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Adaptive inspection planning using a digital twin for quality assurance

Leon Reuter[a]*, Berend Denkena[a], Marcel Wichmann[a]

[a]*Institute of Production Engineering and Machine Tools (IFW), An der Universität 2, 30823 Garbsen, Germany*

* Corresponding author. Tel.: +49-511-762-18211; fax: +49-511-762-5115. *E-mail address:* reuter@ifw.uni-hannover.de

Abstract

The integration of a digital twin into inspection planning enables a novel procedure that reduces avoidable inspection times and costs. This paper shows a method for component-specific adaption of inspection plans by feeding back data-based quality results into inspection planning. An initial evaluation of the method on a real aerospace aluminum component is carried out using a 3-axis milling process. Machine learning based quality models were implemented for the inspection features shape deviation and surface roughness. With the knowledge gained, the inspection time for the process can be reduced by up to 75 % per component.

Keywords: IP; digital twin; quality assurance; machine learning; adaptivity

1. Introduction

The aerospace industry is characterized by high quality requirements. For example, the international standard EN 9100 describes requirements for quality management systems in the aerospace industry [1]. However, the current inspection process of a workpiece does not add value to the workpiece and causes a high expenditure of time and costs. Particularly due to small-series production of large components made of aluminum or titanium, it is not always possible to reduce the scope of inspections by means of sample-based inspection planning (IP). In the present application, however, a 100 % inspection leads to an inspection time of 4.5 h for the optical measurement of a sill beam. An adaption of the scope is therefore necessary in order to reduce avoidable inspection efforts in quality assurance. It is already shown that the use of a digital twin can be useful for optimizing the production system [2]. In this context, the virtual measurement result can be used as a filter to reduce avoidable inspection efforts [3]. For this purpose, only inspections of workpieces that cannot be unambiguously classified into the categories "OK" and "not OK" are defined as necessary inspection efforts. In this paper, the potential of a digital twin based adaption of the inspection plan is demonstrated.

2. State of the art

The task of IP is to design quality inspections for the various manufacturing steps of products or service delivery stages. During IP, the inspection steps, procedures, methods and finally the inspection plans are developed [4]. Already more than thirty years ago, Neumann devised an approach to automated IP that is still frequently referred to today. This results in a distinction between product-dependent and product-independent planning components within IP. The work focuses on a reduction of the experience-based steps within the product-dependent IP in small-series production [5]. Based on Neumann, further work has been done in the following years to increase the degree of automation within IP [6,7]. According to Hwang et al., the number of measurement points is a key element to achieve sufficient measurement accuracy within quality inspection. Therefore, to reduce the subjectivity of the inspection planner, a knowledge-based IP system was developed for the automated generation of effective and consistent inspection plans [8]. Ahmed et al. dealt with experience-based, product-related IP in the context of Industry 4.0. Here, the relevant knowledge is collected, stored and used in a higher-level system of intelligent, virtual product

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development. The use of experience knowledge thus leads to an improvement in product-related IP in the early phases of product development [9]. Ascione et al. already provide the first work on the generation of adaptive inspection plans for coordinate measuring machines. Using Gaussian process models, the next measuring point of the workpiece is selected based on the predictions as well as the uncertainty of the shape deviation. Iteratively, the next point to be inspected is selected and then measured until a termination criterion is met [10].

Data-based approaches for virtual inspection of workpiece quality are necessary for an adaptive IP. The prediction of straightness and roundness of milled surfaces based on internal drive signals was investigated by Brecher et al. To predict the quality parameters, a neural network with the following input parameters is used: drive currents, spindle current and speed, as well as encoder positions. The results show highly accurate prediction results in the application used [11, 12]. Another approach for virtual inspection of machined workpieces is provided by Königs and Brecher. Measured process forces of a dynamometer, the recorded axis positions of the control and a process-parallel material removal simulation are used. A comparison of the virtually obtained results with the conventional measurement results yields a maximum deviation of 3 µm. However, the approach has so far been limited to simple flank milling processes [13]. To predict the milled surface roughness, Khorasani and Yazdi achieved a surface roughness prediction accuracy of over 99 % in their studies for flute milling [14]. Further work on surface roughness prediction based on neural networks or genetic algorithms can be found in [15, 16]. Moreover, it should be considered that the selected modeling approach has an impact on the accuracy of the developed model. For example, Denkena et al. show that the resulting root mean square error of the model has a high dependence on the selected modeling approach and the hyperparameters [17].

The current state of the art shows that there is potential in the use of data-based predictions for quality inspection. However, research results are mainly limited to simple machining processes, so there is not yet sufficient knowledge about the applicability of virtual inspection methods for industrial use cases. Furthermore, from a scientific point of view, IP has not progressed much in recent years. A holistic approach by feeding back virtual measurement results into the IP is not yet state of the art. However, such an approach would lead to a significant reduction of the efforts in quality control.

3. Approach

Within the CAD-CAM chain, inspection planning usually takes place in parallel with or following CAM planning (s. Fig. 1, step 1). As described, classical inspection planning usually takes place once for a specific product. All steps of the quality inspection are thus generally defined. An individual adaptation of the necessary inspections per workpiece is not carried out. Adaptive IP extends the classical IP in two essential aspects. First, it integrates a digital twin into the planning process. Secondly, the initial inspection plans are adapted on this basis (s. step 5).

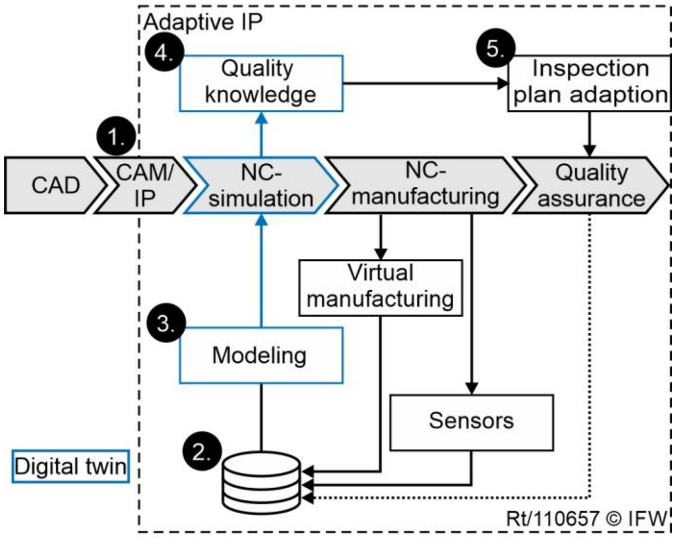

Fig. 1. Method for adaptive IP

After the machining process of the workpiece, all relevant manufacturing data (machine, sensor, simulation and quality data) must be stored in the form of a digital footprint of the workpiece (s. step 2). Based on this, the modeling of the workpiece quality takes place in the subsequent step 3. If not already available, virtual inspection equipment must first be developed to enable data-based quality inspection. These are, for example, regression models that provide the correlation between the input variables from the machine, the sensor system or the simulation with the target quality value. Such models are then used in the NC simulation to determine the achieved quality. The result of the quality modeling is finally new knowledge about the existing workpiece quality (s. step 4). Based on the result, a decision is made on the further quality inspection of the workpiece. Therefore, it is common to categorize them as "OK" and "Not OK". If the virtual quality inspection can also clearly classify the workpiece, no further physical inspection is necessary and the inspection plan is adapted (s. step 5). However, it is possible that the determined quality value is very close to the tolerance limit. In this case, a physical re-inspection is necessary, since it cannot be assumed with sufficient certainty that the virtual quality inspection is unambiguous. In this case, the inspection order remains in the inspection plan. The procedure for determining a threshold value and for adapting the inspection plan will be described in more detail later in this paper.

4. Digital twin for virtual quality inspection

4.1. Data acquisition

This article is based on a use case from the aerospace industry. The sill beam of an Airbus A 350 Cargo has a length of over 4.3 m and functions as a kind of door frame of the cargo hatch at the rear of the aircraft. The surface roughness Ra and the shape deviation ds exist as inspection characteristics whereby in this work the shape deviation is defined as the distance in terms of amount between the actual and nominal shape. A complete geometry inspection of a single sill beam takes about 4.5 h. The potential for adaptive IP of the workpiece is therefore definitely present here. A demonstrator component of the sill beam was hence derived (s. Fig. 2). Table 1 shows the cutting parameters used.

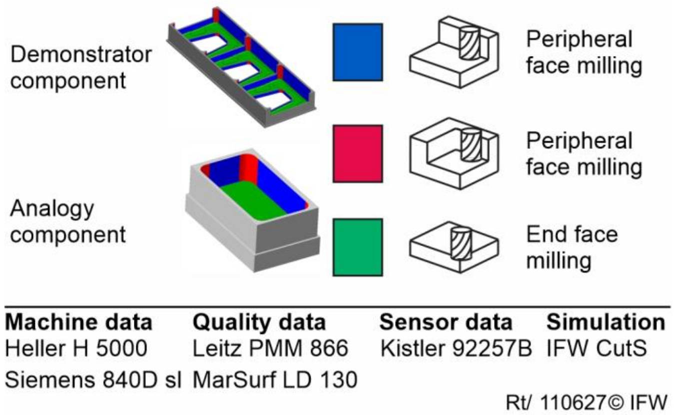

Fig. 2. Experimental setup

Table 1. Design of experiments

Name	Peripheral face milling	End face milling
Feed rate v_f	2,190; 3,960 mm/min	2,190; 3,960 mm/min
Depth of cut a_p	20 mm	0.3; 1.4 mm
Width of cut a_e	0.3; 1.4 mm	7; 14 mm

Virtual quality inspection using a digital twin requires the recording and synchronization of different data streams (s. Fig. 3). As part of the work, a digital twin was set up within the dexel-based material removal simulation IFW CutS [18]. For the simulation of the real machining process, a dexel resolution of 20 dexels/mm and a cycle time of 0.001 s are used.

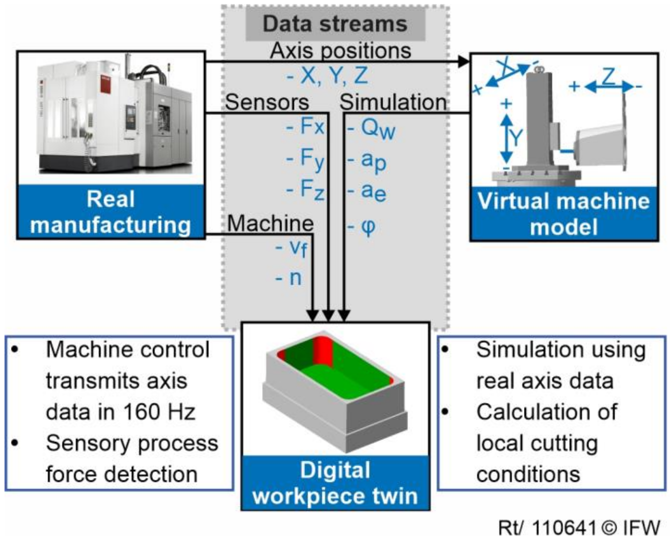

Fig. 3. Approach to virtual quality inspection

Furthermore, the interpretation of the axis positions is carried out using the real axis positions which are read out from the machine control (Siemens 840D sl). The data is logged via a TCP/IP interface at a frequency of 160 Hz. For this, the commercially available communication library "ACCON-AGLink" from Deltalogic is used. The following NC variables are readout from the machine control (s. Table 2).

Table 2. Relevant data from the machine control

Name	Definition NC variable*	Unit
Current axis position in the workpiece coordinate system	actProgPos	mm
Current spindle speed	actSpeed	U/min
Current feed rate	actFeedRateIpo	mm/min

* according to SINUMERIK 840D sl NC Variable and Seam Position Signals, List Manual, Version 4.5 SP2

Additionally, process forces are recorded during the machining process using a Kistler M9257B dynamometer. By means of process forces, additional indicators that influence the workpiece quality (e.g. tool wear) can be taken into account. The inclusion of axis and spindle currents is also conceivable. However, this was not implemented in this article. During data preprocessing, the active force F_a was calculated from the tangential F_t and normal force F_n. Finally, the maximum force of the active force $F_{a,max}$ is included in the virtual quality inspection. Within the material removal simulation, additional local cutting conditions are calculated for each simulation step (s. Table 3). By these, the process knowledge can be additionally extended. By using calculated cutting conditions, additional information (e.g. material removal rate Q_w or tool wrap angle φ) can be used that influence a quality deviation.

Table 3. Relevant simulation variables from IFW CutS

Name	Unit
Material removal rate Q_w	mm^3/s
Depth of cut a_p	mm
Width of cut a_e	mm
Tool wrap angle φ	°

Furthermore, quality data is recorded tactilely. The roughness values are recorded using a MarSurf LD 130 (λ_c = 0.8 mm, lr = 0.8 mm, ln = 4 mm). The shape deviation data is recorded using a Precision Coordinate Measuring Machine of type Leitz PMM 866 at a distance up to 0.25 mm. The alignment of the workpiece geometry to the nominal geometry is based on the best-fit method. A probe ball with a diameter of 3 mm is used to measure the shape deviation. The probing accuracy is about 0.3 µm. According to DIN ISO 1101, the shape deviation is recorded by Chebyshev.
Finally, the last step of data acquisition consists of synchronizing the data streams. This procedure was programmed in MATLAB software (s. Fig. 4). The basis for the material removal simulation is the read-out machine data. Based on the axis positions, the virtual machine axis are moved within the simulation. Parallel to the virtual production of the workpiece, the relevant cutting conditions are calculated. Finally, both the axis positions and the cutting conditions can be exported together from the simulation. Furthermore, the quality data is recorded in a locally resolved manner. Thus, the measuring points are to be defined in the workpiece coordinate system. Based on the axis positions, which are also read out in the workpiece coordinate system, the associated simulation

data can be determined using the least squares method. Consequently, the time t of the process is also known. This is necessary to compare the already filtered force data (low pass filter = 350 Hz) with the synchronized data streams. At time t, the corresponding force value is extracted from the data. $F_{a,max}$ is then calculated as the average value of the $F_{x,max}$ and $F_{y,max}$ values for a full milling tool revolution. After that, a data set is available, which can be used for further investigations.

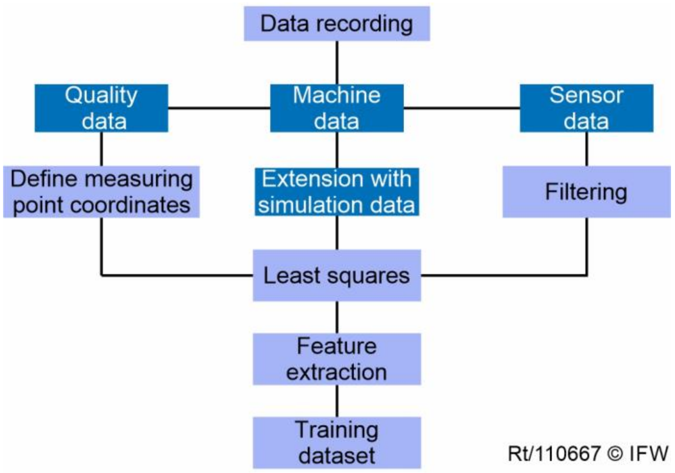

Fig. 4. Approach of data synchronization

4.2. Modeling

First, significance analysis of the data sets is carried out to make a selection of suitable input parameters for the virtual quality inspection (s. Fig. 5). The Pearson coefficient was used as an indicator for the significance of the input parameter A compared to the output parameter B (s. Eq. 1).

$$\rho(A,B) = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{A_i-\mu_A}{\sigma_A}\right)\left(\frac{B_i-\mu_B}{\sigma_B}\right), \qquad (1)$$

where μ_A and σ_A are the mean and standard deviation of A and μ_B and σ_B are the mean and standard deviation of B. A value of 1 shows a perfect positive correlation. A value of 0 represents no correlation.

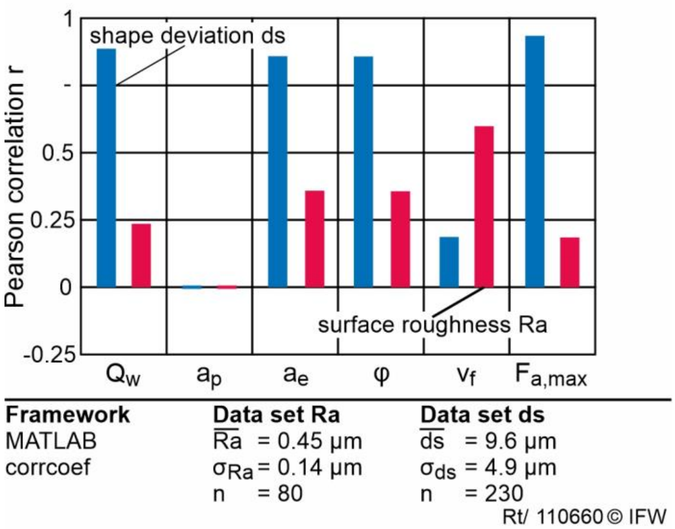

Fig. 5. Significance analysis of the input parameters in relation to the quality target variable

First of all, it should be mentioned that the cutting width a_e has the most significant influence on the material removal rate Q_w due to the selected design of experiment. Therefore, a high relevance of the cutting width a_e and the tool engagement angle φ results in the data sets, which are dependent on each other. Furthermore, the active force $F_{a,max}$ has a high linear dependence on the material removal rate Q_w. The surface roughness Ra, however, depends mainly on the feed rate v_f and the cutting width a_e. Two different data sets were divided for further virtual quality inspection (s. Table 4). Data $set_{m,s}$ initially includes both manufacturing (machine and sensor data) and simulation data. Data set_m, on the other hand, only includes manufacturing data. Thus, the benefit of an additional material removal simulation can be evaluated for the present use case.

Table 4. Relevant simulation variables from IFW CutS

Data set	Feature source	Features
$ds_{m,s}$	Manufacturing and simulation data	$F_{a,max}$, v_f, Q_w, a_e
ds_m	Manufacturing data	$F_{a,max}$, v_f
$Ra_{m,s}$	Manufacturing and simulation data	$F_{a,max}$, v_f, Q_w, φ
Ra_m	Manufacturing data	$F_{a,max}$, v_f

The modeling was done in Python using the library sklearn. Due to the small size of the available data sets, a nested cross-validation was performed. In addition, model building was performed for 30 iterations. Each iteration had a different assignment of training and test data sets (random states). For a better comparability, the mean value as well as the standard deviation of the comparison metrics (e.g. Mean absolute error (MAE)) were formed. In the context of this work, the potential was initially investigated by using machine learning methods in comparison to heuristic regression methods for the present use case. Furthermore, the influence of adding simulation data (material removal rate Q_w and tool engagement angle φ) on the prediction result was investigated. As methods of supervised learning, Support Vector Regression (SVR), Gradient Boosted Trees (GBT), Gaussian Process Regression (GPR) and Decision Tree (DT) were compared. Linear Regression (LR) and Bayesian Ridge Regression (BR) were used for comparison with heuristic methods (grey background in Fig. 6 and 7).

Considering the prediction results of the shape deviation ds in Fig. 6, it is first shown that machine learning methods are suitable for quality prediction. Thus, GPR provides the best prediction result with a MAE of 0.8 µm. Including the standard deviation, a mean absolute percentage error (MAPE) between 8.5 % and 11.5 % can be expected. In contrast, heuristic methods (grey background) show a 40 % higher MAE. On average, this is 1.3 µm. This corresponds to a MAPE of 13.5 %. Furthermore, when examining the prediction results, it can be seen that the modeling uncertainty can also be reduced by using machine learning methods. While the MAE varies by ± 0.22 µm with heuristic methods, the uncertainty with GPR is ± 0.11 µm. Hence, the investigations show that significantly more stable prediction results can be achieved with machine learning methods and thus represent an added value for data-based quality inspection. Additionally, it is noticeable that already by using manufacturing data a reliable quality prediction is made. Thus, the addition of simulation data during flank milling does not lead to an improvement in the prediction quality. These results can be explained by the fact that there is a high linearity between the input variables in the data set. Thus, the material removal rate Q_w, the cutting width a_e, the tool engagement angle φ as well as the active force $F_{a,max}$ have a comparably high linear dependence on the shape deviation ds.

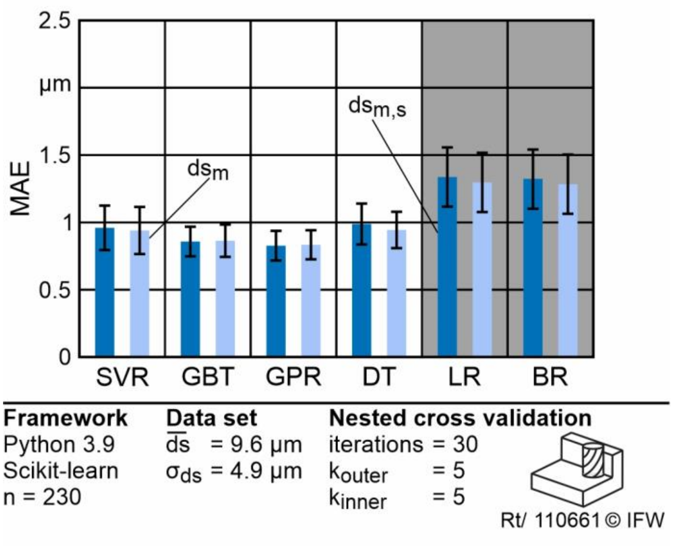

Fig. 6. Prediction results of shape deviation ds

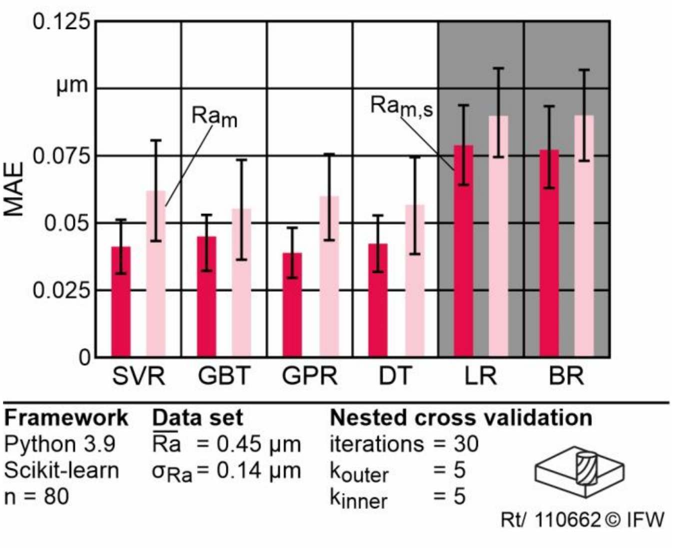

Fig. 7. Prediction results of surface roughness Ra

The results that machine learning methods can significantly increase the prediction quality are also shown in Fig. 7. Compared to heuristic methods (grey), the MAE can be reduced on average from 0.079 µm to 0.039 µm by using GPR, which corresponds to a reduction of almost 50 %. Furthermore, it could be demonstrated among all the models used that the addition of simulation data leads to an increase in the prediction quality when modeling the surface roughness Ra. The largest reduction of the MAE was achieved by using the SVR and the GPR (-34 %). Furthermore, it can be seen that the prediction uncertainty could be reduced by using machine learning methods and the addition of simulation data. The standard deviation of the prediction results could be reduced by 45% when using the SVR. A comparable result could also be obtained by using the GPR and the GBT. Overall, a MAE between 0.03 µm and 0.048 µm can be achieved when predicting the surface roughness Ra, which corresponds to a MAPE between 7.1 % and 11.1 %. Using heuristic methods, a MAE of 0.079 µm (MAPE of 19.7 %) is expected.

Overall, it can be seen that when comparing the prediction quality of ds_m and Ra_m, the prediction of shape deviation ds without simulation data works much more reliably. This can be explained by the fact that there is a large linear dependency between the input and output variables (s. Fig. 5). Accordingly, fewer independent variables are included in the dataset. However, an increase in the influence of the simulation data is expected if more complex geometries are investigated.

5. Inspection plan adaption

Considering the previous results, it has been shown that data-based quality inspection based on machine learning can provide a reliable prediction of workpiece quality. By integrating the trained models, a virtual quality inspection can be performed within the digital twin. Based on the inspection result, the existing part quality can now be visualized by coloring the workpiece depending on the virtual inspection result. The result of the virtual quality inspection always has a certain variance compared to the conventionally measured quality. The adaption of the inspection plan, which is based on the virtual inspection result, therefore considers the uncertainty associated with the prediction. For this purpose, a threshold value t_h has to be defined, which represents the uncertainty of the inspection result. This is then available in an interval (± t_h). Using the example of the shape deviations ds, eqs. 2-4 show the output of the virtual quality inspection.

$$\{ds_t \mid ds_{meas} - t_h \leq ds_t \geq ds_{meas} + t_h\}, \tag{2}$$

$$\{ds_t \mid ds_{meas} - t_h \geq ds_t \leq ds_{meas} + t_h\}, \tag{3}$$

$$\{ds_t \mid ds_{meas} - t_h \leq ds_t \leq ds_{meas} + t_h\}, \tag{4}$$

with the target value ds_t, the actual value ds_{meas} and the threshold value t_h. The target value ds_t contains the nominally required quality specification as well as the permitted tolerance (e.g. ds_t = 15 µm). As an example, one way to define the threshold t_h could be the level of MAPE (e.g. 10 %) of the underlying data set. Consequently, each measurement result ds_{meas} is calculated with 10 % measurement uncertainty. Subsequently, a rule-based adaption of the inspection plan is performed. If the quality target is outside the virtual inspection result, no further classical inspection of the workpiece is performed (s. Fig. 8 a)). The inspection result may be significantly below the specification (e.g. 12 µm ± 1.2 µm, eq. 2) or above the specification (e.g. 18 µm ± 1.8 µm, eq. 3). In both cases, no further inspection is necessary, since it could be safely classified as OK or NOT OK. This reduces the inspection effort defined in the original inspection plan by the inspected characteristics. However, if the quality target is within the result interval (e.g. 14 µm ± 1.4 µm, eq. 4), there is no clear inspection certainty, so another quality inspection is required. In this case, the inspection plan cannot be reduced (s. Fig. 8 b). In this case, a further classical inspection of the feature is necessary.

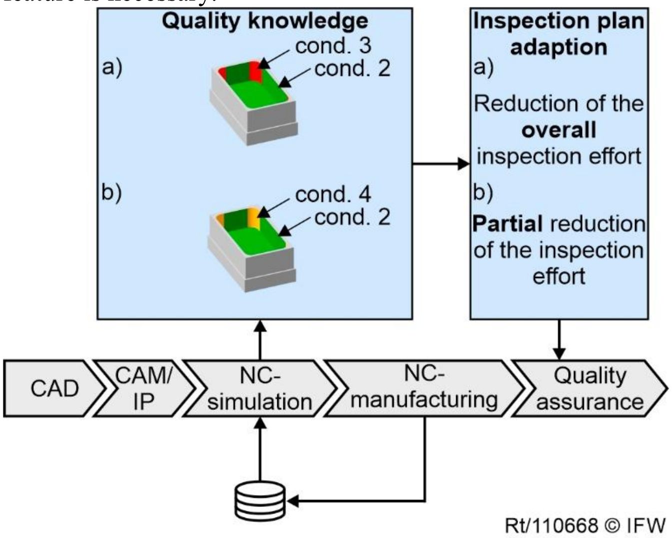

Fig. 8. Inspection plan adaption

As already explained, the duration for geometrical inspection of a sill beam is 4.5 hours. With a 100 % virtual inspection, the time-consuming physical inspection can be reduced to only the necessary measuring points. However, the major part (approx. 75 %) of a sill beam consists of the inspection features presented in this paper (straight flanks as well as surface roughness). Such workpiece features can already be inspected with a high degree of reliability using data-based inspection, so that time-consuming, traditional inspection can be dispensed with. If avoidable inspection efforts of 75 % can be saved, already 3.4 h inspection time per sill beam can be saved.

6. Summary and outlook

This work presented a novel approach of adaptive inspection planning using a digital twin that can reduce manual inspection efforts for geometric measurement of a sill beam by up to 4.5 h. Until now, current IP methods have lacked adaptive procedures to react to possible manufacturing errors at an early stage and reduce inspection efforts. One possibility for the integration of virtual inspection methods lies in the use of data-based machine learning approaches. These have clear advantages over heuristic methods in terms of prediction accuracy. Furthermore, it can be beneficial to expand the knowledge required for data-based prediction with additional simulation variables such as the metal removal rate Q_w or the tool engagement angle φ. However, since every virtual measurement result is subject to a certain degree of uncertainty, a safety factor should be taken into account in order to subsequently reduce avoidable inspection efforts. In the context of this work, this factor was assumed to be constant (e.g. the level of the MAPE). In further work, additional modeling possibilities of uncertainty consideration in the context of adaptive IP will be researched. Furthermore, the investigations for data-based quality prediction will be extended to other workpiece segments, such as the pocket radius. This will lead to an improvement in virtual inspection results and adaptive IP.

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References

[1] DIN Deutsches Institut für Normung e. V. Quality Management Systems – Requirements for Aviation, Space and Defence Organizations. Berlin: Beuth Verlag; 2018
[2] Stjepandic J, Sommer M, Denkena B. DigiTwin: An Approach for Production Process Optimization in a Built Environment. Berlin: Springer; 2022.
[3] Denkena B, Wichmann M, Reuter L. Kostenvorteile durch adaptive Prüfplanung. ZWF 2022;117:178-181.
[4] Hering E, Triemel J, Blank HP. Qualitätsmanagement für Ingenieure. 5th ed. Berlin: Springer; 2003.
[5] Neumann A. Automatische Prüfplangenerierung: Automatisierungs-konzept, beispielhaft realisiert für eine Bearbeitungstechnologie, das Drehen. Dr.-Ing. Diss. Darmstadt; 1992.
[6] Effenkammer D. Entwicklung einer durchgängigen CAD-basierten Prozesskette für die Qualitätsprüfung mit Koordinatenmesstechnik. Dr.-Ing. Diss. Aachsen; 2002.
[7] Janovsky P. Systematik für eine CAD-basierte Prüfplanung und deren praktische Umsetzung. Dr-Ing. Diss. Aachen; 2003.
[8] Hwang I, Hongchul H, Ha S. Hybrid neuro-fuzzy approach to the generation of measuring points for knowledge-based IP. Int J Prod Res 2002; 40: 2507-2520.
[9] Ahmed MB, Majeed F, Sanin C, Szczerbicki E. Experience-Based Product IP for Industry 4.0. Cybern Syst 2021;52: 296-312.
[10] Ascione R, Moroni, G, Petrò S, Romano D. Adaptive inspection in coordinate metrology based onkriging models. Precis Eng 2013; 37: 44-60.
[11] Brecher C, Ochel J, Lohrmann V, Fey, M. Merkmalsbasierte Qualitätsprädiktion durch maschinelles Lernen. ZWF 2019; 114: 784-787.
[12] Brecher C, Ochel J, Lohrmann V, Frey M. Maschinelles Lernen zur Prädiktion der Bauteilqualität. Erweiterung eines Ansatzes zur merkmalsbasierten Qualitätsprädiktion durch künstliche neuronale Netze. ZWF 2020;115: 834-837.
[13] Königs M, Brecher C. Process-parallel virtual quality evaluation for metal cutting in series production. Procedia Manuf 2018; 26:1087-1093.
[14] Khorasani, AM, Yazdi MRS. Development of a dynamic surface roughness monitoring system based on atrificial neural networks (ANN) in milling operation. Int J Adv Manuf Technol 2017; 93: 141-151.
[15] Vasanth, XA, Paul PS, Varadarajan, AS. A nerual netowrk model to predict surface roughness during turning of hardened SS410 steel. Int J Syst Assur Eng Manag 2020;11: 704-715.[
[16] Kant G, Sangwan, KS. Predictive Modelling and Opimization of Machining Parameters to Minimize Surface Roughness using artificial Neural Network Coupled with Genetic Algorithm. Procedia CIRP 2015; 31: 453-458.
[17] Denkena B, Dittrich MA, Lindauer M, Mainka J, Stürenburg L. Using AutoML to Optimize Shape Error Prediction in Milling Processes. Proceedings of the Machining Innovations Conference 2020: 160-165.
[18] Denkena B, Böß, V. Technological NC Simulation for Grinding and Cutting Processes Using CutS. In: Arrazola PJ, editor. Proceedings of the 12th CIRP Conference on Modelling of Machining Operations: May 7-8, 2009, Donostia-San Sebastián, Spain. Arrasate-Mondragón, Gipuzkoa: Mondragon Unibertsitateko; 2009, 563–566.