Journal of Machine Engineering, 2018, Vol. 18, No. 2, 85-96
ISSN 1895-7595 (Print) ISSN 2391-8071 (Online)

Received: *13 December 2017* / Accepted: *02 March 2018* / Published online: *25 June 2018*

predictive maintenance, analysis,
precision, predictive model

Ricarda Regina SCHMITT[1*]
Robert DECRESSIN[1]
Franz DIETRICH[1]
Klaus DRÖDER[1]

DETECTION OF WEAR PARAMETERS USING EXISTING SENSORS IN THE MACHINES ENVIRONMENT TO REACH HIGHER MACHINE PRECISION

This paper presents methods to plan predictive maintenance for precision assembly tasks. One of the key aspects of this approach is handling the abnormalities during the development phase, i.e. before and during process implementation. The goal is to identify abnormalities which are prone to failure and finding methods to monitor them. To achieve this, an example assembly system is presented. A Failure Mode and Effects Analysis is then applied to this assembly system to show which key elements influence the overall product quality. Methods to monitor these elements are presented. A unique aspect of this approach is exploring additional routines which can be incorporated in the process to identify machine specific problems. As explained within the paper, the Failure Mode and Effects Analysis shows that the resulting quality in a case study from a precision assembly task is dependent on the precision of the rotational axis. Although the rotational axis plays a significant role in the resulting error, it is hard to explicitly find a correlation between its degradation and produced parts. To overcome this, an additional routine is added to the production process, which directly collects information about the rotational axis. In addition to the overall concept, this routine is discussed and its ability to monitor the rotational axis is confirmed in the paper.

1. INTRODUCTION

Forward-looking error detection and prevention is a difficult task, especially in precision assembly because of tight tolerances. At the same time, the error prevention offers great potential as expensive defects are avoided. Within this paper, possibilities are shown how the need of machine maintenance, especially on precision automated assembly systems, can be recognized and planned. Such methods will help to predict failures. With this information, it will be possible to react before problems occur. From the user side, this allows planned maintenance instead of unplanned down time increasing throughput. Additionally, such methods extend the machine life. This paper will show an approach for predictive maintenance in a case study.

[1] TU Braunschweig, Institute of Machine Tools and Production Technology, Braunschweig, Germany
[*] E-mail: Ricarda.Schmitt@tu-braunschweig.de
DOI: 10.5604/01.3001.0012.0935

For this purpose, first the assembly system is presented. With the help of a FMEA (Failure Mode and Effects Analysis), it is shown that wear of the robot axes is one of the most important points to reach high assembly tolerances. Now a possible indication for a detailed analysis of the chosen axis is given, with the help of a power measurement during the production process. In the next step, the actual main measurement cycle is introduced. In this measurement, the robot moves in increment steps above the systems integrated bottom camera. Its positions are continuously tracked and evaluated. This method looks at adding redundent information about the system, which allows inaccuracies in the axes to be detected. Inaccuracies in positioning will be detected immediately. Within the final portion of this paper, a real world example is explored. Here an axis which has seen heavy usage is examined.

1.1. STATE-OF-THE-ART

A conceptualization of maintenance can be represented by the three factors reliability, availability and physical wear of machines [1, 2]. Using these parameters, it is possible to create a statement about the health of a machine. According to [DIN EN 13306] [3], a maintenance strategy can be defined as a “management approach to management objectives” such as detection of a potential defect, determination of the wear consumption, avoidance of downtimes.

In general, maintenance of machines can be clustered into three main categories (see Fig. 1): the reactive strategy, the preventive strategy and the predictive maintenance strategy. Within the reactive strategy measurements are only taken if a failure appears. Thus, the machines are used until they fail. On one hand, a maximum use of the wear medium can be reached, but on the other hand, there is no possibility to plan manufacturing stops. Spare parts must also be available at all times. This maintenance strategy is also called “Run-To-Failure Maintenance” [5].

The preventive maintenance strategy controls systems at periodic intervals. In this way it is desired that there are no machine malfunctions. Breakdown time and failure rate can be minimized. Spare parts and wear parts are not used effectively as parts which are susceptible to wear or breakdown are changed at regular intervals. In addition, detailed documentation and experience are necessary to establish reasonable maintenance intervals. [6].

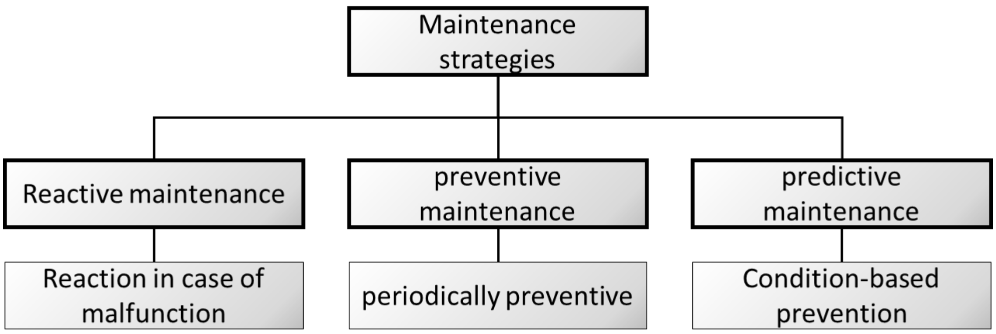

Fig. 1. Maintenance strategies [4]

Predictive maintenance is a major issue in the prior concept. The main aim is to ensure the machine maintenance in accordance with the machine state. In this way a maximum use of the wear medium is possible. Maintenance is plannable and effective. The principal works as follows: If the operating parameters are within a defined operating range, the wear medium can be used, if the limit values are exceeded, it must be replaced [7, 8].

For the purpose of predictive maintenance, continuous monitoring of the machine parameters is necessary. Mobley classified the five main inspection procedures to: visual inspection, vibration monitoring, process parameter monitoring, thermography and tribology [8]. The visual inspection is mostly used in form of operator inspection. In general, all test methods are usable. The most important prerequisite is a non-destructive test method.

Tribology is especially interesting for cutting processes. Thermography is very useful in processes that heat up strongly. In precision assembly, this is not the case. For vibration-monitoring and process-parameter-monitoring, additional sensors are usually added to the machine [9, 10].

For the inspection of vibrations, a common analysis method is the FFT (fast Fourier transformation). Patil and Geikwad [9] used this to find mechanical defects in rotating electrical machines. Dempsey and Afjeh [11] combined the FFT with an analysis of the lubricant. With additional partials, they simulate wear of machine components. Verl [12] also follows a similar approach. Through investigation of positioning data, repeatability and reversal error of machine, Verl found defects on one machine axis in a laboratory environment. In this approach, no additional sensors were added, just the machine intergraded positioning sensors were used. Hoshi [13] also shows, that it is possible to draw conclusions about the state of the system by recording the machine motion. Also, the monitoring of parameters, like the used energy by the machine, is a good strategy. Combining the generated energy data with learning algorithms can result in behaviour patterns of the machine and can help to detect anomalies [14].

Finally, the found machine abnormalities have to be communicated to the operator. He closes the maintenance loop and initiates the maintenance action. Uhlmann [15] indicates how to build human machine interaction. For example, maintenance instructions could be communicated in this way.

In the state of the art, different methods to acquire information about the machines health and to initiate maintenance action were shown. In the sum, most approaches use additional sensors for measuring abnormalities [18, 19]. Only Verl [12] just used integrated sensors. In this case, however, no real functional verification of the used sensors was carried out.

2. DETECTION OF WEAR PARAMETERS

In this paper, a new approach for detecting the need of machine maintenance with internal sensors will be introduced. The focus within this paper is on a predictive maintenance approach without additional sensor technology.

2.1. DESCRIPTION OF THE TECHNICAL STRUCTURE

The chosen assembly task is a precision assembly task. Special features that result from precision assembly are that the accuracies are kept within very tight tolerances on the order of less than 25 µm. To help achieve this, the assembly is set in a cleanroom with controlled temperature and humidity parameters. In addition, the mounting machine is a precision assembly robot with high accuracies of the positioning axis. The assembly robot has a repeatability of 1 µm in *x*-, *y*-, and *z*-axis. The complete technical structure can be seen in Fig. 2. The main elements used for manipulation tasks, in this paper, are the gripper and a chuck for part handling. In addition to the axes encoders, sensors such as a camera in the head of the robot, as well as a camera in the working area of the robot are included in the system. Additional height information can be gained by a laser sensor integrated within the robot head. This sensor basis is similar to commercially available precision and collaboration robots [16].

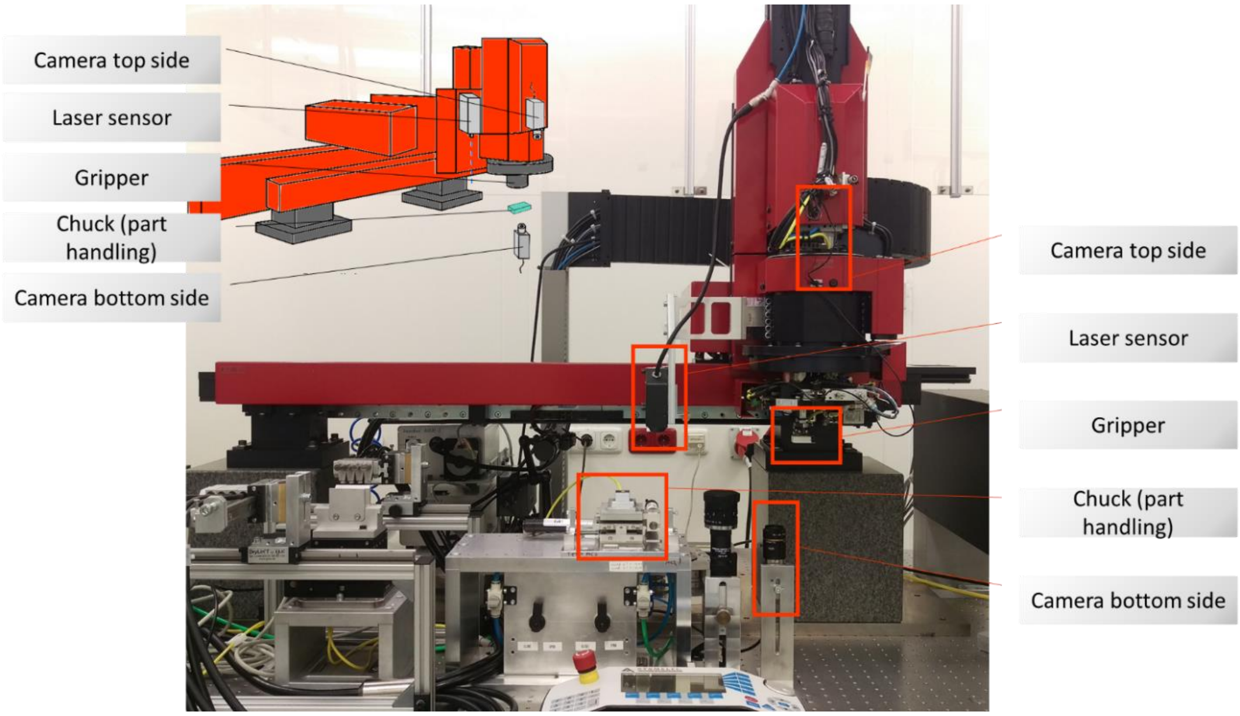

Fig. 2. Technical offset

Next, with the help of an FMEA method (see [16]) mechanical wear in precision assembly systems is identified as one of the most important points for reaching high accuracies. In Table 1 an extract of the results of the FMEA are presented. The weighting of the errors can be found in the RPN (risk priority number). The errors explored within this paper are all originate from the machine. In addition to the machine itself, further errors can be found in the areas process, product and environment. As can be seen in Table 1 the most important errors are offset errors and axis wear. Offset errors mostly arise by the fact of machine delay or disturbing bodies introduced in the technical offset. While offset errors occur stochastically, wear parameters can be described as a function of time.

Table 1. Result of an FMEA to identify the most important influence factors for position errors in assembly tasks

ID	Error	frequency	importance	discoverability	RPN
2	Offset-Error	9.2	7	10	644
4	Higher axis wear	2.6	7	7.9	144
5	Controler deviation	3.5	4	10	140
41	System external machan. Vibrations	1.8	4	7.6	55
66	UV-fiber not properly aligned	2.6	4	1.9	20
67	UV-fiber bent	2.6	4	1.7	18

2.2. IDENTIFYING OF CRITICAL POSITIONS WITH THE HELP OF POWER MEASUREMENT

For identifying the need of maintenance, it is important to have a secure sign for further measurements. Figure 3 presents a sketch, that shows in which form a redundant (indication) measurement results in an axis measurement which allows the health to be determined. A good indicator can be the measurement of the power use of a single axis [13]. With such a measurement, it is possible to continuously search for abnormalities in the process. Another indicator can be the continuous monitoring of robot positions. For example, if components are gripped from magazines the gripping position should not fluctuate greatly. If fluctuations still occur, further investigations should follow. However, it is only an indicator and further measurements must follow to clarify if maintenance is really necessary. Further measurements often take more time and cannot be performed during the production, but they can be placed in production breaks.

Now the required measuring cycles for detection of abnormalities in the robots axis are explained. First, the power measurement that serves as an indicator is presented. In Fig. 4 and Fig. 5 it is observable that the rotational axis has abnormalities (wear effects) at special positions. Here a comparison between an axis area without wear and an axis area with wear is done. To find errors, an algorithm was used that looks for outliers based on an expected mean. In addition, the derivative of the function searches for local extrema. This combination makes it possible to find power peaks and resulting potential wear points. For this robot it is known, that the rotational axis has wear. That is why this axis is chosen for later experiments.

The next step is to introduce incremental measurement of the robot axis (seen in Fig. 3). The theory behind it is to divide the axis into smaller sections and to move along each. The camera records the robot movement, and then the measured lengths of the divided axis areas can be compared. All measured axis sections should have the same length as long as the axis is wear-free. This measurement is time-consuming and will only be performed if signs of wear from the previous measurements are present. To cover the area of 0.05° it takes about 45 minutes. This type of measurement must be timed in production breaks.

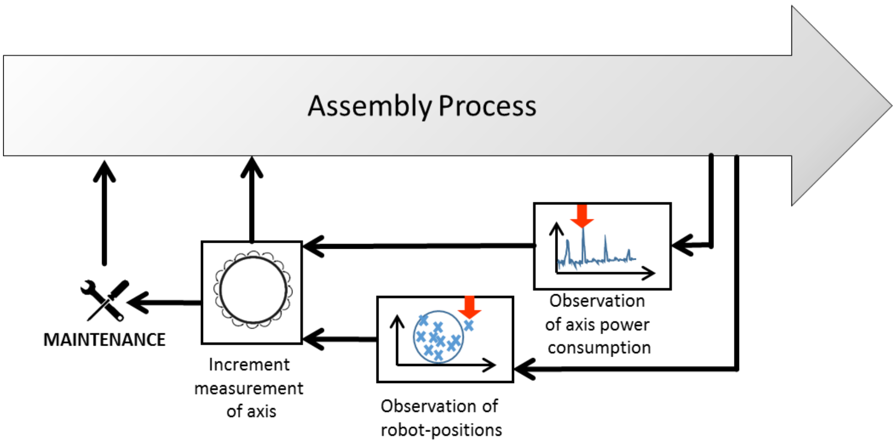

Fig. 3. Implementation of indicator measurements

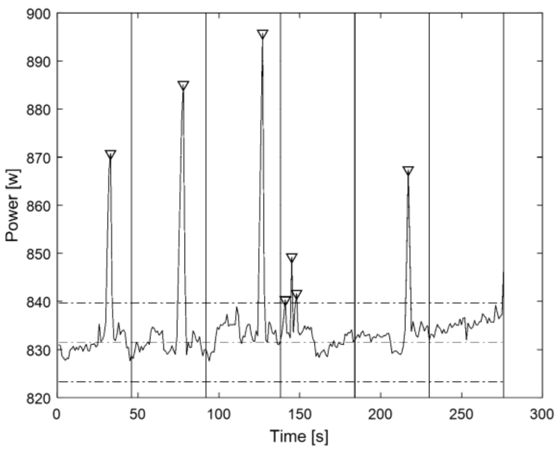

Fig. 4. Detection of critical positions rotational axis

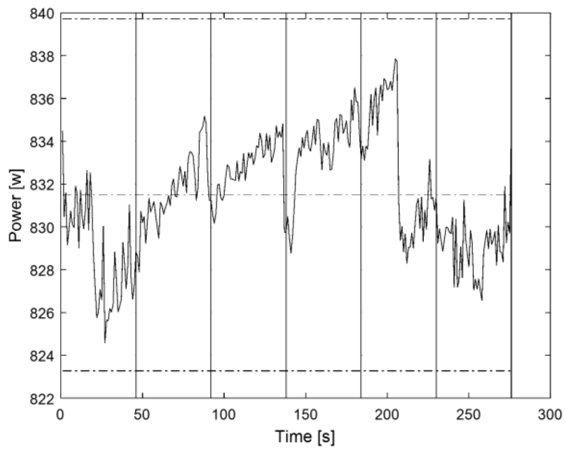

Fig. 5. As comparison a linear axis without wear

2.3. MEASUREMENT OF POSITIONING ACCURACY OF A SELECTED AXIS USING THE IMAGE VISION

The previously described theoretical procedure of incremental axis measurement is now applied to the robot. To measure the positioning accuracy of the rotational axis of the robot, a test cycle, described above, was programmed and integrated using the image vision. This measurement takes advantage of sensors which are already found within the assembly system. As can be seen in Fig. 6, the robot moves a gripped part above the bottom camera and observes its motion. The experimental measurement scheme, behind this motion ,can be seen in Fig. 8. The acquired images of this measurement (seen in Fig. 7) show the underside of the attached object. The object contains a pattern that is detectable with the image processing. This way a relative position of the axis can be calculated and logged. The resulting pixel positions of the camera can be transferred to the robot coordinate system by means of a coordinate transformation. This can then be compared with the incremental encoders of the robot.

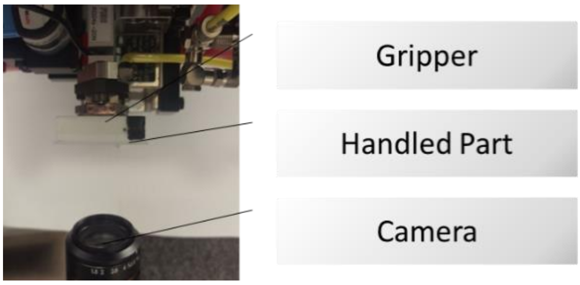

Fig. 6. Experimental structure in detail

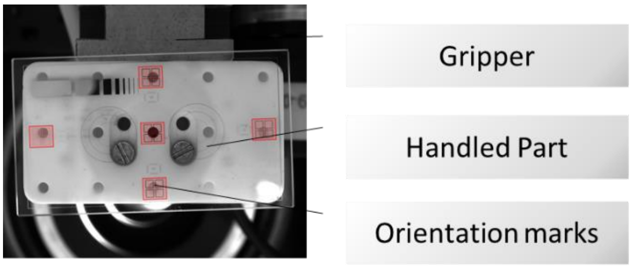

Fig. 7. Acquired image of the bottom camera. Measuring the real movement of the robot

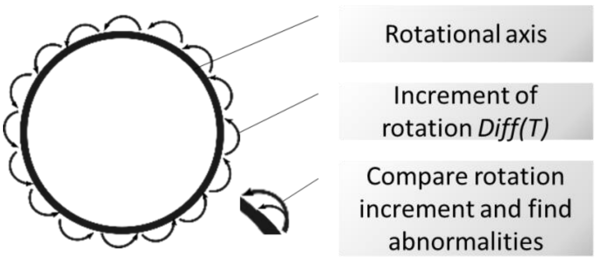

Fig. 8. Experimental measurement scheme

The measurement program was created so that the smallest increment (0.001°) of the rotational axis was moved over a set region (set point ± 0.5 degrees). Based on the results of the power measurements, the set point for the following measurements was chosen. At the end of each step, a picture was acquired using the image vision (bottom camera) and additionally the position of the robot was recorded, with the help of the axis encoders. This enables redundant measurement information and thus a comparison between the two values is possible.

In order to detect irregularities in the movement of the robots' axis, each increment is compared with its successor. In case the difference between predecessor and successor becomes near to zero there are no irregularities. Otherwise, it must be assumed that the robot movement is not constant. In Fig. 8 a scheme to visualize the measurement is given.

The proposed experiment was repeated three times, each time about the same set point. In Fig. 9 a comparison between three experiments all done at the same heavily used axis area is shown. On the x-axis the steps of the robots' movement are plotted in degrees.

On the y-axis the different *Diff(T)*, explained in the scheme above (Fig. 8), is plotted also in degrees. In the case of an axis without errors, the data should be similar to a line about 0.001°. In the case of the experiments visualized in Fig. 9, it is observable that all three experiments have peaks (marked with a star) which are located across the entire experiment range. In Fig. 9, it is noticeable that many peaks occur systematically at the same location. About 77 % of all peaks are found in a comparative experiment at the same location. There is an algorithm, which is able to identify the main critical peaks in a movement. For this purpose, hard limits such as the standard deviation as well as criteria such as the slope change of the graph are investigated.

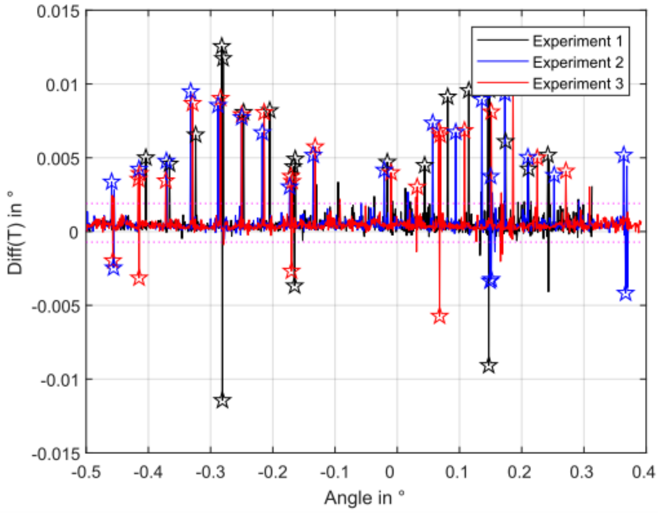

Fig. 9. Detection of abnormalities (marked with a star) in axis movement

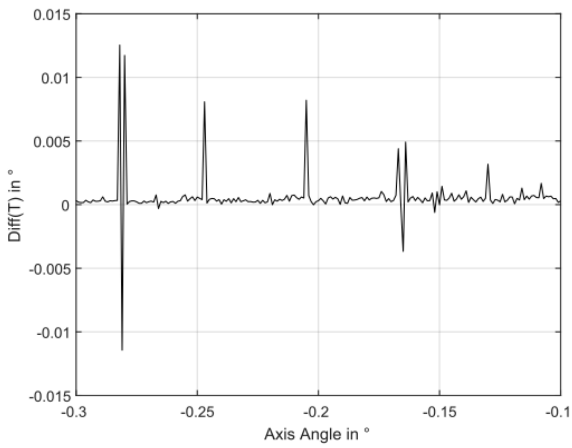

Fig. 10. Axis area with abnormalities
(Axis range about 11.65 to 11.9 °)

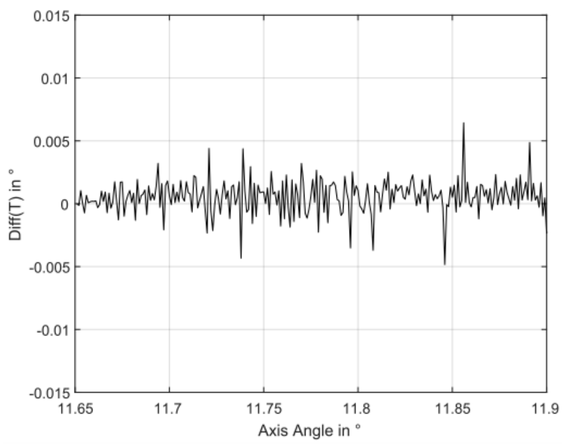

Fig. 11. Axis area without abnormalities
(Axis range about –0.3 to –0.1°)

The axis range considered in Fig. 9 has a set point of 0 degree ± 0.5° range because their poor axis behavior, with many abnormalities is assumed with the help of the power measurement (Fig. 4 and Fig. 5). To proof this assertion the rotation measurement is repeated for other axis areas. The comparison measurements can be seen in Fig. 10 and Fig. 11. As you can see, there is a clear difference between the axis area of Fig. 10 (–0.3° to –0.1°) and Fig. 11 (11.65° to 11.9°). The deviation from the predecessor is plotted on the y-axis. High peaks mean strong position jumps. Figure 11 shows no oscillations but compensating fluctuations in positioning. The figures show, that the area of –0.3° to –0.1° is heavier in use than the area of 11.65° to 11.9°, which also corresponds to the real usage of the axis in production.

3. PROOF OF CONCEPT

To prove that the identified heavy used areas of the axis influence the accuracy of an assembly of two components, another attempt is made. A final repeatability measurement using the image vision (top camera) is performed. The experimental offset used for this purpose is shown in Fig. 12. Even this offset is part of the normal manufacturing environment of the robot. The robot takes a picture of the component placed on an active chuck (shown in Fig. 12) and calculates the position. Now the component is gripped, lifted and set down again. A new picture is taken and the resulting new position is calculated. The recorded positions of the component are plotted in Fig. 13 and Fig. 14.

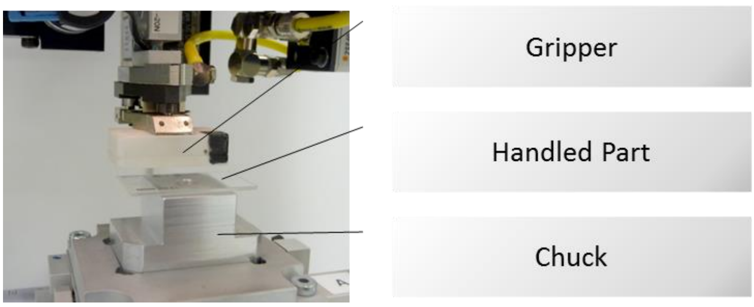

Fig. 12. Experimental offset for accuracy measurement

Figure 13 shows the x-position about the y-positon of the handled component. It can be seen that the axis range without wear (about 11 degrees) has a distribution (circle represent 1 sigma), which is only the half of the heavy used axis range (about 0 degrees). The size of the distribution can be recognized by the radius (arrow) of the distribution cloud (Fig. 13). Furthermore, it is noticeable that the position clouds are not evenly distributed. There is a trend to recognize. This trend can be explained by slipping the component in one direction. Since the placed component is measured, handled, and measured again within the experiment, the position error increases after each handling because it adds up. The starting / target position is marked with a cross in Fig. 13.

Figure 14 shows the change in component torsion over the number of trials. This is done in degree, so the highest value is about 0.12 °. Within precision assembly, this range is of significance. The heavily used area has more peaks (marked) over the section than the good axis area. In addition, the angle measurement shows a trend.

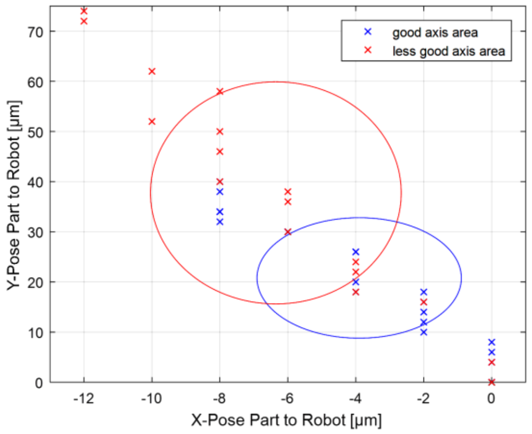

Fig. 13. Position of placed component. Comparison of axis range with (around 0°, here red) and without (around 11°, here blue) wear

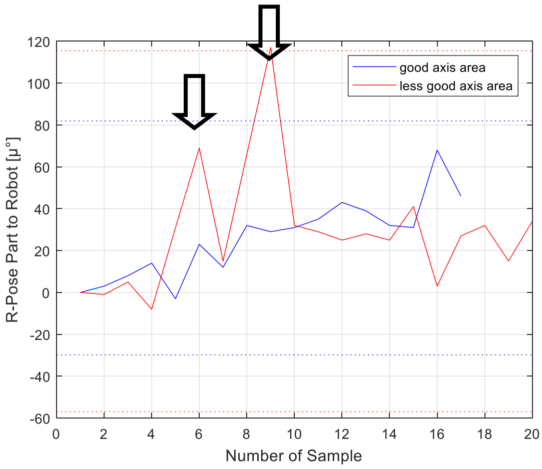

Fig. 14. Angle of placed component. Axis range around 0° in red, axis range around 11° in blue

After all the measuring cycles, that have been shown in Fig. 3, have been checked properly, a statement about this maintenance schedule can be made. In conclusion, the assumption that the found heavy used axis areas influence the positioning accuracy can be confirmed. Thus, both the proposed indication measurement (measurement of the power consumption of the robot) and the actual measuring cycle (measurement of the positioning behavior of the robot) are suitable.

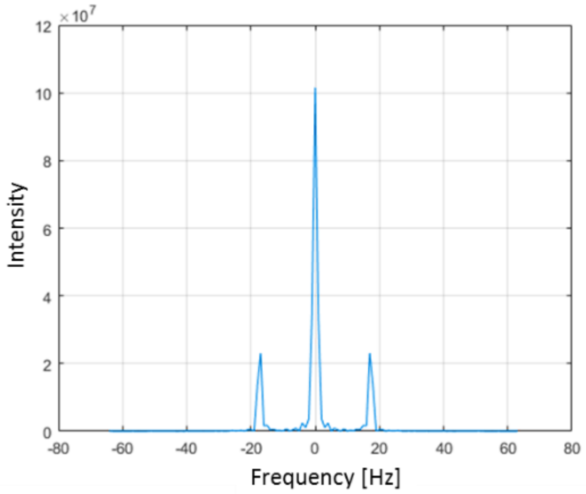

Fig. 15. Determination of the robot's FFT before axis maintenance oscillates

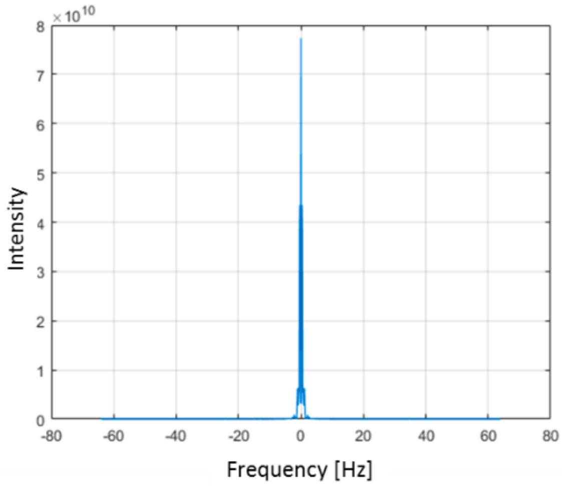

Fig. 16. Determination of the robot's FFT after axis maintenance

In an additional case study, an FFT analysis of the axes showed that axis maintenance leads to better movement behavior. The frequency response was recorded before and after maintenance. Clear differences can be seen in this, see Fig. 15 and Fig. 16. If axis wear is detected using the proposed measuring principle, it can be demonstrated that the movement behavior improves after maintenance.

4. CONCLUSION

The goal of predictive maintenance is to minimize unproductive times. In addition, machines should only be serviced if necessary and there is a sign for abnormalities. In order to find such signs of wear, some measuring methods have been proposed in this paper. These measuring methods were all validated on experiments.

In summary, this paper has presented two indicator measurement cycles and also demonstrated their function. It was further shown with a third measuring cycle that it is possible to confirm these indicators during production breaks. For all measurements carried out, only system integrated sensors were used. Only additional axis movements that can be carried out during production breaks have been integrated. The presented system is thus able to carry out such a diagnosis completely independently and without the help of additional hardware. It was finally shown, that the abnormalities found also have an actual influence on the positioning of components and with that, influence of the accuracy of assemblies.

This presented method introduces a new methodology in the field of predictive maintenance and was validate in a case study. Looking ahead, the functionality that was previously only tested in the laboratory environment needs to be tested in a real manufacturing environment.

REFERENCES

[1] RENTSCHLER U., 1995, *Fehlertolerantes Präzisionsfügen, volume 104 of ISW Forschung und Praxis*, Berichte aus dem Institut für Steuerungstechnik der Werkzeugmaschinen und Fertigungseinrichtungen der Universität Stuttgart. Springer Berlin Heidelberg, Berlin, Heidelberg and s.l.

[2] AHMAD R., KAMARUDDIN S., AZID I., ALMANAR I., 2011, *Maintenance management decision model for preventive maintenance strategy on production equipment*: Springer.

[3] Europäische Norm. Din 13306: Instandhaltung – Begriffe der Instandhaltung, September 2015.

[4] STRUNZ M., 2012, *Instandhaltung: Grundlagen - Strategien - Werkstätten. Springer*, Berlin and Heidelberg.

[5] AHMAD R., KAMARUDDIN S., AZID I., ALMANAR I., 2011, *Maintenance Management Decision Model for Preventive Maintenance Strategy on Production Equipment*, Springer.

[6] MATYAS K., 2002, *Ganzheitliche Optimierung Durch Individuelle Instandhaltungsstrategien*, Industrie Management, 18, 13-16.

[7] PARK K.S., 1993, *Condition-Based Predictive Maintenance by Multiple Logistic Function*, IEEE Transactions on Reliability, 42/4, 556-560.

[8] MOBLEY R.K., 2002, *An Introduction to Predictive Maintenance*, Butterworth-Heinemann, Amsterdam and New York, 2nd ed.

[9] PATIL S., GEIKWAD J., 2013, *Vibration Analysis of Electrical Rotating Machines Using FFT: A Method of Predictive Maintenance*, IEEE, DOI: 10.1109/ICCCNT.2013.6726711.

[10] FAYYAD, U.M., 1996, *Advances in Knowledge Discovery and Data Mining*, Menlo Park, Calif.: AAAI Press; MIT Press.

[11] DEMPSEY P., AFJEH A., 2002, *Integrating Oil Debris and Vibration Gear Damage Detection Technologies Using Fuzzy Logic*, NASA Center for Aerospace Information.

[12] VERL A., HEISEL U., WALTHER M., MAIER D., 2009, *Sensorless Automated Condition Monitoring for the Control of the Predictive Maintenance of Machine Tools*, CIRP Annals – Manufacturing Technology, 58/1, 375-378.

[13] HOSHI T., 2006, *Damage Monitoring of Ball Bearin*g, CIRP Annals – Manufacturing Technology, 55/1, 427-430.

[14] [ESTER M., SANDER J., *Knowledge Discovery in Databases*, Techniken und Anwendungen. Berlin, New York: Springer.

[15] UHLMANN E., et al., 2017, *Intelligent Pattern Recognition of SLM Machine Energy Data*, Journal of Machine Engineering, 17/2.
[16] UHLMANN E., HOHWIELER E., GEISERT C., 2017, *Intelligent Production Systems in the Era of Indutrie 4.0 – Changing Mindsets and Business Models*, Journal of Machine Engineering, 17/2.
[17] SCHMITT R., RIEDEL J., 2017, *A Methodology for a Structured Process Analysis of Complex Production Processes with a Small Database*, WGP-Kongress.
[18] CHEN K.Y., LEE H.Y., TU S., 2016. *Study on User's Satisfaction of Enterprise Resource Planning System - An Example of manufacturing*, International Symposium on Computer, Consumer and Control (IEEE), 1010-1011.
[19] YANG L., SHEU S.H., 2006, *Integrating Multivariate Engineering Process Control and Multivariate Statistical Process Control*, Int. J. Adv. Manuf. Technol., 29/1-2, 129-136, DOI: 10.1007/s00170-004-2494-8.