

Defining requirements for integrating information between design, manufacturing, and inspection

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ABSTRACT

Industry desires a digital thread of information that aligns as-designed, as-planned, as-executed, and as-inspected viewpoints. An experiment was conducted to test selected open data standards' ability to integrate the lifecycle stages of engineering design, manufacturing, and quality assurance through a thorough implementation of a small scale model-based enterprise. The research team set out to answer: from design, through production, and final inspections, what are the hurdles that a manufacturer would face during the development of a fully linked and integrated information chain? The research team was not able to fully link all the required information, but value for industry was still identified. This paper presents the results of the experiment, provides guidance on how to overcome or mitigate identified challenges, and discusses the benefits or incentives to be gained from tracing or linking information through multiple stages a product lifecycle.

KEYWORDS

data interoperability; model-based enterprise; digital thread; digital twin

1. Introduction

To better understand and address the challenges faced in linking all stages of a manufacturing and design process, an investigative fabrication process was designed and enacted as part of a collaboration between the National Institute of Standards and Technology (NIST) and The Manufacturing Technology Centre (MTC). This collaboration sought to test selected open standards' ability to integrate the lifecycle stages of engineering design, manufacturing, and quality assurance through a thorough implementation of a small scale model-based enterprise (MBE). Lessons learned through this exercise have been recorded and digested in such a manner as to both inform further development of standards as well as encourage the adoption of the most useful and effective existing standards. In this paper, the primary standards of interest are ASME Y14.41, ASME Y14.47, ISO 16792, ISO 10303-242, MTCConnect, and ANSI/DMSC Quality Information Framework (QIF). The activities and results of the collaboration

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14 are described in this paper. The work of this collaboration builds upon past work and
15 introduces novel contributions with studying a standards-based information integra-
16 tion from multiple sources using automatic data-alignment strategies.

17 At the onset, the most fundamental question and goal of this work was to under-
18 stand the capabilities and limitations of implementing a standards-based information
19 integration throughout the lifecycle of a product. From design, through production,
20 and final inspections, what are the hurdles that a manufacturer would face during the
21 development of a fully linked and integrated information chain? How can these obsta-
22 cles be overcome or mitigated? What benefits or incentives can be gained from tracing
23 or linking information through multiple stages of a product lifecycle – thus, creating
24 a “digital thread” across the lifecycle? A digital thread is an integrated information
25 flow that connects all the phases of the product lifecycle using accepted authoritative
26 data sources (Kraft 2016; Hedberg Jr et al. 2016; Wardhani and Xu 2016). The digital
27 thread focuses on integrating all phases of the product lifecycle for making efficient and
28 effective measurements of the lifecycle in support of data-driven methods (Hedberg,
29 Bajaj, and Camelio 2020).

30 While we explored the research questions around the goals of this work, the results of
31 our research point to the reality that a standards-based information integration is not
32 achievable today because the standards do not data-alignment strategies without sig-
33 nificant human intervention. Our results show that the popular data standards used in
34 industry do not support automatic data alignment. Therefore, instead of documenting
35 implementation schemes, we provide recommendations to the Standards Development
36 Organizations (SDOs) for enhancing the standards that we expect would enable auto-
37 matic data-alignment capabilities. We also expect that once automatic data-alignment
38 capabilities are realized, researchers should then be able to discover methods for im-
39 plementing and transferring standards-based information integration to practice.

40 **2. Background**

41 During a survey of the current state of the industry, as well as first-hand experience
42 during the exemplar manufacturing collaboration designed for this work, we found that
43 the alignment of information across lifecycle stages is primarily accomplished with in-
44 tense amounts of human labor, if at all. At the date of this publication, there is still
45 not a broadly applicable process or tool that allows for the automation of information
46 alignment and cross-stage analysis that can link multi-stage information. An example
47 of such an information trace would be to correlate as-measured data (QIF) backwards
48 through as-fabricated (MTCConnect), as-planned (NC Code), and as-designed (STEP)
49 data to aid in determining the source of production defects (e.g., design flaw, equip-
50 ment degradation). Given this lack of standardized method for linking between the
51 manufacturing process stages, this paper describes our experiment exploring avenues
52 for automating the process and provides recommendations and requirements for inte-
53 grating this information.

54 **2.1. Manufacturing Standards**

55 Throughout the lifecycle of a manufactured product, there are a plethora of standards
56 that information and data associated with that product are subject to. This makes
57 the integration of such data exceedingly challenging as few of these standards were
58 created with interoperability in mind, instead each being designed for its own specific

59 purpose. This section reviews many of the standards relevant to lifecycle product
60 production. In order, the review includes: ASME Y14.41, ISO 16792, ISO 10303-242
61 (STEP), MTConnect, and ANSI/DMSC QIF. It should be noted that this is not
62 a complete list of standards applicable to a computer-numerically controlled (CNC)
63 manufacturing process; many different standards could have been used in addition or
64 as an alternative to those reviewed here.

65 *2.1.1. Standards for Design Requirements in Digital Drawings*

66 With the uptake of computer-based design software, the American Society of Mechan-
67 ical Engineers (ASME) released ASME Y14.41 to define requirements of model-based
68 product definition in computer-aided design (CAD) software (American Society of
69 Mechanical Engineers 2019). Focusing primarily on geometric dimensioning and toler-
70 ancing, ASME Y14.41 presents methods for organizing product definition data within a
71 CAD file and was created primarily to allow CAD information to become an additional
72 resource for manufacturing and inspection criteria. Where applicable, it recommends
73 annotating the model with design requirements in three-dimensional (3D) space near
74 the associated geometry, or in some cases, additionally using an engineering drawing
75 graphic sheet to indicate requirements.

76 The ASME Y14.41 is a trusted standard of industrial practices for a company to
77 best utilize digital CAD information. This standard allows for cross interpretation
78 between design, machining, and inspection aspects of the product lifecycle. This stan-
79 dard became the basis for the international standard ISO 16792:2006 (International
80 Standards Organization 2015).

81 Like the ASME standard, ISO 16792 prescribed requirements for documenting 3D
82 digital models. The rules include requirements for preparation, revision, and presenta-
83 tion of digital product definition data. Many of the explicit requirements address ele-
84 ments that are significantly different, or not included in older standards for drawings.
85 Our model-based definition (MBD) data made use of syntactic notes and annotations
86 connected to semantic geometric dimensions and tolerances (GD&T) and 3D anno-
87 tation views or presentation states as is mandated by the ASME and International
88 Standards Organization (ISO) standards.

89 An additional document, ASME Y14.46 (American Society of Mechanical Engineers
90 2017), is a draft standard for trial use and seeks to extend the design rules to describe
91 complex parts, and features unique to additive manufacturing.

92 *2.1.2. Standards for Design Information*

93 The international standard for describing product data in a computer interpretable
94 manner independent of the construction software is defined in ISO 10303-242 (In-
95 ternational Standards Organization 2014). S^Tandard for the Exchange of Product
96 Model Data (STEP) is designed for exchanging files between software used at different
97 stages of the product lifecycle, including: CAD, computer-aided engineering (CAE),
98 computer-aided manufacturing (CAM), computer-aided inspection (CAI), product-
99 data management (PDM) / enterprise data modeling and other computer-aided tech-
100 nologies (CAx) systems.

101 In this project we used the S^Tandard for the Exchange of Product Model Data
102 Application Protocol 242 (STEP AP242) standard to drive the CAM process. We
103 started with native SolidWorks CAD files and created derivative STEP AP242 models
104 from this. The same native format was also used to create QIF files which were used

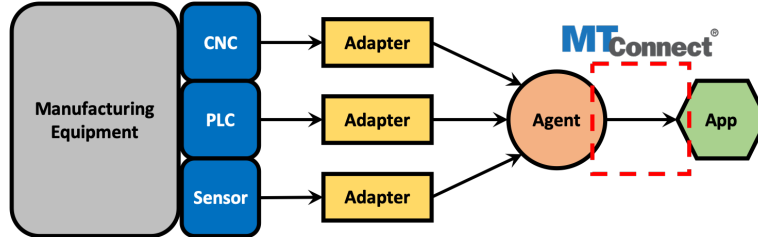


Figure 1. Overview of basic MTCConnect architecture; the standard only specifies the output of the Agent as highlighted by the red-dashed box (after Sobel (2015)).

105 in the measurement parts of the workflow.

106 2.1.3. Standards for Manufacturing Information

107 MTCConnect is an American National Standards Institute (ANSI) accredited open,
 108 read-only, and extensible data-interoperability standard that offers a vocabulary and
 109 relevant semantics for manufacturing equipment to provide structured, contextualized
 110 data with no proprietary format (MTCConnect Institute 2018). Figure 1 shows the basic
 111 MTCConnect architecture. An Adapter is an optional piece of software or hardware that
 112 collects and filters data from a device and publishes this data to an Agent. An Agent is
 113 a Hypertext Transfer Protocol (HTTP) server that provides a Representational State
 114 Transfer (RESTful) interface for a client application. It organizes and manages data
 115 from one or more adapters and creates and publishes a response document based on
 116 requests from a client.

117 During the work presented in this paper, we used the MTCConnect standard to
 118 extract data from the CNC machine to capture key manufacturing parameters. This
 119 standard enables conversion of raw machine data to a machine-readable format for
 120 further analytics to be carried out. Investigations have been reported into applying the
 121 standard to large scale production facilities including aircraft production (Venkatesh
 122 et al. 2016).

123 2.1.4. Standards for Quality and Inspection Information

124 QIF is an ANSI accredited that aims to enable seamless flow of information within
 125 computer-aided quality measurement systems (Digital Metrology Standards Consor-
 126 tium 2018). QIF supports metrology data from all areas of the process chain, from
 127 design, through inspection and measurement resource planning, to execution, results
 128 evaluation, and statistical analysis.

129 As with the MTCConnect standard, QIF files are based on Extensible Markup Lan-
 130 guage (XML) enabling them to be integrated easily with other applications, including
 131 Internet and network-based applications. The QIF standard is used throughout this
 132 experiment to govern the flow of information from the design through to measurement
 133 stage. An illustration of data flow taken from the QIF standard documentation is
 134 shown in Figure 2 (Digital Metrology Standards Consortium 2018).

135 Unlike many other standards considered, the QIF XML schema used to define the
 136 file formats are considered part of the standard. Therefore, an implementation of this
 137 standard not using the schema fully would not be conforming to the standard. This is
 138 of particular relevance for standardization, interoperability, and automation tools. It
 139 means that the difficulties experienced with the integration of other data standards is
 140 less likely to affect the QIF standard. As more companies adhere to this standard, the

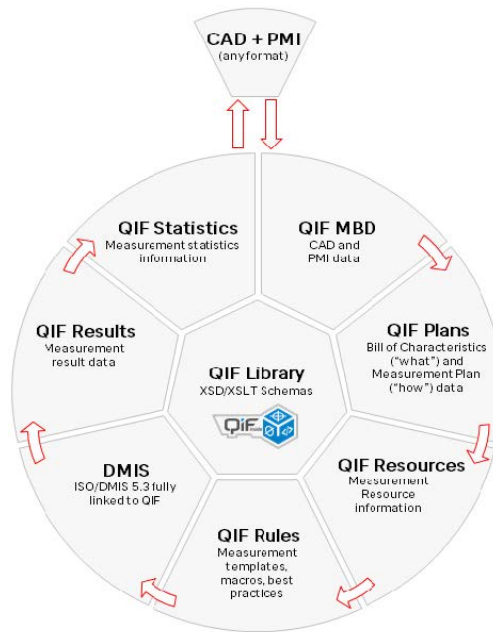


Figure 2. Overview of basic QIF information architecture; around the QIF core library are the six QIF application-specific information models, Model-Based Definition (MBD), Plans, Resources, Rules, Results, and Statistics (reproduced from Digital Metrology Standards Consortium (2018)).

141 market will see a reduction in variability of commands that exists between different
 142 equipment vendors allowing for more concise and broadly applicable software solutions
 143 to be developed.

144 **2.2. Technology for Manufacturing Integrating Information**

145 There are many existing technologies that aim to facilitate or augment the integra-
 146 tion of production lifecycle information. Investigations into these technologies showed
 147 that a majority of off-the-shelf products have limited scope and are not structured to
 148 enable automated cross-domain (e.g., design, fabrication, inspection) data alignment.
 149 As additionally shown through our work on this paper, significant effort is required to
 150 manually align data. Our efforts revealed both strengths and weaknesses of the exist-
 151 ing technologies in extended previous work and automate some level of data alignment
 152 to enable information mining and data analytics.

153 *2.2.1. Model-Based Enterprise*

154 Information technology advances (e.g., data analytics, service-oriented architectures,
 155 and networking), coupled with operational technology (e.g., hardware and software
 156 for sensing, monitoring, and control of product and processes), have enabled a digital
 157 revolution promising to reduce costs, improve productivity, and increase output quality
 158 (Childerhouse and Towill 2011; Wu et al. 2013). These two facts are motivation for why
 159 the manufacturing sector of industry is working to connect each phase and function
 160 of the product lifecycle. We recognize that the problems and promises are not novel,
 161 but rather emerging technologies are now available that enable novel approaches to
 162 implement solutions that may have been ahead of their time (Mckay 2003; Wang, Ong,

163 and Nee 2018). The advances information and operation technology have coalesced into
164 an effort being called MBE.

165 MBE is represented by several constituent components. A workshop titled “MBx:
166 Peeling Back the Layers of MBE” conducted during the 2016 MBE Summit (Carlisle
167 2016), set out to define several critical components of the MBE that included design,
168 engineering analysis, manufacturing, systems engineering, sustainment, testing, evalu-
169 ation, and quality. Our work presented in this paper was most concerned with MBD,
170 model-based manufacturing (MBM), and model-based quality (MBQ). The following
171 are the proposed definitions from the workshop for MBD, MBM, and MBQ:

172 **MBD:** The authoritative digital-data set based on a 3D geometric model that defines
173 the end-item requirements for a product.

174 **MBM:** An environment [in that] the Design Data can be consumed by the value
175 stream to plan, produce, fabricate, assemble, inspect and certify, [and] maintain
176 and sustain parts and assemblies to meet requirements.

177 **MBQ:** The conformance of the physical product and process to the requirements of
178 digital product definitions and process specifications using measurement plan-
179 ning, execution, and evaluation in combination with 3D annotated models and
180 associated data.

181 The MBD, MBM, and MBQ domains have different data requirements, such as the
182 identification of shape, features, and characteristics. MBE requires adopting model-
183 based data standards to effectively integrate the different kinds of data for efficient
184 reuse and exchange between product-lifecycle phases (Hedberg Jr et al. 2017a). How-
185 ever, traceability of requirements and activities is paramount to ensuring effective func-
186 tioning supply chains (Khabbazi et al. 2011). Moreover, data interoperability between
187 design activities (e.g. product and assembly design) and manufacturing activities (e.g.
188 fabrication, assembly, and quality assurance) must be consistent (Hedberg Jr et al.
189 2017b). Hedberg Jr et al. (2017b) recommend using ISO 10303-242 (STEP AP242)
190 (International Standards Organization 2014) to represent the as-designed configuration
191 of products and MTConnect and QIF to represent the as-fabricated and as-measured
192 configurations. Aligning these three representations would enable quicker and easier
193 knowledge building based off experience in the product lifecycle. The goal of our work
194 here is to evaluate the capability for integrating various types of standards-based data
195 available in the MBD, MBM, and MBQ domains – particularly MTConnect and QIF.

196 2.2.2. *Data Mining*

197 A well annotated and aligned set of integrated data is necessary for extracting vi-
198 tal information that might otherwise be inaccessible or impractical to synthesize. For
199 example, using appropriate techniques, integrated data could be used to obtain knowl-
200 edge of the factors influencing the quality of production parts. This in turn could be
201 translated into actionable information or policies to improve quality and or produc-
202 tion efficiency. The capture and contextualization of such actionable information is
203 directly linked to data mining across the lifecycle stages to produce information about
204 a process.

205 Several studies (Fischer et al. 2015; Hedberg Jr et al. 2016; Trainer et al. 2016; Hard-
206 wick and Sobel 2017) investigated integrating MBE components and/or standards-
207 based data. Hedberg Jr et al. (2016) compared paper-based processes to model-based
208 processes and identified a potential savings of 75 percent in cycle-time. Fischer et al.
209 (2015) and Trainer et al. (2016) also compared paper-based processes to model-based

210 processes using STEP AP242 to study the return-on-investment benefits and develop
211 tools for closing some gaps identified by Hedberg Jr et al. (2016). Lastly, Hardwick
212 and Sobel (2017) automated measurement of producing a product using semantic
213 tolerances, requirements sent using STEP AP242, measurements streamed using MT-
214 Connect, and results returned using QIF.

215 To utilize all these varied data sources and structures, robust algorithms must be
216 identified and tested. A variety of data mining techniques that have been identified as
217 strong candidates for use in manufacturing include clustering, classification, regression,
218 and decision-tree learning (He et al. 2009; Liang 2015). Case in point, decision-trees
219 have been shown to be effective in improving yield in the manufacture of semicon-
220 ductor devices (Chien, Wang, and Cheng 2007) and for drawing qualitative links be-
221 tween manufacturing parameters and the geometrical forms of drilled holes (Mason,
222 Rahman, and Maw 2017). Recently the use of regression-tree learning has also been
223 demonstrated as an effective technique for predicting part quality (Maw, Whicker,
224 and Rahman 2017). These techniques may be feasible for optimizing the accuracy of
225 features on the part in our and future investigations.

226 3. Methodology

227 The goal of this work is to explore and quantify the capabilities of integrating data
228 and information between design, manufacturing, and inspection. As part of this, a
229 secondary effort focused on identifying key process variables for determining optimal
230 manufacturing parameters. MTC played the role of an original equipment manufactur-
231 er (OEM) and NIST played the role of a contracted design house and manufacturer.
232 The test case was an assembly designed with input from both parties and was man-
233 ufactured at NIST. Each component of the assembly also underwent a first-article
234 inspection and 100 percent inspections at NIST. Data was collected at each step in
235 the workflow – STEP AP242 and NC Code sheets for design information, MTCConnect
236 from manufacturing data, and QIF for quality data. The assembly components were
237 then shipped to MTC, where an incoming and receiving inspection was conducted. The
238 aim in this process was to determine the ability to effectively and efficiently integrate
239 the data collected throughout this process.

240 The success criteria was identified as the ability to automatically align the features
241 and characteristics across each data set. ASME Y14.5-2009 (American Society of Me-
242 chanical Engineers 2009) standard defines a feature as “a physical portion of a part
243 such as a surface, pin, hole, or slot or its representation on drawings in models, or in
244 digital data files.” ANSI/QIF Part 1-2015 (Digital Metrology Standards Consortium
245 2018) standard defines a characteristic as “a control placed on an element of a feature
246 such as its size, location or form, which may be a specification limit, a nominal with
247 tolerance, a feature control frame, or some other numerical or non-numerical control.”
248 A design of experiments (DOE) is leveraged to induce variability in one of the parts in
249 a structure. The DOE should enable linking any variability to its source. Any linking
250 requires aligning data about the features and characteristics.

251 Our work builds on the previous studies, but includes some novel additions. First,
252 our work is the first investigation that used an assembly in the experiments. Reviewing
253 the literature, all past model-based studies used single components as their test cases.
254 Studying an assembly introduces a more realistic level of product complexity. Indus-
255 try applies tolerances to features in definition of product components because those
256 components must fit together in an assembly to realize the product. Studying only

257 the data of a single component does not provide the full context in the overall quality
258 of the assembly. Therefore, industry must review the quality of all components of a
259 product and the relationship of each component to the assembly for understanding
260 the quality of the product.

261 Second, our study tests data integration from multiple sources. The design and QIF
262 data come from multiple vendors, suppliers, and tools. Collecting and integrating data
263 from multiple sources is closer to a real MBE supply chain. More closely matching a
264 real supply chain is a significant enhancement over previous work.

265 **3.1. *Design of the Digital Assembly Definition***

266 Test cases from the NIST “MBE PMI Validation and Conformance Testing Project”
267 (Lipman et al. 2017) were the starting point for the design of the assembly used in
268 our study. Specifically, we used Fully-Toleranced Test Cases (FTC) 7 (box), 8 (lid),
269 and 9 (mounting plate) (Lipman 2017). The decision to start with the FTC models
270 was because these models had already undergone expert review and were designed to
271 be an assembly. This minimized the time required to develop a valid assembly for our
272 work.

273 While we started with three models, we did make a few changes to ensure the
274 assembly would meet all the needs of our study. First, we scaled down the original size
275 of the designs to reduce the cost of the manufacturing step by allowing us to utilize
276 a smaller 3-axis mill that had time available in its production schedule. Second, we
277 added some additional features to all of the parts to increase the diversity of the types
278 of characteristics. Lastly, we converted each design to standard metric units since the
279 original designs used imperial units.

280 The complete assembly is comprised of the box, lid, and mounting plate, derived
281 from the FTCs, an acrylic window to mount in the lid, and standard hardware procured
282 through a third-party. All data from the work presented here, including the CAD
283 models, are available in a published data set from Hedberg Jr et al. (2018).

284 No two-dimensional (2D) drawings were produced for the assembly or its compo-
285 nents. All the product definition was included as product and manufacturing infor-
286 mation (PMI) in the 3D CAD model. PMI included the typical information included
287 historically on a 2D drawing, including dimensions, tolerances, and notes. PMI, in
288 models, also includes meta-data stored as model attributes. Embedding the PMI in
289 the CAD model enables shorter planning cycles in both manufacturing and inspec-
290 tion. For example, the inspection planner can use tools that read the characteristics’
291 requirements directly from the model. This eliminates the need for manual, human-
292 based data entry, which also reduces the risk of injecting errors into the process. Also,
293 PMI added to the model, in accordance with the ASME Y14.41-2012 (American Soci-
294 ety of Mechanical Engineers 2012) standard¹, will provide additional functionality to
295 the user – the features associated with the PMI will highlight when selected by the
296 user. 3D geometry combined with PMI provides a rich set of capabilities where both
297 a computer and a human have interpretable information available for consuming the
298 digital product definition in a process.

¹The 2012 edition of ASME Y14.41 was selected because the latest edition was not publicly available at the time the models were generated in this work.

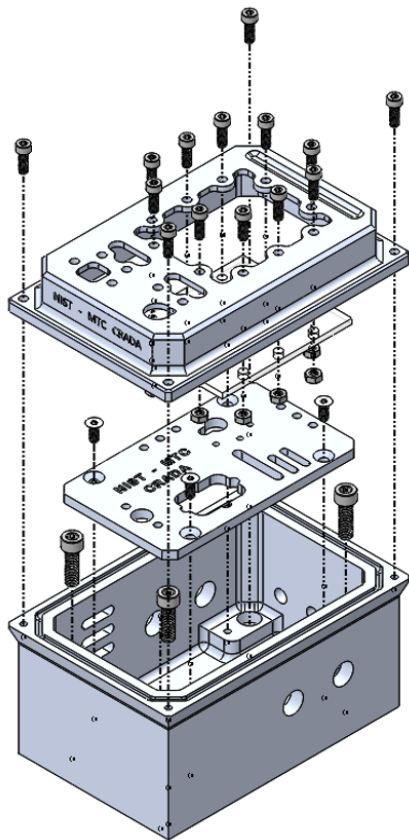


Figure 3. Presentation of the Exploded View, as displayed inside the CAD system, of the assembly test case showing all components

299 **3.2. *Design of Experiments for Manufacturing Parameters***

300 The influence of machining-process parameters on the quality of the final product
301 is a complicated problem to model. Rather than modeling the problem, a DOE was
302 proposed to control the parameters of data that would allow for the identification of
303 strong correlations of machining parameters for this particular case. The experiment
304 focused on the 16 hole features on the plate within our assembly.

305 We wanted to analyze the form error of the manufacturing process above the noise in
306 the machining (and measurement) process. We decided not to make entirely identical
307 parts as this would likely only achieve one single manufacturing signature type and
308 background noise. The process parameters were changed sufficiently to distort the
309 parts above the noise level and produce multiple manufacturing-signature types. The
310 aim was to understand how much these process parameters affect variation in the part.

311 Tool length, tool speed, and feed rate were the three parameters chosen to be con-
312 trolled for pocketing processes during the experiment to produce variation in the qual-
313 ity of the part. These parameters were identified as being the ones that are commonly
314 varied in machining to modify the part. Initial values were specified at the recom-
315 mended settings for given tools and component material. Each variable then had either
316 one or two varied states to induce part variation. The variations were controlled to
317 ensure the full parameter space is covered systematically rather than varying param-
318 eters based on a random choice. Table 1 shows the DOE matrix, where “*” markers
319 indicate the mean value between maximum and minimum manufacturer recommended
320 values. Additional labels indicate the varied states of the respective parameter.

321 The DOE approach provided a reduced number of parameter sets and reduced
322 number of variants of each control parameter. Confidence in the results and the re-
323 peatability of the process would come from analysis of the quality of the holes as a
324 group.

325 Mason, Rahman, and Maw (2017) showed that the tool length, tool speed, and
326 feed rate are critical variables within the drilling of holes in mild steel components.
327 Understanding the sensitivity of each control parameter with regard to how much
328 effect its variation has on the final part made of aluminum, relied on expert knowledge
329 of the machining specialists. The values used for each tool used for the manufacture
330 of these parts can be found in Table 2.

331 A new cutting edge was to be used at the start of every component such that
332 tool wear can be reduced and monitored. Temperature and humidity readings were
333 recorded at the start of production for each component. Fixturing was only done once
334 after the initial material-preparation phase was completed. All subsequent machining
335 operations were performed in-station to minimize alignment errors.

336 **3.3. *Manufacturing and Inspection Planning and Execution***

337 Both manufacturing and inspection planning were completed using model-based meth-
338 ods. We used commercially available software to program the fabrication and inspec-
339 tion programs. The various software packages were selected for their “off-the-shelf”
340 support of the QIF standard and required no customization.

341 The CAD models were imported directly into the planning software with each
342 model’s PMI utilized to the fullest extent supported by the software packages. The
343 fabrication program’s paths and tooling selections were automatically determined by
344 the CAM software when possible, but the majority of the decisions were made by the
345 machining specialist based off his experience and knowledge. A numerical control (NC)

Table 1. DOE design matrix

| Part Number | Tool Length | Cutting Speed | Feed Rate |
|-------------|-------------------|-------------------|-------------------|
| 01 | Short* | Fast* | High* |
| 02 | Short* | Fast* | Medium |
| 03 | Short* | Fast* | Low |
| 04 | Short* | Medium | High* |
| 05 | Short* | Medium | Medium |
| 06 | Short* | Medium | Low |
| 07 | Short* | Slow | High* |
| 08 | Short* | Slow | Medium |
| 09 | Short* | Slow | Low |
| 10 | Long | Fast* | High* |
| 11 | Long | Fast* | Medium |
| 12 | Long | Fast* | Low |
| 13 | Long | Medium | High* |
| 14 | Long | Medium | Medium |
| 15 | Long | Medium | Low |
| 16 | Long | Slow | High* |
| 17 | Long | Slow | Medium |
| 18 | Long | Slow | Low |
| 19 | Operator's Choice | Operator's Choice | Operator's Choice |
| 20 | Operator's Choice | Operator's Choice | Operator's Choice |

*Recommended Value

Table 2. Process parameters for pocketing process of holes in the DOE

| Tool Name | Tool Length | | Cutting Speed | | | Feed Rate | | |
|--------------------------|-------------|-------|------------------------|--------|------|-------------------|--------|-----|
| | Short* | Long | Fast* | Medium | Slow | High* | Medium | Low |
| | Inches | | Revolutions Per Minute | | | Inches Per Minute | | |
| 0.093 inch End Mill | 0.375* | 1.375 | 12k* | 9k | 6k | 36* | 27 | 21 |
| 0.125 inch End Mill | 0.375* | 1.375 | 12k* | 9k | 6k | 36* | 27 | 21 |
| 0.25 inch End Mill | 0.5* | 1.5 | 12k* | 9k | 6k | 140* | 110 | 80 |
| 0.5 inch End Mill | 0.75* | 1.75 | 12k* | 9k | 6k | 140* | 110 | 80 |
| 0.5 inch Counter Sink | 1.0* | 2.0 | 1k* | 0.75k | 0.5k | 2* | 1.5 | 1 |
| 3.0 inch Face Mill | n/a | n/a | 5k* | 3.75k | 2k | 120* | 90 | 60 |
| 0.125 inch Engrave | 0.375* | 1.375 | 12k* | 9k | 6k | 40* | 30 | 20 |

*Median Recommended Value

346 program was generated and post-processed for the 3-axis mill fabricating the parts.
347 Machine and process data was captured during the program run using MTConnect-
348 compliant adapters and agents.

349 For the inspection, the NIST coordinate-measurement machine (CMM) was pro-
350 grammed automatically using the CMM manufacturer’s programming tool. The pro-
351 gramming tool read the characteristics directly from the CAD model’s PMI, deter-
352 mined the needed CMM-probe configurations, and generated an execution-time opti-
353 mized inspection program. The time to generate the first-article inspection programs
354 for each part took less than ten minutes per part. The measurements and inspection
355 results were captured in a database in real-time and then exported as QIF Results at
356 the completion of the inspection.

357 The MTC CMM was a different manufacturer from the NIST CMM. The MTC
358 CMM was programmed using a combination of third-party software package and the
359 Dimensional Measuring Interface Standard (DMIS) for execution. The CAD model was
360 translated into QIF MBD and imported into the third-party software. The software
361 automatically read the PMI, recognized the features and characteristics for inspection,
362 set datum structures, and assigned both a lightweight point strategy and simple scan
363 strategies to the features. The CMM program was exported to DMIS 5.2 for execution
364 on the CMM. The measurements were exported from the CMM manufacturer’s soft-
365 ware to a DMIS *.out* file. The DMIS measurements file was imported to the third-party
366 software and the inspection results were exported as QIF Results.

367 **3.4. Data and Information Flow**

368 Integrating data from different sources is critical to extract information and knowl-
369 edge which contains links between the manufacturing parameters and the final quality
370 of features on the part. For example, to draw a link between the part quality and
371 machining parameters at a specific time, it is necessary to obtain both measurement
372 data (in QIF format) and machine parameters (encoded in the machine’s G-Code) in
373 the same format to carry out further operations. Once this has been carried out it is
374 also imperative that the integrated data is stored in a format that is easily readable
375 by the software carrying out data mining. The format of the final information in the
376 knowledge base must be easily readable by both humans and machines; a format such
377 as comma-separated value (CSV) is most appropriate as this is easily read by com-
378 monly used data analysis software such as Microsoft Excel, Matlab, R, Python and
379 any other analytics tools.

380 An important element of the data flow is the monitoring and collecting of NC-
381 Code execution data from the CNC machine using an MTConnect adapter. This data
382 contains in-process measurements of important machining parameters including feed
383 rate and tool-rotation speed. By converting this to simulated G-Code, it is possible to
384 determine the machine parameters at a given time. This level of traceability is essential
385 to any data-manipulation operations as it enables data mapping to be carried out.

386 This traceability also gives a mechanism to make comparisons between the prede-
387 fined parameters such as tool length, tool speed, and feed rate specified in the machine’s
388 code and the actual values of these parameters recorded in-process. Part quality could
389 then be linked to both the parameters specified to the machine and the true values
390 of these parameters as measured in process. This step is currently being investigated
391 further as the tools to perform such an action are not available. Development of such
392 tools is an important step to automate the process and enable data analytics for the

Table 3. QIF Results for Aprox. 20 Assembly Units

| Assembly Item | Failed Tests | Mean % Deviation From Nominal | Number of QIF Tests | Units Tested |
|---------------|--------------|----------------------------------|------------------------|--------------|
| Box | 0 | 33.74% | 47 | 18 |
| Cover | 1 | 12.46% | 27 | 20 |
| Plate | 51 | 33.63% | 31 | 20 |

393 extraction of knowledge.

394 Figure 4 illustrates the data flow throughout the data capture stages, including
 395 the different sources of data and the different standards which these data fall under.
 396 MTConnectR, a package within the R high-level programming language designed for
 397 statistical analysis (Joseph et al. 2017), was used to convert the extracted process
 398 data from the CNC machine code to the MTConnect XML format. The specific ma-
 399 chine tool used to produce the parts did not report tool-path positions. Therefore, the
 400 MTConnectR package was also used to simulate the tool-path position and align it
 401 to the collected execution data using a dynamic time warping method (Helu, Joseph,
 402 and Hedberg 2018). The resulting data output and alignment from the MTConnectR
 403 package provided a structured dataset that was used in the data-mining portions of
 404 the study.

405 4. Results

406 All of the data collected in this study is available in Hedberg Jr et al. (2018). The
 407 analysis of the produced parts centered around relating the machining input parameter
 408 specifications to the end quality measurements. The specific design features from each
 409 part could not be autonomously aligned with the recorded QIF tests due to inconsistent
 410 naming conventions between the separate sources of information. Despite this, there
 411 is much that can be learned from the analysis of the quality features for each of the
 412 separate parts produced.

413 4.1. QIF Results

414 During the course of this work a total of 20 assembled units were machined with
 415 QIF test results taken on each of the manufactured units. Of the three parts of the
 416 assembly, the Box exhibited zero quality test failures, the Cover showed one, and the
 417 Plate returned a total of 51 failed tests across the 20 units manufactured. From the
 418 results listed in Table 3, we can see that although the Plate had the most quality
 419 test failures (deviations found to be beyond the specified tolerances), the Box had the
 420 highest average deviation from nominal across all tests.

421 To some degree, the failures within the Plates were expected as the machining pa-
 422 rameters were varied beyond recommended values to help correlate them to resulting
 423 quality. However, as seen in Figure 5 the quality results from the Box units show a
 424 strong bi-modal distribution for many of the captured test, with 14 of the 47 tests
 425 showing strong tendencies to be at the lower end of the allowable tolerance values.
 426 Almost all of these poor test results relate to the positioning of the respective feature.
 427 As the large deviations from nominal are consistent across all the units tested, the
 428 poor quality issues could be a result of bad tolerance selection, inadequate machining
 429 capabilities, or some other mis-specification of the machining parameters. By moni-

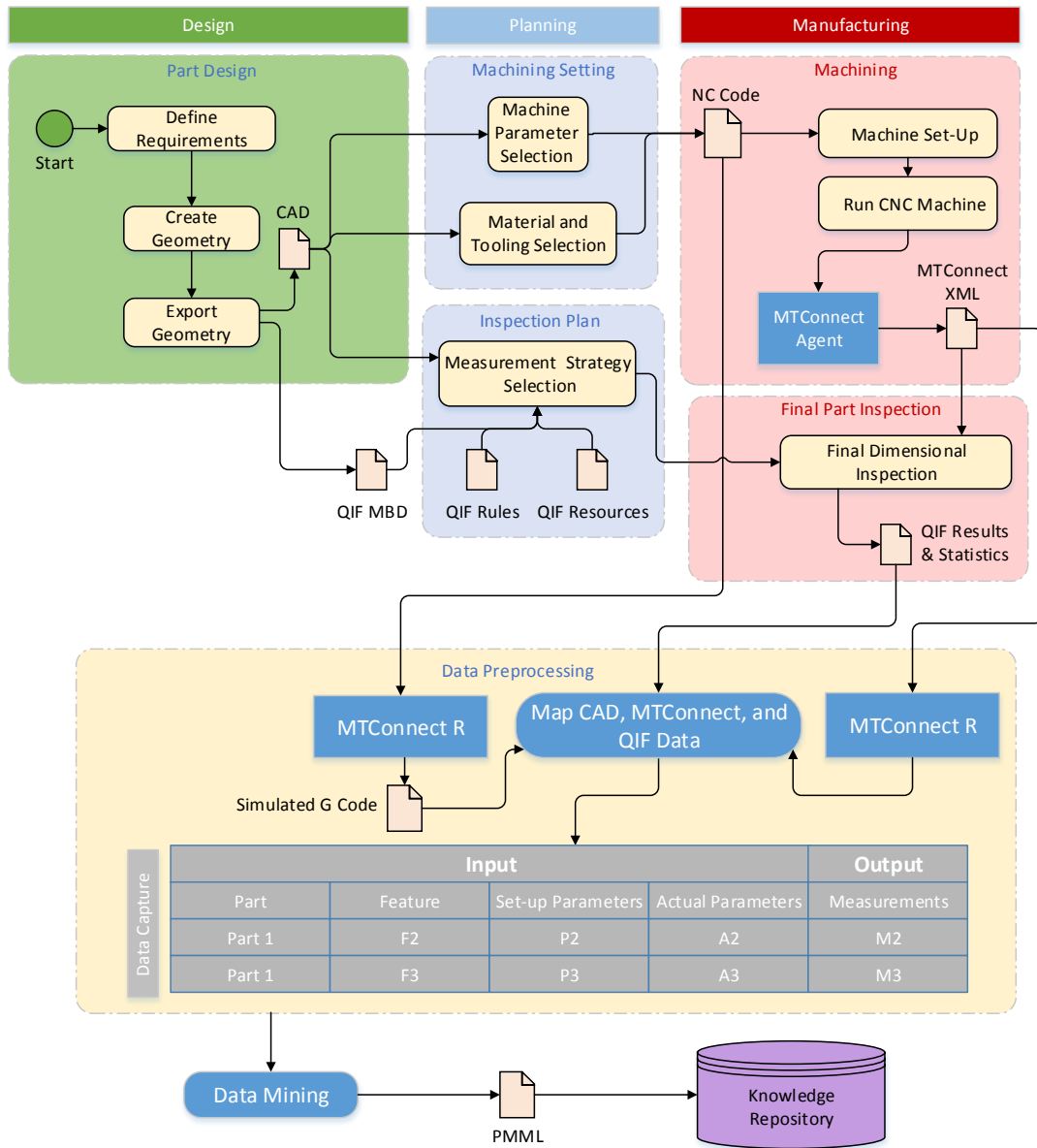


Figure 4. The flow of data and information within this investigation. The diagram shows data flows between the design, planning, and manufacturing phases. The data is then combined in the data preprocessing task to support the data mining and knowledge building activities.

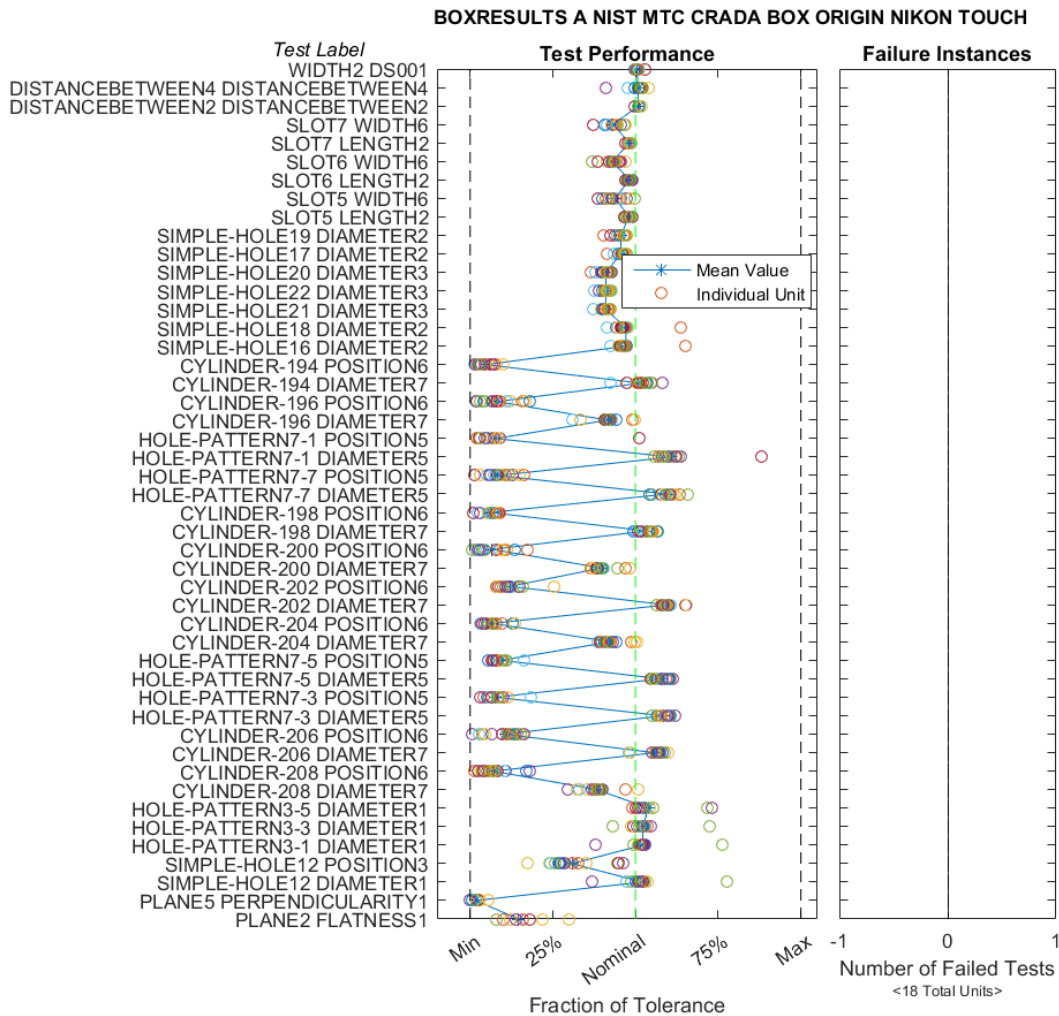


Figure 5. QIF Test Results for Individual Box Units as Percent of Tolerance Span

430 toring for such anomalous quality behavior despite a lack of failures, an investigation
 431 could be triggered to not only help trace down the problem, but perhaps suggest a
 432 solution.

433 Conversely, the test performance for the 20 Cover units was very strong across nearly
 434 all tests. Of the 27 individual quality tests performed, only one showed deviations more
 435 than approximately 10 percent from nominal, and the large majority less the five
 436 percent. Of those tests found to show large deviations, only one exhibited a grouping
 437 largely not centered near nominal. Strangely perhaps, the test with the worst average
 438 deviation did not produce a failure. Again, such anomalies can be monitored and
 439 trigger deeper investigations. A full description of the Cover QIF results can be found
 440 in Figure 6.

441 The quality test deviations in the Plate units show a stark increase in the number
 442 of failures compared to those found in the other assembly parts, particularly in six
 443 of the total 20 Plate units tested. Figure 7 shows very clearly that the units labeled
 444 10-18 have a clear increase in the average quality deviation and number of failures. Not
 445 coincidentally, this corresponds to the parts listed in Table 1 as using the “Long” tool

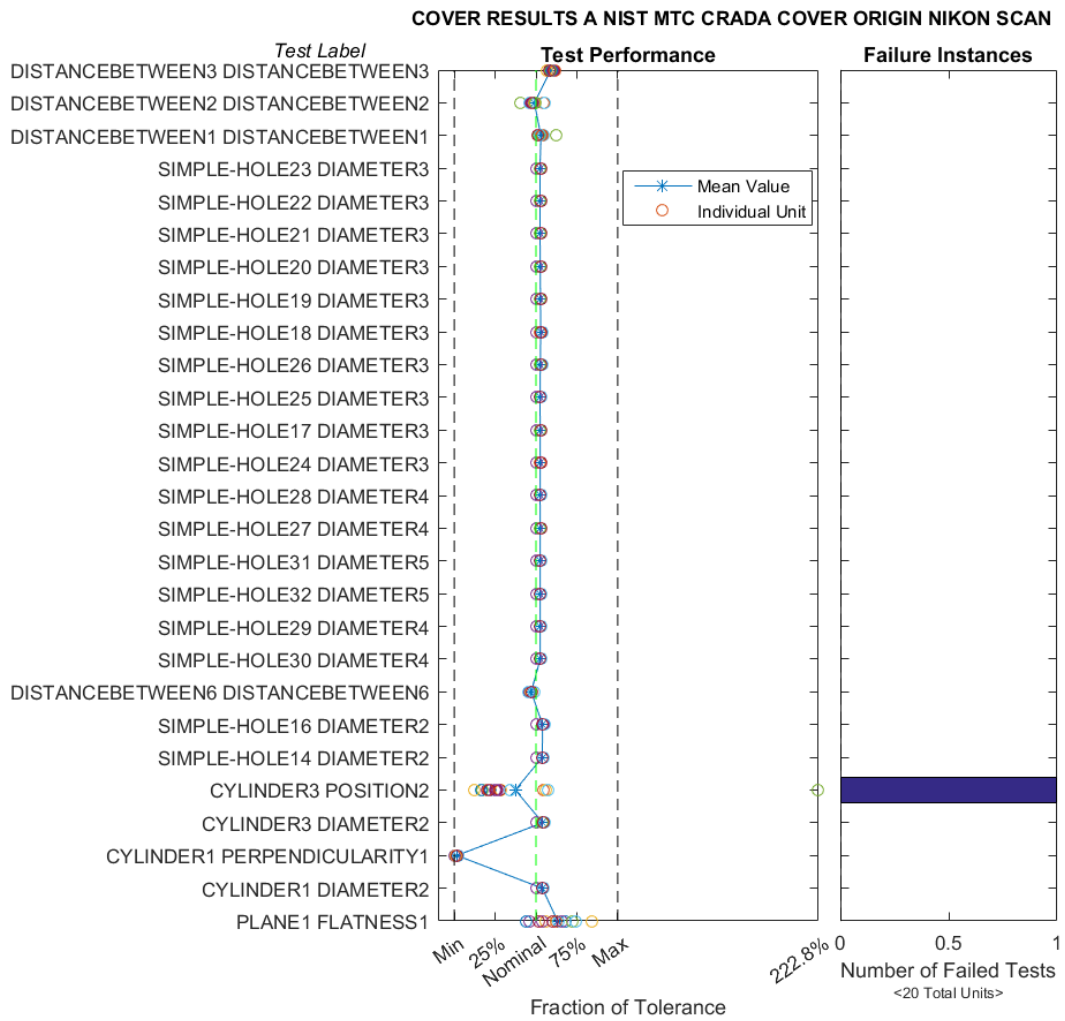


Figure 6. QIF Test Results for Individual Cover Units as Percent of Tolerance Span

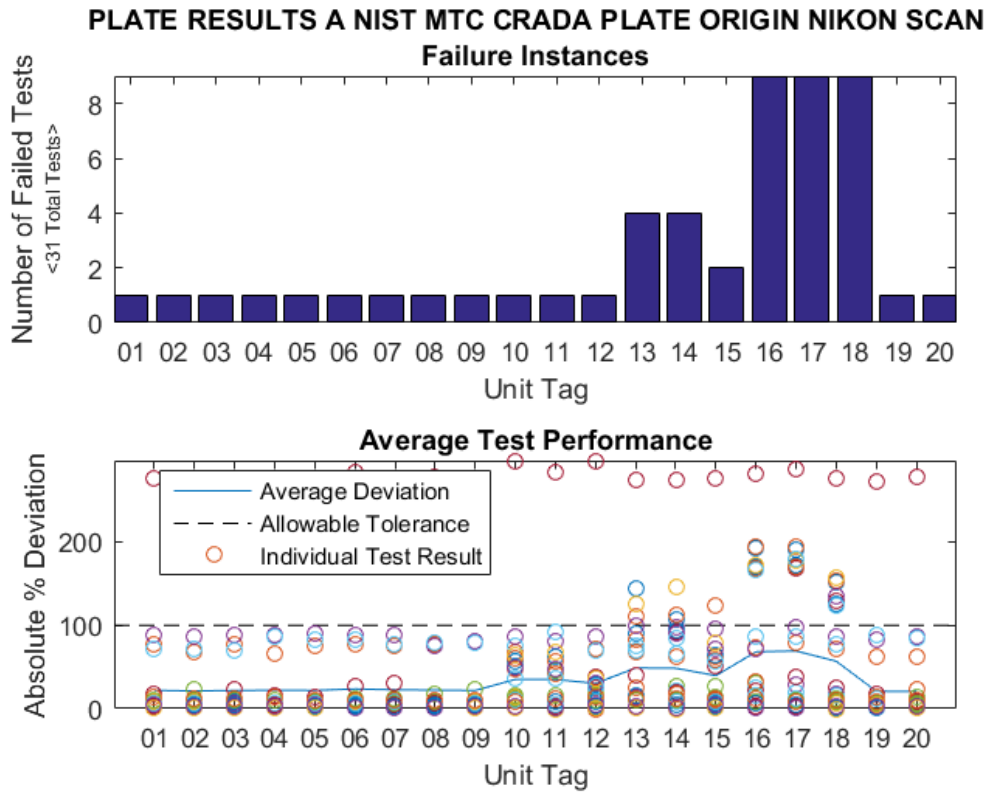


Figure 7. QIF Test Results for Individual Plate Units as Percent of Tolerance Span

446 lengths. A more detailed analysis matching machining parameters to quality within
 447 the Plate units is presented in the next section.

448 A very notable test failure is the “Cylinder 3 Radius 1” test (see Figure 8). All 20 of
 449 the manufactured units failed this test regardless of the various machining parameters
 450 employed during the manufacturing. This lends highly to the supposition that the
 451 error is derived from some requirement of the design. This could be a tolerance mis-
 452 specification, a feature that is not obtainable with the current plant machinery, etc.
 453 By directly linking the feature identified with this test to a design side feature, quick
 454 investigations into alterations can be created early in test production runs of new
 455 products.

456 It is interesting to note that all three assembly structures exhibited some of their
 457 worst quality test performance in tests relating feature position, perpendicularity, and
 458 flatness. this could indicate a shortcoming of the tolerancing, the ability of machines
 459 themselves to produce these features, or in the equipment used to measure these tests.
 460 Given that the respective units were produced on multiple machines with different
 461 manufacturers, this would tend to indicate either incorrect tolerancing or testing abil-
 462 ity. Directed and coordinated analysis of quality data across multiple parts, can help
 463 to identify larger anomalies that might not be apparent when focusing on singular unit
 464 quality test results.

PLATE RESULTS A NIST MTC CRADA PLATE ORIGIN NIKON SCAN

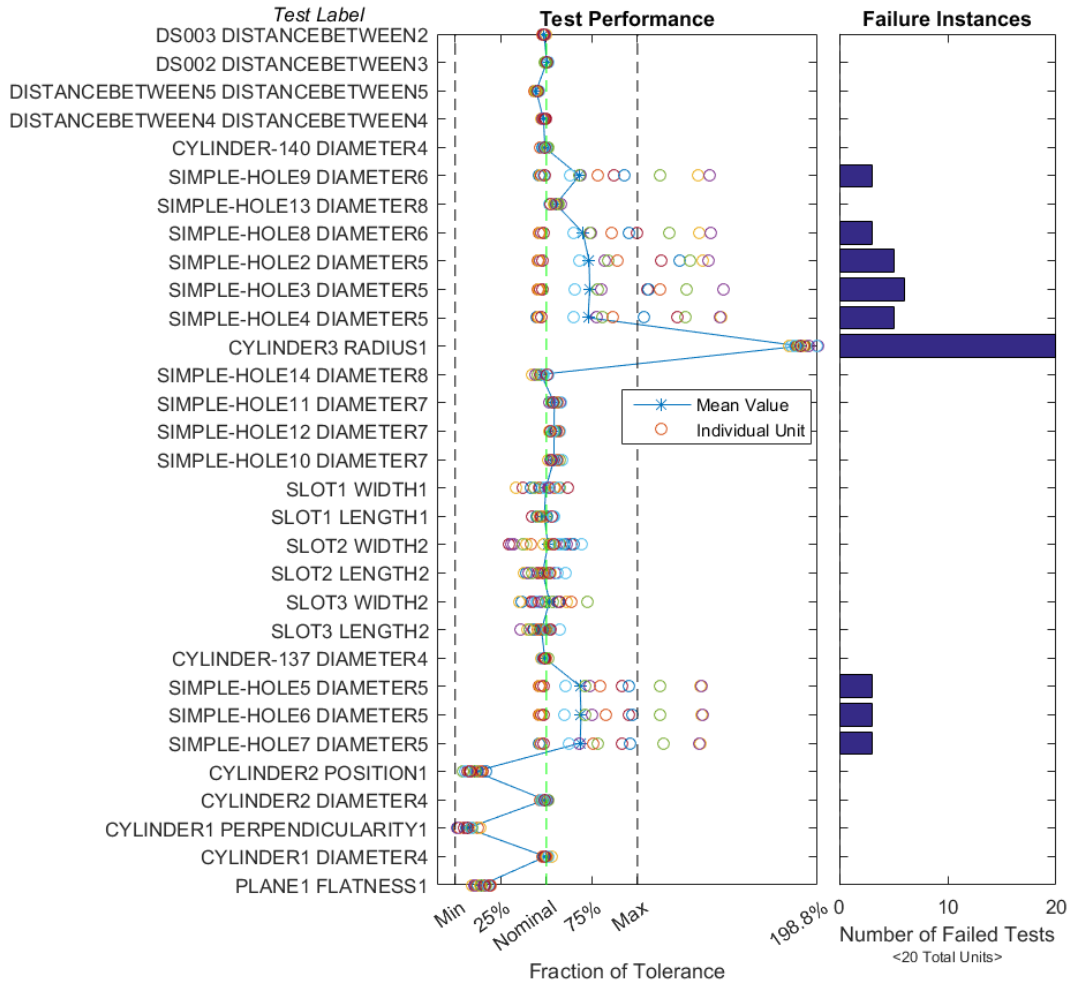


Figure 8. QIF Test Results for Individual Plate Units as Percent of Tolerance Span

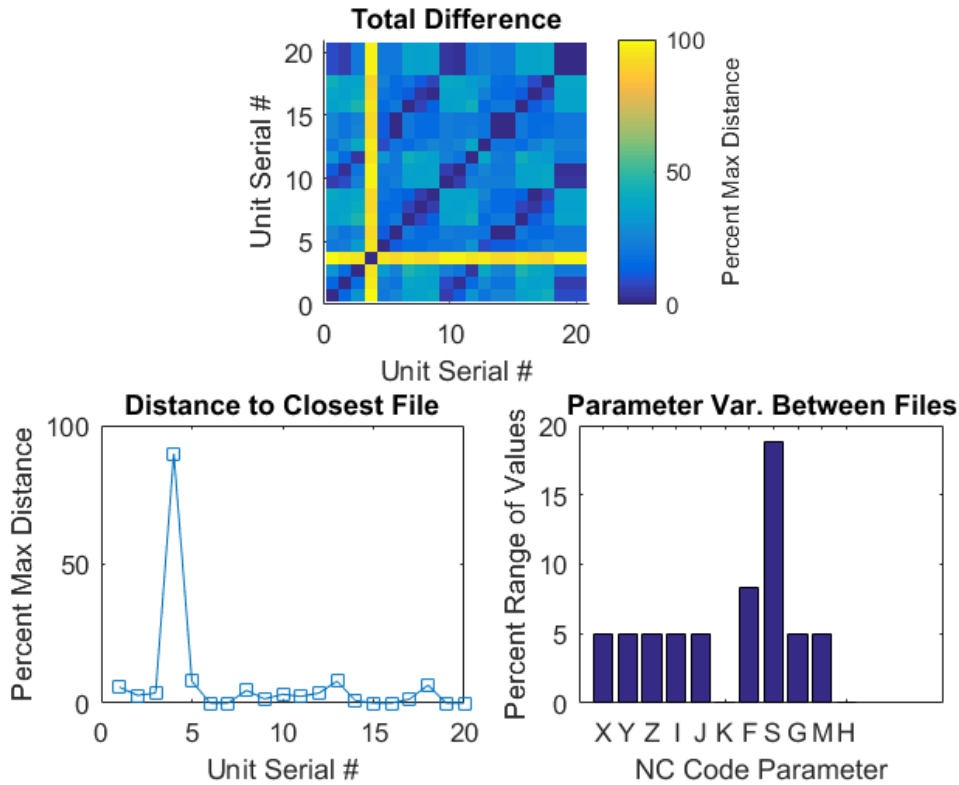


Figure 9. Difference Between Plate Units Input NC-Code Files

465 **4.2. Machining Parameter Analysis**

466 For the 20 manufactured Plate units, the machining parameters were varied as pre-
 467 scribed in Table 1. As can be seen in Figure 7, nearly half of the units exhibit a marked
 468 increase of the average deviation from nominal in the QIF recorded tests. These devi-
 469 ations can be directly correlated with the machining parameters chosen to direct the
 470 production of each unit.

471 For this analysis, an aggregation of the relative and actual values for these param-
 472 eters is interpreted directly from the respective NC-Code input files. The exception
 473 to this is any reference to “Tool Length,” which is not directly recorded in the stan-
 474 dard NC-Code file format. Figure 9 shows the calculated differences between the 20
 475 Plate manufacturing input files. Please note that the files for units 7 and 16, as well as
 476 those for 6 and 15 are functionally identical. The only notable difference between these
 477 plates is the selection of the tool length, which is recorded external to the NC-File. The
 478 parameters collected to compare the machining of these parts were those that related
 479 to the spatial cutting path of the tool (X, Y, Z, I, J, K), the cutting speed (S), the
 480 feed rate (F), as well as preparatory commands and other miscellaneous inputs (G, M,
 481 H). Although this work is limited to 11 parameters within the NC-Code, for broader
 482 scale operations the analysis could be extended to all possible parameter inputs of
 483 NC-Code.

484 To characterize the relationships between the quality and the input machining param-
 485 eters for these Plates, explicit interpretations of the input NC-Code is not needed.
 486 Instead, characterizations of the various parameter sequences were developed and com-

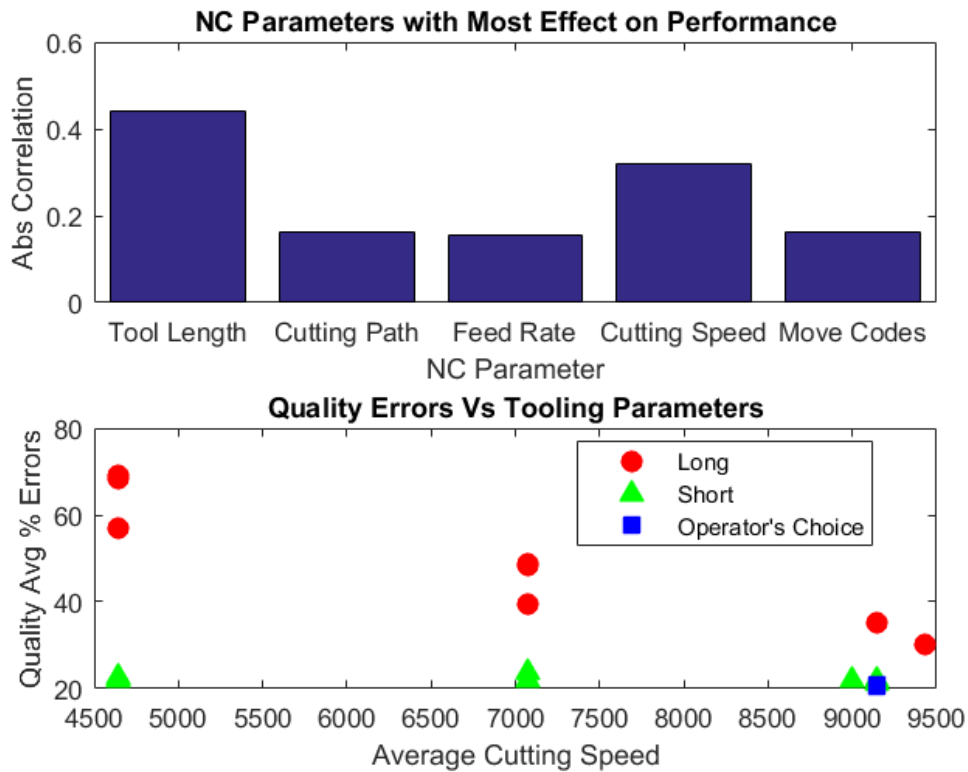


Figure 10. Effect of Machining Parameters on Quality

487 pared on a relative scale. Ultimately, the selection of this characterization is somewhat
 488 arbitrary and matters only in its ability to capture the relative meaningful differences
 489 between the files. Towards this end, those parameters relating similar aspects of the
 490 machining process have been averaged together to allow a more meaningful interpretation
 491 of the results.

492 When looking for machining parameters that have the biggest effect on the qual-
 493 ity of a part, a correlation analysis can quickly reveal strong trends. Figure 10 shows
 494 the average correlation between the various selected machining parameters and the
 495 recorded quality test results. Based on the upper plot, selection of Tool Length is the
 496 most important parameter, closely followed by the Cutting Speed. Somewhat intu-
 497 itively, but also highlighted by the lower plot of Figure 10, the influence of Cutting
 498 Speed on quality is greatly influenced and exacerbated by Tool Length selection. This
 499 can be extrapolated to infer that parameter selection is not a one to one influence on
 500 the part quality; a confluence of various parameters can have complex end effects on
 501 the part quality.

502 Despite noting that the effects of selecting one parameter may have influence over
 503 the effects of others, simple trends can easily be identified in analyses and be used
 504 to infer a quasi-optimal set of machining parameters; particularly if more in depth
 505 characterization of the NC-Code inputs and variations are made. Even when removing
 506 the confounding factor of Tool Length and only focusing on units produced with the
 507 Short Tool Length, there is a clear trend of better average quality with increasing
 508 Cutting Speed and Feed Rate (see Figure 11). This could be extrapolated such that
 509 one might expect even better quality if both were increased beyond the prescribed set

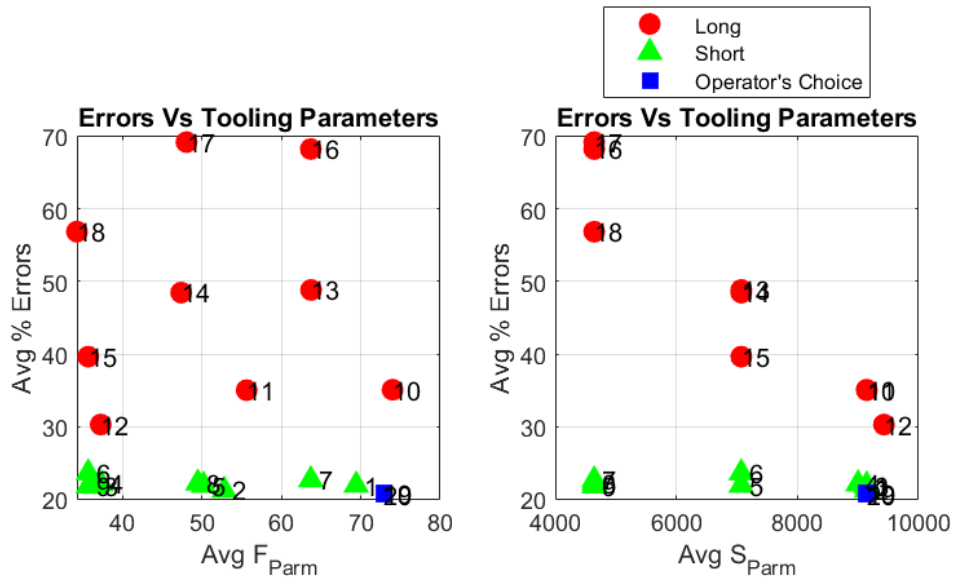


Figure 11. Effect of Speed and Feed Parameters on Quality

510 of values, and in fact this exactly what is observed with the Operator's Choice' units
 511 produced (19 and 20) represented by blue squares in Figure 11.

512 A full detailing of the correlation to the various QIF tests to the recorded machining
 513 parameters is presented in Figure 12. From these results it is clear that the selection
 514 of tool length has the biggest effect on the quality of various hole diameters, followed
 515 closely by slot lengths. Interestingly, this and other observations made during this
 516 analysis were corroborated by the operators who noted that:

- 517 • Longer tool lengths caused more vibration thus more chatter on the finish
- 518 • Slower RPMs caused chips to gather in flutes of smaller diameter end mills
 519 causing swirls on finish
- 520 • Parts 16-18, the lower RPMs caused some of the holes to cut oversized due to
 521 flexing of small diameter, long length end mills

522 5. Gaps, Challenges, and Recommendations

523 Several gaps and challenges were observed during our study. In particular, we were not
 524 able to fully automate the data alignment of the CAD (as-designed data), MTConnect
 525 (as-executed manufacturing data), and QIF (as-measured / as-inspected data) due to
 526 several reasons discussed in this section. However, time savings and knowledge were
 527 realized during the analysis of the all the data.

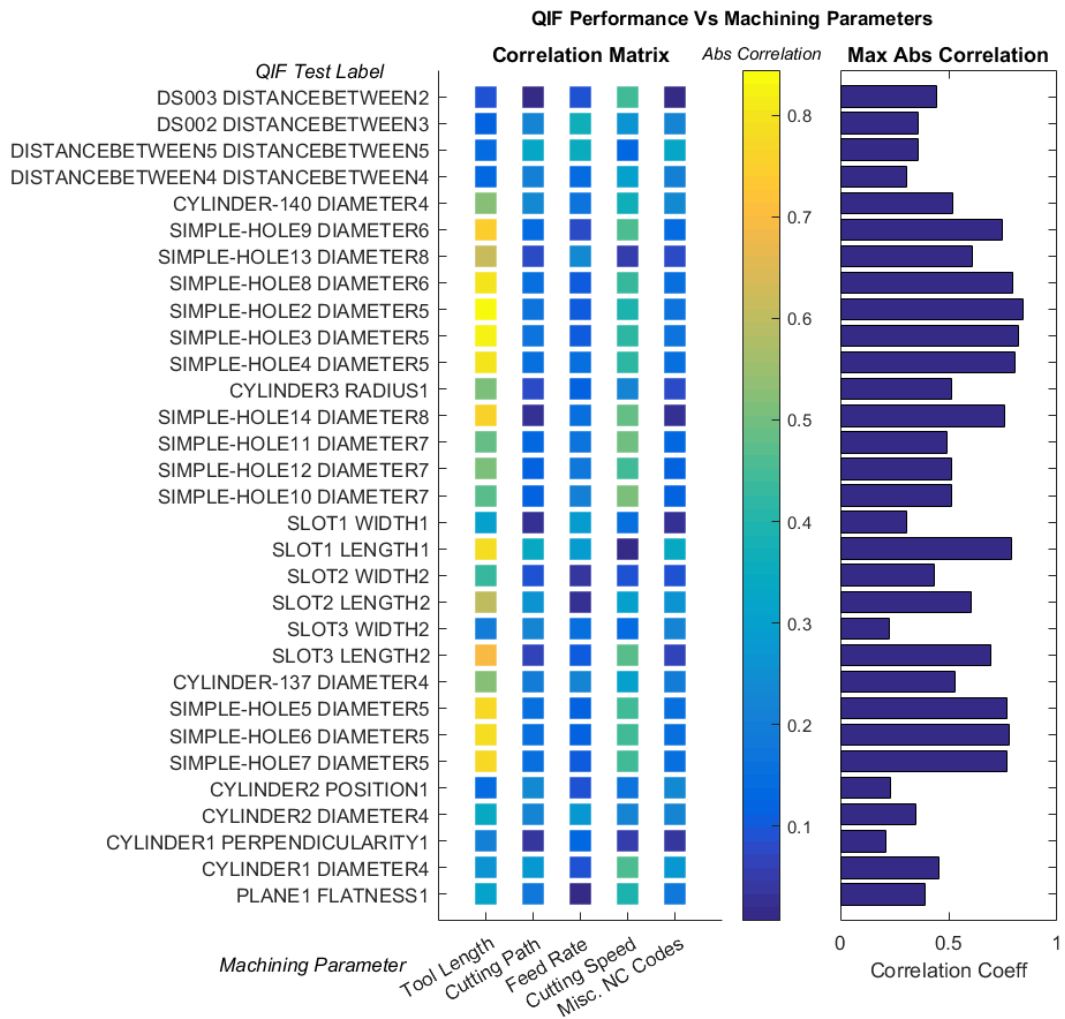


Figure 12. Correlation of Machining Parameters to Individual Quality Tests

528 5.1. Gaps and Challenges

529 5.1.1. Data Formats

530 Fischer et al. (2015) and Trainer, Barnard Feeney, and Hedberg Jr (2015) showed
531 that data can be mapped and aligned between data formats available in CAD, CAM,
532 and CAI applications. However, considerable amount of technical experience and time
533 is required to complete the mappings. In addition, we observed that the context or
534 viewpoint of a data element could be different between each of the data formats. For
535 example, a grouping of shape elements are considered a “feature” in the CAD appli-
536 cation and data formats for design, but in the metrology data formats, the feature is
537 defined with further context (e.g., hole, slot, pocket). This mismatch between view-
538 points makes it difficult to quickly ascertain information and knowledge from aligning
539 data sets retrieved from different phases of the product lifecycle.

540 Further, we observed that there still remains little to no way to provide feedback to
541 design, even in a model-based environment. The best case is still to use screen-shots
542 with markup and then email them to the design authority. Industry needs a way to
543 directly and efficiently capture feedback within the various data sets and then exchange
544 that information between phases (e.g., design, manufacturing, quality) of the product
545 lifecycle. However, this requires more than application support. The data formats used
546 to exchange data between the phases of the lifecycle must support interoperability of
547 the feedback data. To date, no standards-based data format supports iterative and
548 incremental changes – analogous to “track changes” in a word-processing document
549 – in data for the purpose of feedback. Commercial CAD verification and validation
550 tools are available that provide a “change vector” by analyzing variation between one
551 version of a CAD file and subsequent version. However, this does not provide a clear
552 feedback mechanism for industry. Industry requires an explicit feedback mechanism
553 supported by the various domain-specific standard-based data formats.

554 5.1.2. Manufacturing Data Collection

555 The only requirement of an MTConnect implementation is that the device of interest
556 provide the data item `AVAILABILITY`, which indicates the ability of the device to
557 provide data. Because of this requirement, there is no minimum set of data that
558 one may expect from an MTConnect-compliant device. Most implementations of the
559 standard are enabled by a vendor- or third-party-provided Adapter that communicates
560 the native data from the device to the MTConnect Agent. This limits the user to data
561 selected by the Adapter developer, which in turn may be limited by the data exposed
562 by the device controller. Some vendors provide Adapters that provide a full feature
563 set from the device or allow the user to select from a larger set of data items, but
564 these types of Adapters are not commonly available in a wide variety of MTConnect-
565 compliant devices. For example, the three-axis machining center used for this research
566 had a limited set of available data items as shown in Table 4.

567 Table 4 shows that position is not a data item that is supported by the MTConnect
568 implementation of the machine used in this study. The lack of position data is a
569 critical challenge when attempting to link design, manufacturing, and inspection since
570 linking as-designed, as-planned, as-executed, and as-inspected data is done through
571 the features of a part. Because we did not have position data, we had to integrate the
572 as-executed data by relying on the current block number being executed as reported by
573 our MTConnect implementation (see Section 3 and Figure 4 for more information).
574 This approach allowed us to manually integrate data flows from different lifecycle

Table 4. Data available from Hurco VMX24 machining center

| Category | Data Item | Description | Units |
|-------------|--------------------------------|--------------------------|---------|
| Sample | ACCUMULATED_TIME | Program runtime | sec |
| | ACCUMULATED_TIME | Spindle time | s |
| | AVAILABILITY | Availability of data | n/a |
| | PATH_FEEDRATE (ACTUAL) | Actual feedrate | mm/s |
| | ROTARY_VELOCITY (ACTUAL) | Actual spindle speed | rev/min |
| Event | EMERGENCY_STOP | Emergency stop status | n/a |
| | EXECUTION | Program status | n/a |
| | LINE | Executed block number | n/a |
| | PART_COUNT (ALL) | # of completed cycles | n/a |
| | PATH_FEEDRATE.OVERRIDE | Feed override | % |
| | PATH_FEEDRATE.OVERRIDE (RAPID) | Rapid override | % |
| | PROGRAM | Name of executed program | n/a |
| | PROGRAM.EDIT_NAME | Name of edited program | n/a |
| | ROTARY_VELOCITY.OVERRIDE | Spindle speed override | % |
| TOOL_NUMBER | Current tool identifier | % | |

575 stages. Future efforts to automate this integration would require the flexibility to
576 obtain additional data items such as position.

577 Another important challenge when collecting manufacturing data is the inability to
578 control the sampling rate, which is dictated by the Adapter and implementation of the
579 MTCConnect standard for the device of interest. For example, the primary responsibility
580 of a machine-tool controller is to manage the machining process. Providing data via
581 an MTCConnect Adapter is a secondary concern, which means that the sampling rate
582 may decrease if the controller is executing a more complex toolpath. Similarly, legacy
583 equipment may be limited in its ability to provide data at a reasonable sampling rate
584 because the equipment itself lacks the capability due to age. Okuma provides Adapters
585 that have the flexibility to increase the sampling rate, but this capability requires the
586 user to decrease the number of data items that may be collected. The feasibility of
587 such a trade off would be dependent on the use case of interest.

588 5.1.3. Data Linking and Analysis

589 The results of our research show that we were unable to explicitly link feature-to-
590 feature between each data set collected from the different phases of the lifecycle. The
591 root cause for this failure is because there is no persistent identification of features
592 between the standards-based data formats. When we translated the CAD model from
593 the proprietary CAD format to the neutral standards-based STEP AP242 format, the
594 feature identifiers from the CAD system were lost. Further, the MTCConnect identifiers
595 are connected to data elements and do not contextualize any features that are linkable
596 semantically back to the CAD data. Lastly, QIF supports a universally unique identifier
597 (UUID) for each data element defined by QIF, but unless the application generating
598 QIF Results uses the same plan, there is no way to generate QIF Results data sets
599 from two different locations and have the same feature and characteristics identifiers
600 between all the data sets.

601 We were successful in visually linking and aligning the data sets collected during
602 our research. However, all linking was completed manually using significant human

603 input, analysis, and inference. The visualization was helpful to analyze observations
604 from the data, such as how spindle speed and feed rate related to part features during
605 the fabrication process. But, an analyst would generally only want to generate visual
606 analytics if a significant issue arises with the part in manufacturing or quality. Other-
607 wise, the value gained from generating the visualizations are not worth the time and
608 cost it requires to generate the visualizations.

609 **5.2. Positive Outcomes and Recommendations**

610 While several gaps and challenges were observed during our research, there were also
611 successes and benefits identified. Specifically, the applicable standards (e.g., MTCon-
612 nect, QIF) work great within their domain of expertise (e.g., fabrication, inspection).
613 MTConnect provides a rich data dictionary to capture and analyze what is occurring
614 during the execution of machining programs. The streaming MTConnect data not only
615 allows an analyst to determine the status of the machine (e.g., availability, controller
616 mode, level of utilization), but also variation of parameters (e.g., cutting path, spindle
617 speed, feed rate) can be analyzed between part runs, such as dynamic time warping
618 (Helu, Joseph, and Hedberg 2018).

619 Moreover, QIF also provides a rich data dictionary, but only for metrology applica-
620 tions. QIF enables the ability to define an inspection plan, capture results, and store
621 metrology statistics. Our work and others (Fischer et al. 2015; Trainer, Barnard Feeney,
622 and Hedberg Jr 2015; Morse et al. 2016) have shown that the data covered by QIF
623 can be exchanged quickly and aggregated into commercially available metrology soft-
624 ware for further analysis. QIF adoption among metrology solution providers is growing
625 quickly and the standard is stable and mature for capturing and exchanging inspection-
626 related information.

627 However, the outcome of our research has led to two recommendations to harness
628 further benefits. First, each domain (e.g., fabrication, inspection) needs better aligned
629 adoption of the standards by solution providers. While MTConnect and QIF have
630 seen steady adoption growth, the data elements that each commercial application pro-
631 vides using the two standards' data dictionaries varies from one application to the
632 next. Industry needs the type of data retrievable from applications to be harmonized
633 among the solution providers. One way this could be achieved is through implementer
634 forums. For example, the CAx-IF² brings CAD solution providers together to develop
635 recommended practices for implementing ISO 10303 (STEP AP242) standards within
636 data translators and validation tools. We have observed within the STEP community
637 that the CAx-IF accelerates the adoption and implementation of the ISO 10303 appli-
638 cation protocols within CAD tools. MTConnect and QIF would benefit from similar
639 organizations and activities.

640 Second, there is a need for standards harmonization across the domains, particu-
641 larly in the area of identifying entities (e.g., persistent ID). While we were successful
642 in manually generating visual analytics by overlaying the MTConnect and QIF data
643 with the CAD geometry, we could not automatically align the data in a semantic way.
644 Having persistent identification of entities between each data set would enable the abil-
645 ity to automatically align and data mine the information to develop knowledge about
646 what occurred through the cyber-physical transformation of the product throughout
647 the lifecycle. An example of a persistent ID is a UUID attached to features and char-
648 acteristics represented in a CAD model. Then, a CAM application could embed the

²More information available at <https://www.cax-if.org/>

649 UUIDs in the NC program, which could be captured using MTConnect in a similar
650 way as g-code line number. For metrology, the UUIDs for features and characteristics
651 could be stored as using the QIF Persistent Identifiers (QPID) definition in the QIF
652 standard. Having the full chain of persistent identification would enable effective and
653 efficient automated mapping between all the data sets. Manual alignments require
654 significant human capital and an automatic data alignment must be achieved if indus-
655 try is expected to adopt novel data analytic approaches for generating lifecycle-wide
656 knowledge. Using a UUID as a persistent identifier mapped across multiple data sets
657 could satisfy this requirement.

658 **6. Conclusions**

659 This paper set out to present the activities and results of testing several popular
660 manufacturing standards used in the context of smart manufacturing. We presented
661 a test of the open, consensus-based standards' ability to integrate lifecycle stages
662 in a small-scale implementation of MBE. We conducted a design, build, inspect ex-
663 periment to help inform the understanding and performance of the manufacturing
664 standards. Studying data-mining methods, data-integration techniques, and imple-
665 mentation schemes were some of the goals of our work. However, making significant
666 progress in these goals were not achieved because our data integrations could not
667 leverage automatic data-alignment strategies. The results of our work show that the
668 popular data standards used in industry do not support automatic data alignment.
669 Therefore, we pivoted to providing recommendations to the SDOs for enhancing the
670 standards that we expect would enable automatic data-alignment capabilities. We also
671 expect that once automatic data-alignment capabilities are realized, researchers should
672 then be able to discover methods for implementing and transferring standards-based
673 information integration to practice.

674 We provided two recommendations to the SDOs. First, industry needs standardiza-
675 tion of the data elements available across different implementations of the standards.
676 The SDOs for MTConnect and QIF should consider requiring a select set of data el-
677 ement types, while continuing to make other element types optional. Requiring a set
678 of element types would ensure industry can extract a common baseline of data across
679 all operations. Second, industry needs the standards to provide and/or harmonize the
680 ability to generate persistent identifiers (IDs) of features across data sets to enable
681 monitoring the realization of products as they move through the phases of the entire
682 product lifecycle.

683 The SDOs may partially address our recommendations by setting up implementer
684 forums where solution providers and industry can come together to generate recom-
685 mended practices for conforming to the standards. The forums would assist with har-
686 monizing the implementations of each standard between the various solution providers
687 who offer applications using the standards. Addressing the recommendations from our
688 work herein would provide industry with a universal baseline of knowledge extraction
689 and further support interoperability of data across the phases of the product lifecycle.

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695 **Disclosure statement**

696 The work presented in this paper is an official contribution of the National Institute
697 of Standards and Technology (NIST) and not subject to copyright in the United
698 States. Certain commercial systems may be identified in this paper. Such identification
699 does not imply recommendation or endorsement by NIST. Nor does it imply that the
700 products identified are necessarily the best available for the purpose.

701 **Acronyms**

702 **2D** two-dimensional. 9

703 **3D** three-dimensional. 4, 7, 9

704 **ANSI** American National Standards Institute. 5

705 **ASME** American Society of Mechanical Engineers. 4

706 **CAD** computer-aided design. 4, 9–11, 13, 22, 24–26, 31

707 **CAE** computer-aided engineering. 4

708 **CAI** computer-aided inspection. 4, 24

709 **CAM** computer-aided manufacturing. 4, 11, 24, 26

710 **CAX** computer-aided technologies. 4

711 **CMM** coordinate-measurement machine. 13

712 **CNC** computer-numerically controlled. 4, 5, 13, 14

713 **CSV** comma-separated value. 13

714 **DMIS** Dimensional Measuring Interface Standard. 13

715 **DOE** design of experiments. 8, 11, 12, 31

716 **FTC** Fully-Toleranced Test Case. 9

717 **GD&T** geometric dimensions and tolerances. 4

718 **HTTP** Hypertext Transfer Protocol. 5

719 **ID** identifier. 27

720 **ISO** International Standards Organization. 4

721 **MBD** model-based definition. 4, 7, 13

722 **MBE** model-based enterprise. 2, 7, 9, 27

723 **MBM** model-based manufacturing. 7

724 **MBQ** model-based quality. 7

725 **MTC** The Manufacturing Technology Centre. 2, 8, 13

726 **NC** numerical control. 11, 13, 21, 27

727 **NIST** National Institute of Standards and Technology. 2, 8, 9, 13

728 **OEM** original equipment manufacturer. 8

- 729 **PDM** product-data management. 4
730 **PMI** product and manufacturing information. 9, 11, 13
- 731 **QIF** Quality Information Framework. 2–5, 7–9, 11, 13, 14, 22, 25–27, 31
732 **QPID** QIF Persistent Identifier. 27
- 733 **SDO** Standards Development Organization. 3, 27
734 **STEP** STandard for the Exchange of Product Model Data. 4, 26
735 **STEP AP242** STandard for the Exchange of Product Model Data Application Pro-
736 tocol 242. 4, 7, 8, 25, 26
- 737 **UUID** universally unique identifier. 25–27
- 738 **XML** Extensible Markup Language. 5, 14

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