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CASE REPORT

Disparate Data Integration Case for Connected Factories Using Timestamps

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Abstract:

Manufacturing data integration of machine, process, and sensor data from the shop floor remains an important issue to achieve the anticipated business value of fully connected factories. Integrated manufacturing data has been a hallmark of Industry 4.0 initiatives, because integrated data precipitates better decision-making for cost, schedule, and system optimizations. In this paper, we extend work on optimizing manufacturing costs, describing an algorithm using timestamps to integrate previously unassociated quality and test information, estimating the redundancy of lower-level test and inspection operations to later upper-level test and inspection operations. This integration enables us to better identify and eliminate redundant tests. We managed to achieve strong agreement between subject matter experts and our algorithmic solution. The timestamp matching of the heterogenous databases relieves the burden on subject matter experts and provides a pathway to the more integrated factory of the future, eliminating redundant tests, and ultimately reducing product costs and speeding throughput.

Keywords: Quality history record, Test results database, Deming, Redundant operations, Optimized operations, Reduced cost, Disparate databases, Data linking, Connecting databases

Introduction

In 2017, our team began focusing more purposefully on data analytics for manufacturing test, with the specific mission to reduce test costs for our aerospace and defense business unit (1). To understand the scope of the challenge, we first measured manufacturing test data quality, and studied ways to improve it (2). Our deepened understanding of the data enabled us to identify common characteristics of Raytheon's test platforms that facilitated test cost improvements (3), which can contribute 29% of the discrepancies and cost at system integration for aerospace test systems (4).

When discussing potential test optimizations with Subject Matter Experts (SMEs), we became aware of the bill-of-materials plus operations view (5), which visually depicts parts and the manufacturing operations performed on those parts before they are further assembled into other parts that make up a product (see Figure 1). We developed a visualization using the bill-of-materials plus operations depiction using the open source d3.js framework (6), so our team could more easily evaluate the entire bill-of-materials (BOM) within the context of the embedded operations and processes. Doing this allowed us to consider elimination of some expensive manufacturing test operations (7) (see Figures 1 and 2 for images of a bill-of-materials plus operations example: BOM tree view, and zoomed into view with operations visible), which we later extended to consider non-value-added inspection operations (8).

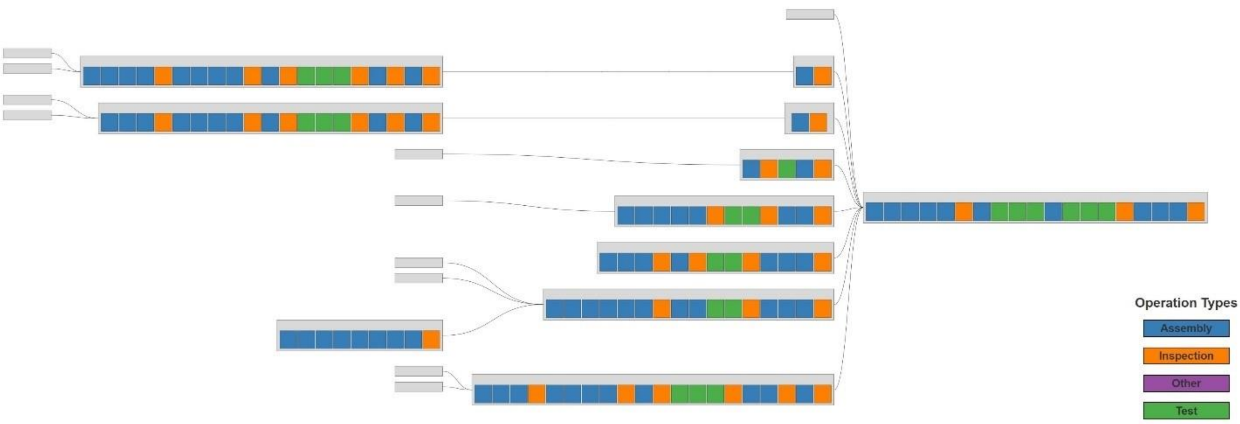

Figure 1 - Production flow visualization parts and operations view (grey boxes are parts; colored boxes inside are operations)

Raytheon has historically developed one database to record quality history records for production hardware, and several other databases for different purposes, such as consumables' expiration dates (e.g. an epoxy's expiration date), calibration data, and test results (e.g. parametric data taken from the unit). Given Raytheon's history dating back to 1922, the various companies it has acquired, and merged with, a variety of databases with different data, formats, and underlying purposes must be considered for integration; the disparate databases in this paper are one example.

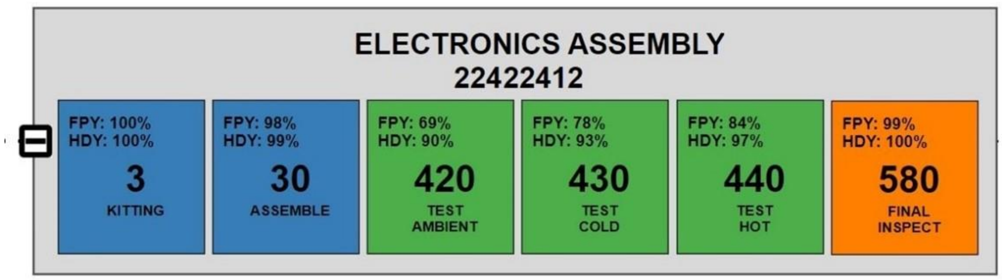

Figure 2- Part with assembly (blue), test (green) and inspection (orange) operations numbered 3, 30, 420, 430, 440, and 580

More recently, our group has become interested in examining the economics of test and inspection operations, and using some of W. Edward Demings previous work (9), we began investigating how to automatically determine if lower-level test or inspection operations are redundant, or are subsets of, later (upper-level) operations. We outline in this paper a method by which to align two disparate databases (quality history records [QHR], and test result records [TRR]) by means of an algorithm, so that we can estimate the redundancy of lower-level test operations (i.e. operations earlier in the build) to later (upper-level) test operations. This method has enabled us to reduce test cost and increase throughput of our test resources.

Ohno famously identified seven wastes in Toyota production systems (10). Excessive testing can be characterized as over-processing waste (11), and our work seeks to eliminate nonvalue-added testing of complex manufactured products. In this paper, we integrate additional test and quality information to identify test redundancies, reduce manufacturing costs, and increase production speeds, by means of an algorithm described herein.

A. Industry 4.0 and CPS (cyber-physical systems)

The development of algorithms for manufacturing data integration is recognized as an obstacle to achieving Industry 4.0 to organize and control contributing value-adding systems (12). Representation of cyber-physical systems like complex manufacturing is central to Industry 4.0 (13). Manufacturing systems can be represented as cyber-physical systems (CPS) in which autonomous computational entities coordinate, and require data integration for optimization (14). Lee et al. propose a 5-layer cyber-physical system architecture for Industry 4.0 manufacturing systems (15), while Coronado et al. present a simple cyber-physical system to provide data integration into a digital representation of the factory, i.e. a digital twin, moving toward Industry 4.0 using timestamps (16). Cyber-physical system models form important underpinnings of digital twin representations, beginning in aerospace (17).

B.CPS and digital twins

Cyber-physical systems and digital twins, while not exactly the same, have similar features, and both contribute to optimized ("smart") manufacturing solutions (18). Digital twins can be leveraged to simulate aspects of production environments, including relevant data and models (19). Digital twins have a basis in lean manufacturing approaches, attempting to be systematic about reducing cost and improving throughput (20). Digital twins integrate data from across the product lifecycle to achieve iterative optimization (21). In their literature review of digital twins, Kritzinger et al. identify three levels of data integration (digital model, digital shadow, and digital twin) (22). A digital model is the least capable, in that it does not specify automation of data exchange between a physical object and a digital object. Our work is best characterized by a digital shadow, as it combines two one-way data flows between physical objects and coordinates with a digital object. A digital twin includes data flows in both directions between a physical object and a digital object.

In their 2021 literature review on digital twins, Liu et al. point out that data integration remains challenging (23). Manufacturing data integration is necessitated for insights to continually optimize in competitive environments (24). Optimized manufacturing drives efficiencies that are increasingly predicated on larger and more varied datasets that need to be understood, harmonized, and shared (25). Csalodi et al. provide a systematic review of optimization algorithms in the Industry 4.0 context (26). Lim et al describe a generic digital twin architecture for engineering product family design and optimization (27). Fernandez-Viagas and Framinan detail shop floor scheduling benefits of real-time information integration in Industry 4.0 (28). Jiang et al. discuss plant-wide optimization using digital twins (29).

C.Heterogeneous data integration

The quality and test datasets we describe comprise existing distributed heterogeneous data that can enrich bill-of-materials plus operations visualizations, making traceability information for our connected factory more useful (30). The datasets are both heterogeneous and autonomous, in that they were developed independently of each other, originally for different purposes by different organizations (31). Yan et al. describe challenges of integrating heterogeneous data in applications for predictive maintenance in Industry 4.0 (32), and Groger discusses the challenges of integrating and reconciling heterogeneous data in a global manufacturing organization for building an Industry 4.0 analytics platform (33).

Kumbhar et al. use timestamps on event logs to populate digital twins and consider specifically how to handle data conflicts (34). Mayr, Luftensteiner, & Chasparis describe mining event logs for continuous manufacturing process state data from sensors (35). Zhu et al. describe three types of semantic heterogeneity in temporal data that are barriers to data integration (representational, ontological, entity) (36); our work is primarily representational, as it leverages timestamps to reconcile disparate data elements across datasets.

As part of continuing efforts to improve the bottom line there has been focus put on trying to optimize production. We have focused some effort on determining if we can reduce the work content in manufacturing by identifying redundant operations and the economic benefit of removing them (9).

Raytheon tracks production quality history records (QHR) in System Analysis Program Development (SAP), enterprise resource planning software that is widely known by large manufacturers. This data is referred to as the Quality History Record (QHR) and it is part of the deliverable product. Quality history records include: the part number, serial number or batch number, manufacturing order number, dates and times the operations start and stop, the employee that recorded the operation, the pass or fail results, and the nonconformities. The QHR has very little in the way of parametric data.

The test equipment is typically what generates the majority of the parametric data (such as voltages and resistances, counts, decibels). The test equipment, for historical and cybersecurity reasons, is separated from the network that the Quality History Records (QHRs) are on. The test data is recorded in the Test Results Records (TRR) Database, categorized into Divisions (usually based upon contract or physical area), then divided/parsed into partitions based upon the test file's header information such as part number, and test name. (see Figure 3).

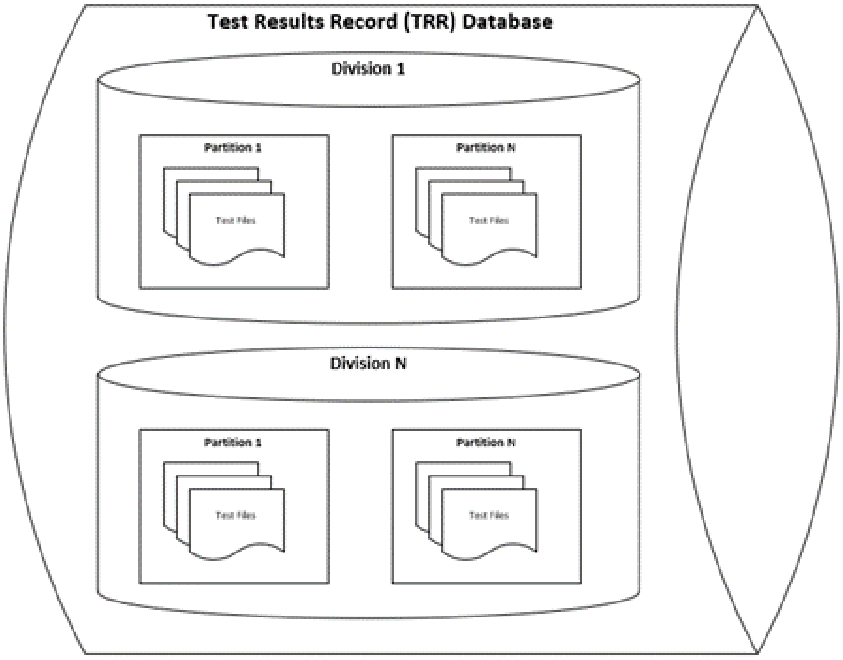

Figure 3– Test Results Database Architecture

Some data within the QHRs and the TRRs do overlap, such as part number, and serial number. (See Figure 4) Most importantly there are no identifiers in the test result files that can uniquely link the Test Results Records to the Quality History Records and the test operation name or number where it was generated. That means there is no direct method to look up the names or identification of the test files and match them to the Quality History Records (QHR).

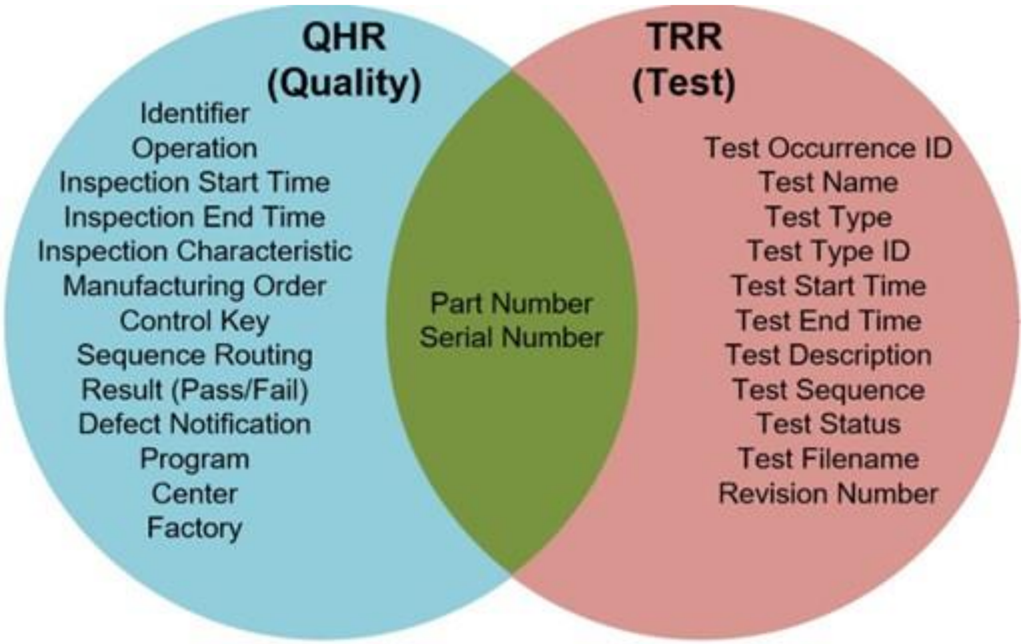

Figure 4- QHR and TRR Records and Common Fields

Many of our previous efforts have focused on using data that was available in a single database and extracting value from it, such as on consolidating QHR data into a concise visual presentation (5) (7), which does not include any parametric test data, or using test data to determine test equipment coverage (3). Despite success in these endeavors, there are still many questions that cannot be answered with data from only one database (given the existing database structure).

By being able to link parametric data in the Test Results Records (TRR) to the data in the Quality History Records (QHR) we should be able to enhance various analyses and improve our predictions.

Materials and methods

To connect the two databases, Quality History Records (QHR) and Test Results Records (TRR), we constructed a chronology of events for a typical test sequence for a single part number (PN) and serial number (SN) pair. The QHR database and the TRR Database both contain timestamps, and it was thought that matching the chronology of the typical event would be straightforward. We documented what database recorded the event (if any at all) and the order of events (Table 1).

We discovered that the clocks between the QHR Database and the TRR Database were not perfectly synchronized in all cases, that the operators sometimes did not execute per the standard chronology, and some factories performed a series of tests for one part number serial number (PN SN) combination before recording the data into the QHR, thus resulting in the disordering of some events and the associated data records. All of this meant there was not an exact method to determine what test records (from the TRR) aligned with the quality history records (from the QHR) for any one PN SN pair.

Table 1 - Typical Test Sequence Event

Order	Factory Floor	QHR (quality) Database	TRR (test) Database
1	Find Part		
2	Move part to Area		
3		Start Work Order matching PN & SN	
4	Test Set Up		
5			Operator enters information, such as test type, PN, SN, etc.
6			Start Test
7			Test file created
8	(Possible interaction with test set and unit)		Execute Test
9			Test finishes
10			Test file saved and posts results (Pass/Fail)
11		Record result in Work Order	
12	Remove from Test Set		
13	Move part to next operation		
14		Stop Work Order	

We determined that any one PN SN pair was prone to error for the previously mentioned reasons, but we found for the majority of cases the chronology laid out in Table 1 was followed. We devised a method to create a score for each part number serial number pair, where each PN SN pair was ranked regarding the QHR operation that linked to the Test Results Record (TRR) partition. This rank score reflects which TRR partition is mostly likely a result of the test operation of interest.

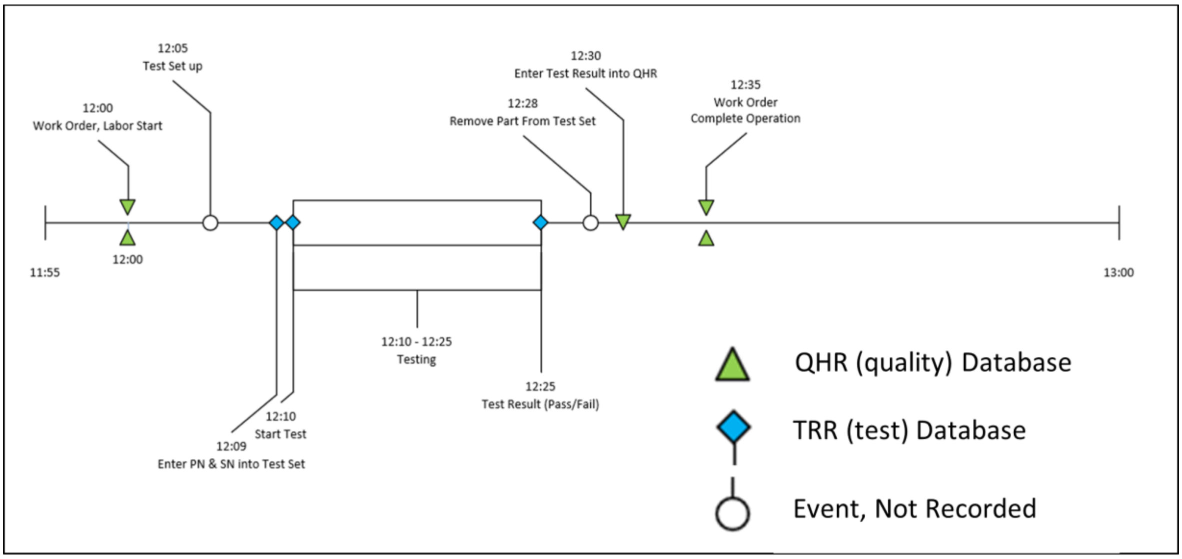

Figure 5 - Chronology of Sample Test Event

Details of test events

The scoring algorithm worked by reading in each QHR and TRR record. Each of the associated QHR records were cleansed to remove information that was not applicable to the analysis, such as rework. Additionally, the authors found that the serial numbers did not always match between the two databases (QHR and TRR). Sometimes the serial number's (SNs) preceding alpha characters in the QHR were not included in the TRR. However, removing all alpha characters in the SN fields of both records, could in rare cases, result in SNs that were not unique. To remedy this data quality issue, alpha characters were only removed from the SN in cases where the TRR record did not match the QHR record. Other data cleanup activities included trimming whitespace, making characters all upper case, and converting dates and timestamps to datetime.

For each test result, the algorithm loops through each part number to identify a Test Occurrence ID and Operation link for that part number (PN). Part numbers are of the basic form, XXX-Y, where XXX is the root number, and the numbers after the dash are versions of that basic root. While exploring the data in the test results database, we determined the part number in some partitions was truncated, i.e. only the root number was present, and therefore would not match the exact/true part number that was in the QHR database (the QHR always reports the complete PN). The part number from the QHR was reduced to its root form by truncating the dash and anything afterwards and thus we were able to provide part number matches in these edge cases as well.

A list of serial numbers (SNs) was created for each reduced part number based on the intersection of SNs shared between the QHR and TRR. Part number serial number (PN SN) matching can be problematic for reasons that include serializing changes over time and across the development life cycle (37) and data quality (38) (39). Erroneous serial numbers were removed from our analysis, as in (40).

For each serial number in the intersection list, we filtered QHR records to only contain those where the QHR End Date/Time stamp was after the latest TRR Test End Date/Time stamp. This filtering was done, because according to the chronological process outlined (Table 1 & Figure 5), there would not be a valid associated QHR record prior to the TRR Test End Date/Time stamp. The final score was calculated by dividing one by the difference in minutes between the QHR timestamps and the closest TRR timestamp (e.g. 1/time difference), thus more heavily weighting the QHR events that occur just after the end of the test (as recorded by the TRR).

(0.1) $$\text{Score} = \sum \frac{1}{\left(QHR_{Time} - TRR_{Time}\right)}$$

Equation 1 - Scoring

Table 2 - Serial Number Score Table

Part Number	Serial Number	Inspection Start Time (QHR)	Test End Date/Time (TRR)	Delta in Minutes	Score
xxxx	xxxx	3/23/2020 7:48:54 AM	3/23/2020 7:39:49 AM	9.083	0.110
xxxx	xxxx	3/23/2020 7:55:03 AM	3/23/2020 7:39:49 AM	15.233	0.066

Next, a summarized score was obtained at the serial number level. We looked for one record per a serial number and operation combination (from the QHR), because in the following steps we take a sum of the scores across multiple serial numbers (SNs) and want to ensure we are not summing values across the same SN and Operation. This was accomplished by grouping based on serial number (SN) and filtering for the earliest Inspection Start Time. In rare cases multiple operations can have the same Inspection Start Time for a given serial number. When this occurred, the same SN had multiple records with the same score.

Table 3 - Summarized Score Table

Serial Number	Operation	Score	Earliest Inspection Start Time (QHR)
Xxxx	aaa	0.110	2020-03-23 07:48:54
Xxxy	bbb	0.008	2020-05-08 09:25:53
Xxxz	ccc	0.006	2020-05-20 13:07:49
Xxxww	aaa	0.130	2021-02-16 22:39:52
Xxxww	ccc	0.130	2021-02-16 22:39:52

Using the summarized score table (Table 3), part number scores were calculated across the serial numbers by first grouping by operation and then summing. The resulting table of PN scores by operation was then sorted in decreasing order by Score (Table 4). The recommended operation for linking the Test ID for the part number is the one with the highest score.

Table 4 - Part Number Score Table

Operation	Sum Score	N (Count of Serial Numbers)
AAA	77.882	97
BBB	60.150	92
CCC	0.130	1

This process was repeated for all part numbers and across all partitions.

The algorithm's performance was tested against a sampling of manually created links. Subject Matter Experts (SMEs) reviewed the two disjoint databases and determined the operations linking the Test IDs for a test results partition. The SMEs created 840 part number and operation pairs linked to test result partitions between the databases. The algorithm generated 671 links. Of the links generated by the algorithm, 256 were common links with the SME created links. Of these 256 links, the algorithm and SMEs agreed on the operation linking the partition Test ID 76% of the time (Table 5). Figure 6 is the empirical cumulative distribution, a normal probability plot of time delta from QHR to TRR.

Table 5 - Summary Metrics

SME provided links	840
Generated links	671
Shared links	256
New links created	415

Matching shared links	Shared links not matching
195	61
76% ± 4% (90% confidence)	**24% ± 4%**

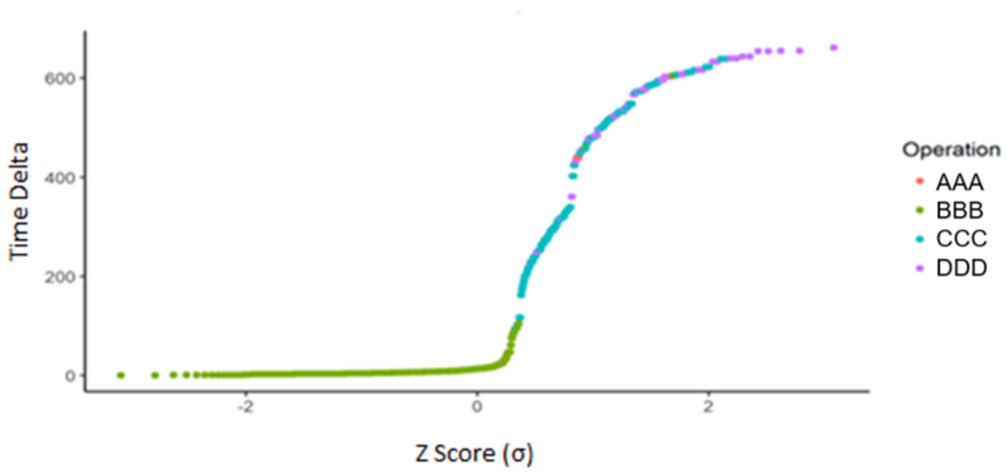

Figure 1 - Example of a Normal Probability Plot of Time Delta From QHR to TRR

Discussion

Table 5 showed a reasonably good ability of the algorithm to link the test files to the proper operation and it was concluded that this level of agreement with the SMEs was sufficient to trust the results on test result partitions not already scored/linked by SMEs (knowing that about 1 in 4 results would be incorrect). This level of accuracy was acceptable, because the downstream analysis based on the merged data did not require a high-fidelity dataset to make recommendations of possibly redundant operations (8) (9). The goal of joining the data from the disparate data sources was to apply Deming's analysis to redundant operations. Since each recommended redundant operation for removal was to be evaluated by program personnel that would be intimately familiar with the factory, it was not necessary for all recommendations to be correct. Essentially, the team was tasked with providing a narrowed down, manageable list of possible operations for removal that could be tackled by a subject matter expert (SME). The SME's job was to down select, from the recommendation list, those operations to be removed and provide a recommendation to the Production/Process Control Board. The additional connectedness of quality and test information has resulted in manufacturing test optimizations, specifically reduced testing and delivery time, and suggesting the increased connectedness moves us toward lean manufacturing goals (41).

Our initial aim was to make a reasonable set of recommendations to SMEs to facilitate test and inspection reductions, which we accomplished, but should also be recognized as a limitation of the work. Future work could include instrumenting feedback loops into the algorithm where improvement was possible via learning, with an eventual goal of reducing and then eliminating the need for SME involvement.

Conclusion

There will inevitably be separate and distinct databases that a business will want to use or leverage, and ultimately the longer the business has been around or the more businesses it has acquired, the more databases there will be (which might overlap, be entirely distinct, and could be completely novel). We had success in merging two such databases at Raytheon by mapping the databases' event chronology. Using this chronology map we identified many instances when the databases did not align, however, we were able to match most data to a fairly high degree of accuracy (≈76%), estimating the redundancy of lower-level test and inspection operations to later upper-level test and inspection operations. The matched and aligned data between the databases allowed for a large-scale analysis that otherwise would not have been possible since it required information that was split between these databases. The large-scale analysis between the databases was used to assess the overall health and efficiency of our business unit, and all promising leads, that would not have been possible without this data mapping, were pursued for test reduction.

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