A Learning Method for Automated Disassembly

Julius Wolff, Torge Kolditz, Annika Raatz

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Julius Wolff[1*], Torge Kolditz[1] and Annika Raatz[1]

[1] Institute of Assembly Technology, Leibniz Universität Hannover, Germany
*wolff@match.uni-hannover.de

Abstract. While joining tolerances, and therefore forces, are known in the assembly process, the determination of disassembly forces is not possible. This is caused by changes in the product properties during the product operation, which has multiple reasons such as thermal or mechanical stress on the product. Regarding the planning of disassembly tasks, disassembly times and tools cannot be planned properly. They have to be determined in the process or stay undefined, which can result in damaging of the product.

This article shows an approach to describe the necessary disassembly forces without having to investigate the complex physical influences caused by the usage of the product. To do so, a Learning Method is developed, which is sustained by a Lookup-Table for the estimation of disassembly forces based on basic input data such as hours of operation and operating characteristics. Missing values will be interpolated by using multiple linear regression. The concept will be illustrated in the example of a turbine blade connection.

Keywords: Disassembly, Automation, Planning, Turbine Blades

1 Introduction

The disassembly properties of a product depend on the assembly connections, which can be divided into detachable and non-detachable connections. With regard to a product-friendly disassembly, detachable connections are preferred and fixed connections, such as welded connections, are avoided. However, detachable connections can solidify to a high degree so that they seem to be fixed. In contrast to an assembly process, where joining forces are known due to defined product properties, disassembly forces are therefore unknown.

To make the disassembly and thereby the whole regeneration cycle, plannable, cost efficient and component-saving, it is necessary to be able to estimate the necessary disassembly forces. Knowledge of the disassembly forces is fundamental for the planning of disassembly tools and times. This is particularly worthwhile for products with valuable components like the engine of an airplane.

In a product's life cycle the disassembly is arranged directly after the product operation. The defined joining tolerances are lost and the assembly joints of highly stressed products solidify to an unknown degree. With regard to the example of turbine blades, reasons for the solidification of their connection to the turbine disc are the high temperatures and operation forces, and the intrusion of foreign particles like sand and corrosion. During the disassembly process, this lack of knowledge about the degree of solidification can cause a damage to the connecting partners, originating in the undefined reaction forces acting inside the connections. The exact calculation of the disassembly force is not possible, because a simulation would require exact knowledge about all the operation conditions (composition of air, intrusion of foreign particles) at any point in the operating phase of the engine.

An approach that seems more promising is the assignment of the disassembly forces to the operation history of the product. To do so, a Learning Method for determining the necessary disassembly force based on the input of different parameters by the user is developed. The method is developed with the support of a learning Lookup-Table. As an example of a disassembly connection, the connection of a blade and a disk of a high-pressure turbine of an aircraft engine is considered.

2 Related Work

The disassembly of turbine blades is usually characterized by manual labor. This is due to the unknown state of the assembly connection. In order to describe the undefined forces with a physical model of all the several influences on the solidification state, a big effort would be required, which remains unsuccessful in the worst case [1]. This process of solidification can have various causes. In a turbine, hot gas corrosion and adhesion are major wear mechanisms. Hot gas corrosion is caused by components of the fuel and the air (e.g. sea salt) flowing through the engine and produces solidifications in the contact surfaces of a connection. Surface corrosion can increase the loosening torque of a screw, for example, up to 45% [2]. Adhesion in contrast is caused by molecular interactions on the boundary surfaces of the assembly connection. Deformations of roughness peaks and the separation of material fragments can increase the adhesion forces [3]. Besides the solidification caused by separated particles of the connection itself, foreign particles like sand can cause additional blockades in the connection.

The various causes and their interaction for solidification complicate the calculation of the necessary disassembly forces beforehand. This lack of forces requires an increased flexibility in the process and the turbine blades are therefore knocked out of the disc manually, using simple tools such as a hammer. High manual forces are difficult to control, and thus damage can occur [4]. Especially in the regeneration of products with a high value, it is necessary to use methods that save the components from damage. One disk of a high-pressure turbine has around 70 blades, so that an automated disassembly of these blades can be economically viable [4]. To choose the right dimension of tools, the disassembly forces have to be estimated.

A simplified solidification model was developed, to describe the solidification and the resulting disassembly forces of a connection. Figure 1 shows the solidification model. It becomes clear that the disassembly force $F(z)$ and the weight load mg of the turbine blade have to exceed the solidifying force $R_z(z)$. Only with a slight exceeding, can component-saving disassembly be achieved. The disassembly force therefore follows to:

$$F(z) > R_z(z) - m \cdot g \tag{1}$$

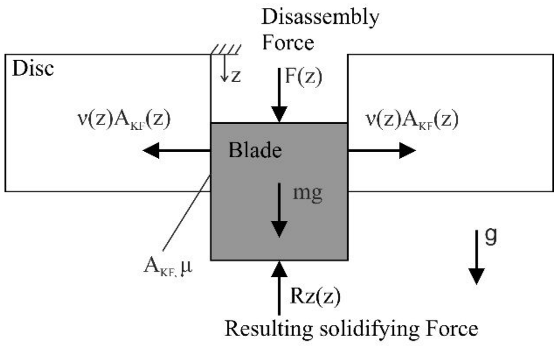

Fig. 1. Simplified solidification model

Since the weight load is in general much lower than the solidifying force, the centre of attention is the solidifying force $R_z(z)$. The solidifying force is determined by the contact surfaces A_{KF} of the joining partners, a solidification pressure v of the components to each other and the coefficient of static friction μ. Following the simplified model, the solidifying force can be described as:

$$R_z(z) = \mu \cdot v(z) \cdot A_{KF}(z) \tag{2}$$

Nevertheless, research showed that the solidifying force is not only dependent upon the absolute amount of the contact surface, but also upon the geometry of the connection. Figure 2 shows two types of connections that are common in the aviation industry. Each connection geometry has its specific solidifying characteristics, so that a method for the quantification of R_z would be helpful for the predictive determination of disassembly forces.

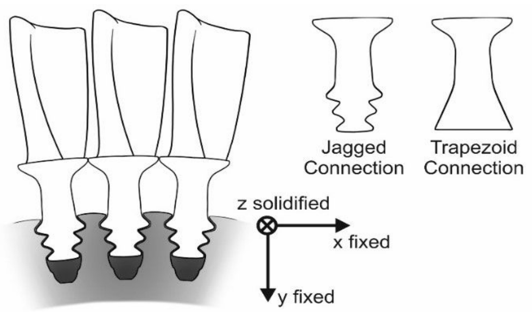

Fig. 2. Connection geometries of turbine blades

3 Learning Method for Disassembly Processes

The major requirement for a Learning Method is a known history of the product. This narrows the number of products where the Learning Method can be of use. Most of the consumer products that are fed into the regeneration cycle have an unknown usage history. Nevertheless, there are products or components of high value and/or high safety-relevance, which need a recording of the product's history - for example the recording of the hours of operation, which determine the maintenance intervals. For the engine of an airplane, a lot of information are available about the product's history: The hours of operation are recorded anyway and since an airplane is navigating using GPS, data about the characteristics of operation (flight over sea or desert) are also known. In the following a Learning Method is described, which implements a product's usage history into the disassembly planning.

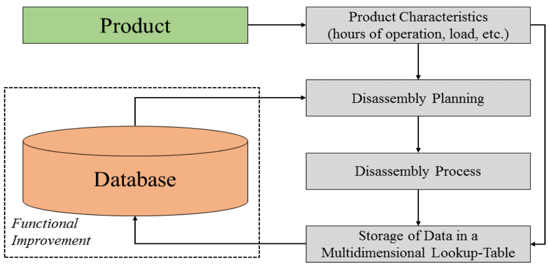

Fig. 3. Schematic layout of the Learning Method

Figure 3 shows the schematic layout of the Learning Method. In a first step, the relevant characteristics regarding the product history such as hours of operation or workload are collected. In the disassembly planning, already acquired data and the characteristics of the product are used to estimate the parameters of the disassembly process. During the disassembly process, data that are useful for future reference are collected and stored into the database.

The database has the structure of a multidimensional Lookup-Table, which grows bigger and more accurate with each disassembly process. In the following, the input of product characteristics, the structure of the Lookup-Table and the multiple linear regression used in the disassembly planning are explained in detail.

3.1 Product Characteristics

The first step is the input of the necessary data. In the case being considered here (turbine blades), the necessary data are the hours of operation of the turbine, the characteristics of the flight routes (e.g. over desert or sea) and the geometry of the blade. The hours of operation are of great interest, because of an enormous impact on the degree of solidification.

Frequent flights over desert and sea can increase hot gas corrosion and solidification in general, as described in Chapter 2. While the hours of operation are put in unprocessed, the characteristics of the flight have to be converted into a number. The number has to represent the impact on the solidification done by the different flight routines. It is taken into account that short flights are particularly demanding due to the lower flight altitude and a higher number of take-offs. The best case is only long-distance flights over land, which will then be represented by the characteristic factor “1”. The worst case would be the short-distance flight over desert and sea, which would be represented by the factor “5”. Depending on the actual history, which will always be somewhere between those extreme cases, a rational number between one and five will be calculated.

The geometry of the blade also has an influence on the disassembly force. In contrast to the characteristics of flight, there are no intermediate values that can be calculated, because there are no fluent transitions between different geometries. This has an impact on the structure of the Lookup-Table, which will be explained in the next section.

By determining the disassembly forces of various combinations of input data, the Lookup-Table grows bigger and more detailed. Given the event that the user puts in a combination of input data that has never been disassembled, an approximated disassembly force has to be interpolated by multiple linear regression. The regression is supported by all disassembly forces that have been recorded at that time. After the actual disassembly took place, the recorded disassembly force is stored in the Lookup-Table for future reference and for improving the regression.

3.2 Lookup-Table

The structure of the exemplary Lookup-Table is very simple. Since there are three input variables, a three-dimensional matrix is needed to store the discrete values for the disassembly force depending on the input data. A closer look at the input variables shows that the geometry of the blade only has a limited number of discrete values, while the hours and characteristics of operation, theoretically, can have an infinite number of values. Dividing the three-dimensional matrix into layers, each represents one geometry. Without fluent transitions between different geometries, there is no need to interpolate values between those layers. This reduces the multiple linear regression by one dimension, which leaves a two-dimensional linear regression. The disadvantage of this method is that every new geometry has to be taught from scratch. The advantage is the simplicity of the calculation, which is possible without a big effort during the disassembly. For every geometry, there is an independent two-dimensional matrix, within which the regression is calculated.

3.3 Multiple Linear Regression

The multiple linear regression is the key to the success of the Lookup-Table. Using regression, it is not necessary to calculate or simulate the disassembly force based in physical models, but instead the disassembly force can be approximated using interpolation from already disassembled data. In the following, a short introduction of multiple linear regression is given, followed by an example, to show how the regression works.

Multiple linear regression can deliver an output which is dependent on multiple input variables [5]. In the case of turbine blade disassembly, there are three inputs (hours of operation, characteristics of operation, geometry) of which only the hours and the characteristics of operation are considered for the multiple linear regression, because for the geometry no intermediate values exist that could be interpolated. The equation for the regression thereby follows to:

$$Y_i = \beta_1 X_{i,1} + \beta_2 X_{i,2} + \beta_3 X_{i,3} + e, \;\; i = 1, \dots, n \tag{3}$$

In this equation, Y_i is the output of the observation i, while $X_{i,1}$, $X_{i,2}$ and $X_{i,3}$ are the input data. The input $X_{i,1}$ is usually set to 1 to introduce a constant into the regression model. Furthermore, n is the number of observations and β_1, β_2 and β_3 are the parameters of the regression. The output Y shows a natural diversification, so that the calculated regression will not intersect with all output values [5]. Therefore, a residuum e is added to the equation.

3.4 Example of Use

Table 1 shows a Lookup-Table for a fictional geometry. In this case, 50 turbine blades with different operation histories have already been disassembled.

Table 1. Disassembly Forces [N] of turbine blades with different operation histories

Geometry A		Hours of Operation [1000h]									
		1	2	3	4	5	6	7	8	9	10
Characteristics of Operation	1	100	220	317	430	525	610	700	821	903	1043
	2	230	380	421	490	620	712	860	980	1110	1200
	3	250	432	576	632	778	890	910	1000	1150	1200
	4	370	570	600	790	800	870	1119	1150	1200	1300
	5	570	600	703	845	930	1120	1180	1200	1350	1470

Figure 4 shows the disassembly forces of table 1 as a function of the input data. It also illustrates the multiple linear regression of the disassembly forces. In this example the values are evenly distributed, which, of course, will not be the case in reality. Still, the example illustrates how the Lookup-Table works after 50 blades with different operation history have been disassembled.

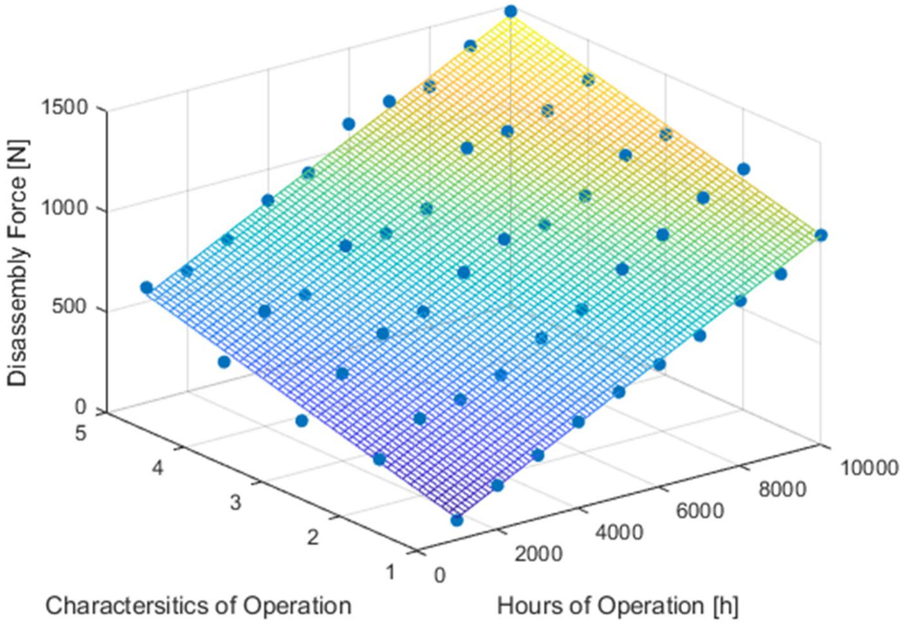

Fig. 4. Multiple linear regression of the disassembly forces of a turbine blade

The multiple linear regression shown in Figure 4 has the parameters:

$$\beta_1 = -91.5733;\ \beta_2 = 0.1028;\ \beta_3 = 103.6400.$$

Using these parameters, every combination of operation hours and characteristic of operation can be determined. For example the disassembly of a turbine blade with 6,400 operation hours and a characteristic factor of 2.7 would have an estimated disassembly force of 846.175 N calculated using the interpolation shown in equation 4.

$$Y = -91.5733 + 0.1028 \cdot 6400 + 103.6400 \cdot 2.7 = 846175 \tag{4}$$

Figure 5 shows the corresponding dot (red) in the regression known from Figure 4. The value interpolated using the regression is an estimation of the actual disassembly force and is used to choose the right tools and as an initial value for the control system. During the disassembly, the actual disassembly force is measured and afterwards stored in the Lookup-Table. The matrix has grown by one entry and the regression is calculated again, to make it more reliable for future estimations.

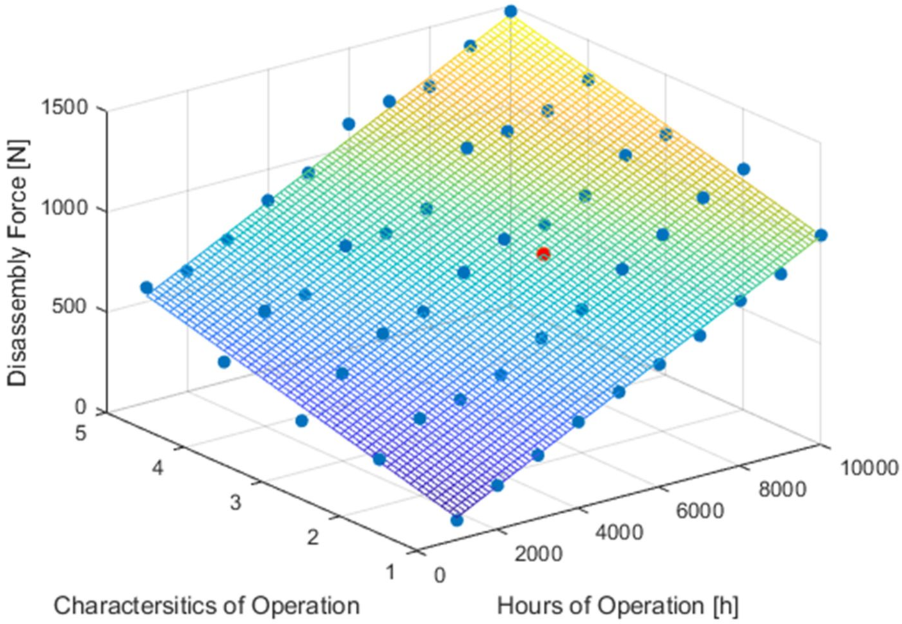

Fig. 5. Calculated disassembly force for 6.400 hours of operation and a characteristic factor of 2.7

3.5 Mean value

Variances in the process are taken into account by calculating the mean value from two identical products with an identical history. In this case a disassembly force for a turbine blade with the history and geometry is already stored in the Lookup-Table, and thus a mean value is generated. The disassembly forces of turbine blades even from the same engine vary to a certain degree, so that a mean value is the best way to counteract these variations. However, the generated value is not an arithmetic mean, but is created using Equation 5:

$$h_{i,j,k,new} = \frac{h_{i,j,k,old} \cdot h_{i,j,k,number} + F_{disassebly}}{h_{i,j,k,number} + 1} \quad (5)$$

In this equation, $h_{i,j,k,new}$ represents the new value of the Lookup-Table, while $h_{i,j,k,old}$ represents the old value of the Lookup-Table in dependence to the three input variables. $h_{i,j,k,number}$ is a scalar entry in a counter matrix that contains how often a combination of the three input variables has been selected from the Lookup-Table. $F_{disassembly}$ is the measured disassembly force which is needed to carry out the disassembly task. After the mean value is generated, the corresponding counter $h_{i,j,k,number}$ is increased by one. This way the forces measured at each disassembly are all brought into the mean value equally and outliers do not have a critical impact on the mean value stored in the

Lookup-Table. Thus, the existing entries are improved and, on the other hand, are continuously expanded, so that the learning process would be usable in a real repeatable disassembly task.

4 Conclusion and Outlook

At this time, all the input data and the corresponding disassembly forces are fictional for showing the Learning Method for disassembly tasks. Nevertheless, it was shown that the multiple linear regression is suitable for the requirements of the disassembly process. The storage of disassembly forces of products with a known history benefits the planning of the regeneration process. Using a force sensor in the disassembly tool and a software environment for storing the forces, the implementation of the Learning Method would be very simple.

In future work, the aim is to feed the process with data from real disassembly processes, to see if the concept of a Learning Method also works in a real environment. After filling the matrixes with a set of values from past disassembly processes, the multiple linear regression has to deliver disassembly forces for future disassembly processes, to examine the reliability of the process.

When the Learning Method has proven its reliability it will be implemented in a test stand, where solidified connections are disassembled in an automated process, and the disassembly forces can be measured and regulated.

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