PREDICTING THE SERVICE LIFE OF MECHANICAL SYSTEMS CONSIDERING THEIR BLOW-UP MODE OPERATION

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DOI: 10.17973/MMSJ.2024_10_2024003

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This article presents a novel approach to predicting the service life of mechanical systems. Forecasting is based on the assumption that the product's behavior under operating conditions should be considered as the system's behavior operating in a blow-up mode. According to this, the information signal recorded when monitoring the technical condition of a product must contain a periodic component. The method is based on isolating this component and then approximating it with a model. The model of this component is described by a log-periodic function. The model parameters include the operating time of the product before repair and are determined in the periodic component approximation process by this model.

KEYWORDS

Product vibration, service life, log-periodic component, blow-up mode

1 INTRODUCTION

In the modern world, where technology plays a key role in various fields of activity, predicting the life of mechanical systems is becoming an integral part of ensuring the reliability and efficiency of technical devices. Constant attention is being paid to solving this problem [Klosterman 2018, Ding 2019, Cempel 2000], but the desired solution has not yet been obtained [Lad 2016]. The service life of products is ensured by the quality of their manufacture [Nahornyi 2016, Panda 2023] and is maintained under operating conditions [Nahornyi 2019, Panda 2019]. Currently used methods for predicting the product's service life are based on determining the time coordinate intersection point trajectory of the monitored parameter with its maximum permissible value according to the standards [Nahornyi 2023]. However, the structural materials' mechanical properties dispersion, the product manufacturing quality instability, and the operating conditions variety lead to unpredictable variations in the product's actual service life and, consequently, errors in its prediction [Sornette 2002, Sholomitsky 2009, Jurko 2011, Monkova 2013, Michalik 2014, Panda 2014 & 2021, Baron 2016, Mrkvica 2016, Macala 2017, Balara 2018, Chaus 2018, Duplakova 2018, Sukhodub 2018 & 2019, Pandova 2018 & 2020, Flegner 2019 & 2020, Harnicarova 2019, Zhou 2023].

To eliminate these errors, it is necessary to monitor the behavior of the controlled parameter trajectory during the period between repairs to predict the product's timely stopping moment for repairs.

Such an approach to predicting will allow optimizing the resources used, increasing the efficiency and sustainability of technical systems.

2 RESEARCH METHODOLOGY

The theoretical basis of the methodology for predicting the product service life, examples of it presented in this article, is the consideration of the product behavior in operating conditions, as the mechanical system behavior "developing in a blow-up mode" [Zaborowski 2007, Adamcik 2014, Svetlik 2014, Rimar 2016, Olejarova 2017 & 2021, Sedlackova 2017, Catlos 2018, Labun 2018, Gamec 2019, Murcinkova 2019, Pollak 2019 & 2020, Straka 2018a,b, Vagaska 2021, Nahornyi 2023, Panda 2023].

If the exacerbation moment is considered to be the moment of the product's life exhaustion, requiring it to be stopped for repairs, then the process of its functioning can also be classified as exacerbation modes. In this case, the information signal controlled during the product operation is considered the sum A_{SUM} of the smooth (trend) B_{TR} and the variable A_{PER} components.

$$A_{SUM} = B_{TP} + A_{PER} \qquad (1)$$

The periodic component A_{PER} is determined from the information (total) signal A_{SUM}, by decomposing it into empirical modes [Myasnikova 2020].

$$A_{PER} = -0.25A_{SUM\,i-1} + 0.5A_{SUM\,i} - 0.25A_{SUM\,i+1}. \qquad (2)$$

The log-periodic function is used as a model A_{MOD} of the periodic component A_{PER} (3).

$$A_{MOД} = A_0\cos(\omega\cdot Ln(T - t_i) + \varphi). \qquad (3)$$

Expression (3) contains three unknown parameters: the required product service life - T, frequency - ω and phase - φ of log-periodic oscillations and is a predictive model. These values are determined by minimizing the difference (4) between the periodic component values A_{PER} (2) and the calculated predictive model values (3).

$$\sum_i^m (A_{PERi} - A_{MODi})^2 \Rightarrow min. \qquad (4)$$

In practice, the periodic component A_{PER} (2) is not one, but a multi-frequency oscillation, therefore, when minimizing (4) parameters, a trigonometric polynomial (Fourier series) composed of log-periodic functions is used as a predictive model A_{MOD} (model No. 2).

$$A_{MOD} = \frac{a_0}{2} + \sum_{k=1}^{m}\begin{bmatrix} a_k\cos(k\cdot\omega\cdot Ln(T - t_i)) \\ + b_k\sin(k\cdot\omega\cdot Ln(T - t_i)) \end{bmatrix}. \qquad (5)$$

The coefficients a_0, a_k, b_k of series (5) are determined from the following expressions:

$$\begin{cases} a_0 = \dfrac{1}{t_0 - t_m}\displaystyle\int_{t_0}^{t_m} A_{PER}\cdot\frac{1}{T - t}dt, \\ a_k = \dfrac{2}{t_0 - t_m}\displaystyle\int_{t_0}^{t_m} A_{PER}\cdot\cos\left(k\cdot\frac{2\pi}{t_0 - t_m}\cdot Ln(T - t)\right)\cdot\frac{1}{T - t}dt, \\ b_k = \dfrac{2}{t_0 - t_m}\displaystyle\int_{t_0}^{t_m} A_{PER}\cdot\sin\left(k\cdot\frac{2\pi}{t_0 - t_m}\cdot Ln(T - t)\right)\cdot\frac{1}{T - t}dt. \end{cases} \qquad (6)$$

The trend component B_{TR} according to the exacerbation mode theory [Nahornyi 2023] is described by the following model

$$B_{TR} = B_0\cdot(T - t_i)^{-\alpha}. \qquad (7)$$

Accordingly, the total signal model A_{mod}^{sum} taking into account (1), (3), and (7) has the following form:

$$A_{mod}^{sum} = B_0 \cdot (T - t_i)^{-\alpha} + A_0 \cos(\omega \cdot Ln(T - t_i) + \varphi). \tag{8}$$

In the general case, the total signal model A_{mod}^{sum} considering (5) has the following form (model No. 1):

$$A_{mod}^{sum} = B_0 \cdot (T - t_i)^{-\alpha} + \frac{a_0}{2} + \sum_{k=1}^{m} \left[\begin{array}{l} a_k \cos(k \cdot \omega \cdot Ln(T - t_i)) \\ + b_k \sin(k \cdot \omega \cdot Ln(T - t_i)) \end{array} \right]. \tag{9}$$

Both models have a common parameter T - the required product service life. This parameter is determined analytically by summing the minimum deviations of model No. 1 from the total signal A_{SUM} and model No. 2 from the periodic component A_{PER} (10).

$$U = \sum_{i=1}^{n} (A_{SUM} - A_{mod}^{sum})^2 + \sum_{i=1}^{n} (A_{PER} - A_{MOD})^2 \Rightarrow \min. \tag{10}$$

3 RESULTS

The purpose of the experimental investigations part is to demonstrate the effectiveness of predicting the product's service life under the assumption that their functioning is considered as the mechanical system operating in the "blow-up mode".

The subject of the research was to determine the operating time before the repair of various designs and purposes mechanical systems. The research methodology consisted of analytically determining, using formula (10), the sum of the minimum deviations of models No. 1 and No. 2 from the product's vibration level recorded under their operating conditions [Kostyukov 2014].

3.1 *Valve life forecast*

Fig. 1 shows the valve vibration trend recorded during its technical condition monitoring.

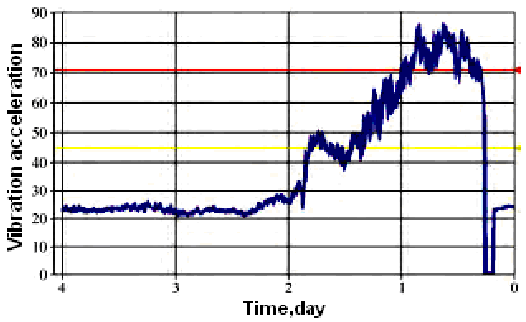

Figure 1. Valve vibration trend (total signal A_{SUM}) [Kostyukov 2014]

Fig. 2 presents the digitizing result of the data A_{SUM} initially used for forecasting, shown in Fig. 1, and these data approximation by model No. 1.

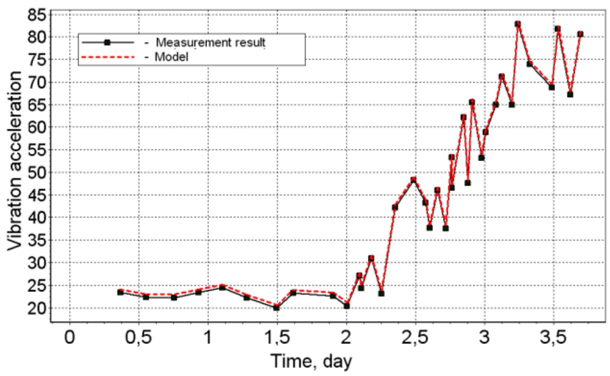

Figure 2. Approximation of the initial data A_{SUM} by model No. 1

Fig. 3 shows the periodic component A_{PER} and its approximation results by model No. 2.

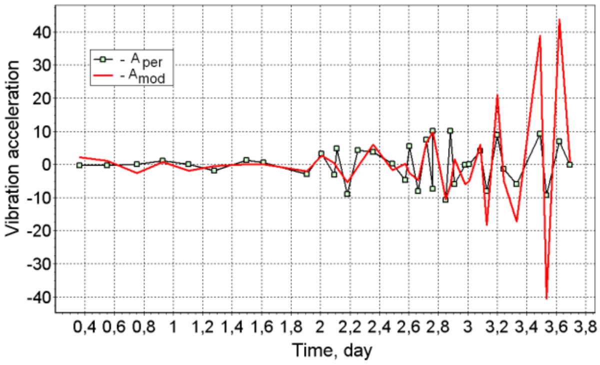

Figure 3. Approximation of periodic component A_{PER} (2) by the forecast model A_{MOD} (model No. 2)

The operating time forecast before repair T is shown in Fig. 4.

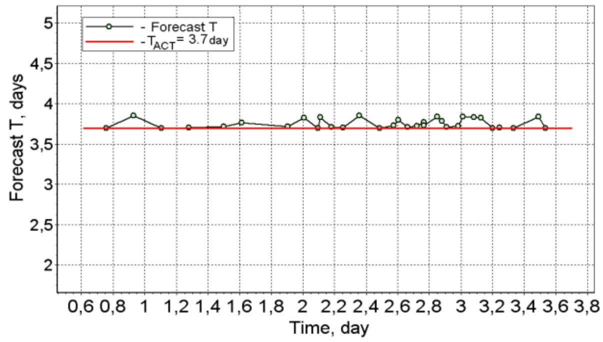

Figure 4. Actual operating time before repair T_{ACT} and its forecast T

Tab. 1 shows the forecast of valve operating time before repair depending on the time point at which the forecast was determined.

Table 1. Valve life forecast (average life value 3.8 days)

Time of forecasting, days	3.4	3.5	3.6	3.7
Forecast developments to failure, days	3.8	3.8	3.7	3.7

3.2 *Cylinder life forecast*

3.2.1 *Vibration control in the radial direction*

Fig. 5 shows the trend of cylinder vibration in the radial direction, recorded during its technical condition monitoring.

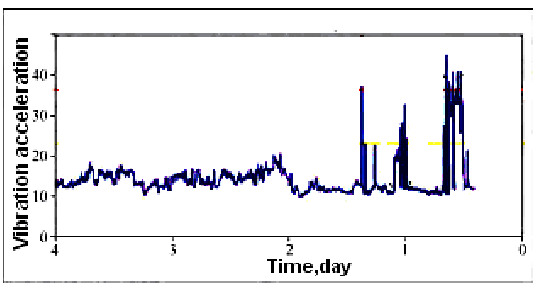

Figure 5. Vibration trend on the cylinder. Radial direction [Kostyukov 2014]

Fig. 6 shows the digitizing result of the data A_{SUM} initially used for forecasting, shown in Fig. 5, and these data approximation by model No. 1.

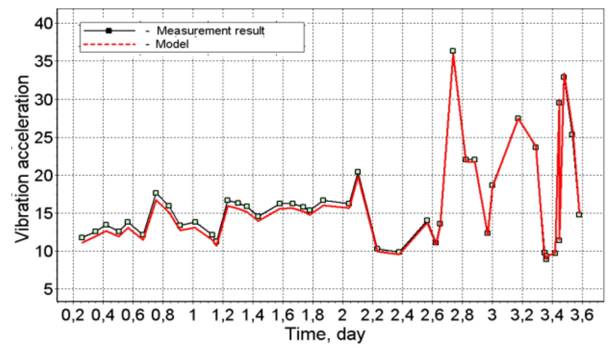

Figure 6. Approximation of the initial data A_{SUM} by model No. 1

Fig. 7 shows the periodic component A_{PER} and its approximation results by model No. 2.

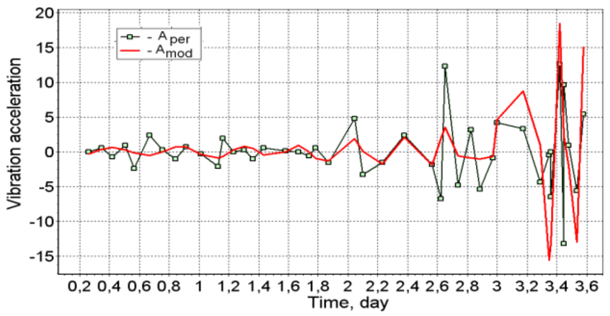

Figure 7. Approximation of periodic component A_{PER} (2) by the forecast model A_{MOD} (model No. 2)

The operating time forecast before repair *T* is shown in Fig. 8.

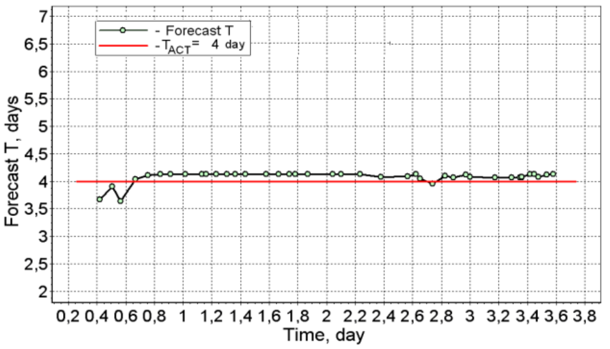

Figure 8. Actual operating time before repair T_{ACT} and its forecast *T*

Tab. 2 shows the cylinder operating time forecast before repair depending on the time point at which the forecast was determined.

Table 2. Forecast of cylinder life (average life value 4.1 days)

Time of forecasting, days	3.3	3.4	3.5	3.6
Forecast developments to failure, days	4.1	4.1	4.1	4.1

3.2.2 Monitoring vibration in the longitudinal direction

Fig. 9 presents the trend of cylinder vibration in the longitudinal direction, recorded during its technical condition monitoring.

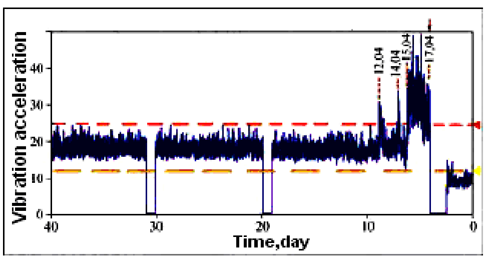

Figure 9. Vibration trend on the cylinder. Longitudinal direction [Kostyukov 2014]

Fig. 10 shows the digitizing result of the data A_{SUM} initially used for forecasting, shown in Fig. 9, and these data approximation by model No. 1.

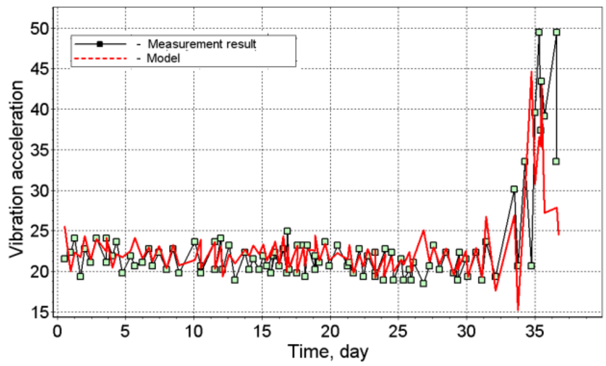

Figure 10. Approximation of the initial data A_{SUM} by model No. 1

Fig. 11 shows the periodic component A_{PER} and its approximation results by model No. 2.

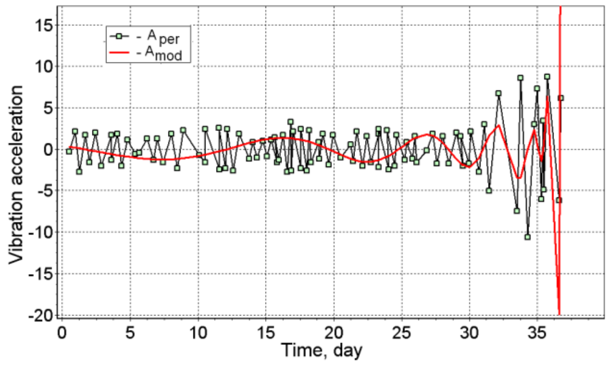

Figure 11. Approximation of periodic component A_{PER} (2) by the forecast model A_{MOD} (model No. 2)

The operating time forecast before repair *T* is shown in Fig. 12.

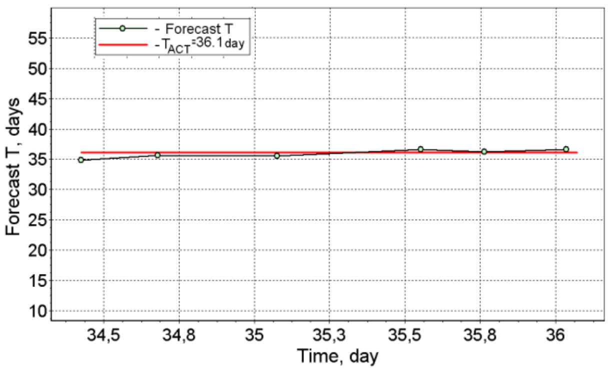

Figure 12. Actual operating time before repair T_{ACT} and its forecast *T*

Tab. 3 shows the cylinder operating time forecast before repair depending on the time point at which the forecast was determined.

Table 3. Forecast of cylinder operating time before repair (average operating time 36.2 days)

Time of forecasting, days	35.1	35.6	35.8	35.8
Forecast developments to failure, days	35.5	36.6	36.6	36.6

3.3 Vibration control of the front motor bearing

Fig. 13 shows the vibration velocity trend of the electric motor front bearing, recorded during its technical condition monitoring.

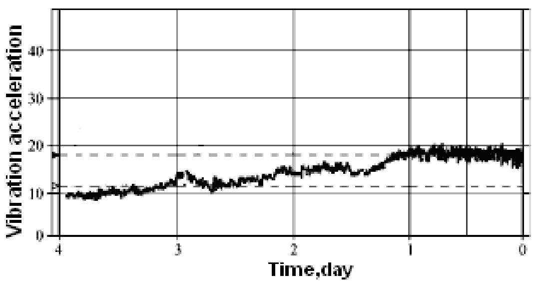

Figure 13. Vibration trend of electric motor front bearing [Kostyukov 2014]

Fig. 14 shows the digitizing result of the data A_{SUM} initially used for forecasting, shown in Fig. 13, and these data approximation by model No. 1.

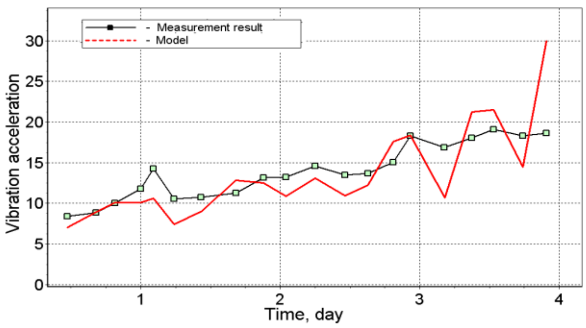

Figure 14. Approximation of the initial data A_{SUM} by model No. 1

Fig. 15 shows the periodic component A_{PER} and its approximation results by model No. 2.

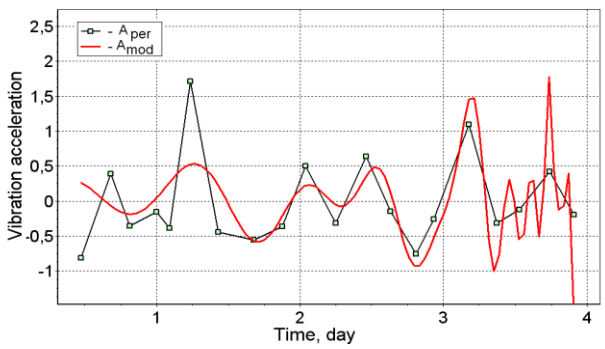

Figure 15. Approximation of periodic component A_{PER} (2) by the forecast model A_{MOD} (model No. 2)

The operating time forecast before repair T is shown in Fig. 16.

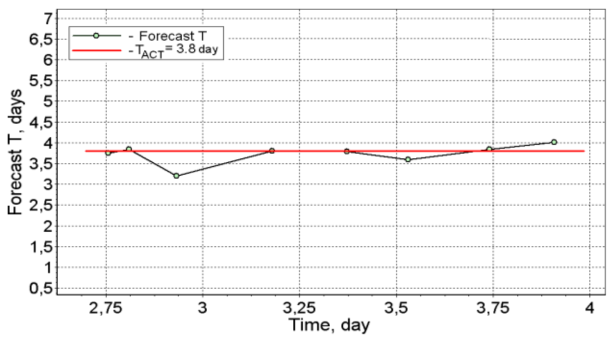

Figure 16. Actual operating time before repair T_{ACT} and its forecast T

Tab. 4 shows the forecast of the bearing operating time before repair depending on the point in time when that forecast was determined.

Table 4. Forecast of operating time of the front bearing of the electric motor before repair (average operating time 3.8 days)

Time of forecasting, days	3.4	3.5	3.7	3.9
Forecast developments to failure, days	3.8	3.6	3.8	4.0

3.4 *Monitoring vibration of the pump front bearing*

Fig. 17 shows the bearing vibration velocity trend installed in the pump, recorded during its technical condition monitoring.

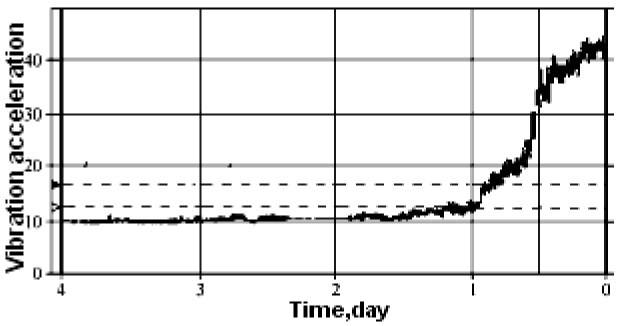

Figure 17. Pump bearing vibration trend [Kostyukov 2014]

Fig. 18 shows the digitizing result data A_{SUM} initially used for forecasting, shown in Fig. 17, and these data approximation by model No. 1.

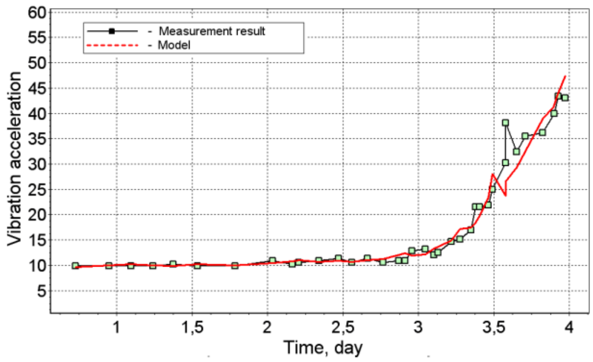

Figure 18. Approximation of the initial data A_{SUM} by model No. 1

Fig. 19 shows the periodic component A_{PER} and its approximation results by model No. 2.

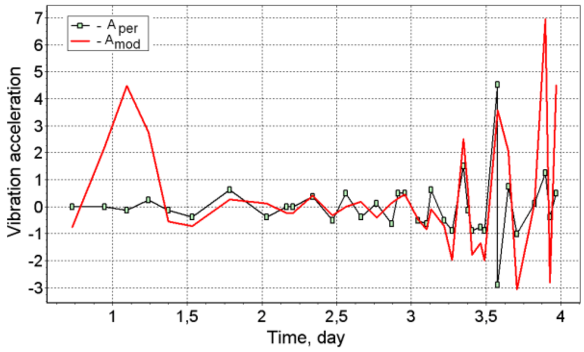

Figure 19. Approximation of periodic component A_{PER} (2) by the forecast model A_{MOD} (model No. 2)

The forecast of bearing operating time before repair T is shown in Fig. 20.

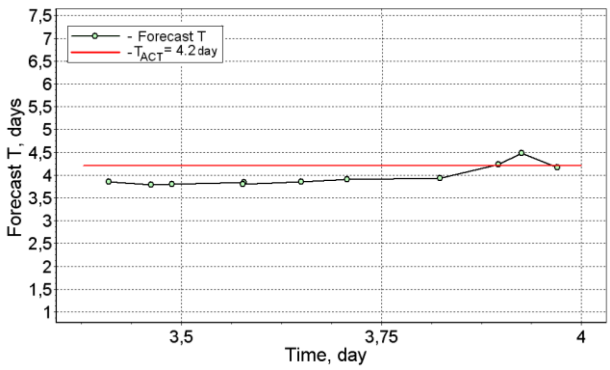

Figure 20. Actual operating time before repair T_{ACT} and its forecast T

Table 5 presents the forecast of the bearing operating time before repair depending on the point in time when that forecast was determined.

Table 5. Forecast of pump front bearing operating time before repair (average operating time 4.2 days)

Time of forecasting, days	3.7	3.8	3.9	4.0
Forecast developments to failure, days	3.9	4.2	4.5	4.2

4 CONCLUSIONS

The validation results of the methodology confirmed the fact that the initial data for forecasting obtained during the monitoring of the technical condition of variously designed products (Fig. 1, 5, 9, 13, 17) contain a periodic component (Fig. 3, 7, 11, 15, 19). The analysis of the periodic component, conducted according to the methodology is discussed in the article, allowed for predicting the product's operating time before repair. In all cases, the predicted operating time corresponds to its achieved value (Fig. 4, 8, 12, 16, 20; Tab. 1-5). Examples of the new methodology for predicting the mechanical product's service life are also discussed in the article. The results of the methodology's validation revealed its effectiveness and confirmed the assumption that the product's functioning process can be viewed as a process developing in the blow-up mode. Thus, the relevant task of predicting the mechanical system's service life is solved. The methodology discussed in the article can be recommended for predicting the service life of various products, differing in design and purpose.

ACKNOWLEDGMENTS

This work was supported by the project VEGA 1/0226/21 of Scientific Grant Agency of the Ministry of Education, science, research and sport of the Slovak Republic and the SAS.

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