Prediction of Disassembly Parameters for Process Planning based on Machine Learning

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Abstract. The disassembly of complex capital goods is characterized by strong uncertainty regarding the product condition and possible damage patterns to be expected during a regeneration job. Due to the high value of complex capital goods, the disassembly process must be as gentle as possible and being adaptable to the varying und uncertain product's state. While methods based on data mining have already been successfully used to forecast capacity and material requirements, the determination of the product's or component's condition has become apparent in the recent past. Despite the rapid increase in sensor technology on capital goods such as aircraft engines and their use for condition monitoring due to countless interfering effects, it is only possible to react spontaneously to the product's condition. So far, we have concentrated on product condition-based prioritization of disassembly operations in a logistics-oriented sequencing strategy. In this article, we present an approach to predict disassembly process-planning parameters based on operational usage data using machine learning. With the prediction of disassembly forces and times, processes, tools and capacities can be efficiently planned. Thus, we can establish a component-friendly disassembly process adaptable to varying product conditions. In this article, we show the successful validation on a replacement model of an aircraft engine.

Keywords: Disassembly planning; Regeneration; Machine Learning.

1 Introduction

In order to expand the lifetime of complex capital goods, they must be maintained and overhauled regularly. That allows the monetary value to be continued into further service phases by maintenance, repair and overhaul (MRO) [1]. However, high stress on components and the resulting effects of wear on them lead to the partial or complete loss of their initially designed product properties. From an economic and ecological point of view, an efficient regeneration process can be useful, especially with regard to the regeneration of complex capital goods and their components [2]. The research of the Collaborative Research Center (CRC) 871: "Regeneration of Complex Capital Goods" addresses this issue and the process steps for the regeneration of lost component properties of such capital goods, using aircraft engine's high-pressure turbines (HPT) as an example [3]. Particularly with regard to the capacity planning of the regeneration process, a critical process step from an economic point of view is the component-protecting disassembly of undefined solidified connections between HPT blades and disks. The joints solidify during the engine's service life depending on operating parameters, e.g. operating hours, landing-takeoff (LTO) cycles, and environmental influences, e.g. flight routes over sea or deserts. After disassembling individual components, a detailed inspection is performed, and the regeneration effort is identified.

Due to the high number of turbine blades, the technologically complex component properties, and thus economic aspects, a component-protecting disassembly process of these components is of high relevance for the actual regeneration of a complex capital good. Damage to the blades must be avoided to prevent the need for spare parts and successful regeneration. Also, the disassembly of the individual blades, as the last component when disassembling the engine, must be performed fastest possible to prevent unnecessarily long slack times for components disassembled prior [1,4]. Due to the uncertain condition of the blade-disk joint, the disassembly is carried out by manually or hydraulic hammering out. Performing the disassembly by highly qualified personnel ensures the adaptability to the unknown und varying condition of the operational solidified joint, in order not to irreparably damage or destroy the complex and sensitive components.

In this article, we present an approach to predict the effort for disassembly tasks based on the engine's usage. Using the example of HPT blades, we show the implementation and usage of a learning model that predicts tool dimension and disassembly time, increasing the workload information in order to plan and prioritize disassembly tasks [1]. However, since we cannot use components with a real product history for the experiment due to availability, the approach is validated on a replacement model.

2 Related Work

Due to environmental conditions, the turbine's hot exhaust gas mixture and high tensile loads during typical operation, its blading is subjected to three major influences: fatigue, corrosion and creep [5]. These influences can negatively affect the properties of the components, which requires regular maintenance and overhaul, as well as regeneration at the end of their life cycle. As a result of the service life and the previously mentioned influences, solidification mechanisms occur in the joint between the blades and the turbine disk. Usually, it requires a complex and costly disassembly process of these components during the regeneration of the capital goods. Depending on the degree of solidification, a defined breakaway force has to be applied to the disassembly object for the detaching movement of the components. Currently, different disassembly strategies are used for this process and the loosening of these solidified joints. The individual blades can be released from the turbine disk by hydraulic extraction using a special pulling device [6]. With this tool, the blade is dismantled hydraulically by pulling out in the axial direction of the turbine disk using a hook slide located between the gap of the turbine disk and the blade root. Due to the necessary support of the device on the disk and the positioning cycles after each individual disassembled blade, this disassembly strategy is considered to be very timeconsuming. There is also an increased risk of component damage, such as pressure notches on the components, due to contact points between the disassembly objects and the device. Another strategy is to hammer the blades out of the turbine disk with hydraulic or manual hammer blows. This leads to an undefined high introduction of non-reproducible disassembly forces into the disassembly object, which can lead to irreparable damage to the components. Therefore, highly trained and qualified employees generally perform the disassembly tasks [7].

The time required for this disassembly step during regeneration depends on the degree of solidification between blades and disk. Due to the high number of blades (e.g. 64 in a IAE V2500 engine, according to the manufacturer), this is a critical process step that significantly influences the actual capacity planning of the regeneration. Therefore, it is highly relevant for capacity planning to obtain exact knowledge of the expected damage pattern on the components already in an early planning horizon. Also, due to the loss of knowledge of the blade disk joints condition, the planning of workforce, disassembly times and tools can only be adaptively performed when the engine has already been partially disassembled.

That challenge is addressed by predictive maintenance. Ran et al., for example, summarized in their work the primary purpose of predictive maintenance as the reduction of costs, elimination of unexpected downtime and the improvement of availability and reliability of systems [8]. As an approach, Eickemeyer developed a damage library to predict the effort for the regeneration of capital goods, such as aircraft engines [9]. He defined temporal model categories to optimally perform workforce, resources or time planning. The categories are divided into long-term, from a timeframe of several months up to a year, medium-term, of several weeks and short-term, of hours during regeneration. The database has information on 650 regenerations so far performed, containing data such as operating hours, LTO cycles or engine type. A Bayesian network processes that data to predict the regeneration effort for particular assemblies or components.

Based on Eickemeyer's research, we present our work on setting up a learning model to predict the regeneration effort of disassembling HTP blades with the engine's operational data as input. As aforementioned, the challenge of the disassembly is the loss of knowledge of the blade disk joints condition. Using the learning model, we achieve the prediction of disassembly tools and time before the initial disassembly sequence. In order to set up the learning model, we identified potential factors influencing the disassembly effort, using the response surface method as explained in the following.

3 Setup

The regeneration of turbine blades requires a component-protecting disassembly of the solidified joints between the individual blades and the turbine disk. In [10], we introduced and presented a replacement model of a solidified blade disk joint. Since no operational solidified turbine blade disk joints were available in our investigation, we used an external force by clamping the turbine disk segment with a defined clamping force F_{Cl}. That induces a contact pressure on the joint's contact surfaces, replicating the solidification. By varying the external force, we achieve a variation of different operation scenarios, like differing flight hours or LTO-cycles. That results in a solidification force $F_S(z)$ opposing the disassembly of the blade. Therefore, the disassembly force $F_D(z)$ must be greater than $F_S(z)$ to initiate a disassembly movement. However, $F_D(z)$ must not exceed a material-specific maximum to prevent damaging the blade root [11].

In order to ensure an automated, reproducible and component-protecting disassembly process of these components with an optimum cycle time, the further procedure is based on a vibration-aided disassembly. The vibration, induced by a piezo stack actuator, is superimposed on the disassembly movement, and it is positioned in an electrically operated linear drive on the disassembly [8]. As known from the literature, vibration superimposed on a movement reduce the coefficient of friction [12]. Using as a tool in the disassembly, it reduces the disassembly force required to detach the solidified connections between the turbine blades and disk [13]. In order to determine the degree of solidification and thus also the necessary capacity utilization prior to the actual regeneration, information on previous regenerations can be used as input data.

As shown by Eickemeyer in [9], using machine learning (Bayesian network) can predict the regeneration effort. However, in this work, we use the replicated model of the solidified joints [10] to train the learning model to predict disassembly tools and times. Based on the joint's condition, suitable feed motion and piezo parameters in order to ensure an optimum cycle time while ensuring a component-protective disassembly of the turbine blades are selected. In the first step, we use the response surface method (RSM) to identify and characterize the input variables, like the clamping force as the solidification replacement or the vibration's parameters [14,15]. As a result, we obtain information on how they influence the disassembly force needed to dismantle the blades. In the second step, we use the RSM's result, to set up a learning model, able to predict the disassembly force based on the joint's condition. Integrated into the disassembly tool, it also sets the parameters to execute a component-friendly disassembly while achieving low disassembly times.

4 Results

As aforementioned, we use the RSM to identify and analyze the disassembly process of solidified HPT turbine blade disk joints. Depending on the solidification condition, a prediction of planning parameters becomes possible with the calculated optimal parameters.

4.1 Characterization of disassembly parameters

The initial step of the RSM analysis is the identification of the inputs and outputs. Since we aim to identify the influences on the disassembly force, we will set F_D as the system's output. The input factors are accordingly the clamping force F_{Cl}, representing the operational data, the piezo stack actuator vibration's characteristics, such as amplitude, frequency and waveform and the disassembly speed v_D, defined as disassembly length $l_D(z)$ per disassembly time. The piezo actuator allows the use of three waveforms, sinusoidal, triangle and sawtooth, representing a categorical factor, with the experimental design repeated for each category. Using a face centred composite design of experiments (CCF), we performed 72 randomized experiments in order to investigate the relationship and interaction of each input (Table 1).

Table 1. Levels of influential parameters in CCF

Factor	Low (-1)	Medium (0)	High (+1)
Clamping force F_{Cl}	2,000 N	3,500 N	5,000 N
Disassembly speed v_D	1 mm/s	5.5 mm/s	10 mm/s
Frequency f_{Pi}	10 Hz	35 Hz	60 Hz
Amplitude A_{Pi}	10 µm	55 µm	100 µm
Waveform WF_{Pi}	Sinusoidal	Triangle	Sawtooth

The following analysis using multiple linear regression (MLR), we can set up an equation which predicts the disassembly force depending on the inputs and their interactions, as in Equation 1:

$$\widehat{F_D} = \beta_0 + \beta_1 \cdot F_{Kl} + \beta_2 \cdot f_{Pi} + \beta_3 \cdot v_D + \beta_4 \cdot A_{Pi} + \beta_5 \cdot WF_{Sin} + \beta_6 \cdot WF_{Tri} + \beta_7 \cdot F_{Kl} \cdot f_{Pi} + \beta_8 \cdot F_{Kl} \cdot v_D + \beta_9 \cdot F_{Kl} \cdot A_{Pi} + \beta_{10} \cdot F_{Kl} \cdot WF_{Sin} + \beta_{11} \cdot F_{Kl} \cdot WF_{Tri} + \beta_{12} \cdot f_{Pi} \cdot v_D + \beta_{13} \cdot f_{Pi} \cdot A_{Pi} + \beta_{14} \cdot f_{Pi} \cdot WF_{Sin} + \beta_{15} \cdot f_{Pi} \cdot WF_{Tri} + \beta_{16} \cdot v_D \cdot A_{Pi} + \beta_{17} \cdot v_D \cdot WF_{Sin} + \beta_{18} \cdot v_D \cdot WF_{Tri} + \beta_{19} \cdot A_{Pi} \cdot WF_{Sin} + \beta_{20} \cdot A_{Pi} \cdot WF_{Tri} \quad (1)$$

The individual factors are each influenced by a coefficient β_i in the regression equation, describing the factor's influence on the disassembly force. After the experimental procedure, we evaluated the results using the analysis of variance (ANOVA) [15]. Among other information, we also obtain a statement on whether the model is statistically significant. That examines whether the model can be applied as calculated, i.e. whether the input variables significantly influence the output variable as calculated. The determination of the validity in predicting the disassembly force according to the regressions equation (Equation 1) is determined by the p-value. If the p-value is less than 0.05, the model can be considered significant, i.e. it is robust in predicting the disassembly force. With the calculated p-value lower than 0.001, we can assume that the model is valid.

In addition, we evaluate the goodness of fit by calculating the coefficient of determination R^2 and the adjusted-R^2. Adding more input variables to the equation always increases R^2, even if the variable has no influence. The adjusted-R^2 indicates the percentage of variation explained only by the inputs that actually affect the output. An R^2 value of 0.9714 and an adjusted-R^2 value of 0.9602 indicate a good model fit using MLR. Therefore, we can assume a sufficient precision of the prediction accuracy.

According to the RSM procedure, we calculated the optimal setting parameters to reduce the disassembly force in the next step. We perform a comparison with varying disassembly speed and vibration waveform to demonstrate the results. We particularly highlight these two factors, since the speed regards the time and capacity aspect, and varying the waveform showed a dependence on the reduction of the disassembly force in preliminary experiments. Table 2 shows the values of each input factor. The tests are executed with a disassembly with a clamping force of 4,000 N and the shown parameters for the piezo stack actuator.

Table 2. Optimal parameters to minimize the disassembly force

Fixed Parameters	
Clamping force (F_{Cl})	4,000 N
Amplitude (A_{Pi})	100 µm
Frequency (f_{Pi})	60 Hz
Varying Parameters	
Disassembly speed (v_D)	1 mm/s, 5.5 mm/s, 10 mm/s
Waveform (WF_{Pi})	Sinusoidal and Triangle

We performed the disassembly tests in a randomized order. Table 3 shows the results of 45 runs, each the mean value of the maximum disassembly force. In addition, we present the percentage reduction compared to without vibration.

Table 3. Result of the reduction of the maximum disassembly force

	v_D = 1 mm/s	v_D = 5.5 mm/s	v_D = 10mm/s
F_D without vibration	2,157 N	2,139 N	2,144 N
F_D w. sinusoidal vibration	1,717 N (-20.4 %)	1,950 N (-8.8 %)	1,931 N (-9.9 %)
F_D w. triangle vibration	1,802 N (-16.5 %)	1,910 N (-10.7 %)	2,022 N (-5.7 %)

We achieved the maximum reduction of the disassembly force at a sinusoidal waveform and a disassembly speed of 1 mm/s. The maximum reduction decreases with increasing disassembly speed when superimposing the triangle vibration. However, when using sinusoidal vibration, the influence of the disassembly speed is more complex. In addition, the waveform also influences the maximum reduction of the disassembly force, depending on the disassembly speed. Based on the results, we can develop a learning model in the following step that can predict process parameters for a component-protecting disassembly.

4.2 Learning model to predict disassembly parameters

In order to predict disassembly process parameters, we developed a learning model. Based on operational usage data of an aircraft engine, tool dimension for a component-protective and disassembly times for capacity planning are the primary determinants. However, as mentioned initially, we approximate these data through the replacement model. A variation of the clamping force represents different operational usage of the aircraft engine [10]. Using the experiment's data described in chapter 4.1, we train another regression model to predict the disassembly force based on the preset clamping force, representing the aircraft engine's usage. In addition, we executed further disassembly runs with random levels of the influential factors to obtain a test subset to test the trained model, with the split between training and test data being 80 to 20 %.

To evaluate the learning model, we calculate the coefficient of determination R^2 and the symmetric mean absolute percentage error (sMAPE). As discussed in the literature, they are used to evaluate machine learning studies [16]. An R^2 of 0.9248, close to 1, and sMAPE of 8.594 %, close to 0 %, indicate a good predictive performance of the learning model.

Integrated into the control of the disassembly device, tool parameters such as the values of the piezo stack actuator are automatically adjusted. The input parameters for the learning model are the maximum disassembly force according to material-specific limits and the clamping force set at the disassembly test rig, replicating the joint's solidification. Additionally, an operator has to specify the maximum disassembly speed. The disassembly speed, which mainly determines the time per disassembly operation, serves as the key influencing variable on the disassembly force. The learning model attempts to keep the disassembly speed as fast as possible while at the same time adhering to the force limit. It then calculates the difference between predicted and given maximum disassembly force by varying the piezo stack actuator's parameters, amplitude, frequency and waveform. The difference is necessary to determine by how much the predicted force is less than the given force. That results in the setting parameters for disassembly at maximum disassembly speed while the force limit is not exceeded and the difference is within a predefined safety interval.

Figure 1 shows an exemplary disassembly process of ten blades being successively disassembled. The disassembly speed is increased step by step up to the maximum speed (in the shown example 6 mm/s) while never exceeding the force limit by varying the adjustment parameters of the piezo stack actuator. If the force limit might be exceeded, either the speed is reduced, or the disassembly is stopped. That will prevent any possible damage to the blade root.

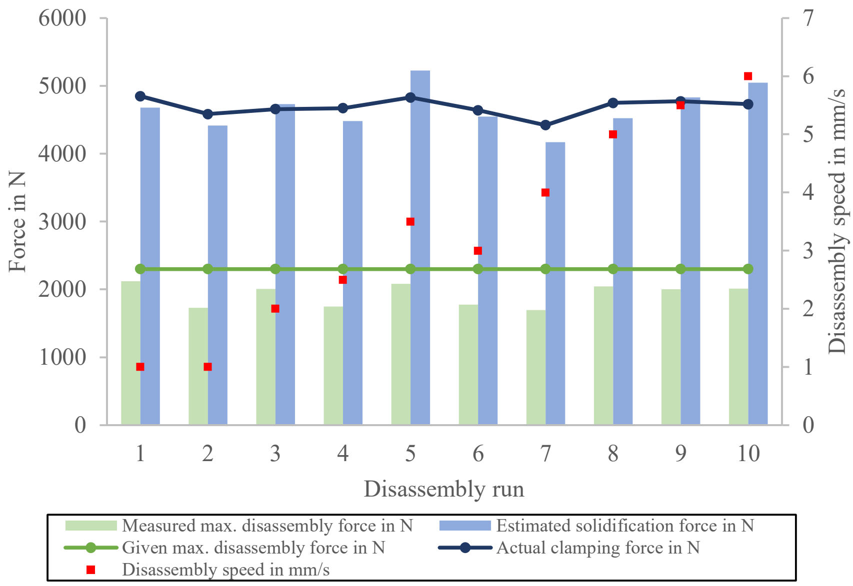

Fig. 1. Diagram of an exemplary disassembly process including ten runs

That results in the following disassembly scenario for capacity planning: Based on the known operational data of the engine, the learning model predicts reasonably accurate the disassembly force. If an engine is to be disassembled with an identical operational history to an already known and disassembled engine, the setting parameters already learned can be reused. However, assumed an engine is to be disassembled of an unknown type or a flight scenario that has not yet been disassembled. In that case, the disassembly force is calculated based on previously executed disassembly runs by the learning model. The example in Figure 1 shows that only a few disassembly runs are needed until a target speed of 6 mm/s, set by the operator as the maximum disassembly speed, is reached. Thus, if the engine type or flight data is unknown, within a short approximation interval of, in our case, ten out of 64 blades, approx. 15 % of the disassembly runs, the learning model adapts to the target disassembly speed. The data collected can then be integrated into the learning model's database to enhance and improve its performance.

For capacity planning, it follows that disassembly time and tool dimension can be predicted depending on the knowledge of the engine's condition. With a minimum number of disassembly runs to achieve the optimal setting parameters, an efficient disassembly process planning can be realized. That allows the disassembly process, characterized by a high degree of uncertainty, to become plannable and adaptable to the unknown product's condition.

5 Conclusion and Outlook

This paper presents the development of a learning model to predict disassembly parameters for optimal process and capacity planning. An aircraft engine's operation leads to a loss of knowledge of its assembly joint's condition. The exemplary investigated connection of the HPT blades and disks solidifies to an unknown extent. Therefore, it is challenging to predict the data, such as tool dimensioning and disassembly time, required for the disassembly process. Resources, machines or workforce can thus only be determined in short-term during disassembly.

In order to tackle that challenge, we developed a learning model which predicts the disassembly force to perform a component-protective disassembly. By adding the disassembly time as the crucial factor for time capacity planning, we were able to show its dependence on the disassembly force. That allows the planning of tools and temporal capacity based on the engine's operational data, such as flight hours, routes, or LTO-cycles.

We identified influential factors during the disassembly on needed dismantling forces using the response surface method. With the aid of superimposed vibration, we reduced the maximum needed disassembly force to overcome the solidification force induced by the joint's solidification. The subsequent multiple linear regression allowed the disassembly force to be described as a function of the influencing variables. These include the clamping force as a replacement model of operational solidification, the vibration's adjustment variables, and the disassembly speed. The reduction of the maximum disassembly force due to vibration, thus allowing an increase of the disassembly speed.

From the results of the RSM, we then developed the learning model to predict the disassembly force based on the clamping force as the replacement model for the joint's solidification. Based on that prediction, the control chooses optimal setting parameters for the piezo stack actuator adhering the material-specific maximum force limit (Figure 1). That enables the execution of a component-protecting disassembly. The learning model can considers the target disassembly speed, set by an operator. Depending on the knowledge of the joint's condition in comparison with already disassembled blade disk joints, the learning model increases the speed as fast as possible. In our example, only a few disassembly runs were required. With the predicted knowledge of required disassembly duration and tool dimensioning and thus operating resources and workforce, the disassembly as the initial step in the regeneration chain can be planned so that resources are used optimally and slack times are prevented. Thus, disassembly process planning can already be carried out on a medium-term planning horizon, as the engine's operation data provides the database.

In future work, the application of the learning model should be applied and confirmed on components with a real usage history. Also, a comparison of multiple linear regression to artificial neural networks (ANN) showed an advantage in the predictive accuracy of the MLR. That was possibly due to the small database of training data. Other machine learning approaches such as ANN or Bayesian networks should be compared by expanding the amount of input and training data.

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References

1. Lucht, T., Heuer, T., Nyhuis, P.: Disassembly sequencing in the regeneration of complex capital goods. In: Nyhuis, P.; Herberger, D.; Hübner, M. (Eds.): Proceedings of the Conference on Production Systems and Logistics : CPSL 2020. Hannover: Institutionelles Repositorium der Leibniz Universität Hannover, 12-20 (2020). DOI: https://doi.org/10.15488/9642
2. Seliger, G.: Montage und Demontage. In: Grote, KH., Feldhusen, J. (eds) Dubbel. Springer, Berlin, Heidelberg (2005). https://doi.org/10.1007/3-540-26620-8_127
3. Aschenbruck, J., Adamczuk, R., Seume, J.R.: Recent Progress in Turbine Blade and Compressor Blisk Regeneration. Procedia CIRP 22, pp. 256–262. (2014) https://doi.org/10.1016/j.procir.2014.07.016
4. Heuer, T., Lucht, T., Nyhuis, P.: Material Disposition and Scheduling in Regeneration Processes using Prognostic Data Mining, Procedia Manufacturing, Volume 43, 208-214, (2020) https://doi.org/10.1016/j.promfg.2020.02.138

5. Bräunling, W.: Flugzeugtriebwerke, Springer-Verlag, Berlin Heidelberg (2001). https://doi.org/10.1007/978-3-642-34539-5
6. Hohmann, S.: Method and device for dismantling a turbine blade, ALSTOM Power N.V. 1101 CS Amsterdam (NL), (European Patent No. EP1149662, 2001). https://data.epo.org/publication-server/document?iDocId=1925273, last accessed: 04.05.2022
7. Tao, W., Huapeng, D., Jie, T., Hao, Wa.: Recent Repair Technology for Aero-Engine Blades, Recent Patents on Engineering Vol. 9, No 2, pp. 132-141. (2015) http://dx.doi.org/10.2174/1872212109666150710184126
8. Ran, Y., Zhou, X., Lin, P., Wen, Y., Deng, R.: A Survey of Predictive Maintenance: Systems, Purposes and Approaches (2019).
9. Eickemeyer, S.C.: Kapazitätsplanung und -abstimmung für die Regeneration komplexer Investitionsgüter, Dissertation Leibniz Universität Hannover, Garbsen: Berichte aus dem IFA
ISBN: 978-3-944586-77-9 (2014):
10. Bluemel, R., Raatz, A.: Experimental Validation Of A Solidification Model For Automated Disassembly. In: Herberger, D.; Hübner, M. (Eds.): Proceedings of the Conference on Production Systems and Logistics: CPSL 2021. Hannover: Institutionelles Repositorium der Leibniz Universität Hannover, 339-348 (2021). https://doi.org/10.15488/11250
11. Middendorf, P., Blümel, R., Hinz, L., Raatz, A., Kästner, M., Reithmeier, E.: Pose Estimation and Damage Characterization of Turbine Blades during Inspection Cycles and Component-Protective Disassembly Processes. Sensors 2022, 22(14), 5191 (2022) https://doi.org/10.3390/s22145191
12. Littmann, W., Storck, H., Wallaschek, J.: Sliding friction in the presence of ultrasonic oscillations: superposition of longitudinal oscillations. Archive of Applied Mechanics 71, 549-554 (2001). https://doi.org/10.1007/s004190100160
13. Mullo, S.D., Pruna, E., Wolff, J., Raatz, A.: A vibration control for disassembly of turbine blades, Procedia CIRP, Volume 79, 180-185 (2019) https://doi.org/10.1016/j.procir.2019.02.041
14. Stöber, M., Müller, D., Thümmler, A.: Einsatz der Response-surface-Methode zur Optimierung komplexer Simulationsmodelle, Technical Report 05003, ISSN 1612-1376 (2005), http://dx.doi.org/10.17877/DE290R-7704
15. Witek-Krowiak, A., Chojnacka K., Podstawczyk D., Dawiec A., Pokomeda, K.: Application of response surface methodology and artificial neural network methods in modelling and optimization of biosorption process. Bioresource Technology, Volume 160, 150-160 (2014). https://doi.org/10.1016/j.biortech.2014.01.021
16. Chicco, D., Warrens, M.J., Jurman, G.: The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. PeerJ. Computer science, 7, e623, (2021). https://doi.org/10.7717/peerj-cs.623