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Model-Based Definition for Non-Rigid Variation Simulation II: Feeding the Digital Twin with Data from the Quality Information Framework (QIF)

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Abstract

Increasing computing powers, advanced software, and smart technical devices for collecting and processing manufacturing data have turned the Digital Twin (DT) concept into a practical instrument for real-time geometry assurance. However, implementing the DT for geometry assurance in industry requires selecting an appropriate infrastructure that guarantees a seamless flow of geometry and deviation information across design, production, inspection, and variation simulation. The Quality Information Framework (QIF), an inspection-focused standard for Model-Based Definition, can address this challenge and close currently open gaps in the Digital Thread for geometry assurance. This article proposes an operational integration framework that uses QIF to set up the DT for non-rigid variation simulation. An inverse mapping algorithm divides Finite Element meshes into subsets representing the QIF features in variation simulation. The identified features connect the simulation model with the measurement information, which is directly embedded in QIF and linked to the features. Measured size, location, orientation, and form deviations of a batch of parts are exchanged collectively via QIF, automatically mapped on shell meshes, and used for DT applications without losing the link to the physical counterparts. An exemplary implementation of the framework and its application to find optimal part matching for a sheet metal assembly emphasizes the potential of QIF for feeding the DT.

Keywords: Model-Based Definition; Quality Information Framework (QIF); Geometry Assurance; Digital Twin; Variation Simulation; Selective Assembly

1. Motivation

Manufacturing process variability is natural and unavoidable [1]. Far back in time, individual manufacturing served the needs of low-volume batches [2]. It was common to compensate for deviations in production individually for each part and assembly [2]. Scaling up to series production led to the idea of part interchangeability in the 18th century and has been the basis of industrial production ever since [2]. Part interchangeability is based on tolerances that limit the deviations of critical dimensions and geometry elements, ensuring pure random assembly of parts with imperfections to in-spec products [3]. Approximately two hundred years later, individualized production is back in a different guise. Fast simulation models linked with in-line inspection data allow the creation of Digital Twins to perform optimization for geometry assurance in real-time and mitigate part deviations through smart decisions on the assembly level [4]. The Digital Thread, intertwining the systems, processes, and various multi-sourced information flows, is essential in empowering the Digital Twin (DT) for real-time geometry assurance [5, 6]. This article proposes an operational integration framework based on the Quality Information Framework (QIF) standard, creating a seamless flow of part geometry deviation information from inspection to the simulation model, the core of the DT for geometry assurance. The article is structured as follows. Building upon a reflection on related works and the identified research question in Section 2, Section 3 introduces the idea to feed the DT for geometry assurance of sheet metal assemblies with deviation information exchanged through QIF. The proposed strategy is applied in Section 4 to find the optimal matching of sheet metal parts joined by spot welding. Section 5 finally summarizes this article and provides an outlook on future research directions.

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2. Related works and research question

A thorough geometry assurance process has proven effective in continuously verifying, reducing, and monitoring variation over the entire product life-cycle [4]. Variation simulation plays a central role therein since it can predict the response of the assembled product to variation originating from the part manufacturing and assembly processes early on [1]. It is always based on a model for representing part geometry and deviations, and a model for propagating the deviations on the assembly level [1]. Finite Element meshes excel at realistically representing shape deviations [7] and non-rigid part behavior [1], and can be combined with contact modeling to simulate the assembly of deviated parts [8]. Hence, meshes are well-suited for simulating the non-linear effects of joining compliant sheet metal parts [9].

Traditionally, design engineers specify tolerances to put limits on the part variation [1]. Statistical tolerance analysis simulates the random assembly of parts and gives statistical predictions on the assembly response primarily based on estimated input distributions and shapes of the parts covering the tolerance zones [10]. An alternative to relying solely on assumptions is gaining knowledge from real or virtual experiments [11]. Deviation information from probabilistic process simulations or actual part measurements is used to directly feed deviation information back to variation simulation or to find statistical characteristic patterns on the geometrical deviations [11].

The idea of incorporating actual deviation data into simulation has been revitalized by the growing technical feasibility to inspect all parts in-line within production [4]. The possibility of having digital copies of all physical parts describing the geometry and their deviations is the foundation to create DTs to perform real-time optimizations [4, 12]. The DT for geometry assurance can be implemented in the design, pre-production, and production phases [4]. The latter focuses on making real-time optimizations within production to mitigate part deviations through smart assembly. Building largely upon the models developed for statistical purposes [13], challenges arise primarily in making them ready for in-line decisions in real-time [4].

Real-time simulation readiness is tightly connected to the challenge of bringing inspection information to simulation. The DT concept can only be realized if all information flows from different sources are tied to a coherent Digital Thread [11]. Still, collecting and processing high-quality 3D scan data in manageable sizes and creating a flow of deviation information is essential since it is the backbone for all potential DT applications within the geometry assurance process [5, 14]. Model-Based Definition (MBD) can help to set up the Digital Thread by centralizing all Product and Manufacturing Information (PMI) within one 3D model [5]. MBD has been well established for years, supporting the flow of Geometric Dimensioning and Tolerancing (GD&T) specification from CAD to variation simulation, primarily through the neutral, standardized STEP AP242 and JT format, ensuring system interoperability [15, 16]. Exchanging deviation information from measurements in an MBD way is, however, still in its early days. QIF, formalized as ISO 23952:2020 [17], has been recognized as a promising MBD standard not only for automating but especially for enriching variation simulation with measurement information [12, 15]. QIF semantically links part geometry, topology, and GD&T specification information from the design phase with a comprehensive set of inspection information, including the final measurement results and statistics [17]. Hence, QIF can provide information for variation simulation used in both product design and product realization stages to make either statistical predictions or feed the DT [16] (see Fig.1).

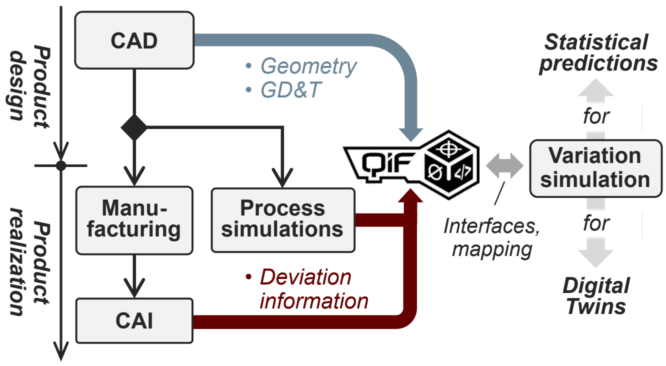

Fig. 1. Using QIF to enrich variation simulation with GD&T and deviation information for statistical predictions or DT-based optimizations [18].

Related works generally highlight QIF's potential for geometry assurance [11, 16], emphasize its suitability for transferring synthetic deviation information from numerical process simulations [16], propose methods to map geometry and GD&T information from QIF to meshes to automate statistical tolerance analysis [16, 19], and illustrate deviation information flow from inspection to structural simulations [20]. Methods, implementations, and detailed studies that go beyond general frameworks or concepts for using QIF to feed the DT for geometry assurance with part deviation information are currently missing. For this reason, this article focuses on the research question of how to bring deviation information from inspection to variation simulation via QIF to support DT-based geometry assurance decisions in the production phase. Spot-welded sheet metal assemblies and their challenges provide the context for this article.

3. QIF-informed Digital Twin for geometry assurance of sheet metal assemblies

A geometry assurance DT is a digital replica of a physical assembly system, including the parts and fixtures used during the joining operations [21]. The basis of the DT is an assembly model that simulates the joining process steps with their physics while considering the actual, measured geometries of all parts [21]. Since sheet metal parts are relatively thin and not of too complex shapes, their geometry can be represented by mid-surface shell meshes, thereby reducing simulation time. The individual parts with known actual geometries are positioned using locators and constrained via clamps within the fixtures [8]. During joining simulation, contact modeling prevents parts in contact zones from penetrating each other while creating zero-contact gaps where parts are spot welded, before the joined assembly is released from the fixture and spring back effects occur [21]. Once the simulation model is set up, it can be used in production to make individualized decisions, for instance, to match individual parts (also known as selective assembly), adjust locators, or optimize joining sequences [4].

The overall prerequisite is that all necessary information can flow between the physical and the digital representations. This paper focuses on setting up the flow of part deviation information via QIF. First, Section 3.1 analyzes QIF for helpful information to be fed to the DT. Second, Section 3.2 presents strategies for exchanging the identified information between QIF and variation simulation.

3.1. Representing DT information in QIF

The central idea of the QIF standard is to consolidate all quality information into a unified format. Following the provided XML schema definition templates, files are formatted as XML documents to be carried through the entire quality ecosystem and support the involved upstream and downstream applications [17]. For this reason, QIF is split into seven application areas, where the objects within each application area information model are linked both within and across multiple areas through unique identifiers (id) [17].

The QIF MBD area is mainly used to represent a product as a set of components, described through their part topology, geometry, and PMI, in particular GD&T specification information [17]. A semantic GD&T annotation is expressed through a *characteristic*, i.e., a control put on a *feature*, that is semantically coupled to one, multiple, or only portions of corresponding geometry elements [17] (see Fig. 2, left). Optionally, it references further objects, such as a datum reference frame [17].

Characteristics and *features* are described through *items*, *nominals*, and *definitions* [17]. An *item* represents one instance, refers to a *nominal* data object that can refer to a *definition* object, giving information that is common to a feature type and shared between items, and adds information to define a unique instance [17]. The *items* serve as a link between specification and deviation information. After planning, executing, and analyzing the measurements, potentially supported by information from additional QIF application areas, the derived information is added to the *Results*. A *PlaneFeatureMeasurement*, for instance, refers back to the corresponding *PlaneFeatureItem* via a *FeatureItemId* element (see Fig. 2, mid). The position and orientation of a measured plane can be characterized by its actual location and normal (see Fig. 2, mid). Note that Fig. 2 is only a small excerpt, reduced to some main information and exemplarily shown for a plane feature and one feature measurement. A part typically has multiple characteristics applied to one or multiple different features. Holes and slots, for instance, are defined as *CylindricalFeature* and *OppositeParallelPlanesFeature* in QIF and include feature-specific elements, such as a derived *Axis* or *CenterPlane* [17]. All *MeasuredCharacteristics* and *MeasuredFeatures* obtained from a single physical part are collected together in one *MeasurementResults* element [17]. *MeasuredPointSets* may be added to store information on the measurement points [17]. Relationships to an *ActualComponent* object, characterized by a *SerialNumber*, and additional traceability information on the *SampleNumber* and *LotNumber*, ensure that the link to the physical counterpart and the manufacturing batch is preserved [17] (see Fig. 2, right). Following this general logic, *MeasurementResults* for multiple parts are embedded as a set within the QIF Results part of a single QIF file, linking to both the ideal, virtual, and actual objects. While a link to the ideal geometry is needed to automatically transfer inspection results to simulation, a link to the actual part is essential to feed DT decisions from the virtual back into the physical environment. The next section will focus on how to use these links to bridge the gap between inspection and variation simulation.

3.2. Mapping DT information from QIF to mesh-based variation simulation models

3D scanning incoming parts as a whole is a common way to digitize parts in-line [4]. The registered point clouds or derived surface meshes are fed directly to the assembly model layer of the DT. While this approach is straightforward, the deviation information is stored part-by-part, isolated from the nominal geometry and the tolerance specifications.

QIF overcomes this limitation but requires processing the measurements to embed them in existing QIF files and link them to other information (see section 3.1). Thus, deviation information is not stored for the entire part but captured separately for each characteristic and feature. This information must be mapped to the geometry representation used for the assembly simulation – typically, to mid-surface shell meshes for sheet metal assemblies. Mapping deviation information thus re-

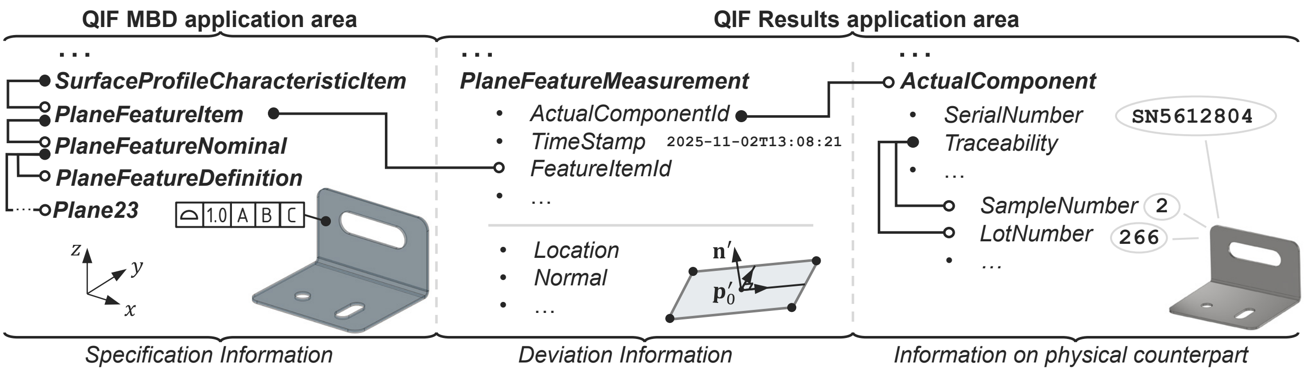

Fig. 2. Relationships between QIF MBD and Results information objects creating traceability between MBD and deviation information, and the physical part.

quires first identifying the QIF nominal features in the nominal mesh $\mathcal{T}$, and second, propagating the deviations stored in QIF to the corresponding mesh portions.

3.2.1. QIF feature identification in shell meshes

When using mid-surface shell meshes, the 3D part volume collapses onto a 2D mid-surface derived from the part's medial geometry. Hence, multiple features defined on the part's skin are represented by the same mesh portion, shifted from the skin to the mid-surface by δ_{xyz} (see Fig. 3 a)). To tackle these challenges, a mapping algorithm introduced in [19] is adopted in [18]. It identifies a set of mesh nodes $\mathbf{Q}$, collecting $\mathbf{q}_i$, $i = 1, \ldots, n$ points, as QIF feature representatives using links to the Boundary Representation (BREP) geometry objects, for example, a *Plane23*. Using the inverse surface description $\mathbf{S}_j^{-1}(\mathbf{q})$ of $\mathbf{S}_j(u, v)$ allows mesh nodes, represented in the 3D Euclidean space with x-,y-, z-coordinates, to be mapped to the 2D parametric domains of the respective geometry face j with the parameters u, v, so it can be verified whether they lie within their domain definition and thus belong to them. As a result, mesh nodes are linked to the individual geometrical faces and thus, indirectly, to all other QIF information, not only the specification but also the deviation information (see Fig. 3 a)). More details are given in [18].

3.2.2. Deviation propagation on shell meshes

Modifying the nominal mesh, whose nodes are indirectly linked to the *MeasurementResult* objects, depends on the available QIF information. *CharacteristicMeasurement* elements give information in the form of a scalar value, which defines the size of the deviation zone d. The actual shape is not covered and has to be guessed within the deviation zone based on assumptions or prior knowledge (see Fig.3 b)). For DT applications, this information is insufficient to make individual decisions when the actual part geometry is decisive.

FeatureMeasurement elements describe the measured geometries by a set of intrinsic characteristics assuming an ideal form. A *PlaneFeatureMeasurement*, for example, covers information on its *Normal* and *Location*. With the *PlaneFeatureNominal* information, the location and orientation deviation can be derived. For mapping this information on the shell mesh, the established link between the geometrical faces $\mathbf{S}_j$ and their representation in their domains through the mapped parameters u, v is useful. By modifying the underlying surface description $\mathbf{S}'_j$, an individual nodal displacement vector for all mapped points can automatically be derived to shift all nodes to $\mathbf{Q}'$ (see Fig.3 c)) [18]:

$$\mathbf{Q}' = \mathbf{Q} + \mathbf{S}'_j(u, v) - \mathbf{S}_j(u, v) \tag{1}$$

Eq. (1) is valid for features of ideal form under the assumption that rotational and translational displacements are small [18]. Even though an optional *Form* element specifies the deviation magnitude, it does not provide further details about the actual shape. If used, the shape needs to be assumed. If a *FeatureMeasurement*, however, further links to measurement points $\mathbf{P}$ given in a *MeasuredPointSet*, the measured shape can be mapped on the mesh $\mathcal{T}$. This is particularly relevant when the form matters, for example, when features are in contact. Deviations mapping from measured points onto meshes is well established in inspection. Available methods are, for example, based on nearest-neighbor searches, normal-based projections, or point-to-surface projections. For pre-alignment of the meshes, the measured feature locations and orientations can be used. Note that $\mathbf{P}$ represents the part's skin, while $\mathbf{Q}$ represents the mid-surface. Hence, the shift δ_{xyz} needs to be considered (see Fig.3 d)).

A further challenge arises when features collapse into lower-dimensionality entities [18]. Holes and slots, for instance, perpendicular to the mid-surface, lose their thickness information. If simulation uses only the midpoints of these features as locators, it suffices to obtain the actual feature locations. By systematically mapping all information for a single *MeasurementResult* object to the shell mesh, a digital replica of the part geometry is built, while preserving the link to the real part. Having the as-inspected status of multiple samples from a batch captured in a single QIF file, and using the proposed strategies, allows the assembly model to be automatically fed with actual part geometries and to perform DT optimizations.

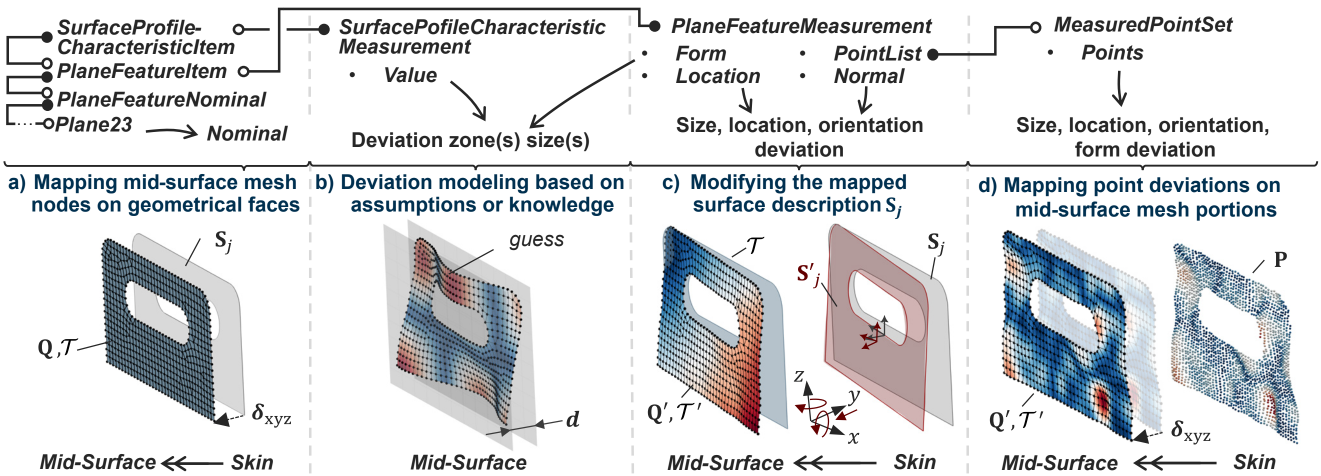

Fig. 3. Different ways to store deviation information in QIF and strategies to map it to mid-surface shell meshes for variation simulation. Deviations are exaggerated.

4. Application

The following section illustrates the so far methodically elaborated idea of a QIF-informed DT by a practical application and leads into a concluding discussion.

4.1. Case study and implementation

The spot-welded assembly in focus, inspired by a case study given in [23], is composed of two 0.8 mm-thin sheet metal parts with a stiffness of 210 GPa. Fig. 4 a) shows the assembly model defined in the software RD&T to simulate the joining process of the sheet metal parts [25]. Part compliance is considered using the Method of Influence Coefficients, enabling mechanically informed deformation behavior without performing a full stress-based FEA for each sample [9, 22]. A 4-2-1 locating scheme is used to position the parts, then join them at 14 weld points, release them from the weld fixture, and inspect the absolute deviation of the location of the cut-out center point as a critical Key Characteristic (KC). Fig. 4 b) shows hole, slot, and plane features identified in the respective mid-surface shell mesh.

The QIF files describing the as-designed status were exported from Autodesk® Inventor® Professional 2026. Open-source code for reading and writing QIF [24] was used to append synthetic measurement results for a batch of $N = 25$ parts each to the QIF files and to map them to the shell meshes. Given

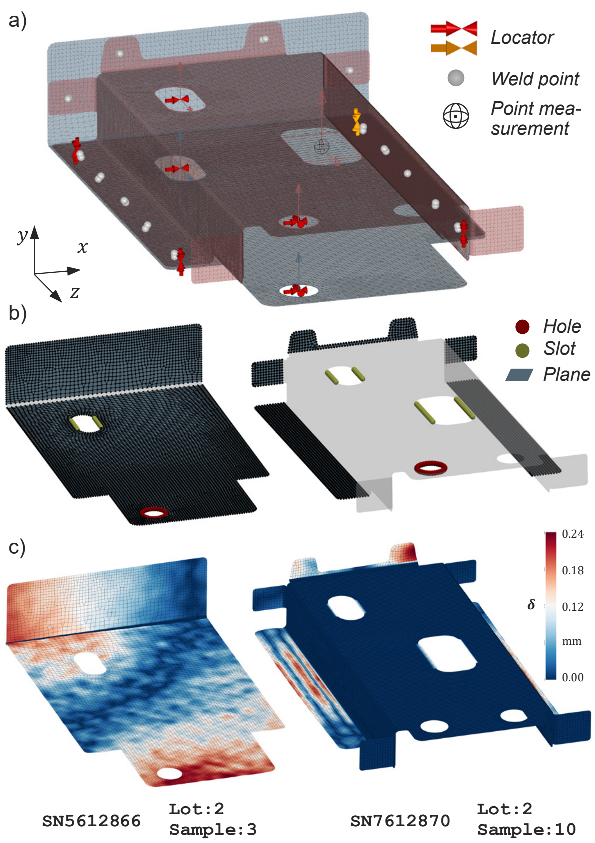

Fig. 4. Case study: a) RD&T model with part shell meshes, locators, weld points, and virtual measure; contact points are suppressed for better visibility. b) Measured features of both parts. c) Two sample shell meshes with mapped deviations exchanged through QIF.

the actual geometry of each part, an optimal part matching can be found by optimization. The objective is to find a permutation $\boldsymbol{\pi} : \{1, 2, \ldots, N\} \rightarrow \{1, 2, \ldots, N\}$, that minimizes the mean $\hat{\mu}$ and variation $6\hat{\sigma}$ of the KC over all N assemblies [21]:

$$\min_{\boldsymbol{\pi}} . \left[\, w_1 \cdot \hat{\mu}(\boldsymbol{\pi}) \;+\; w_2 \cdot 6\hat{\sigma}(\boldsymbol{\pi}) \,\right]. \tag{2}$$

Simulated annealing was used to solve Eq. (2) in Python, with RD&T called at each iteration to predict the KCs for each intermediate solution $\boldsymbol{\pi}^{*}$. The weights were chosen to $w_1 = w_2 = 0.5$ in this study. Two scenarios were considered in this study:

I. Neglecting form deviations using *FeatureMeasurements*.
II. Mapping the actual shapes from *MeasuredPointSets*.

Fig. 4 c) illustrates two samples with deviations mapped from *MeasuredPointSets* onto the shell meshes (scenario II).

4.2. Results and discussion

The optimizer converged in both scenarios after 1000 iterations, yielding an optimal pairing of all 25 parts for the given batch. Mapping only location and orientation deviations (see Fig. 3 c)) from QIF on the shell mesh led to $\hat{\mu}_{\mathrm{I}} = 0.065$ mm, $6\hat{\sigma}_{\mathrm{I}} = 0.190$ mm. Mapping the deviation information from the measurement points (see Fig. 3d)), in comparison, resulted in a higher mean and variance value $\hat{\mu}_{\mathrm{II}} = 0.155$ mm, $6\hat{\sigma}_{\mathrm{II}} = 0.336$ mm. The results do not imply that form deviations must always be taken into account, but rather raise awareness that the level of detail may affect the reliability of the final DT decisions. The deviation information mapping strategy may also lead to different final part-matching decisions, fed back to the assembly line. As an example, sample #1 and #3 obtained for the lower and upper part were paired in scenario I, while #1 and #13 were found to be a good match in scenario II. Note that the case study is to be understood as an exemplary application. Although the choice of weighting factors influences the results, their sensitivity to robustness is not further studied in this article. Furthermore, Eq. (2) can be extended to include conformance limits in line with ISO 14235 to account for measurement uncertainties in the decision.

Although the example highlights the benefits of augmenting and harvesting QIF files for DT applications, further research is needed to detail the proposed strategy. It needs to be studied how the QIF information string can be used and combined effectively with other strings, creating a strong Digital Thread for geometry assurance, verified in an industrial setting with more complex parts and assemblies, real inspections, large amounts of data, and measurement uncertainties, to ensure its readiness for real-time use. The simulation results are sensitive to both the density of the mesh and the *MeasuredPointSets*. For this reason, detailed studies are essential to find a compromise between accuracy, efficiency, and the related number of data to store, and how to handle missing information. Since QIF provides a systematic way to store traceable inspection data, it facilitates the creation of standardized datasets for deriving and learning manufacturing signatures. By using QIF, datasets collected over time are automatically pre-labeled and can be used to train machine learning models to predict deviations in early design phases of next product generations with similar geometry and processes. As the time required for QIF parsing and mapping, on the order of a few seconds depending on the number of features and measurement points, is negligibly small relative to optimization runtimes of several hours, standardized datasets can facilitate training fast-prediction models to replace the computationally expensive variation simulations within DT optimization loops, thereby enabling dynamic decision-making in production in real time [21].

5. Summary and outlook

This article proposed a QIF-based framework to create a seamless flow of part deviation information from inspection to non-rigid variation simulation. Linking all part geometry and deviation information, exchanged via a single mutual QIF file, to the respective shell mesh portions used as the geometrical representation in simulation enables the Digital Twin to be automatically fed and to make decisions at part and batch levels. Although the presented case study emphasized its potential, future research is needed to evaluate the strategy's usability to support real-time geometry assurance in the series production of more complex assemblies.

Acknowledgements

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