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Dynamic Pricing Model for Batch-Specific Tolerance Allocation in Collaborative Production Networks

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Abstract

In high-tech production, non-conforming products can result from an unfavorable combination of components, even if the individual components are within specification. Quality control strategies aiming to prevent said combinations such as selective assembly, adaptive manufacturing, or tolerance allocation haven't been applied across company borders yet due to the lack of incentives to share data and adapt parameters. The article presents a pricing model to incentivize batch-specific tolerancing of supplier parts. We use Taguchi's loss function to quantify the expected quality costs based on the resulting distribution of the product's predicted functional deviation after assembling varying batches of matching components.

Keywords: Quality Assurance; Tolerance Allocation; Supply Chain Collaboration; Selective Assembly; High-Precision Products; Global Production Networks

1. Introduction

Growing competitive requirements in the industry and increasing quality expectations of customers demand innovative solutions that increase the value-added share in the production of high-precision products [1–3]. However, in high-tech production, even when all geometrical specifications are maintained, the production of non-functional end products is possible due to unfavorable combinations of components [1,4–6]. In addition, continuing cost pressure and sustainability requirements are demanding companies to efficiently utilize components that are produced close to the technological manufacturing limit. [1,5,6]

To meet these challenges, quality control strategies such as selective assembly or adaptive manufacturing are used [1,5]. Quality control strategies enable the production of high-precision products from less precise components by shifting technological complexity into production control [5]. To guarantee high product quality and to account for correlation and specification uncertainty, quality control strategies often aim at the product's function directly instead of focussing on geometrical specifications [5,7,8]. They are therefore called function-oriented quality control strategies. In order to apply such a control strategy within production, a functional model is necessary that predicts the functional deviation of the end product based on measured features of the assembled components. [5,9,10]

However, those quality control strategies are most often only used within factory boundaries, as no measurement data is usually being shared between partners of the supply chain [6,11]. Nevertheless, cross company quality control would be beneficial for all partners, since tolerances for the supplied components could be widened while improving the quality of the end product at the same time [6,11–13].

Therefore, the goal of this study is to develop a method to evaluate varying batches of high-precision components based

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on their predicted impact on the end product's functional deviation and the resulting predicted quality costs. By knowing the financial impact of a batch of supplied components, the method provides a willingness to pay for specific supplier batches to improve the overall quality. Based on this, incentives can be derived that enable a batch-specific definition of tolerances for supplier parts which paves the way towards a tolerance-free, function-oriented series production.

The study is presented as follows: The next section presents foundations on function-oriented quality control and introduces the novel quality control strategy of batch-specific tolerance allocation. In section 3 the state of the art regarding the quantification of quality costs in quality control strategies and tolerancing is discussed. Afterwards, the pricing model for batch-specific tolerance allocation is introduced in section 4. Subsequently, the article is summarized and further research is discussed in the concluding section.

2. Function-Oriented Quality Control Strategies and Batch-Specific Tolerance Allocation

As stated before, function-oriented quality control strategies are a way to enable the production of high-precision products such as dental instruments, precision gear boxes, or injectors from lower precise components [1,3–5,14]. The most known control strategy is *selective assembly*. Here, components are sorted into classes (also called groups) based on their measured features or their influence on the functional deviation. The classes of compensating components are then allocated respectively to reduce functional deviation and quality costs of the resulting product. Additionally, many more different quality strategies exist (see Figure 1). [5,6,15]

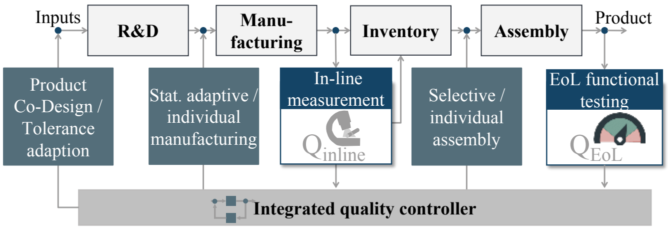

Figure 1 Overview of different function-oriented quality control strategies within factory borders illustrated as different quality control loops [4–6]

In assembly, the pairing of components can also be done individually to find the best fitting counterpart based on the components' measurement data (*individual assembly*). In the manufacturing of the components, parameters can be adapted either individually to produce the best fitting counterpart (*individual manufacturing*) or by shifting nominal values to produce compensating batches or reproduce specific classes for selective assembly (*statistically adaptive manufacturing*). By means of product co-design, even *tolerances* can be *widened* by implementing quality control strategies that are able to compensate for low precision components. A broad overview of the state of the art of function-oriented quality control strategies within factory borders is given in [4], [5], and [6].

Silbernagel et al. [6] introduce a novel logistical quality control strategy, called batch allocation, that can be combined with existing strategies. The idea is to match varying batches of the components to be joined before they enter assembly based on the components' batch-specific distribution of functional deviations. So, the assembly is provided with the best distributions available to compensate opposing effects.

Based on this strategy, *batch-specific tolerance allocation* will become possible. In the context of this work, batch-specific tolerance allocation is defined as the individual definition of a component's functional (and therefore geometrical) tolerances for a specific batch based on the distribution of the functional deviation of the counterpart's corresponding batch (cf. [12,16]). In contrast to this, tolerance widening (or tolerance adaption) as introduced before by means of product co-design is understood as a general, long-term definition of tolerances.

So, batch-specific tolerance allocation is the real time batch-specific definition of a component's tolerances, given the batch-specific distribution of the functional deviation of a matching component. Although, this strategy is similar to statistically adaptive manufacturing, it doesn't need to specify which nominal value has to be shifted and whether nominal values have to be shifted at all. It rather is just a definition of which components are to be accepted. This is particularly promising when being applied across company borders, since it is not possible to adapt nominal values at the supplier's factory. However, for a supplier to accept such a scenario, financial incentives are needed to compensate for additional efforts. Therefore, it is necessary to be able to quantify the impact of a batch of component A (produced by the supplier) given a batch of component B (produced internally) on the end product's function and resulting quality costs. Figure 2 shows a typical process chain for batch-specific tolerance allocation.

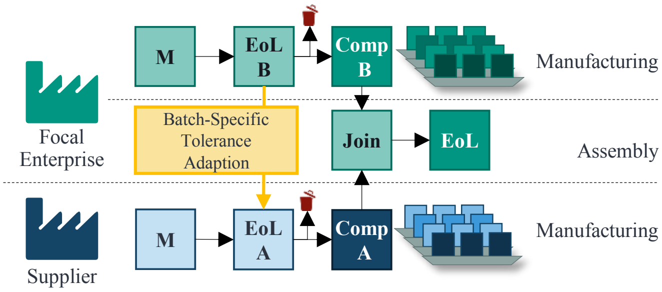

Figure 2 Typical Process Chain for Batch-Specific Tolerance Allocation

The following section presents the state of the art on quantifying quality costs based on functional deviations in quality control strategies and tolerancing to analyze to what extend methods are available to derive incentives for batch-specific tolerance allocation.

3. Quantifying Quality Costs in Function-Oriented Quality Control and Tolerancing

In traditional quality engineering views, all products within the tolerance limits are considered to be of equal quality and free of defects. As long as products are within tolerance, there are no quality costs considered. Accordingly, a product with features outside the upper (USL) or lower specification limits (LSL) is defective and must either be reworked at a cost or declared as scrap. The associated costs amount to a uniform value A_0 for all products outside the tolerance limits. [17]

Taguchi et al [18] offer a different view on product quality. They define quality losses as "*the economic losses imparted by the product to society after being shipped to a customer*" [18]. Therefore, losses occur for any deviation from the nominal value. Thus, any deviation, no matter how small, is seen as a defect that leads to quality degradation, causing losses and costs. The losses increase quadratically with deviation from the target value up to the tolerance limits (see Figure 3 and eq. (1)). For deviations that fall outside the tolerance limits, the loss does not increase further and maintains a uniform, fixed value. The loss function has its minimum at the nominal value. Accordingly, reaching the functional target is desirable for both quality and cost reasons. This popular phenomenon is therefore called Taguchi's loss function. [17,18]

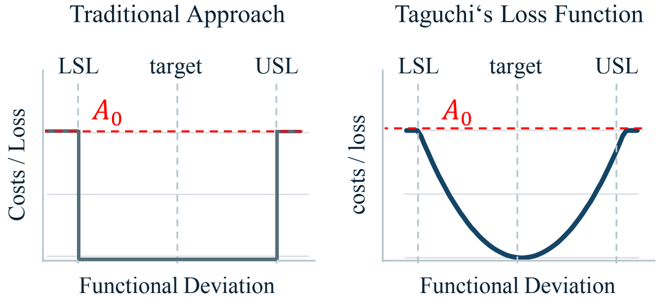

Figure 3 Explanation of Taguchi's loss function opposed to the traditional view on product quality (following [17,18])

$$L(y) = k(y-m)^2 \quad \text{with:} \quad k = \frac{A_0}{(\Delta spec)^2}, \quad \Delta spec = \frac{USL - LSL}{2} \tag{1}$$

Kannan et al. [15] use Taguchi's loss function in a selective assembly scenario for the joining of a shaft into a bore. They implement a genetic algorithm (GA) to find the optimal group sizes and allocations for the selective assembly strategy. After assembly, the resulting components are grouped similar to the classes in the applied selective assembly strategy. Thus, the quality loss can be calculated and minimized using the group mean y_s as shown in eq. (2) instead of computing the loss based on the real value of the resulted assembly clearance (see also Figure 4). [15]

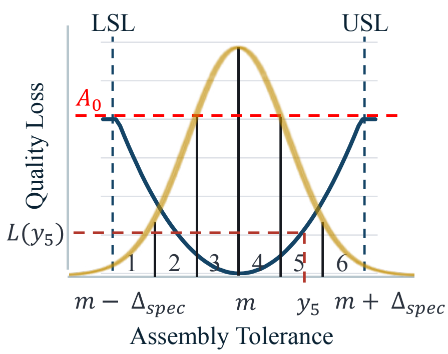

Figure 4 Taguchi's loss function applied in selective assembly for grouped functional assembly variations (following [15])

$$L(y_s) = k(y_s - m)^2 \quad \text{with:} \quad y_s = \frac{C_{s,max} + C_{s,min}}{2}, \forall\, s \in S \tag{2}$$

Babu & Asha [19] investigate a selective assembly scenario for the joining of a shaft, similar to [15]. In order to accept resulting components in a nominal interval within the specification limit, instead of focusing on the mean value alone, they introduce a symmetric interval-based Taguchi (SIT) loss function. Hence, there is a target interval of desirable feature values with bounds m_1 and m_2. Within this target interval, the loss is 0. Outside the target interval, the loss function increases quadratically up to the tolerance limits. Afterwards, following [15] the quality loss is computed. [19]

Matsuura [20] investigates the optimal group sizes for a selective assembly strategy to minimize assembly clearance. The industrial use case is demonstrated in the joining of pistons in engine production. The author provides a numerical solution for general convex loss functions to determine an optimal assembly class division instead of Taguchi's loss function with squared error losses. In this case, A_0 corresponds to the cost of reworking a defective component at the tolerance limits. [20]

Wagner [21] uses Taguchi's loss function to calculate the quality costs in a simulation-based valuation of strategies for function-oriented quality control. He introduces a methodology to compare all quality control strategies introduced in [5] based on a digital twin of production. Thus, quality control strategies can be investigated technologically and monetarily before implementation. However, although he uses a functional model within the quality control strategies, the loss is not predicted, but only calculated for the actual functional value in the functional test points. Furthermore, the approach doesn't account for cross-company quality control and batch-specific information. [5,9,21]

Muthu et al. [22], Hsieh [23], Choi et al. [24], Cheng & Maghsoodloo [25], and Peng et al. [26], among others, use the general Taguchi loss function to determine the total cost of a component, depending on the allowable deviation, with the goal of a minimum cost tolerance design. In these approaches, the total cost consists of the manufacturing cost and quality costs computed with Taguchi's loss function. The manufacturing costs are further split into fixed costs and costs that are variable with the specification width (costs incurred to produce a single part to a specific tolerance). [22]

To sum up, Taguchi's loss function is often used in tolerance design and allocation for computing quality costs [22–26]. Furthermore, quality control strategies for high-precision products such as selective assembly and adaptive manufacturing are studied heavily [1,4,5] and some scholars also use Taguchi's loss function to calculate the resulting quality costs to evaluate the outcome [15,19–21,27].

However, there is no approach that predicts the functional deviation and the resulting quality costs of assembled high-precision products based on varying component batches to compute the willingness to pay for a batch-specific tolerance allocation of the supplied components. To close this gap, the following chapter introduces a dynamic pricing model for batch-specific tolerance allocation.

4. Dynamic Pricing Model for Batch-Specific Tolerance Allocation

We propose a model to evaluate the impact of a batch of component A (produced by a supplier) given a batch of component B (produced internally) on the end product's function and quality costs. Based on this, incentives can be derived to successfully implement batch-specific tolerance allocation in a supply chain scenario (see Figure 2). Both components have one or more quality critical features. Other costs than quality costs are considered fixed in this scenario.

First, the model has to be able to predict and compare the functional deviations of different components' batches based on the batch-specific data. For this, we follow [6] and [9]. The variables are explained in detail in the nomenclature at the end of this section. Based on a functional model (3), sub-models of the components can be derived (4). Afterwards, the functional deviation of the component can be predicted (5). [6,9]

$$\tilde{y}_{q,j} = \tilde{f}_q(\boldsymbol{x}_j) \tag{3}$$

$$\tilde{f}_q(\boldsymbol{x}_{K,j}) \approx \sum\nolimits_{i \in K} (x_{i,j} * c_{q,i}) \quad with \quad c_{q,i} = \frac{\partial \tilde{f}_q}{\partial x_i} \tag{4}$$

$$\tilde{\Delta}_q(\boldsymbol{x}_{K,j}) = \tilde{f}_q(\boldsymbol{x}_{K,j}) - \mu_{K,q} = \tilde{\Delta}_{q,j,K} \approx \sum\nolimits_{i \in K} \left((x_{i,j} - \mu_i) * c_{q,i} \right) \tag{5}$$

Next, the distribution of the functional deviation after the assembly of batches of component A and B is derived. The distribution of a specific batch K_k of component K is given by its probability mass function (6) [6]. Of course, the distribution of the predicted functional deviations of the resulting combination $C_{ab} = C_c$ is subject to the applied assembly strategy. If assembled randomly, the functional deviation can be computed as the convolution of the probability mass functions of A_a and B_b (7) [6]. In case of an individual assembly strategy, the functional deviation of the resulting batch can be estimated by an *ascending-descending-heuristics*. Therefore, the parts of batch A_a are sorted in ascending order, while batch B_b is sorted in descending order with regards to the functional deviation (8). For selective assembly strategies, the resulting functional deviation is given by the applied allocation heuristics like GA or AIS (see e.g. [15,27]).

$$p_{K_t}(\tilde{\Delta}_{q,j,K}) = P(K_t = \tilde{\Delta}_{q,j,K}) \tag{6}$$

$$p_{C_c}(\tilde{\Delta}_{q,j,C}) = \sum_{k=-\infty}^{\infty} P(A_a = k) P(B_b = \tilde{\Delta}_{q,j,C} - k) \tag{7}$$

$$\overrightarrow{C_c} = \overrightarrow{A_{a,asc}} + \overrightarrow{B_{b,desc}} \tag{8}$$

After having predicted the resulting functional deviation of assembling batch A_a and B_b based on the assembly strategy, the associated predicted quality loss can be computed inspired by [15] (see eq. (2) in section 0). Therefore, the resulting functional deviation is grouped into S classes. We recommend to use an uneven number of classes to have a separate class for the functional target. $|S| - 2$ classes should be within the tolerances of the functional test point, which leaves one class on each side binning the parts to be predicted out of specification. Thus, the partially defined loss function can be derived (9). Afterwards, by multiplying the number of parts $n_{q,s}$ with the associated quality loss $L(y_{s,q})$ for each class $s \in S$ the distribution of the resulting quality costs is determined (10) (see Figure 5). By summing up the resulting costs of all classes, the predicted quality costs in a functional test point are derived (11). In case of more than one test point, the costs can be weighted relative to the historic proportion of the product being rejected in the specific test point (12a) [6]. It could also be necessary to consider products outside the specification separately, since the product is rejected as soon as one test point is out of specification (12b). The resulting quality costs of assembling batch A_a and B_b is given by $\tilde{c}_{Qu,A_a,B_b}$ (13).

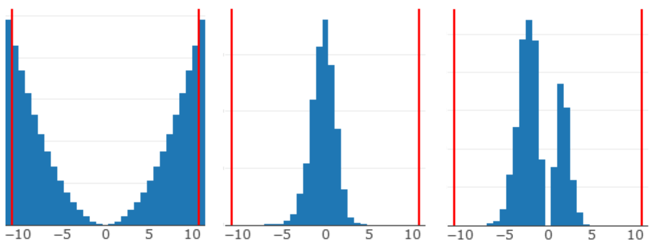

Figure 5 Deriving the distribution of the resulting quality loss based on the predicted functional deviation of assembling two component batches

$$L(y_{s,q}) = k_q (y_{s,q} - \mu_{K,q})^2 \quad with: \quad k_q = \frac{A_0}{(\Delta_{spec,q})^2}, \quad \Delta_{spec,q} = \frac{USL_q - LSL_q}{2}, \quad y_{s,q} = \frac{C_{s,q,max} + C_{s,q,min}}{2}, \forall\, s \in S, q \in Q \tag{9}$$

$$\tilde{c}_{Qu,C_c,q,s} = L(y_{s,q}) * n_{q,s} \tag{10}$$

$$\tilde{c}_{Qu,C_c,q} = \sum\nolimits_{s \in S} \tilde{c}_{Qu,C_c,q,s} \tag{11}$$

$$\tilde{c}_{Qu,C_c} = \sum\nolimits_{q \in Q} (w_q * \tilde{c}_{Qu,C_c,q}) \tag{12a}$$

$$\tilde{c}_{Qu,C_c} = \sum\nolimits_{q \in Q} \left(w_q \sum\nolimits_{2}^{|S|-1} \tilde{c}_{Qu,C_c,q,s} \right) + \max_{q \in Q}(A_0 * n_{q,1}) + \max_{q \in Q}(A_0 * n_{q,|S|}) \tag{12b}$$

$$\tilde{c}_{Qu,A_a,B_b} = \tilde{c}_{Qu,C_c} \tag{13}$$

Subsequently, by comparing different combinations of batches, the individual impacts of the component batches can be derived. The combinations are compared by subtracting their corresponding predicted quality costs. Therefore, it is necessary to define benchmark or standard batches K_{std} for the individual components. The standard batch could be either a normally distributed, central batch with a c_p value of 1,33 (see [17]) or the long-term distribution of the component's functional deviation derived by historical data. Either way, the assembly of A_{std} and B_{std} should lead to the calculated, standard quality costs $\tilde{c}_{\mathrm{Qu},\mathrm{A_{std}},\mathrm{B_{std}}}$.

As demonstrated in Figure 6, several conclusions can be drawn by comparing different combinations C_c, especially when taking standard batches into account. Furthermore, by keeping one of the component's batch fixed, the impact on the quality costs of the other component's batch is derived, e.g. with respect to its standard batch. From the focal enterprise's perspective, now a willingness to pay (WTP) for a specific batch of the supplied component A given a specific batch B_b produced inhouse can be computed ($WTP_{A_a|B_b}$). In the example given in Figure 6, due to a poorly distributed batch B_b (red curve), the decision-maker would have a very high WTP for A_a, since the expected quality costs $\tilde{c}_{\mathrm{Qu},\mathrm{A_{std}},\mathrm{B_b}}$ would be twice the calculated quality costs $\tilde{c}_{\mathrm{Qu},\mathrm{A_{std}},\mathrm{B_{std}}}$.

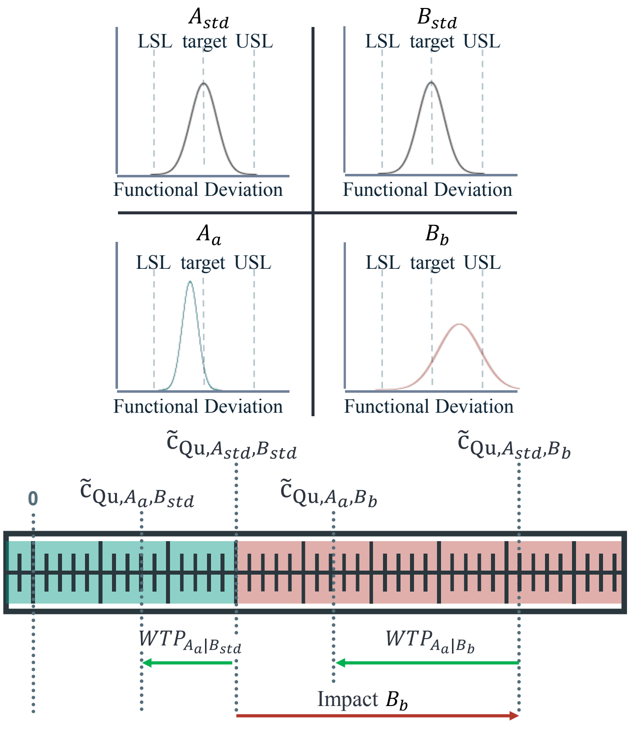

Figure 6 Deriving the willingness to pay for a specific batch of component A given a batch of component B

Finally, based on the WTP for specific batches, financial incentives can be derived to motivate the supplier towards a batch-specific tolerance allocation by compensation his associated efforts. Therefore, for a given batch B_b, an ideal counterpart batch $A_{ideal|B_b}$ can be derived subject to the applied assembly strategy. In case of an applied individual assembly strategy, this could e.g. be performed by mirroring the distribution of the functional deviations of B_b on the y-axis. The WTP for $A_{ideal|B_b}$ serves as an upper limit of money to spend on incentives. Based on that, a proportion of the WTP to be kept could be defined and the incentive system can be designed in close collaboration with the supplier. The approach can also be applied internally to design a quality-cost-oriented transfer pricing scheme that accounts for additional efforts in previous processes which safe costs in assembly.

Although the approach has been introduced for one batch of each component, it can be easily applied to a multiple batch scenario by performing batch allocation before computing the predicted quality loss. Afterwards, the tolerance-allocation could be performed for each batch individually or aggregated.

Table 1 Nomenclature of the variables used.

Nomenclature

$\tilde{f}_q(\mathbf{x}_j)$	Functional model in a functional test point $q \in Q$
$\mathbf{x}_j$	Feature vector of the data $x_{i,j}$ for an observation $j \in J$
$x_{i,j}$	Data the quality critical feature $i \in I$ for observation $j \in J$
x_i	Quality critical feature $i \in I$
$c_{q,i}$	Sensitivity coefficient of feature $i \in I$ with regards to functional test point $q \in Q$ as partial derivative
$\tilde{f}_q(\boldsymbol{x}_{K,j})$	Functional sub model of a component K with more than one quality critical feature
$\mathbf{x}_{K,j}$	Feature vector of the data $x_{i,j}$ of the component-specific quality critical features for observation $j \in J$
$\tilde{\Delta}_{q,j,K}$	Functional deviation of an observed component $\mathbf{x}_{K,j}$ from an ideal component
$\mu_{K,q}$	Target functional influence of a component K on the functional test point $q \in Q$
μ_i	Target value of a quality critical feature $i \in I$
$p_{K_k}(\tilde{\Delta}_{q,j,K})$	Probability mass function of given batch K_k of component K interpreted as random variable
K_k	Given batch $k \in \{1 \ldots n\}$ of component K
$C_{ab} = C_c$	Resulting batch $c \in \{1 \ldots n\}$ of the combination C of two components A and B. c gives the number of the object in the permutation. C_c can also be interpreted as a batch K_k.
n	Number of observed batches for each component
$\overrightarrow{K_k}$	Vector of predicted functional deviations of batch K_k
$\overrightarrow{K_{k,\mathrm{asc}}}$	Vector of pred. funct. deviations of K_k in ascending order
$\overrightarrow{K_{k,\mathrm{desc}}}$	Vector of pred. funct. deviations of K_k in descending order
K_{std}	Expected standard batch of component K
$L(y_{s,q})$	Quality loss of $y_{s,q}$ by means of Taguchi's loss function
$y_{s,q}$	Mean value of class $s \in S$ of distribution of functional deviation in test point $q \in Q$
k_q	Quality loss coefficient for the specifications of $q \in Q$
A_0	Inefficiency costs (e.g. scrap or rework) for parts outside the specification limits
$\Delta_{\mathrm{spec,q}}$	Range between specification limits of test point $q \in Q$
USL_q	Upper Specification Limit of the functional deviation in functional test point $q \in Q$
LSL_q	Lower Specification Limit of the functional deviation in functional test point $q \in Q$
$C_{s,q,min}$	Lower limit of class of funct. deviation $s \in S$ for $q \in Q$
$C_{s,q,max}$	Upper limit of class of funct. deviation $s \in S$ for $q \in Q$
$\mathrm{n_{q,s}}$	Number of parts in class $s \in S$ for $q \in Q$
$\tilde{c}_{\mathrm{Qu},K_k,\mathrm{q,s}}$	Predicted quality costs of batch K_k in $s \in S$ for $q \in Q$
$\tilde{c}_{Qu,K_k,q}$	Total predicted quality costs of batch K_k for $q \in Q$
$\tilde{c}_{Qu,K_k}$	Total predicted quality costs of batch K_k
$\tilde{c}_{\mathrm{Qu,A_a,B_b}}$	Total pred. quality costs of assembling batches A_a and B_b
$\mathrm{w_q}$	Weighting factor of test point $q \in Q$
$WTP_{A_a\|B_b}$	Willingness to pay for batch A_a given batch B_b
$A_{ideal\|B_b}$	Ideal counterpart batch A_a given batch B_b
c_p	Process capability index
I	Set of quality critical features
J	Set of observations
Q	Set of functional test points
S	Set of classes of functional deviation

5. Summary and Outlook

In this article, a novel pricing model for batch-specific tolerance allocation in the production of high-precision products has been introduced. The model evaluates batches of high-precision components based on the predicted distribution of their functional deviation after assembly by means of the resulting quality costs. Using the gained transparency on the contributions to quality costs of the varying batches of different components, incentives can be derived to motivate suppliers to initiate a cross-company, batch-specific tolerance allocation strategy. The successful implementation of function-oriented, batch-specific tolerance allocation in the supply chain is a decisive step towards the vision of a tolerance-free series production of high-precision products.

In further studies, we aim at validating the approach in a real production environment by also taking measuring uncertainty and other data quality issues into account. A better data quality is leading to more precise predictions of the resulting functional deviation. Therefore, the associated function-oriented quality control strategies should perform even better. By computing the resulting quality costs, an ideal design of measuring equipment and data infrastructure could be calculated. Also, incentives that compensate suppliers for better data quality can be derived. Furthermore, the integration of supplier data is of utter importance for the functional model. Thus, the development of common ontologies to achieve interoperability of measuring data will be studied. Additionally, other tolerance-cost optimization approaches could be adapted for finding ideal batch-specific tolerances or $A_{ideal|B_b}$.

The approach has been implemented as a proof of concept web service in Python and JavaScript and will be available on GitHub after closing of the associated research project [28].

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