# CONDITION-BASED MAINTENANCE OF COMPLEX TECHNICAL SYSTEMS

**ANTON PANDA[1], VOLODYMYR NAHORNYI[2]**

[1]Faculty of Manufacturing Technologies with a seat in Presov, Technical University of Kosice, Presov, Slovak Republic

[2] Sumy State University, Department of Information Technologies, Faculty of Electronics and Information Technologies, Sumy, Ukraine

**DOI: 10.17973/MMSJ.2025_11_2025041**

**e-mail: anton.panda@tuke.sk**

This paper examines condition-based maintenance (CBM) of complex technical systems using aircraft engines as an example. CBM requires continuous vibration monitoring to predict the optimal moment for scheduled maintenance. At any given moment, an engine may exist in multiple possible states, only one of which is realized. This set of possible states represents the physical potential of the system. To determine the actual state, this study proposes using Harrington's desirability function, which establishes a relationship between linguistic assessments of an engine's technical condition and normalized numerical intervals.

**KEYWORDS:**

Aircraft engine, condition-based maintenance, complex technical system, vibration monitoring, Harrington's function, linguistic assessment.

## 1 INTRODUCTION

Modern aircraft engines are characterized by high standards of design and manufacturing, ensuring stable performance over extended periods. Advances in technology have enabled engines to be equipped with monitoring sensors that provide objective data on their operational condition [Zaborowski 2007, Olejarova 2017, Chaus 2018, Matiskova 2021]. These developments facilitate a shift from scheduled maintenance to condition-based maintenance, optimizing operating costs and improving aircraft reliability [Kostochkin 1988, Monkova 2013, Balara 2018, Pollak 2020, Duhancik 2024].

One of the key indicators providing objective information about engine condition is vibration level. Vibration analysis helps detect dynamic changes preceding failures. This study applies the theory of dynamic systems operating in a "blow-up mode" to predict engine lifespan based on vibration analysis [Baron 2016, Murcinkova 2018, Flegner 2019 & 2020]. This approach provides accurate information about an engine's actual condition and enables highly precise maintenance predictions [Straka 2018a,b].

Decision-making regarding the criticality of an engine's technical condition is formalized using a desirability function. This function correlates linguistic evaluations of technical parameters in physical scales with numerical intervals of the desirability function, allowing for efficient condition-based maintenance [Michalik 2014, Nekrasov 2017 & 2020, Kuchar 2018, Harnicarova 2019].

The demonstration of the effectiveness of this approach is the primary objective of the present study.

## 2 RESEARCH METHODOLOGY

In dynamic systems developing in a blow-up mode, a periodic process is superimposed on the primary trend of a monitored parameter. This process can be described by a mathematical model [Vagaska 2017 & 2021], where one of the coefficients corresponds to the moment of system failure or a radical change in its operating conditions [Nagornyi 2016, Panda 2014 & 2020, Pandova 2020, Sukhodub 2018 & 2019, Nahornyi 2022].

Such modes are described by the following equation:

$$\frac{dx}{dt} = x^{1+1/\alpha}. \tag{1}$$

The solution of this equation increases indefinitely as it approaches the critical moment tft_f:

$$x(t) \sim \left(t_f - t\right)^{-\alpha}. \tag{2}$$

To obtain a practical solution, we transition from the real indicator aa to a complex one, leading to the following equation:

$$x(t) = \mathrm{Re}\sum_k a_k \left(t_f - t\right)^{-\alpha + k\beta i} = \left(t_f - t\right)^{-\alpha} \cdot F\left(\ln\left(t_f - t\right)\right). \tag{3}$$

The function $F(\cdot)$ is represented by multiple harmonics, characterizing the system's nonlinear behavior in blow-up mode. However, in practical applications [Panda, 2024], the function is often approximated by its first harmonic:

$$x(t) = \left(t_f - t\right)^{-\alpha} \cdot \left(a_0 + a_1 \cos\left(\beta \cdot \ln\frac{t_f - t}{\tau}\right)\right). \tag{4}$$

This expression defines a smooth trend over which log-periodic oscillations are superimposed. These oscillations act as precursors, signaling an approaching blow-up moment $t_f$. As $t \to t_f$ approaches, the oscillation frequency increases indefinitely, satisfying the dynamic law governing blow-up mode. The continuous rise in log-periodic oscillation frequency allows for early detection of catastrophic processes long before $t_f$.

If we interpret the exhaustion of engine life $T$ as the blow-up moment $t_f$, then engine can be classified as operating in blow-up mode.

To improve engine life prediction accuracy, it is essential to isolate the sensitive log-periodic component of the recorded signal [Panda 2021 & 2022, Kurdel 2022]. This requires separating the total periodic signal from the smooth trend and analyzing it independently during the operational period [Zakhakhatnov 2022].

The periodic component model should undergo direct analysis, fully capturing the complex polyharmonic structure of the recorded signal [Mrkvica 2012, Labun 2018 & 2020].

The monitored parameter $A_{CON}$ (t) is expressed as the sum of a smooth trend $B_{TR}$ and a periodic component $A_{PER}$:

$$A_{CON}(t) = B_{TR}(t) + A_{PER}(t). \tag{5}$$

The trend component $B_{TR}$ is determined using:

$$B_{TR}(t) = A_0 + b \cdot (T - t)^{\alpha}. \tag{6}$$

The periodic component $A_{PER}$ is derived from:

$$A_{PER}(t) = A_1 \cos(\omega \cdot \ln(T - t) - \varphi),$$

where (7)

$$A_1 = C \cdot (T - t)^{-\alpha}; \ \varphi = \pi - \omega \cdot \ln(T - t).$$

Equations (6) and (7) contain four unknown parameters $A_0, \omega, \varphi, \alpha$, which are computed using a specialized computer program.

The program minimizes the difference (8) between the experimentally determined time series $A_{CON}$ (t) and the model expressions (6) and (7):

$$\sum_{i}^{m} \left( A_{CON}(t_i) - B_{TR}(t_i) - A_{PER}(t_i) \right)^2 \Rightarrow \min . \quad (8)$$

In practice, predicting the remaining operational lifespan $T_{RUL}$ is of key interest:

$$T_{RUL} = T - t. \quad (9)$$

Minimization of function (8) is performed stepwise within an expanding time window, moving from left to right. The window expands until the available experimental data is exhausted. The number of forecasted $T_{RUL}$ values forms a predictive time series, with the number of steps equal to the time axis steps $t_i$.

Once the forecasted operational hours $T$ before maintenance is determined, decision-making regarding the criticality of the engine's condition is formalized using the Harrington desirability function.

This function correlates linguistic assessments of an engine's technical condition with normalized numerical intervals d (Tab.1).

**Table 1.** Harrington's Desirability Scale Intervals

| Linguistic Assessment | Desirability Function Interval d |
|---|---|
| Excellent | 1.00 - 0.80 |
| Normal | 0.80 - 0.63 |
| Acceptable | 0.63 - 0.37 |
| Degraded | 0.37 - 0.00 |

Harrington's desirability function is given by:

$$d = \exp\left( -\exp\left( -\frac{t_i}{T} \right) \right). \quad (10)$$

## 3 EXPERIMENTAL SECTION

During the operational period between scheduled maintenance, forecasts are based on analyzing engine vibration along the Y-axis (Fig. 1) [Doroshko 1984].

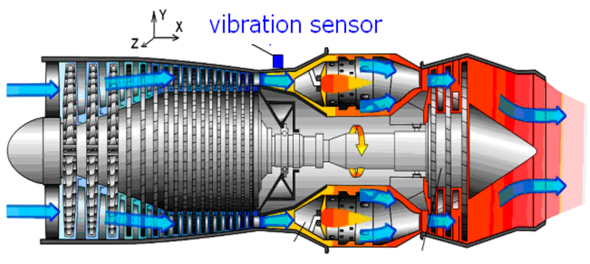


**Figure 1.** Sensor placement on the engine

Approximation of the recorded vibration signal $A_{CON}$ using the predictive model and the point of scheduled maintenance interruption is shown in Fig. 2.

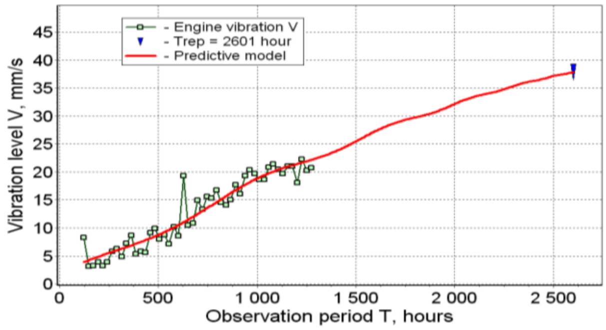


**Figure 2.** Approximation of experimental data using the predictive model

Changes in Harrington's desirability function dd during engine operation are shown in Fig. 3.

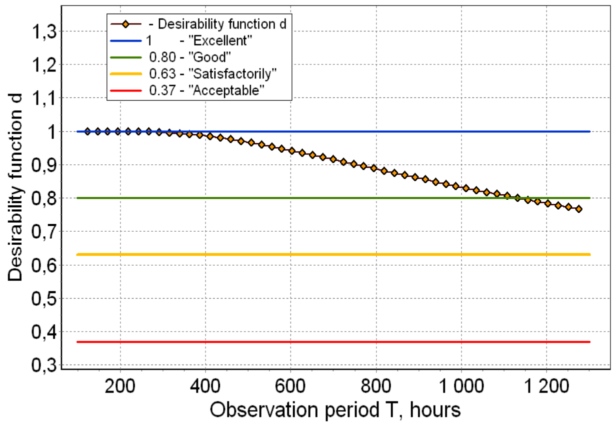


**Figure 3.** Changes in Harrington's function d

The remaining operational lifespan $T_{RUL}$ over time is demonstrated in Fig. 4.

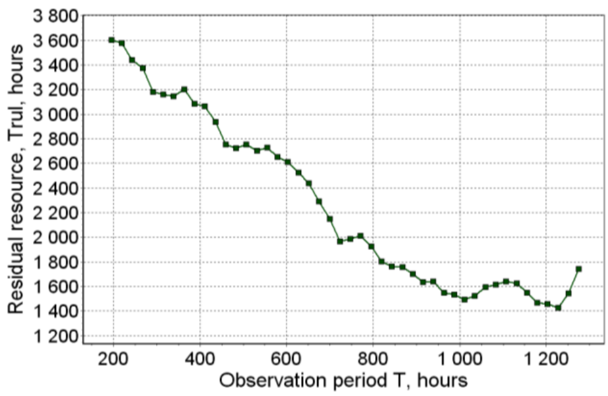


**Figure 4.** Changes in the remaining engine lifespan TRUL

**Table 2.** Predictive protocol

| | |
|---|---|
| Flight Time Before Forecast: | 1275.00 hours |
| Forecasted flight time before maintenance: | 2601.26 hours |
| Confidence interval (P = 0.95): | 2600.46 - 2602.05 hours |

During the observation period (Fig. 3), the engine's condition was classified as "Excellent" according to the desirability function. At 1275 operational hours, the forecast indicated a remaining lifespan of approximately 1400 hours (Fig. 4). The predictive protocol (Tab. 2) estimated a total operational time of around 2600 hours before maintenance.

## 4 CONCLUSIONS

The high level of design, manufacturing, and operation of aircraft engines ensures long-term stable performance. Advances in monitoring technology provide objective data for condition-based maintenance. By treating aircraft engines as dynamic systems developing in a blow-up mode, it becomes possible to mathematically predict operational hours before scheduled maintenance. Harrington's desirability function enables formalization of decision-making regarding engine condition, establishing a correlation between linguistic assessments and normalized numerical intervals. This approach facilitates the transition from scheduled to condition-based maintenance, optimizing operating costs and improving aircraft reliability.

**ACKNOWLEDGMENTS**

The authors would like to thank the KEGA grant agency for supporting research work and co-financing the project KEGA 008TUKE-4/2025.

**REFERENCES**

[Anisimov 2019] Anisimov, V.M., Anisimov, V.V., Krenicky, T. Properties Prediction of Linear Block-Polyurethanes Based on the Mixtures of Simple Oligoethers. Management Systems in Production Engineering, 2019, Vol. 27, Issue 4, pp. 217-220. DOI: https://doi.org/10.1515/mspe-2019-0034.

[Balara 2018] Balara, M., Duplakova, D., Matiskova, D. Application of a signal averaging device in robotics. Measurement, 2018, Vol. 115, No. 2, pp. 125-132.

[Baron 2016] Baron, P., Dobransky, J., Kocisko, M., Pollak, M., Cmorej, T. The parameter correlation of acoustic emission and high-frequency vibrations in the assessment process of the operating state of the technical system. Acta Mechanica et Automatica, 2016, Vol. 10, No. 2, pp. 112-116.

[Chaus 2018] Chaus, A.S., Pokorny, P., Caplovic, E., Sitkevich, M.V., Peterka, J. Complex fine-scale diffusion coating formed at low temperature on high-speed steel substrate. Applied Surface Science, 2018, Vol. 437, pp. 257-270. ISSN 0169-4332.

[Doroshko 1984] Doroshko S.M. Monitoring and diagnostics of the technical condition of gas turbine engines based on vibration parameters. M.: Transport, 1984, 128 p.

[Duhancik 2024] Duhancik, M., Krenicky, T., Coranic, T. Design and Testing of a Measurement Device for High-Speed Bearing Evaluation. Applied Sciences, 2024, Vol. 14, 508. https://doi.org/10.3390/app14020508.

[Flegner 2019] Flegner, P., Kacur, J., Durdan, M., Laciak, M. Processing a measured vibroacoustic signal for rock type recognition in rotary drilling technology. Measurement, 2019, Vol. 134, pp. 451-467.

[Flegner 2020] Flegner, P., Kacur, J., Durdan, M, Laciak, M. Statistical Process Control Charts Applied to Rock Disintegration Quality Improvement. Applied sciences, 2020, Vol. 10, No. 23, pp. 1-26.

[Harnicarova 2019] Harnicarova, M., et al. Study of the influence of the structural grain size on the mechanical properties of technical materials. Materialwissenschaft und Werkstofftechnik, 2019, Vol. 50, No. 5, pp. 635-645.

[Kostochkin 1988] Kostochkin V.V. Reliability of aircraft engines and power plants: Tutorial for aviation specialists of higher education institutions. 2nd Edition revised and supplemented. M.: Mashinostroenie, 1988. 270 p. ISBN 5-217-00128-313.

[Kuchar 2018] Kuchar, J., Kreibich, V., Agartanov, V., Petrik, M. Maintenance and cleaning of heat exchangers. Materials Science Forum, 2018, Vol. 919, pp. 396-403. ISSN 0255-5476. DOI 10.4028/www.scientific.net/MSF.919.396.

[Kurdel 2022] Kurdel, P., Ceskovic, M., Gecejova, N., Labun, J., Gamec, J. The Method of Evaluation of Radio Altimeter Methodological Error in Laboratory Environment. Sensors, 2022, Vol. 22, No. 14, pp. 1-21. ISSN 1424-3210.

[Labun 2018] Labun, J., et al. Possibilities of Increasing the Low Altitude Measurement Precision of Airborne Radio Altimeters. Electronics, 2018, Vol. 7, No. 9., pp. 1-9.

[Labun 2020] Labun, J., et al. A Simple High-Precision 2-Port Vector Analyzer, IEEE Access, 2020, Vol. 8, pp. 196609-196617. ISSN 2169-3536.

[Matiskova 2021] Matiskova, D., Cakurda, T., Marasova, D., Balara, A. Determination of the Function of the Course of the Static Property of PAMs as Actuators in Industrial Robotics Applied sciences, 2021, Vol. 11, No. 16. https://doi.org/10.3390/app11167288.

[Michalik 2014] Michalik, P., Zajac, J., Hatala, M., Mital, D. and Fecova, V. Monitoring surface roughness of thin-walled components from steel C45 machining down and up milling. Measurement, 2014, Vol. 58, pp. 416-428, ISSN 0263-2241.

[Monkova 2013] Monkova, K., Monka, P., Jakubeczyova, D. The research of the high speed steels produced by powder and casting metallurgy from the view of tool cutting life. Applied Mechanics and Materials, 2013, Vol. 302, pp. 269-274.

[Mrkvica 2012] Mrkvica, I., Janos, M., Sysel, P. Cutting efficiency by drilling with tools from different materials. Advanced Materials Research, 2012, Vols. 538-541, pp. 1327-1331. ISSN 1022-6680.

[Murcinkova 2018] Murcinkova, Z., Baron, P., Pollak, M. Study of the press fit bearing-shaft joint dimensional parameters by analytical and numerical approach. Advances in Materials Science and Engineering, 2018, Vol. 2018, DOI: https://doi.org/10.1155/2018/2916068.

[Nagornyi 2016] Nagornyi V.V. Control of the dynamic state of metal-processing technology system and prediction of its resources. Sumy: Sumy State University, 2016, 242 p. ISBN 978-966-657-604-3.

[Nahornyi 2022] Nahornyi, V., et al. Method of Using the Correlation between the Surface Roughness of Metallic Materials and the Sound Generated during the Controlled Machining Process. Materials, 2022, Vol. 15, 823. https://doi.org/10.3390/ma15030823.

[Nekrasov 2017] Nekrasov, A., et al. Sea Wind Measurement by Doppler Navigation System with X-Configured Beams in Rectilinear Flight. Remote Sensing, 2017, Vol. 9, No. 9., pp. 1-17. ISSN 2072-4292.

[Nekrasov 2020] Nekrasov, A., Khachaturian, A., Labun, J., Kurdel, P., Bogachev, M. Towards the Sea Ice and Wind Measurement by a C-Band Scatterometer at Dual VV/HH Polarization: A Prospective Appraisal. Remote Sensing, 2020, Vol. 12, No. 20., pp. 1-15. ISSN 2072-4292.

[Olejarova 2017] Olejarova, S., Dobransky, J., Svetlik, J., Pituk, M. Measurements and evaluation of measurements of vibrations in steel milling process. Measurement, 2017, Vol. 106, pp. 18-25.

[Panda 2014] Panda, A., Prislupcak, M., Pandova, I. Progressive technology diagnostics and factors affecting machinability. Applied Mechanics and Materials, 2014, Vol. 616, pp. 183-190.

[Panda 2020] Panda, A., et al. A novel method for online monitoring of surface quality and predicting tool wear conditions in machining of materials. International Journal of Advanced Manufacturing Technology, 2020, Vol. 123, No. 9-10, pp. 3599-3612. ISSN 0268-3768.

[Panda 2021] Panda, A., Anisimov, V.M., Anisimov, V.V., Dyadyura, K., Pandova, I. Increasing of wear resistance of linear block-polyurethanes by thermal processing methods. MM Science J., 2021, Vol. October, pp. 4731-4735.

[Panda 2022] Panda, A., et al. Ecotoxicity Study of New Composite Materials Based on Epoxy Matrix DER-331 Filled with Biocides Used for Industrial Applications. Polymers, 2022, Vol. 14, No. 16, Article no. 3275. ISSN 2073-4360.

[Panda 2024] Panda, A., Nahornyi, V.V. Monitoring of vibrations and disturbances in industry and nature. Springer Cham, 2024, 113 p. doi.org/10.1007/978-3-031-62190-1.

[Pandova 2020] Pandova, I., et al. A study of using natural sorbent to reduce iron cations from aqueous solutions. Int. J. of Environmental Research and Public Health, 2020, Vol. 17, No. 10, 3686.

[Pollak 2020] Pollak, M., Torokova, M., Kocisko, M. Utilization of generative design tools in designing components necessary for 3D printing done by a robot. TEM Journal, 2020, Vol. 9, No. 3, pp. 868-872.

[Straka 2018a] Straka, L., Hasova, S. Optimization of material removal rate and tool wear rate of Cu electrode in die-sinking EDM of tool steel. Int. J. of Adv. Manuf. Technol., 2018, Vol. 97, No. 5-8 , pp. 2647-2654.

[Straka 2018b] Straka, L., Hasova, S. Prediction of the heat-affected zone of tool steel EN X37CrMoV5-1 after die-sinking electrical discharge machining. J. of Engineering Manufacture, 2018, Vol. 232, No. 8, pp. 1395-1406.

[Sukhodub 2018] Sukhodub, L., Panda, A., Dyadyura, K., Pandova, I., Krenicky, T. The design criteria for biodegradable magnesium alloy implants. MM Science J., 2018, Vol. December, pp. 2673-2679.

[Sukhodub 2019] Sukhodub, L., et al. Hydroxyapatite and zinc oxide based two-layer coating, deposited on Ti6Al4V substrate. MM Science J., Vol. December, pp. 3494-3499.

[Vagaska 2017] Vagaska, A., Gombar, M. Comparison of usage of different neural structures to predict AAO layer thickness. Technicki Vjesnik-Technical Gazette, 2017, Vol. 24, Issue 2, pp. 333-339.

[Vagaska 2021] Vagaska, A., Gombar, M. Mathematical Optimization and Application of Nonlinear Programming. Studies in Fuzziness and Soft Computing, 2021, Vol. 404, Iss. 2021, pp. 461-486.

[Zaborowski 2007] Zaborowski, T. Ekowytwarzanie. Gorzow, 2007, 100 p.

[Zakhakhatnov 2022] Zakhakhatnov, G. The Harrington desirability functions as a criterion for the optimal choice of a grain dryer. News of the Orenburg State Agrarian University, 2022, No. 2, pp. 110-114. doi.org/10.37670/2073-0853-2022-94-2-110-114.

**CONTACTS:**

**Anton Panda, Prof. Eng. PhD.**
Technical University of Kosice
Faculty of Manufacturing Technologies with a seat in Presov
Sturova 31, 080 001 Presov, Slovakia
e-mail: anton.panda@tuke.sk

**Volodymyr Nahornyi**
Sumy State University
Faculty of Electronics and Information Technologies
Department of Information Technologies
2, Rymskogo-Korsakova st., 40007 Sumy, Ukraine
e-mail: v.nahornyi@cs.sumdu.edu.ua