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Data-Based Supply Chain Collaboration – Improving Product Quality in Global Production Networks by Sharing Information

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Abstract

In times of globalization and digitalization, silo mentality and protectionism lead to competitive disadvantages for all partners of a production network. High scrap rates and low supplier margins in the production of high-precision products can be identified as resulting inefficiencies. Supply chain collaboration can contribute to significantly increase product quality by simultaneously reducing the associated costs, globally. We introduce batch allocation as a data-driven method for cross-company quality control of differing component batches based on both, supplier data and internal data. The industrial application is demonstrated within a global production network for manufacturing high-precision products.

Keywords: Global Production; Supply Chain Collaboration; Quality Assurance; Industry 4.0; Closed-Loop

1. Introduction

Manufacturers of high-precision products are facing growing pressure to reduce costs while producing at technological limits. This development is due to increased competition in global markets and a cross-industry rise in the demand for high-precision products [1-3] The required quality can often only be achieved by setting very tight tolerances for the individual components of the final product [3,4]. However, consistently producing those components within said tolerances is almost impossible with existing technological processes. Therefore, manufacturing deviations occur and result in non-conforming components, which are either declared as scrap or reworked at additional time and cost. Furthermore, the combination of two or more conforming components can lead to a non-functional product, when the assembled components are close to their specification limits. [3-5]

To avoid non-conforming components and enable the economical production of high-precision products from lower-precision components, organizational approaches such as selective assembly or adaptive manufacturing exist. The basic idea of these advanced quality control strategies is the proactive avoidance of the aforementioned, unfavorable combinations by pairing counteracting components based on their measured features. [3,4,6]

In global production networks (GPNs) however, the responsibility for maintaining tight tolerances is often passed on to the supplier. Additionally, quality control strategies cannot be applied across companies, often not even within the companies' own production network, because of (measuring) data not being shared [1,6,7]. By means of supply chain collaboration, these unnecessary inefficiencies and costs can be reduced through a higher level of transparency by exchanging data and information within the GPN [2,8,9].

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The goal of this article is to introduce a new quality control strategy, named *batch allocation*, for the production of high-precision products in global production networks. In this novel strategy, batches of different components are paired based on the statistical distributions of their quality-critical features before entering final assembly.

Although the presented approach is enabled by a high degree of transparency within a successfully instated collaboration, the establishment of supply chain collaboration is outside of the scope of the article. However, the associated cost savings can be used to design incentives to steer existing supply chain partners towards a collaborative relationship for instance by compensating the supplier for additional measuring efforts [10,11].

2. State of the art

The benefits of transparency and collaboration in GPNs have already been studied and demonstrated intensively in theory, especially for the so-called bullwhip effect [8,9,12-15]. Although industry solutions and platforms to implement collaboration and transparency exist [16-18], a low degree of collaboration in supply chain relationships can still be observed, and silo mentality prevails [19]. Reasons for this are chiefly a lack of trust or the fear of losing know-how and control [19,20]. Nonetheless, scholars are focusing on developing approaches to successfully initiate and maintain collaborative relationships [10,11]. However, there is no existing approach to improve the product quality of high-precision products in GPNs by exchanging production data in a collaborative relationship.

In literature, there are numerous approaches for managing quality and reducing scrap in the production of high-precision products with the help of quality control strategies (see e.g. [3-5,21-34]). An overview of possible quality control strategies can be found in [4], which has been extended by [5]. Based on Fig.1, these strategies will be discussed in detail.

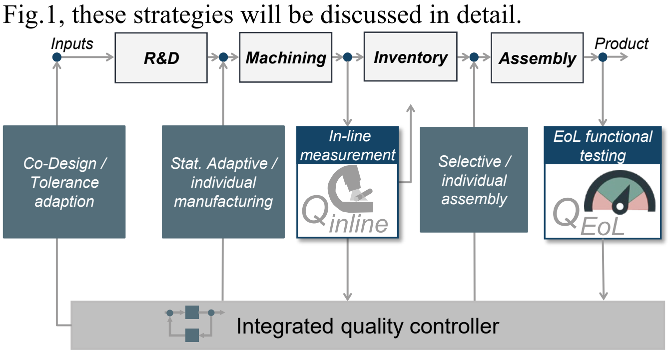

Fig. 1. Overview of existing quality control strategies illustrated as quality control loops in production [4,5].

By categorizing the different strategies, a distinction can be made for both manufacturing (machining) and assembly strategies according to the degree of individualization. Based on the data provided by inline measurement technology, assembly can either be selective or individual. In selective assembly, the components are paired based on their affiliation to previously defined feature classes [5,23,24]. Scholars researching selective assembly, primarily focus on heuristics for solving the class selection algorithm [23,31,35], finding the ideal number of classes [34,36], or reducing surplus parts 32.

Considering the individual assembly, components that best match each other are paired based on their specific feature characteristics [5,26]. Individual assembly offers a much more accurate compensation of counteracting effects, but the requirements concerning data traceability and the pairing of components are correspondingly higher [4,5].

Extending the control loop to the manufacturing of components there are again two ways to intervene corresponding to the degree of individualization: statistically adaptive or individually [4,5]. In statistically adaptive manufacturing, the process parameters are manipulated so that the mean value and therefore the statistical distribution of a specific batch is shifted, e.g., to produce a specific feature class for selective assembly [36]. In individual manufacturing a component is made to fit its previously measured individual counterpart [5].

The main prerequisite for the quality control strategies mentioned before is the availability of the necessary measurement data and complete data traceability [4,5]. Additionally, integrating product knowledge into production is of utter importance [6]. This provides knowledge on how a set of specific quality critical features affects the functional performance of the product. In the approach of [6], this is done by developing a functional model, which predicts the product function before the end-of-line (EoL) functional test based on in-line measurement data [5,6]. Component pairing can also be performed based on geometric features [3,4,37]. However, the latter is only possible for non-complex functional dependencies, like the axial backlash of two components. [2-4, 15, 17]

By knowing the functional dependencies, the control loop can be extended again with respect to the product-production co-design, especially the adaptation of tolerances [5]. For example, by feeding back the knowledge from production to development and allowing the integrated quality controller to compensate counteracting parts, the tight geometrical tolerances of the components can be widened while still maintaining functionality of the end product [5,38].

Despite the massive amount of research conducted in the area of selective assembly and adaptive manufacturing and in the area of GPNs and supply chain collaboration, there is not a single approach concerning advanced, data-based quality control strategies in GPNs or supply chains. While approaches concerning quality management in GPNs or supplier quality management exist (see e.g. [8,14,37,39-45]), those approaches rather focus on detecting errors before delivery to the final customer or identifying and developing quality critical suppliers than on actively avoiding defects by pairing components based on shared supplier data.

3. Research approach

To overcome the limitations mentioned above, we present a novel method to improve the production quality of high-precision products in GPNs based on both, supplier, and internal data. In section 3.1 the underlying principle of the newly developed quality control strategy will be explained.

Afterwards the method will be formalized and a mathematical approach for solving the associated optimizing problem is presented in section 3.2.

3.1. Introducing batch allocation

Due to process variations, it can be assumed that the characteristics of quality-critical features fluctuate to a certain extent, resulting in batch-specific distributions of the quality critical features. The idea of batch allocation is to match the available batches of corresponding components based on the batch-specific distribution of the component's quality critical features and the resulting influence on the product function (see Fig. 2).

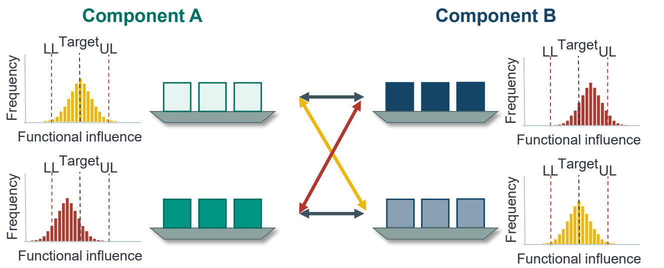

Fig. 2. Pairing corresponding component batches based on the distribution of the resulting influence on the product function

Batch allocation is understood as a quality control strategy within the logistics processes prior to the assembly of the components (see Fig. 3). It is supposed to be implemented additionally to other manufacturing or assembly strategies introduced in section 2. If, for example, an individual assembly strategy is already deployed for the assembly of two quality critical components A and B, batch allocation provides the best available batch of component A to compensate for manufacturing variations of a given batch of component B. Therefore, it optimizes the probability of finding the right match and reduces the probability of surplus parts. Nevertheless, batch allocation can also be implemented without any other quality control strategy, but the outcome might be only slightly better and not worth the effort. A batch-specific adaptive manufacturing strategy of component A based on the shared measuring data of the batches of component B would be another example of combining batch allocation with existing quality control strategies.

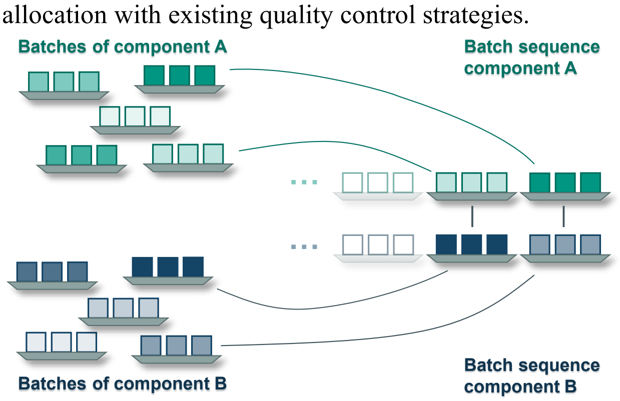

Fig. 3: Underlying principle of batch allocation: determine the sequence of given component batches to improve compensation possibilities

The basic mechanism of batch allocation is comparable to the underlying principle of selective assembly strategies: The classes in selective assembly can be seen as mutually exclusive batches. However, in selective assembly, all classes are available simultaneously in the assembly line, whereas with batch allocation, the pairing takes place prior to assembly and only one batch of each component is used in assembly, reducing inventories at the line.

3.2. Formalization of the batch allocation problem

As stated before, the batch allocation is performed based on the batch-individual distribution of components characteristics and their predicted influence on the product's function. Following [6] a functional model $\tilde{f}_q(\mathbf{x}_j)$ is used to predict the product function in a functional test point $q \in Q$, where $\mathbf{x}_j$ is the feature vector of the measuring data $x_{i,j}$ of the quality critical features $i \in I$ for a given observation $j \in J$ [6]:

$$\tilde{y}_{q,j} = \tilde{f}_q(\boldsymbol{x}_j) \tag{1}$$

The functional influence of a specific quality critical feature $i \in I$ can be identified by computing the sensitivity coefficient $c_{q,i}$ as the partial derivative of the functional model of the functional test point $q \in Q$ with respect to x_i [46]:

$$c_{q,i} = \frac{\partial \tilde{f}_q}{\partial x_i} \tag{2}$$

The predicted influence of a complex component K with more than one quality critical feature can be estimated by summing up the individual influences $i \in K$ [46]:

$$\tilde{f}_q(\boldsymbol{x}_{K,j}) \approx \sum_{i \in K} (x_{i,j} * c_{q,i}) \tag{3}$$

To compare the functional influences of different components, the functional deviation of an observed component $\mathbf{x}_{K,j}$ from an ideal component is determined as follows, with μ_i being the target value of a quality critical feature $i \in I$:

$$\tilde{\Delta}_q(\boldsymbol{x}_{K,j}) = \sum_{i \in K} \left((x_{i,j} - \mu_i) * c_{q,i} \right) = \tilde{\Delta}_{q,j,K} \tag{4}$$

For a given batch K_t of component K interpreted as random variable, the probability mass function is defined as:

$$p_{K_t}(\tilde{\Delta}_{q,j,K}) = P(K_t = \tilde{\Delta}_{q,j,K}) \tag{5}$$

With C being the combination of component A and B, the probability mass function of the predicted functional deviation of the specific combination $C_{ab} = C_c$ can be computed as the convolution of the probability mass functions of A_a and B_b.

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

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

The objective of batch allocation is to optimize the quality of the product. High quality can be interpreted as a central and narrow distribution of the deviations from the functional target (see Fig. 4). Therefore, we propose to use the process capability index C_{pK} of the EoL functional test, more specifically of the predicted resulting functional deviation of the component combination, in the objective function, for two reasons. First, the process capability index C_{pK}, as being defined as the ratio of process limit proximity and tolerance range, considers the mean value and the standard deviation of a random variable. Second, quality managers can interpret the value based on their experience in statistical process control (SPC).

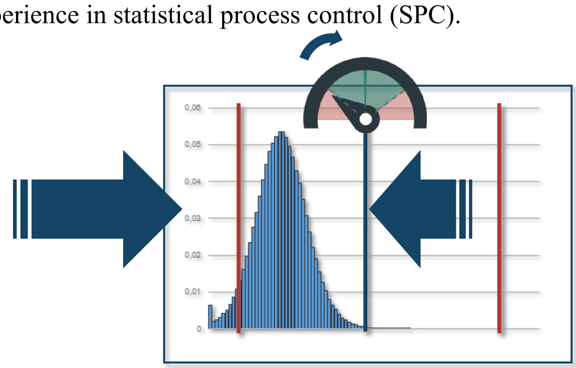

Fig. 4. Illustration of the objective of the batch allocation optimization problem

Hence, for a given set of batches n of each component, the objective function is to maximize the arithmetic mean of the process capability index $C_{pK,q}$ of all combinations over every possible permutation k in a functional test point $q \in Q$:

$$\underset{k=1\ldots n!}{argmax} \frac{1}{n} \sum_{c=1}^{n} C_{pK,q}\left(p_{C_c}(\tilde{\Delta}_{q,j,C})\right) \quad (7)$$

$$C_{pK,q}\left(p_{C_c}(\tilde{\Delta}_{q,j,C})\right) = min\left(\frac{USL_q - E(C_c)}{3\sqrt{Var(C_c)}}; \frac{E(C_c) - LSL_q}{3\sqrt{Var(C_c)}}\right) \quad (8)$$

In cases of multiple counteracting functional test points, a conflict of objectives arises. We propose to use a weighted sum approach to solve the conflict of objectives. The weights are computed as the relative proportion of the product being rejected in the specific functional test point regarding all rejects in the EoL functional test. Hence, the objective function for optimizing the batch allocation problem is defined as:

$$\underset{k=1\ldots n!}{argmax} \frac{1}{n} \sum_{q \in Q} \sum_{c=1}^{n} w_q * C_{pK,q}\left(p_{C_c}(\tilde{\Delta}_{q,j,C})\right) \quad (9)$$

The batch allocation problem can be solved in multiple ways. Depending on the number of batches taken into account for each component, it can be either solved by comparing all possible combinations (brute-force) or by using genetic algorithms, particle swarm optimization or other heuristics to cope with the high complexity.

Table 1. Nomenclature of the variables used.

Nomenclature	
$\tilde{f}_q(\mathbf{x}_j)$	Functional model to predict the product function in a functional test point $q \in Q$
$\mathbf{x}_j$	Feature vector of the measuring data $x_{i,j}$ for a given observation $j \in J$
$x_{i,j}$	Measuring data of the quality critical features $i \in I$ for a given observation $j \in J$
$\mathbf{x}$	Feature vector of the quality critical features x_i
x_i	Quality critical features $i \in I$
$c_{q,i}$	Sensitivity coefficient of quality critical feature $i \in I$ in the functional test point $q \in Q$
$\mathbf{x}_{K,j}$	Feature vector of the measuring data $x_{i,j}$ of the component-specific quality critical features for a given observation $j \in J$
$\tilde{f}_q(\boldsymbol{x}_{K,j})$	Predicted influence of a component K with more than one quality critical feature
$\tilde{\Delta}_{q,j,K}$	Functional deviation of an observed component $\mathbf{x}_{K,j}$ from an ideal component
μ_i	Target value of a quality critical feature $i \in I$
$p_{K_t}(\tilde{\Delta}_{q,j,K})$	Probability mass function of given batch K_t of component K interpreted as random variable
A_a	Given batch $a \in \{1 \ldots n\}$ of component A
B_b	Given batch $b \in \{1 \ldots n\}$ of component B
$C_{ab} = C_c$	Resulting batch $c \in \{1 \ldots n\}$ of the combination C of component A and B with c being the number of the object in the permutation
n	Number of observed batches for each component; also the number of objects in the permutation of a set of combinations C of the components A and B
k	Permutation of a set of combinations C of the components A and B with $n!$ possible permutations
I	Set of quality critical features
J	Set of observations
Q	Set of functional test points
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 $q \in Q$
$C_{pK,q}$	Process capability index of the predicted resulting functional deviation of the component combination in functional test point $q \in Q$
$E(X)$	Expected value of a random variable X
$Var(X)$	Variance of a random variable X

4. Industrial use case

This research work is based on the GPN for the production of injectors of a 1-tier automotive supplier (referred to as focal enterprise). Due to the high demands of injectors, production is subject to very tight geometrical manufacturing tolerances in the range of a few micrometers. Even small changes to quality-critical features could result in non-compliance with the functional targets [47].

Fig. 5 provides a simplified overview of the injector production within the GPN. Two function-relevant components are considered. Component A is manufactured in-house, whereas component B is manufactured by a supplier. The batches of both components enter final assembly FIFO without batch allocation and Component B is joined without any selective assembly strategy (see 2).

Specifically, it can be observed that components are declared as rejects after the EoL functional test at the supplier site due to very tight geometrical manufacturing tolerances. The observed scrap would normally not be observable from the focal enterprise's point of view. From the supplier's point of view, this means very high-quality costs and low delivery reliability, which in turn can be reflected on the focal enterprise's side in higher component prices and in costs due to production downtime, respectively.

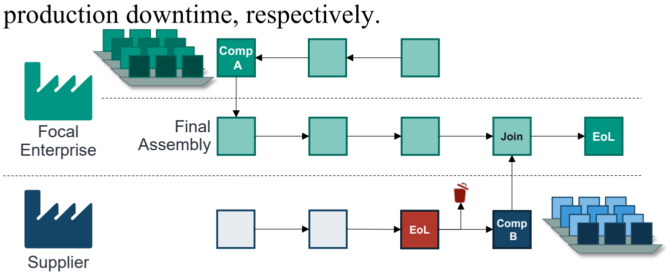

Fig. 5. Illustration of the process chain within the GPN of the industrial use case.

By implementing batch allocation there is enormous potential for widening the specific component's tolerances so a large proportion of the rejects could be used without any loss of functionality of the injector. As this would enable the supplier to offer these parts at a lower price without any disadvantage, a win-win situation for the supplier and the focal enterprise arises. In addition, by implementing an individual assembly strategy with the corresponding injector components based on the shared component data, the focal enterprise's output can be increased further while reducing quality costs.

Discrete event simulation studies conducted with Tecnomatix® Plant Simulation have shown a significant increase in the supplier's and focal enterprise’s first pass yield (FPY) resulting in potential cost savings of up to 2% of the injector's total cost for implementing batch allocation combined with the individual assembly of the corresponding component. However, only simple heuristics for allocating the batches have been used and fixed costs for implementing the quality strategies haven’t been taken into account, yet.

5. Summary and outlook

In this article, we introduced a novel approach to optimize the production quality of high-precision products in GPNs based on batch-specific predicted functional deviations. The novel quality control strategy *batch allocation* can use internal and supplier data to optimize the batch sequence of components entering assembly. As part of an industrial use case, the global production of high-precision injectors, we were able to perform first simulation studies, showing that a higher degree of transparency in supply chain collaboration yields a mutual benefit for the supplier and the focal enterprise by implementing batch allocation.

In further studies, we aim at developing incentives based on the predicted cost savings of a higher degree of transparency to align interests towards a collaborative partnership by compensating the associated efforts of the supplier (e.g. costs for measuring and IT infrastructure). In the simulation study, we only used simple heuristics for solving the batch allocation problem. Hence, to further improve the results, solution algorithms used to find the ideal combination of classes in selective assembly problems will be analyzed to compute the ideal allocation of the available batches.

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