the pump's rotor considering the automatic balancing device and pressure difference regulator. The related static and dynamic characteristics are determined, as well as critical frequencies and dynamic stability of the comprehensive system "rotor – automatic balancing device – pressure difference regulator" are investigated.

The research works [6, 7] are aimed at realizing numerical and experimental investigations of centrifugal compressor stage using the aerodynamic stand and up-to-date software. As a result, the velocity distribution is estimated numerically for the different operating parameters, and related recommendations to increase the efficiency have been proposed. Additionally, the paper [8] realizes the analysis of change of face impulse seal rings for rotary machines, which are completely made of wear-resistant materials. It has been established that the seal rings surfaces are not in contact permanently. This fact allows summarizing the vibration reliability of rotors depends on parameters of seals. Moreover, the approach for the development of intelligent automated systems for lean industrial production ensuring maximum efficiency is presented in the research papers [9, 10].

Nevertheless, despite the above mentioned traditional approaches for carrying out research in the field of providing vibration reliability of rotors, there is a huge amount of research works relating to the use of artificial neural networks (ANN). Particularly, the papers [11–13] are aimed at using wavelet analysis based on artificial neural networks (ANN) for the fault diagnostics of rolling bearings. Particularly, the proposed procedure is illustrated different bearing faults using the experimental data for the rotary machine. The results prove the effectiveness of the proposed classifiers for the detection of the bearing conditions for different success rates. Recently, both of statistical methods to preprocess the vibration signals and artificial neural networks (ANN) for identification their parameters are widely used to detect faults in rotary machines. However, it has been shown [14] that using ANN is more successful in comparison with common approaches.

The periodic multi-component signals measured by accelerometers allow obtaining rich information for the purposes of vibration diagnosis of bearings. However, existing approaches are mostly based on long-term data preprocessing to accurately obtain the fault characteristics. Due to these facts, the papers [15, 16] are aimed at developing the effective methods of transformation of the vibration signal into the plane image. For this purpose, authors proposed to use the convolutional neural network able to acquire the most suitable features. Experimental results proved that the accuracy of proposed approach exceed the common methods of vibration diagnosis.

Fundamentally, in the paper [17], the general scientific and methodological approach for the identification of mathematical models of mechanical systems using artificial neural networks (ANN) is proposed for solving complicated interdisciplinary problems in the field of manufacturing, mechanical and chemical engineering. This approach is based on the comprehensive implementation of the analytical methods of the research, modern methods of numerical analysis, and ANN.

The research works [18, 19] emphasize that the prediction of the remaining useful life for accurate equipment takes the highly significant role for improving reliability and reducing overall maintenance cost. In this paper, the approach based on using ANN is developed for identification remaining useful life prediction of equipment in terms of monitoring the operating conditions. Particularly, the author's methodology is validated for pump bearings using vibration monitoring data, as well as a comparison is proposed between the common approach and method based on using ANN. As a result, the advantage of the proposed ANN method is proved.

The research work [20–23], methods for the identification unbalances in rotor bearing systems is proposed using ANN. The method contains two different approached. The first one operates statistical information and is used to test ANN by the frequency domain. In the second case, the infrequency domain is used.

The ANN method for identification of bearing stiffness characteristics of rotary systems by their critical speeds is presented in the paper [24, 25]. Particularly, the improved mathematical model of free oscillations is proposed and realized by the finite element method (FEM), as well as the related software is developed. Finally, ANN method and the related computational approach are proposed for evaluating bearing stiffness by the critical speeds of the rotor.

Despite the presence of a wide variety of methods for increasing vibration reliability of rotary machines and equipment, there is no unified approach for identification parameters by the experimental data considering compliance of housing parts, nonlinear dependence of bearing stiffness on the rotor speed, as well as gyroscopic moments of inertia of impellers and shell-type parts. Moreover, existing methods need to use the data of preloading rotor by the system of trial imbalances and carrying out additional initial starts of the turbopump unit. Due to the abovementioned, the main aim of the research is to propose and implement the method for identification of nonlinear stiffness characteristics of bearing supports using ANN for ensuring vibrational reliability of the equipment based on mathematical models of their forced oscillations and realizing virtual balancing procedure.

2 Research Problem

Due to the FEM approach, forced oscillations of the rotor is described analytically by the matrix equation

$$([C] - \omega^2[M])\{Y\} = \{D\}\omega^2 \tag{1}$$

with the following parameters: $\{Y\}$ – row-vector $m \times 1$ of axial deflections; $\{D\}$ – row-vector $n \times 1$ of imbalances; m, n – number of measuring and correction planes correspondently; $[C]$ – stiffness matrix; $[M]$ – matrix of inertia; ω – rotor speed.

The first equation can be rewritten in the factored form [26]:

$$[W]\{D\} = \{Y\}, \tag{2}$$

where $[W]$ – rectangular matrix of weighting factors:

$$[W] = \omega^2([C] - \omega^2[M])^{-1}. \tag{3}$$

The problem of identification the system of imbalances is solved analytically by the linear regression procedure:

$$\{D\} = (\{W\}^T\{W\})^{-1}\{W\}^T\{Y\}. \tag{4}$$

However, this equation does not take into account the dependence between stiffness matrix $[C]$, axial deflections $\{Y\}$ and rotor speed ω. Particularly, it is sufficient to practical purposes to consider the following dependence:

$$C_{ij}^{<k>} = c_{ij}^{<0>} + \alpha_{ij}\omega_k^2 + \beta_{ij}|Y_j^{<k>}|, \tag{5}$$

where $i = 1, 2, \ldots, m$ – index of measuring plane; $j = 1, 2, \ldots, n$ – index of correction plane; $k = 1, 2, \ldots, p$ – index of rotor speed; p – number of rotor speeds; $c_{ij}^{<0>}$ – elements of linear stiffness matrix in case of zero rotor speed and axial deflections; α_{ij}, β_{ij} – coefficients needed to be identified.

If $m < n$, the number of rotor speeds must be varied by the number p until the following inequality will be satisfied: $m \cdot p \geq n$. Besides, the Eq. (1) cannot be solved directly. However, the proposed virtual balancing procedure allows identifying imbalances directly under the condition of sufficient reliability of the abovementioned mathematical model. In this case, ANN can be appropriately applied as described below. The related procedure for identification of parameters for rotor bearing stiffness characteristic by combined using FEM, ANN and experimental research is schematically presented in Fig. 1.

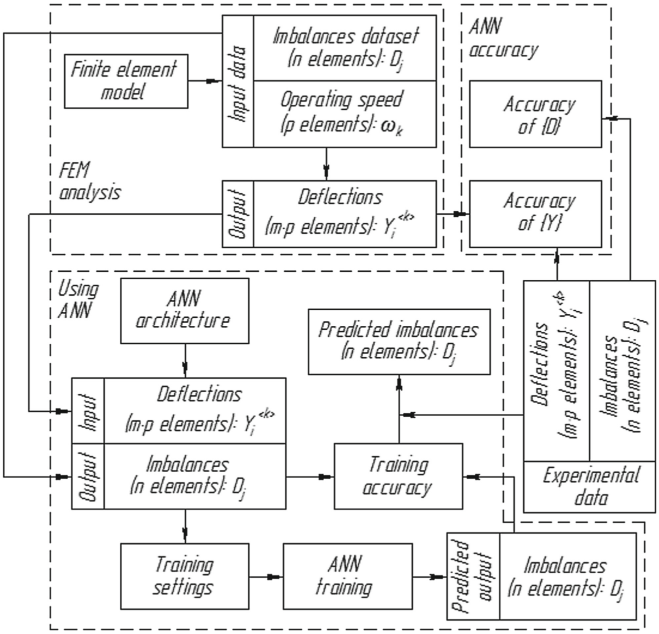

Fig. 1. The design scheme of for identification of parameters for rotor bearing stiffness characteristic by combined using FEM, ANN and experimental research.

The first step includes FEM analysis for calculation row-vector of deflection $\{Y\}$ by the set of imbalances $\{D\}$ for different operating speed ω. As a result of numerical simulation, the input and output data are transferred to the output and input data of the ANN architecture correspondently. After ANN training, the system of imbalances $\{D\}$ is evaluated, as well as training accuracy is calculated. Additionally, the experimental dataset allows obtaining predicting the system of imbalances $\{D\}$. Finally, the comparison of results using ANN and experimental data allows estimating ANN accuracy.

3 Results

The following research of rotor dynamics is realized for the turbopump unit with the design scheme presented in Fig. 2. The unit has $p = 3$ operating speeds: $\omega_1 = 1100$ rad/s, $\omega_2 = 1963$ rad/s, and $\omega_3 = 2215$ rad/s. Previous investigations of bearing stiffness [24] according the critical frequencies of the rotor allows determining the following parameters of the formula (5): $c_1^{<0>} = 1.88{\cdot}10^8$ N/m; $c_2^{<0>} = 2.10{\cdot}10^8$ N/m; $\alpha_1 = 1.223$ N s^2/m; $\alpha_2 = 0.408$ N s^2/m; $\beta_1 = 0.18{\cdot}10^{12}$ N/m^2; $\beta_2 = 2.24{\cdot}10^{12}$ N/m^2.

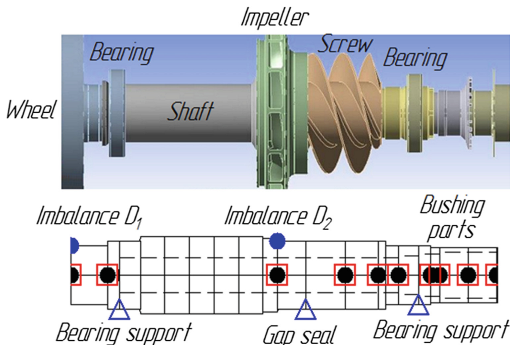

Fig. 2. 3D model of the rotor and its design scheme.

Table 1. The results of numerical simulation

Imbalances, kg mm		Rotor speed, rad/s	Deflections, μm		
D_1	D_2	ω	Y_1	Y_2	Y_3
1	0	1100	13.2	1.1	–1.3
2	0	1100	26.1	2.1	–2.5
3	0	1100	38.9	3.1	–3.7
0	1	1100	1.1	4.7	0.7
0	2	1100	2.2	9.4	1.4
0	3	1100	3.3	14.1	2.1
1	0	1963	64.2	8.8	–6.1
2	0	1963	121.3	15.8	–11.1
3	0	1963	173.4	21.6	–15.4
0	1	1963	9.6	19.8	2.9
0	2	1963	18.8	39.2	5.2
0	3	2215	27.4	58.3	7.0
1	0	2215	102.4	16.7	–9.3
2	0	2215	184.6	28.2	–16.2
3	0	2215	256.0	36.9	–21.8
0	1	2215	19.8	29.5	3.8
0	2	2215	37.4	57.8	6.5
0	3	2215	53.0	85.3	8.4
1	1	1100	14.2	5.8	–0.5
2	2	1100	28.1	11.5	–1.0
3	3	1100	41.7	17.1	–1.4
1	1	1963	71.6	28.0	–2.9
2	2	1963	133.0	53.3	–4.8
3	3	1963	187.8	76.8	–6.3
1	1	2215	115.1	44.3	–4.7
2	2	2215	202.4	81.0	–7.2
3	3	2215	275.7	113.7	–8.7

Due to the design scheme, it is sufficient to use $m = 3$ correction planes for measuring deflections $Y_{1,3}$ – on the bearing supports, and Y_2 – on the gap seal. Additionally, it is sufficient to chose $n = 2$ corrections planes for identifying the following imbalances: D_1 – on the wheel, and D_2 – on the impeller.

As a consequence of numerical simulation using the authors' software "Forced oscillations of the rotor", the results are obtained and tabulated (Table 1).

Using ANN is realized by "Virtual Gene Developer" for the parameters:

(1) topology settings: number of input variables – 9; number of output variables – 2; number of hidden layers – 2; node number of 2nd (hidden) layer – 18; node number of 3rd (hidden) layer – 6;
(2) training set: learning rate – 0.01; momentum coefficient – 0.1; transfer function – hyperbolic tangent; maximum number of training cycle – $5 \cdot 10^5$; target error – $1 \cdot 10^{-5}$; initialization method of threshold – random; initialization method of weight factor – random; analysis update interval – 500 cycles.

The related ANN architecture is presented in Fig. 3. Using the abovementioned software requires transforming all the parameters in dimensionless form with values in a range [–1, 1]. It can be realized by the following transformations:

$$\bar{D}_j = \frac{D_j}{\max\{D_j^{ISO}\}}; \quad \bar{Y}_i = \frac{Y_i}{\max\{Y_j;\ -Y_j\}}, \tag{6}$$

where D_j^{ISO} – the system of admissible residual imbalances according the ISO 1940-1 "Mechanical vibration – Balance quality requirements for rotors in a constant (rigid) state". In the stated case, $\max\{D_j^{ISO}\}$ = 3.0 kg mm. Additionally, $\max\{Y_j, -Y_j\}$ = 275.7 μm (Table 1).

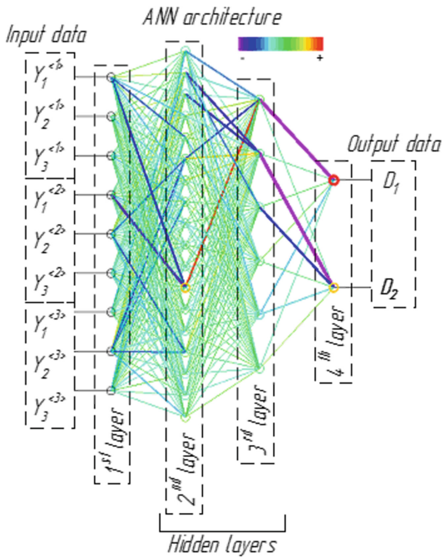

Fig. 3. The ANN architecture with related map analysis.

Table 2. The results of learning process and predicted output in dimensionless values

Input data									Output data		Predicted output	
ω_1 = 1100			ω_2 = 1963			ω_3 = 2215						
$\bar{Y}_1$	$\bar{Y}_2$	$\bar{Y}_3$	$\bar{Y}_1$	$\bar{Y}_2$	$\bar{Y}_3$	$\bar{Y}_1$	$\bar{Y}_2$	$\bar{Y}_3$	$\bar{D}_1$	$\bar{D}_2$	$\bar{D}_1$	$\bar{D}_2$
0.048	0.004	0.0046	0.233	0.032	0.022	0.371	0.061	0.034	0.33	0.00	0.33	0.00
0.095	0.008	0.009	0.440	0.057	0.040	0.670	0.102	0.059	0.67	0.00	0.67	0.00
0.141	0.011	0.013	0.629	0.078	0.056	0.929	0.133	0.079	1.00	0.00	0.10	0.00
0.004	0.017	0.003	0.035	0.072	0.010	0.072	0.107	0.014	0.00	0.33	0.00	0.33
0.008	0.034	0.005	0.068	0.142	0.019	0.156	0.210	0.023	0.00	0.67	0.00	0.67
0.012	0.061	0.008	0.100	0.211	0.025	0.192	0.309	0.031	0.00	1.00	0.00	1.00
0.052	0.021	0.002	0.260	0.102	0.010	0.417	0.161	0.017	0.33	0.33	0.33	0.33
0.102	0.042	0.004	0.482	0.193	0.017	0.734	0.294	0.026	0.67	0.67	0.67	0.67
0.151	0.062	0.005	0.681	0.279	0.023	1.000	0.412	0.031	1.00	1.00	0.10	1.00

The results of learning process and predicted output in dimensionless values are presented in Table 2. As a result of learning process and regression analysis, the following parameters are obtained: sum of error – $2.4 \cdot 10^{-5}$; average error per output per dataset – $1.3 \cdot 10^{-6}$; regression coefficient – 0.999996; slope – 0.998; interception – $3.7 \cdot 10^{-4}$. Finally, using the regression procedure (4) allows evaluating the dimensionless values of residual imbalances $\bar{D}_1 = 0.361$, and $\bar{D}_2 = 0.235$.

4 Discussion

The precise system of imbalances includes the following real values: $D_1 = 1.10$ kg mm, and $D_2 = 0.70$ kg mm. Due to this fact, the common approach for the initial imbalance $\Delta D = 0.10$ kg mm allows obtaining the following imbalances: $D_1 = 1.27$ kg mm, and $D_2 = 0.78$ kg mm. This data is insufficient due to the inappropriate relative errors 15% and 11% correspondently.

However, the results obtained using the proposed ANN method give the following residual imbalances: $D_1 = 1.08$ kg mm, and $D_2 = 0.71$ kg mm. In this case, the relative errors are 1.6% and 0.9% correspondently. Consequently, on the example of the turbopump unit, the effectiveness of using ANN method for ensuring vibration reliability of rotors is completely proved.

Additionally, it can be noted that the further research activities should be aimed at developing the complemented method and related numerical approach for realizing the procedure of identification parameters based on the abovementioned analytical dependencies and method of nonlinear identification of parameters for the comprehensive mechanical system "rotor – bearing supports".

5 Conclusions

As a result, the scientific approach of using artificial neural networks for solving a significant problem of vibration reliability of rotary machines is proposed, and the related methodology is specified. This approach includes analytical dependencies, recent techniques for providing numerical simulations, as well as application of ANN.

The proposed methodology allows refining parameters of the nonlinear mathematical models describing forced oscillations of the rotor as a complicated mechanical system with nonlinearities. Finally, this approach has a significant advantage in comparison with the traditional regression analysis due to the absence of necessity for setting trial imbalances and carrying out additional initial starts.

Finally, the presented material is proved by the research of rotor dynamics on the example of turbopump units for liquid rocket engines, as well as the parameters for ensuring vibration reliability are obtained.

Acknowledgments. The research work reported here was made possible by the research project No. 0117U003931 ordered by the Ministry of Education and Science Ukraine as a result of joint cooperation between the Department of General Mechanics and Machine Dynamics, Department of Manufacturing Engineering, Machines and Tools, and Department of Processes and Equipment of Chemical and Petroleum-Refineries.

References

1. Jardine, A.K.S., Lin, D., Banjevic, D.: Review on machinery diagnostics and prognostics implementing condition based maintenance. Mech. Syst. Sig. Process. **20**(7), 1483–1510 (2006)
2. Gao, Q., Duan, C., Fan, H., Meng, Q.: Rotating machine fault diagnosis using empirical mode decomposition. Mech. Syst. Sig. Process. **22**(5), 1072–1081 (2008). https://doi.org/10.1016/j.ymssp.2007.10.003
3. Pavlenko, I.V., Simonovskiy, V.I., Demianenko, M.M.: Dynamic analysis of centrifugal machine rotors supported on ball bearings by combined using 3D and beam finite element models. In: IOP Conference Series, Materials Science and Engineering, vol. 233, p. 012053 (2017). https://doi.org/10.1088/1757-899x/233/1/012053
4. Pavlenko, I.: Static and dynamic analysis of the closing rotor balancing device of the multistage centrifugal pump. Appl. Mech. Mater. Trans. Tech. Publ. **630**, 248–254 (2014). https://doi.org/10.4028/www.scientific.net/AMM.630.248
5. Pavlenko, I., Trojanowska, J., Gusak, O., Ivanov, V., Pitel, J., Pavlenko, V.: Estimation of the reliability of automatic axial-balancing devices for multistage centrifugal pumps. Periodica Polytech. Mech. Eng. **63**(1), 277–281 (2019). https://doi.org/10.3311/ppme.12801
6. Obukhov, O., Smirnov, A., Gusak, O.: Numerical and experimental investigation of the efficiency of vaned diffuser of centrifugal compressor. In: Institution of Mechanical Engineers - 8th International Conference on Compressors and Their Systems, pp. 649–658 (2013). https://doi.org/10.1533/9781782421702.11.649
7. Gusak, A., Demchenko, O., Kaplun, I.: Application of small-sized low speed axial stages in well pumps for water supply. Procedia Eng. **39**, 35–42 (2012). https://doi.org/10.1016/j.proeng.2012.07.005

8. Tarelnyk, V., Konoplianchenko, I., Martsynkovskyy, V., Zhukov, A., Kurp, P.: Comparative tribological tests for face impulse seals sliding surfaces formed by various methods. In: Advances in Design, Simulation and Manufacturing. LNME, pp. 382–391. Springer, Cham. https://doi.org/10.1007/978-3-319-93587-4_40
9. Trojanowska, J., Kolinski, A., Galusik, D., et al.: A methodology of improvement of manufacturing productivity through increasing operational efficiency of the production process. In: Hamrol, A., Ciszak, O., Legutko, S., Jurczyk, M. (eds.) Advances in Manufacturing. Lecture Notes in Mechanical Engineering, pp. 23–32. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-68619-6_3
10. Pitel, J., Mizak, J.: Computational intelligence and low cost sensors in biomass combustion process. In: Proceedings of the 2013 IEEE Symposium on Computational Intelligence in Control and Automation, IEEE Symposium Series on Computational Intelligence, pp. 181–184 (2013). https://doi.org/10.1109/cica.2013.6611681. 6611681
11. Antoni, J., Randall, R.B.: Differential diagnosis of gear and bearing faults. ASME J. Vib. Acoust. **124**, 165–171 (2002)
12. Chen, D., Wang, W.J.: Classification of wavelet map patterns using multi-layer neural networks for gear fault detection. Mech. Syst. Sig. Process. **16**(4), 695–704 (2002)
13. Raheem, K.F., Karem, W.: Rolling bearing fault diagnostics using artificial neural networks based on Laplace wavelet analysis. Int. J. Eng. Sci. Technol. **2**(6), 278–290 (2010)
14. Jack, L., Nandi, A.: Fault detection using support vector machines and artificial neural networks, augmented by genetic algorithms. Mech. Syst. Sig. Process. **16**(2–3), 373–390 (2002). https://doi.org/10.1006/mssp.2001.1454
15. Wei, Z., Gaoliang, P., Chuanhao, L.: Bearings fault diagnosis based on convolutional neural networks with 2-D representation of vibration signals as input. In: MATEC Web of Conference, vol. 95, p. 13001 (2017). https://doi.org/10.1051/matecconf/201795
16. Jayaswal, P., Verma, S.N., Wadhwani, A.K.: Development of EBP-Artificial neural network expert system for rolling element bearing fault diagnosis. J. Vibr. Control **17**(8), 1131–1148 (2001)
17. Pavlenko, I., Trojanowska, J., Ivanov, V., Liaposhchenko, O.: Scientific and methodological approach for the identification of mathematical models of mechanical systems by using artificial neural networks. In: Machado, J., Soares, F., Veiga, G. (eds.) Innovation, Engineering and Entrepreneurship. HELIX 2018. Lecture Notes in Electrical Engineering, vol. 505, pp. 299–306. Springer, Heidelberg (2019). https://doi.org/10.1007/978-3-319-91334-6_41
18. Tian, Z.: An artificial neural network method for remaining useful life prediction of equipment subject to condition monitoring. J. Intell. Manuf. **23**(2), 227–237 (2012). https://doi.org/10.1007/s10845-009-0356-9
19. Dong, M., He, D., Banerjee, P., Keller, J.: Equipment health diagnosis and prognosis using hidden semi-Markov models. Int. J. Adv. Manuf. Technol. **30**(7–8), 738–749 (2006)
20. Li, B., Yuen, M., James, C.H.: Neural network based motor rolling bearing fault diagnosis. IEEE Trans. Industr. Electron. **47**(5), 1060–1069 (2000)
21. Wang, C.C., Kang, Y., Shen, P.C., Chang, Y.P., Chung, Y.L.: Applications of fault diagnosis in rotating machinery by using time series analysis with neural network. Expert Syst. Appl. **37**, 1696–1702 (2010)
22. Reddy, M.C.S., Sekhar, A.S.: Application of artificial neural networks for identification of unbalance and looseness in rotor bearing systems. Int. J. Appl. Sci. Eng. **11**(1), 69–84 (2013)
23. Wang, P., Vachtsevanos, G.: Fault diagnostics using dynamic wavelet neural networks. Artif. Intell. Eng. Des. Anal. Manuf. **15**, 349–365 (2001)

24. Pavlenko, I., Simonovskiy, V., Ivanov, V., et al.: Application of artificial neural network for identification of bearing stiffness characteristics in rotor dynamics analysis. In: Ivanov, V., et al. (eds.) Advances in Design, Simulation and Manufacturing. DSMIE-2018. Lecture Notes in Mechanical Engineering, pp. 325–335. Springer, Cham (2019). https://doi.org/10.1007/978-3-319-93587-4_34
25. Rojek, I., Kujawińska, A., Hamrol, A., Rogalewicz, M.: Artificial neural networks as a means for making process control charts user friendly. In: Burduk, A., Mazurkiewicz, D. (eds.) Intelligent Systems in Production Engineering and Maintenance – ISPEM 2017. Advances in Intelligent Systems and Computing, vol. 637, pp. 168–178. Springer, Heidelberg (2017)
26. Yashchenko, A.S., Rudenko, A.A., Simonovskiy, V.I., Kozlov, O.M.: Effect of bearing housings on centrifugal pump rotor dynamics. In: IOP Conference Series: Materials Science and Engineering, vol. 233, no. 1, p. 012054 (2017). https://doi.org/10.1088/1757-899x/233/1/012054