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Quality Monitoring Of Coupled Digital Twins For Multistep Process Chains Using Bayesian Networks

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Abstract

The digital representation of physical assets and process steps by digital twins is key to address pressuring challenges like adaptive manufacturing or customised production. Recent breakthroughs in the field of digital twins and Edge-based AI already enable digital optimization of individual process steps. However, high-value goods typically include multiple step process chains including a broad range from generative and additive processes over several steps of material removal up to assembly. Therefore, a digital twin over the holistic process chain is necessary. While even the set-up of representative twins for a single step is already challenging, a concept for monitoring of the interaction and overall quality control of holistic process chains does not exist yet. The paper introduces a machine-learning method based on probabilistic Bayesian networks to monitor the »digital twin quality« of coupled digital twins which includes several sub-instances of digital twins. The approach identifies the contribution of each instance to the overall prediction quality. Furthermore, it is possible to give a range-estimation for the prediction accuracy of the individual sub-instances. It is therefore possible to identify the most influential sub-instances of digital twins as well as their individual prediction quality. With the help of this information, the quality of the digital twin can be improved by considering individual sub-instances in a targeted manner. Finally, a preview emphasises the potential benefits of the quantum computing technology when dealing with parallel computation of large-scale inference models.

Keywords

Digital twin; Process chain model; Digitalisation; Machine Learning; Bayesian Networks; Quantum Computing

1. Introduction

In manufacturing, production processes generally consist of various production steps. The aim of each single step is to perform an ideal processing after specification of a certain target geometry. Naturally, the practical implementation of a step does not conform the theoretical ideal and shows deviations from the target shape. An important issue is how these deviations of a specific step transmit and affect the quality of succeeding dependent steps within the production chain, including interdependencies between multiple steps [1]. The same applies for digital twins, digital representatives providing all relevant information via a uniform interface, of single production steps: A model of such a specific subsystem is subject to individual uncertainties. Furthermore, the digital coupling of sub-models causes additional uncertainties, which are often non-transparent. To enable a qualitative digital twin over the holistic process chain, it is therefore of great importance to identify the quality of each sub-instance of the holistic digital twin as well as the degree of dependencies between coupled sub-instances. With the help of this information, the strength of the impact that single sub-models have on the holistic digital twin's quality can be estimated. For a probabilistic modelling of the quality of single determining factors and their dependencies on each other, Bayesian networks have proved as an appropriate methodology to reproduce such characteristics of a system [2]. Individual factors can be evaluated by the probability of positive outcomes, e.g. holding a tolerance value as to the target geometry, whereas the impacts on dependent factors are represented by conditional probabilities [3].

After providing an overview of various applications, we classify Bayesian network into the context of manufacturing and refer to some related approaches with Bayesian network in this field of application. A technical chapter then introduces the concept of Bayesian networks in more detail and shows how they can identify and estimate the degree of dependencies. Afterwards, we apply this methodology to a real-world manufacturing setup. We use a single digital twin of a milling process in order to access available real machining data for demonstration purposes, which is directly transmissible to the aspired field of multi-step process interdependencies. Finally, we briefly introduce the concept of quantum computing and depict the potential benefits of this computing technology when working with large-scale Bayesian networks.

2. Related work

Bayesian networks, initially introduced by [3] in 1988, have a broad range of applications in various fields of research as well as industrial settings in the context of modelling uncertainty, risk analysis, decision-making processes and error detection [1,4] covering amongst others the application fields of medicine and healthcare [4] as well as finance [5], supply chain management [6] and predictive maintenance [7]. Furthermore, the usage of Bayesian networks has a significant benefit over other Machine learning methods in relation to the required database since this methodology does not explicitly require massively large-scale datasets and can extract accurate and meaningful statements based on limited data [4]. In manufacturing, it is highly challenging to detect the causes of deviations due to heterogeneous data structures and impacts. Particularly this problem is well resolvable using Bayesian networks.

In this context, Bayesian networks are used as a data analytics tool to reduce system faults as they proofed to predict which components of anonymised measurements in manufacturing datasets will fail at the final stage of the production process [8]. Another use case of this methodology is the improvement of quality consistency in assembly processes where the key is to construct a raw network structure that shows the causal relationships and influence factors on quality consistency, exemplary demonstrated for a diesel engine production line [9]. Aside, [10] considers a general quantification of uncertainty in manufacturing processes focussing on the caused energy consumption as a key factor of sustainability performance. In [11] the technique of inverse inference in manufacturing process chains is demonstrated using a Bayesian network to adjust process configurations in order to achieve certain desired properties, also known as inverse analysis.

In recent times, methods of Bayesian optimization are used in manufacturing background to regulate black box models and to proceed hyperparameter optimization [12,13]. Here we strongly want to distinguish the approach of using Bayesian networks from these considerations.

3. Methodology of Bayesian networks for quality monitoring of digital twins

A Bayesian network is a directed acyclic graph whose nodes represent the influencing factors as random variables and whose edges model the dependencies between the factors, directing from the decisive to the dependent factor. The independent variables of the system hold a probability distribution each which indicate the likelihood of different possible status. The dependent nodes are equipped with conditional probability tables in case of using discrete variables. When dealing with continuous variables, the nodes are mostly assumed as normal random variables. To model connections between multiple nodes, the parameters of the Gaussian distribution representing a child node are dependent on the value of its parents [3]. Since our considerations focus on the strength of influence estimation of certain factors based on different pre-defined status, we motivate the usage of discrete nodes. Of course, if we would focus on representing the very physical process of a specific application with a Bayesian network, the required discretisation of factors having a continuous domain causes approximation errors. Here we want to clarify that this specific task differs from the paper's intention of depicting a quality monitoring framework to handle multiple related digital twins, which may represent different physical processes.

In the application of coupled digital twins, Figure 1 gives an example with various sub-instances of the holistic twin showing probabilities of holding a tolerance value, which influences the quality of the combined modelling. For simplification, the variables are assumed to be binary with the probability of $\boldsymbol{P}(+)$ to fulfil a given tolerance criteria for the modelling quality and a probability of $\boldsymbol{P}(-)$ to violate this criteria. As an example, a deviation from a target position with respect to a certain axis can be considered.

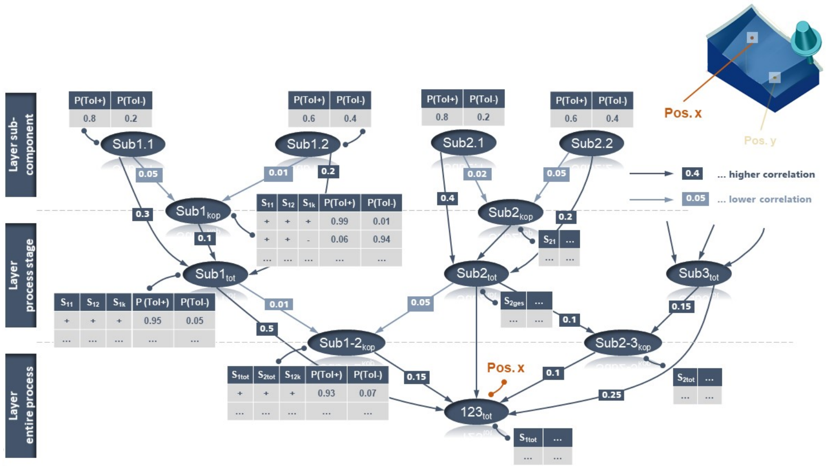

Figure 1: Exemplary Bayesian network for coupled digital twins considering multiple process layers

3.1 Why using Bayesian networks

For the tasks of influence evaluation, deviation analysis and quality improvement of specific machining processes various statistical and ML-based approaches have been proposed. These methods mostly focus on regression and classification models [14], fault tree analysis [15] as well as design of experiment techniques [16]. Often, an advanced adjustment to the considered physical process is required to set up empirical formulas. Bayesian networks allow to make statements on dependencies, strengths of influences and quality without the need of such investigations and enable a comparison between multiple manufacturing processes, which possibly are subject to different physical processes. For such purposes, Bayesian networks especially can cope with highly transient as well as non-linear processes and offer to

- Lean on a limited basis of information,
- Work with uncertain or incomplete data,
- Evaluate the inherent structure of influences,
- Rate the certainty.

Bayesian networks can be build up in three different manners. One way is to use expert knowledge only to construct the network structure, i.e. the dependencies between factors, and define its parameters, namely the (conditional) probabilities of each node. Another approach is to deploy pure datasets without any additional information and learn the network structure as well as the parameters by applying estimation procedures. In between these two ways there is also a hybrid approach using both data and knowledge, which will arise as the appropriate strategy for this paper's application scenario presented in section 4.

3.2 Structure and parameter learning

If the dependencies of the process properties are not specified by domain knowledge, the network structure is learnable either via constraint- or score-based methods. The first set of algorithms use conditional independence test to find the dependencies whereas the score-based approaches produce a series of candidate networks and rank them with correspondent scores [3,17]. Besides, there are hybrid methods like the widely used hill climbing algorithms.

Since the structural dependencies are already defined in the application setup of coupled digital twins (from sub-instances of the holistic twin to coupled models), the key focus is on how to evaluate the degree of these dependencies and to estimate the overall prediction quality. Formally speaking, a Bayesian network with nodes $\boldsymbol{\mathcal{X}} = \{\boldsymbol{X_1}, \dots, \boldsymbol{X_m}\}$ reflects a unique joint probability distribution $\boldsymbol{\mathcal{P}(\mathcal{X})}$ given by the product of all conditional probability tables

$$\mathcal{P}(\mathcal{X}) = \prod_{i=1}^{m} \mathcal{P}\big(X_i \big| \mathrm{Pa}(X_i)\big) \tag{1}$$

where $\mathrm{Pa}(\boldsymbol{X_i})$ depicts the parent nodes of $\boldsymbol{X_i}$, i.e. the variables $\boldsymbol{X_i}$ is dependent on. The conditional probabilities are represented as parameters $\boldsymbol{\theta_{ijk}} = \boldsymbol{\mathcal{P}}(\boldsymbol{X_i} = \boldsymbol{k}|\mathrm{Pa}(\boldsymbol{X_i}) = \boldsymbol{j}), \boldsymbol{1} \leq \boldsymbol{k} \leq \boldsymbol{s_i}, \boldsymbol{1} \leq \boldsymbol{j} \leq \boldsymbol{p_i}$ with $\boldsymbol{s_i}$ specifying the number of states of $\boldsymbol{X_i}$ and $\boldsymbol{p_i}$ the one of its parent nodes. Given a dataset (set of $\boldsymbol{n} \in \mathbb{N}$ samples) $\boldsymbol{\mathcal{D}} = \{\boldsymbol{D_1}, \dots, \boldsymbol{D_n}\}$, we are searching the parameters $\boldsymbol{\theta} = \{\boldsymbol{\theta_{\mathrm{ijk}}}\}$ of the network's conditional probabilities such that samples taken from the Bayesian network with parameters $\boldsymbol{\theta}$ match the data $\boldsymbol{\mathcal{D}}$ best.

The typical principle is to perform maximum likelihood estimation (MLE), i.e. to search for the parameters $\boldsymbol{\theta}$ which have most likely produced the dataset $\boldsymbol{\mathcal{D}}$. A commonly used learning method, which is based on MLE, is the expectation maximization (EM) algorithm. This approach can also cope with incomplete data and iteratively proceeds an expectation- and a maximisation step until convergence. Starting with an initial estimate $\boldsymbol{\theta^0}$ (e.g. a uniform distribution), the former completes the dataset based on the current estimate whereas the latter re-estimates the parameters $\boldsymbol{\theta^t} \rightarrow \boldsymbol{\theta^{t+1}}$ via MLE.

3.3 Inference and strength of influence

After having learned the parameters θ, the Bayesian network offers a compact representation of the conditional probabilities for all influence factors. With the help of the network as a probabilistic reasoning system, the change of each factor's likelihood can be observed if the values of some variables are given. Proceeding inference estimates the updated likelihoods of all dependent characteristics, for instance the quality of the combined modelling in Figure 1. For our consideration of studying the effect that various sub-instances exert on the holistic quality, causal and inter-causal types of inference can be applied.

Inference enables an approach to measure the strength of influence for each node in the Bayesian network based on the conditional probability distributions. In principle, the strength of influence a parent node $X_{par} \in \mathcal{X}$ exerts on a child node $X_{child} \in \mathcal{X}$ is specified by the change in probabilities of X_{child} in case of given evidence for X_{par} compared to the case of no evidence for the parent. In doing so, we assume X_{par} to adopt each possible status individually and measure the particular change in the child's probabilities using a Euclidean distance for probability distributions. Each of these distances is weighted by the likelihood of X_{par} to assume the respective status. The strength of influence a parent node X_{par} has on a child X_{child} thus calculates as

$$I_{X_{par}}(X_{child}) = \frac{1}{\sqrt{2}} \cdot \sum_{j=1}^{s_{par}} \mathcal{P}(X_{par} = j) \sqrt{\sum_{i=1}^{s_{child}} \Big(\big[\mathcal{P}(X_{child} \big| X_{par} = j)\big]_i - [\mathcal{P}(X_{child})]_i \Big)^2} \tag{2}$$

where s_{par} denotes the number of status the factor X_{par} can adapt and s_{child} the number of status for X_{child}, respectively. With $[\mathcal{P}(\cdot)]_i$ indicating the i-th component of a discrete probability distribution, the square root term represents the Euclidean distance of $\mathcal{P}(X_{child})$ and $\mathcal{P}(X_{child}\big|X_{par}\big)$. Furthermore, a normalisation factor in (2) ensures $I_{X_{par}}(X_{child}) \in [0,1]$. Higher values of $I_{X_{par}}(X_{child})$ indicate stronger influences of parent nodes on their children.

4. Practical application

For the evaluation of the presented method, the data of a digital twin of a 3-axis milling operation is used as an example. The generation of these digital twins is described in detail in [18] and provides the data basis for the following method. These digital twins contain all relevant meta and process data acquired during the machining process. The process data includes all measurement and control signals of the machine tool and any additional sensor information that can be determined via additional measurement technology. Specifically, these are the nominal/actual positions, the drive currents, and the nominal/actual speed information of the axes and spindles. All this information is linked to the meta information (tool data, technology data, material data and machine data) [19]. These provide the basis for subsequently integrating technological calculation models (tool engagement models, kinematic models, surface location error models etc.) and thereby generating a digital twin across the complete process chain. In this way, all location- and time-discrete technological information of the tool-workpiece interaction can be calculated and its effect on the produced component can be determined. With the help of Bayesian networks, the factors influencing the position deviations ($\Delta_x, \Delta_y, \Delta_z$) of the TCP are to be determined as a function of the axis-specific jerk ($\boldsymbol{j_x}$, $\boldsymbol{j_y}, \boldsymbol{j_z}$), the spindle load ($\boldsymbol{L_S}$), the axis-specific drive currents ($\boldsymbol{I_x}, \boldsymbol{I_y}, \boldsymbol{I_z}$) and the cutting forces according to the Kienzle cutting force model

$$F_c(\varphi) = k_{c1,1} b h_{(\varphi)}{}^{1-m_c} \tag{3}$$

for the respective milling operations [20]. To determine the cutting forces $\boldsymbol{F_c(\varphi)}$, in addition to the cutting force constants ($\boldsymbol{k_{c1.1}}$,$\boldsymbol{m_c}$), the tool engagement parameters ($\boldsymbol{b}$, $\boldsymbol{h_\varphi}$) must also be determined, which cannot be derived from the pure axis position data of the machine. For this purpose, a material removal simulation (based on a multi-dexel model) based on the actual position of the TCP must be used to determine the time- and location-discrete entry angle $\boldsymbol{\varphi_{in}}$ and exit angle $\boldsymbol{\varphi_{out}}$ together with the chip width of the undeformed chip $\boldsymbol{b}$. For the subsequent calculation of the mean undeformed chip thickness $\boldsymbol{h_m}$ from

$$h_m = \frac{1}{\varphi_c} \cdot \int_{\varphi_{in}}^{\varphi_{out}} h_{(\varphi)} d\varphi = \frac{1}{\varphi_c} \cdot f_z \cdot \sin\kappa\,(\cos\varphi_{in} - \cos\varphi_{out}), \tag{4}$$

the tooth feed $\boldsymbol{f_z}$ must also be calculated. Using the time stamp of the individual tool positions, the feed per tooth $\boldsymbol{f_z}$, can be calculated by numerically differentiating the actual positions in $\boldsymbol{x}$-, $\boldsymbol{y}$- and $\boldsymbol{z}$-directions and using the corresponding actual spindle speed. The calculation of the mean cutting forces $\boldsymbol{\overline{F}_c}$ is specified in [21].

As test machine, a WEMAS VZ-1250 Quick with a HEIDENHAIN TNC620 control was selected. An aerospace component was manufactured on this test machine, for which four successive manufacturing steps are described here as examples (see Figure 2). For all manufacturing steps, the relevant process data is measured with a sampling rate of 2 ms. The exact process for acquiring process data is described in [18]. In the first process step (*face milling operation – T25*), the raw material is face milled, for which the feed movement mainly takes place in the x-direction. In the following processing step (*drilling operation – T26*), a drilling operation takes place, where the main feed movement is in the z-direction. In the subsequent contour milling (*contour milling operation - T27*) and finishing (*end milling operation – T28*), no main feed movement direction can be identified, which is why the determination of the factors influencing the position deviations is particularly relevant for these machining operations.

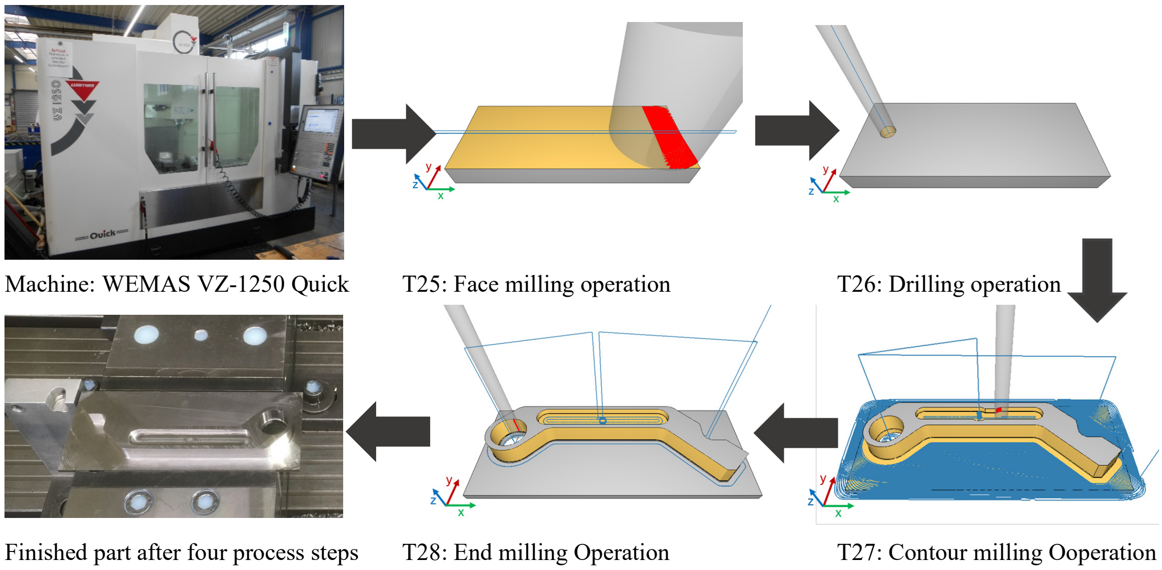

Figure 2: Application scenario using the example of a milling operation

4.1 Network structure and data preparation

Based on expert knowledge, the structure of the Bayesian network is constructed of three layers. The upper layer contains the jerk values of the x-, y- and z-axis and the mean cutting force. It is intended to evaluate the influence of these values on the total positional deviation and the axial deviations. Since preliminary computations show the axial deviations are influential dominated mainly by the jerk on the same axis, these axial deviations are equipped with only a single parent node in order to simplify the network structure. Differences in the strength of influence with respect to the axial jerks are considered on the total deviation. The same procedure applies for the positional deviations in the second layer whose influence on the nominal amperages in the bottom layer are examined. To also include a more global approach of estimating influence, the spindle load is included into the bottom layer and is seen as a consequence of the positional axial deviations. Figure 3 summarises the structure of the constructed Bayesian network. Alongside, other network structures may be considered and compared against each other.

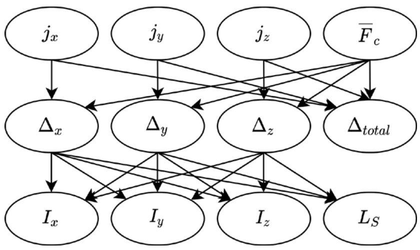

Figure 3: Structure of the Bayesian network

For each part process the recorded data of the presented factors are assembled in a csv-file. A record of factor values belonging to a certain instant of time produce a sample for the parameter learning, i.e. we use each instant of time as an observation. Due to all the factors are on hand as continuous variables, a pre-processing is required to discretise the data. We subdivide the individual factors into three classes. The smallest 10% of values are classified as »small« whereas the largest 10% of values are considered as »large«. The remaining part is squeezed in the group »medium«. This choice is motivated on the one hand to ensure that each combination of the variables' discrete values holds sufficient data records and on the other hand to depict the effects of lighting particular small respectively large measurements of certain influential variables. The nominal amperage streams of data ι_{nom} are primarily smoothed via a running average and centred corresponding to

$$\iota = \left|\iota_{nom} - \iota_{nom}^{smoothed}\right| \tag{5}$$

where furthermore only the absolute amperage values are considered due to the applied discretisation criterion. The latter also deploys on the jerk values. The cutting force is sampled in lower frequency than other measures. Hence, the interim values are interpolated using cubic C^2-splines.

4.2 Learning process and influence evaluation

To handle the Bayesian networks, we use the R-package »bnlearn« as well as the software »GeNIe«. The parameters of the network are learned with the EM-algorithm, which in our case corresponds to the MLE-method using an initial estimate since the considered machining process provides a complete and extensive dataset. Having learned the parameters in the form of the conditional probability tables, we examine the strengths of influence for each node (parent-child-relation) as described in section 3. Figure 4 illustrates the strength of influence calculation by considering changes in the child's probabilities, if evidence on the parent is added, and the comparison of multiple influential variables on a common child node.

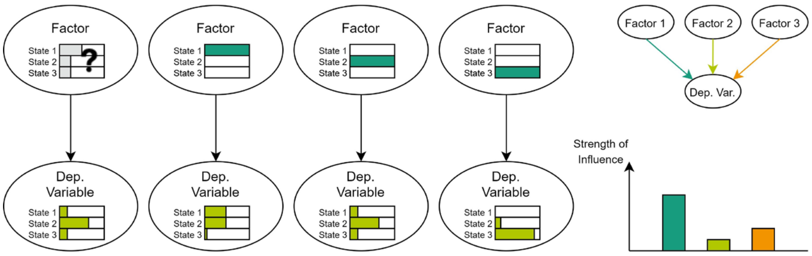

Figure 4: Visualisation of the influence evaluation using (2) and comparison for multiple influencing factors of a common depended variable to identify the dominating factor

An approach to present such single-edge influences combined with the network structure is to watch the strengths of influence as weights to the edges. Thus, we get a global comparison of all degrees of influence and at the same time as local contrasts in relation to a certain node and its parents. To illustrate how to evaluate the dominating influence factors of a specific measure, we exemplary consider the effects of the axial jerks and the cutting force on the total deviation and furthermore the influence of the axial deviations on the spindle load.

4.3 Process characteristics and results of influence analysis

The holistic application is analysed by a group of experts and the characteristics of each single operation (T25 - T28) are exposed for a comparison with and justification of the findings of the presented approach. The face milling operation (T25) is characterised by uniform motion, which leads to small differences in the influence strengths of axial jerks. Slight influences of the jerk of the z-axis result from the approach movements, whereby the approach movement was realised at high speeds (rapid traverse). The axis determining the feed direction compensates for the main influence on the workload of the spindle. The face milling operation exhibits the x-axis whereas the drilling operation (T26) shows the z-axis as the determining one. Furthermore, T26 does not show noteworthy changes in velocity. Together with the just punctual processing of the drilling operation, this results in few influence of the axial jerks on the total deviation. In contrast, we see in the contour milling operation (T27) and end milling operation (T28) comparatively rapid changes in machining velocity and direction, which strengthen the influence of the cutting force. Although the end milling operation (T28) holds smaller forces compared to the contour milling operation (T27), but particularly high axis speeds (finishing operation). Both the contour and end milling process exhibit the x-y-plane as the cutting plane that therefore provides the feed force direction. Hence, the deviations of the corresponding axes should represent the most important influence factors. The same applies for the nominal amperages.

The appertaining strengths of influences for the factors deviation, calculated using (2) with the presented approach, are depicted in Figures 5 and 6.

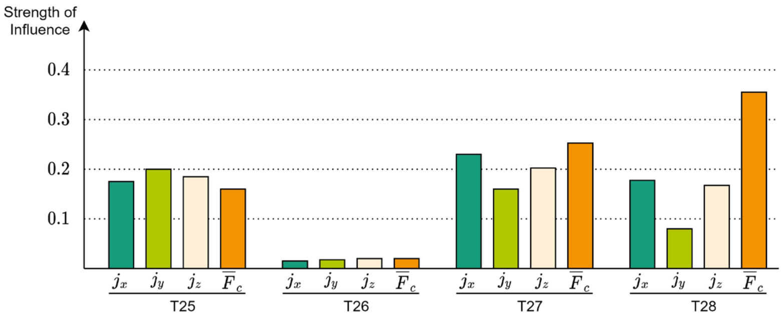

Figure 6: Strength of influence evaluation for axial jerks and Kienzle cutting force on the total deviation Δ_{total} for each process step individually

Figure 5 predicates few differences in the influence strengths for the face milling operation (T25) and drilling operation (T26), which confirms the smooth and regular movement characteristics of both processes. Due to the small-area processing in the drilling operation (T26), the influence strengths of the factors in this operation are particularly small. In contrast, we recognise a significant influence of the cutting force during the contour milling operation (T27) and end milling operation (T28) due to permanent changes in machining velocity and direction. Because of these characteristics, the comparison of the jerks is especially interesting. Thereby, the influence of the jerks of the x- and z-axis dominate the jerk of the y-axis. It has to be considered that the z-direction is considerably influenced by rapid traverse return strokes which do not influence the surface quality. Therefore, we conclude for this application, the greater the speeds, the more dominant the influence of the process-related factors (i.e. the cutting forces) are.

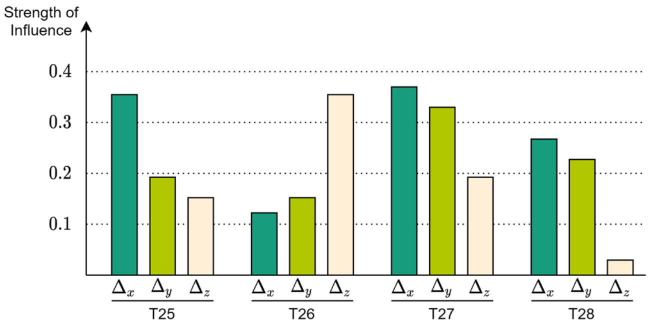

Figure 5: Strength of influence evaluation for axial deviations on the workload of the spindle L_S

Considering Figure 6, the face milling operation (T25) and drilling operation (T26) reflect that the highest estimated influence strengths on the spindle load belong to the axes corresponding to the feed direction. For contour milling operation (T27) and end milling operation (T28) we can identify the deviations of the x- and y-axis as the mainly impacting factors of the workload. With regard to the nominal amperages, the deviations of the x-axis affect the amperages most for the face milling operation (T25), whereas the contour milling operation (T27) and end milling operation (T28) point out the x- and y-axes as the dominating influencing factors, which covers the assessments by the group of experts.

5. Quantum computing and Bayesian networks

Both forward and inverse inference require a high computational effort in Bayesian networks including a large number of nodes. A method to handle such large-scale networks as well as to consider multiple structuring approaches in parallel consists in the technology of quantum computing, which is based on the usage of quantum bits (so called »qubits«). One decisive principle of qubits is superposition, i.e. the capability of qubits to be in the »classical« states of a bit 0 and 1 simultaneously. This characteristic forms the basis to represent the nodes together with their parameters as qubits. The superposition states of a qubit $|\boldsymbol{\psi}\rangle$ are denoted as $|\boldsymbol{\psi}\rangle = \boldsymbol{\alpha}|\mathbf{0}\rangle + \boldsymbol{\beta}|\mathbf{1}\rangle$, where in quantum computing the classical basis states 0 and 1 are represented in Dirac notation. The complex coefficients $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ specify the probabilities of the qubits to segue into a basis state when being measured with $\mathcal{P}(|\psi\rangle = |0\rangle) = |\alpha|^2$ and $\mathcal{P}(|\psi\rangle = |1\rangle) = |\beta|^2$ at what the coefficients of a superposition have to hold $|\alpha|^2 = |\beta|^2 = 1$.

To model a Bayesian network as a quantum circuit, each node is assigned to one or multiple qubits, depending on the number of discrete states the corresponding variable can be in. More precisely, $\lceil \log_2(n) \rceil$ qubits are required to map the n different discrete states of a random variable. The encoding of the probabilities to the parameters is done via rotational gates $R_y(\Phi)$ (for nodes that are not dependent on other factors) and m-times controlled rotational gates $C^m R_y(\Phi)$ [22]. The rotation angles Φ are determined by the parameters of the respective node in the Bayesian network. The second important principle of quantum computing, entanglement, enables to set the dependencies between multiple factors. The corresponding qubits are entangled via the controlled rotational gates, where m corresponds to the number of parent nodes. The assembling of the Bayesian network is sometimes also referred to as qsample encoding [23].

Since in the presented milling process each node holds three states, two qubit are required to encode a factor. Once the network is encoded, we can set evidence via resetting of qubits (analogous to the procedure of Figure 4) and entangle them with ancillary qubits to encode the changed probability distribution of the child node. Then, the change in probabilities is measured via a swap test, which is a procedure of determining how much the states of two quantum registers differ. As the probability distributions are now directly encoded in particular quantum states, the swap test delivers the strengths of influence estimations via (2). The swap test provides a measurement parameter that is positively correlated to the actual distance. Such parameters are calculated as the inner product between normalised vectors, which consist in the qubits' superposition states.

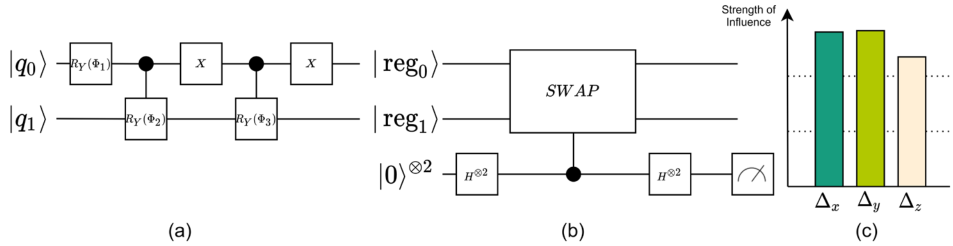

Figure 7: Parameter encoding for a node via rotation angles (a) and measurement of changes in probabilities via swap test (b) as two essential blocks of the quantum circuit, the results for influence estimation on spindle load for T27 (c)

In Figure 7, the parameter encoding in two qubits is shown for a 3-state node. Furthermore, the adequate swap test takes two quantum registers of two qubits each and delivers the result by measuring an ancillary register of corresponding size. To demonstrate the merely capability of the presented quantum algorithm, we implemented this approach on the IBM quantum systems including a quantum simulator with low error rates as well as real quantum hardware. We exemplary evaluated the setup of Figure 6 on the spindle load by the quantum simulator. As an extract, the results for the contour milling (T27) are included in Figure 7, also showing the x- and y-axis as the dominating influence factors.

Besides the advantage in storage, quantum computing offers a potentially quadratically improved runtime performance over conventional computing methods when it comes to inference, which is a subroutine to estimate the strengths of influence. This advantage is gained using a quantum version of rejection sampling as an approximative inference algorithm. The quantum method and its quadratic speedup is thereby based on the technique of amplitude amplification: Starting with a superposition of all possible solutions, the probability amplitude of the correct solution is reinforced gradually with a simultaneous decrease of the other amplitudes. At the end of this procedure, the true solution is given with very high probability.

6. Conclusion and Outlook

This article described how the characteristics of machining processes can be represented as Bayesian networks. After having formalised the measurement to evaluate strengths of influence, we demonstrated the applicability of this approach using a digital twin of a milling operation. In order to utilise available real data of a machining process, we focussed the practical application on a single digital twin, but the presented methodology is directly transmissible to the context of coupled digital twins. The results of the presented approach reflected, on the one hand, the findings on the characteristics of the considered machining process, which underlines the applicability in a correct manner. On the other hand, additional evidence like an increased influence of the process-related factors at higher speeds was obtained. Moreover, the functionality of Bayesian networks and influence estimation is integrated in the context of quantum computing and the consequent potential advantages are depicted. Our current and future research directions are to develop an application to a holistic process chain and domains of different interrelated manufacturing processes along the value chain, and to develop broader quantum circuits capable of covering more complex application scenarios by combining Bayesian network construction and influence estimation in a single quantum algorithm.

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