Towards Zero Defect Manufacturing in Multi-Stage Production Systems

by

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B.S., Operations Research and Management Science
B.S., Economics
University of California - Berkeley, 2017

Submitted to the MIT Sloan School of Management and
Department of Civil and Environmental Engineering
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Master of Business Administration

and

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at the

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Abstract

Implementation of quality improvement methods in multi-stage production systems is essential to manage and quickly eliminate manufacturing quality defects. Many companies tend to prioritize production speed rather than overall throughput, and are hypothesized to be below the optimal level of investment in quality systems when taking into account the full cost of bad quality. While traditional quality management techniques such as six sigma and process control are still valuable and worthwhile tools, recent advancements in technology offer manufacturers the opportunity to augment this tool set with the use of IoT, big data, and advanced analytics.

This thesis addresses the problem of how to build a modern quality manufacturing system that continuously reduces scrap and defect rates in the production process. The study adapts a zero defect manufacturing framework and applies it to the automotive manufacturing industry. Five key activities, including data collection, data integration, data analytics, process control, and defect mitigation are all found to be essential components in the development of a robust quality improvement infrastructure. The process of applying these framework components in the context of an automotive manufacturer's production lines sheds light on both technical and operational challenges and benefits of the quality system enhancement process. Other manufacturers may find this analysis to be a relevant use case and template when constructing or making improvements to their own quality management architecture.

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I would like to start by thanking my internship supervisor, who provided continuous insights into the processes, data, and organizational structure of Company A. They regularly took time to check-in, offer resources, and connect me with relevant stakeholders at all levels of the organization. I would like to extend my gratitude to Company A's production line team at large, who were extremely welcoming and open to recommendations for change.

I also want to thank my academic advisors, Professor Charles Fine and Professor David Simchi-Levi. Charles acted as a valuable sounding board to think through project approaches, and contributed thought-provoking questions and advice. David shared current research relevant to the problem, and provided guidance on how to model and structure analyses.

To my LGO friends: Thank you for being a constant source of support and joy throughout my time in the program.

To my family and partner: Thank you for shaping me into the person I am today, and for encouraging me unconditionally to pursue my educational goals.

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Chapter 1

Introduction

The intent of this thesis is to examine how both traditional quality management principles and emerging zero-defect manufacturing strategies can be applied to improve production yields in a complex, multi-stage production system. Various methods of root cause analysis, process control, and defect mitigation are proposed. The resource costs and feasibility of implementation of methods are also considered in determining the most effective measures for scrap and defect reduction. The subject of study for the thesis is an automotive manufacturing production line at Company A. The results of the thesis include a holistic framework and a case study for developing quality improvement capabilities in a dynamic, multi-stage manufacturing environment.

1.1 Industry Overview

Electric vehicles (EVs) are a critical decarbonization technology with the potential to significantly reduce global emissions from road transport, which constitutes 16 percent of global carbon emissions today [1]. In the US specifically, the hybrid and electric vehicle market has grown by an average of 24 percent per year over the past five years, with 47 percent of hybrid and electric sales currently generated by all-electric vehicles. There are two major types of players in the industry: (1) established auto manufacturers such as Honda, Ford, and Toyota which are seeking to adapt with new electric products due to shifting customer preferences and regulatory requirements,

and (2) exclusively EV manufacturers such as Tesla and Lucid whose missions and central business models are dependent upon the design, manufacture, and sale of all-electric vehicles [2].

Characteristics of this industry relevant to this thesis include high capital intensity and a high rate of technological change [2]. High capital intensity mandates that equipment and space are utilized efficiently in order to spread fixed costs over as many units as possible. This is partially achieved by minimizing nonconforming and reintroduced work in process inventories that disrupt production line efficiency. A high rate of technological change suggests that product design, materials, and tooling are all likely to change rapidly. Having a quality management framework to quickly assess and address issues associated with new processes and products is critical to maintaining competitive advantage.

Finally, part costs and availability are a major consideration for EV industry players. The hybrid and electric vehicle industry is characterized by high vehicle component costs, representing on average 77 percent of revenues, while wages represent only 5 percent of revenues [2]. Furthermore, EV production is constrained by the availability of parts in the global supply chain, including semiconductor chips and battery cells. One electric vehicle company CEO estimates that "all the world's [battery] cell production combined represents well under 10 percent of what we will need in 10 years" [3]. Both the high cost and limited availability of raw materials and components make it especially important to minimize the frequency of scrapped subassemblies. These factors may also lead players to increasingly insource production of upstream parts in order to generate a more reliable supply.

1.2 Problem Statement

In the automotive manufacturing industry, production quality of subassemblies is critical for both downstream assembly processes and for consumer safety. Without proper process monitoring, analysis, and control, the manufacturing process and therefore the production quality of products cannot be improved. While production

speed is generally prioritized during a high growth phase, overemphasis on line speed and underinvestment in quality improvement can cause overall throughput rates to suffer, when accounting for scrapped and reworked units. I observed that underinvestment in quality during the ramp period could create "hidden factories" that hindered the production rate when accounting for yield loss due to non-conforming material. Some of the challenges born from such a situation were the following:

1. How does an organization accurately measure the production and financial impact of nonconforming subassemblies?

2. What quality improvement methodologies are most effective in reducing the occurrence of defects leading to rework or scrap?

3. What system and management capabilities are required to implement and sustain quality improvement practices with minimal human intervention?

1.3 Project Motivation

In 2022, Company A's existing tools and processes in place in its manufacturing lines demonstrated opportunities for improvement to more systematically measure and analyze the root cause of defects. The primary objective of my project was to improve the quality measurement system and reduce the scrap rate (and secondarily to reduce the defect rate) of work-in-process and built inventory. The motivations for this objective were to achieve financial cost savings, to reduce waste environmentally, and to more easily maintain the high quality standards of the manufacturer. Additionally, reducing the scrap rate would have the effect of improving production yields, ultimately improving throughput.

1.4 Thesis Structure

This thesis begins by contextualizing quality management within the sphere of electric vehicle battery manufacturing. It then goes on to examine several common approaches

to improving production quality. Finally, the thesis provides examples and applications of quality improvement methods to build a framework and case study for effective implementation of a quality management system that continuously reduces scrap and defect rates.

- **Chapter 1 - Introduction** provides industry and business context to the problem explored in the thesis, and introduces the objectives and motivations for solving the problem.

- **Chapter 2 - Literature Review** discusses the evolution of quality management literature from the 1930s to present day. It introduces several quality management approaches, both managerial and scientifically-oriented, and comments on the benefits and limitations of each approach. A more recent paradigm, Zero Defect Manufacturing, is described, which forms the primary basis for application to the problem in subsequent chapters.

- **Chapter 3 - Battery Manufacturing Process** provides a high level overview of electric vehicle battery manufacturing, and describes different types of processes which have the potential to cause product variation and nonconformity.

- **Chapter 4 - Quality Data Measurement & Collection** identifies which data are critical to collect from the production line in order to accurately measure and analyze quality issues. It also proposes a process map and data collection infrastructure to efficiently collect quality data.

- **Chapter 5 - Data Integration Platform** summarizes possible sources of data, and describes which are critical to link in order to perform a complete and real-time analysis.

- **Chapter 6 - Root Cause Analysis** explores several methods to determine the root causes of defects, including Pareto analysis, variable correlation, and predictive analysis.

- **Chapter 7 - Applications of Statistical Process Control** applies methods of process control which were introduced in Chapter 2, including the implementation of control charts to track both attribute and variable data.

- **Chapter 8 - Defect Prevention & Defect Propagation Mitigation** proposes multiple strategies to prevent and correct defects based on the findings of Chapter 6 and Chapter 7.

- **Chapter 9 - Conclusion & Future Work** summarizes the end to end quality management process framework executed in the thesis. Practical implementation challenges are discussed, and recommendations for overcoming those challenges are proposed.

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Chapter 2

Literature Review

This literature review covers key paradigms and methodologies within the study of quality management. The characteristics of several methodologies are compared, and their merits are evaluated in their application to present-day, multi-stage manufacturing systems. Both the technical and managerial aspects of the methodologies and tools are discussed.

2.1 Origins of Quality Management

The earliest significant contributions to literature in the field of manufacturing quality management appeared in the 1930s in writings by Walter A. Shewhart, originally a physicist who began developing his quality management principles at a telephone hardware manufacturer, Western Electric Company [4]. The primary objectives underpinning Shewhart's works were to "make the most efficient use of raw materials, maximise the assurance of quality, minimise the cost of inspection, and minimise loss of rejection' [5] Shewhart was the first author to differentiate common-cause variation due to random process variability from assignable-cause variation due to a change in process inputs. Additionally, he designed experiments in industrial settings and developed the foundations of process control with control charts [6].

2.2 Cost of Quality

A critical consideration required to assess the optimal level of quality investment is comparison of the cost of poor quality and the cost of quality implementation and maintenance. Figure 2-1 below depicts both Juran's original and revised cost of quality models [7]. In the original model, with investment in quality improvement programs, a company will initially experience significant reductions in quality failure costs, with cost savings benefits diminishing as quality level increases. As a company ensures a higher and higher level of quality, however, the cost of detecting and preventing quality failures increases at a marginally increasing rate. The optimal level of quality minimizes the total cost curve, where costs of prevention and appraisal are equivalent to quality failure costs. In the revised model, Juran cedes that in some settings prevention and appraisal costs may not increase infinitely as conformance approaches 100 percent, and that total costs may continually decrease as quality levels increase to 100 percent.

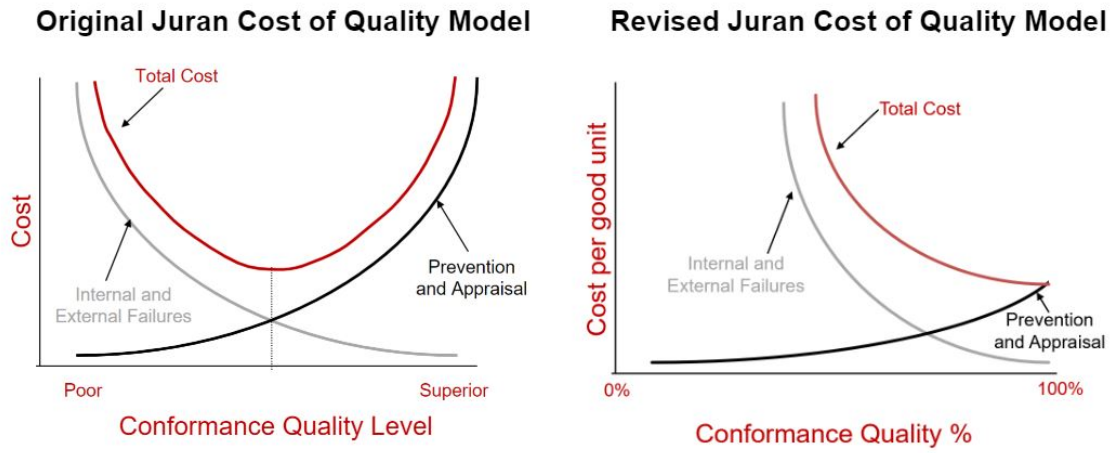

Figure 2-1: Determining Optimal Quality Levels by Comparing Cost to Conformance, Adapted from Juran's Quality Control Handbook, 4th Edition

Examples of the costs associated with quality implementation and maintenance, categorized as prevention and appraisal costs, are summarized in the first column of Table 2.1 below. Additionally, the costs associated with having poor product quality are defined in the second column as internal failure costs (such as scrap material costs)

and external failure costs (such as customer returns). While some of the costs of quality below are straightforward to measure, many are difficult to quantify precisely. Even so, the exercise of estimating visible costs of quality and identifying invisible costs of quality can be useful in evaluating the willingness to pay for investment in quality improvement programs.

Cost of Quality Implementation and Maintenance	Cost of Poor Quality
Prevention Costs New product review Quality planning Supplier capability surveys Process capability evaluations Quality improvement team meetings Quality education and training	**External Failure Costs** Lost business Processing customer complaints Customer returns Warranty claims Product recalls
Appraisal Costs Incoming and source inspection/test In-process and final inspection/test Product, process, service audits Calibration of measuring and test equipment Associated supplies and materials	**Internal Failure Costs** Scrap Rework Re-inspection Re-testing Downgrading

Table 2.1: Examples of Quality Costs, Adapted from Campanella 1999 [8]

2.3 Quality Management Methodologies

2.3.1 Lean Manufacturing

Lean manufacturing is not explicitly a quality management methodology, but rather an approach to operationally efficient manufacturing with primary benefits of reduced waste and defects. The approach was originally born from the Toyota Production System (TPS), developed and realized by Japanese engineers Taiichi Ohno and Eiji Toyoda. The TPS philosophy most relevant to quality management is jidoka, the concept that a machine must come to a safe stop whenever a production abnormality occurs in order to prevent defects from being propagated downstream [9]. Human intervention is then required to immediately address the process variation and prevent future occurrences, therefore eliminating hidden factories in which defects recur over

and over without being resolved for the sake of line speed.

Many companies over time began to admire and adopt elements of the Toyota Production System, and TPS was generalized into the concept of lean manufacturing, popularized in 1990 by the book *The Machine That Changed the World* by James Womack, Daniel Jones, and Daniel Roos. Lean's overarching principle is the removal of waste and non-value added activities in the manufacturing process. Five steps to achieve this objective through implementation are defined in Figure 2-2 below. First, define the value of the product through a customer lens. Second, identify the value and no-value added steps involved in creating the product. Third, remove non-value added waste and ensure the remaining process flows efficiently. Fourth, build products on an as-needed basis based on customer demand. Finally, make continuous efforts to reduce effort, time, space, cost, and defects in the production process [10].

Figure 2-2: Five Steps of Lean Implementation

While the emphasis of the implementation steps above is on improving process flow and efficiency, quality metrics naturally improve from these efforts. When a product spends less total time in process, the chance of the product getting damaged (hit while sitting on the floor, damaged due to deterioration, etc) decreases. Additionally,

simplification and standardization of processes through iterative improvements lead to fewer opportunities for variability.

2.3.2 Six Sigma

Six Sigma, relative to lean, is more explicitly focused on quality improvement than process improvement. The concepts are somewhat reversed in that while lean assumes that process improvements will resolve quality issues, Six Sigma assumes that reducing variation will improve the entire process [11]. The Six Sigma methodology was formalized in 1986 by two Motorola engineers Bill Smith and Mikel Harry [12]. While Six Sigma programs do require initial investment to build measurement and analytics capabilities, the objective is to achieve long-term savings that outweigh the cost of the program. General Electric, for example, who used Six Sigma as a core component of their business strategy, suffered a small net loss in 1996 in the first year of implementation, but reported savings of 750 million dollars by 1998 [13].

The name Six Sigma comes from the idea that a process is so well controlled that it would have to deviate up or down from the mean by six standard deviations in order to generate a defect. While some industries such as aviation do strive for a standard this high, in some industries it is not realistically cost-effective to meet six sigma conformance quality, leading companies to aim for something closer to three sigma in practice. At its core, Six Sigma is a structured problem solving methodology to reduce variation in a system. The five steps involved in reducing variation are Define, Measure, Analyze, Improve, Control (DMAIC).

A brief overview of each step of DMAIC is provided below [14]:

- **Define:** Clearly define the process or product that needs to be improved. Specify project objectives and understand internal and external customer requirements.
- **Measure:** Evaluate process performance by developing a process map and measuring current capabilities and frequency of problems.
- **Analyze:** Analyze the process to determine root causes of variation and poor performance.

- **Improve:** Address and eliminate root causes of problems through experiments for complex process or through iterative solutions that resolve one component of the process.

- **Control:** Monitor the improved process and put in place controls to prevent the issue from recurring in the future.

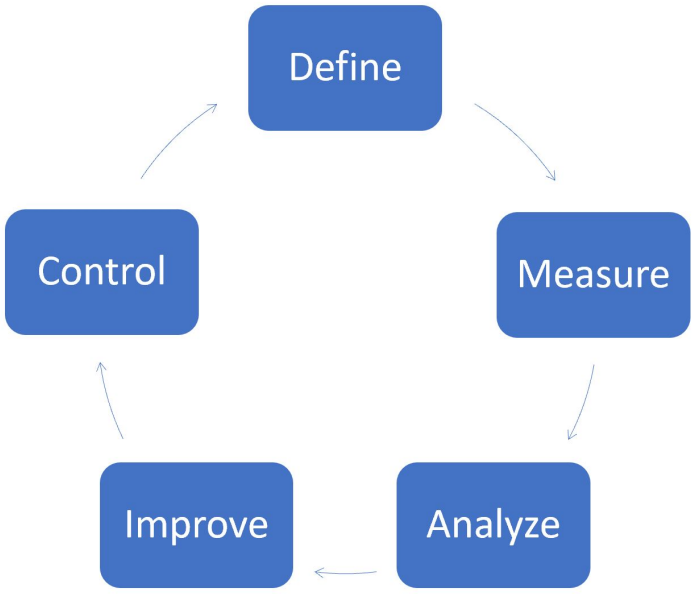

Figure 2-3: DMAIC Problem Solving Methodology

2.3.3 Zero Defect Manufacturing

The term Zero Defect Manufacturing began to appear in the late 1980's as a component of the Total Quality Management approach, pioneered by Edward Deming. The Zero Defect Manufacturing (ZDM) approach is also closely aligned with Philip Crosby's philosophy, who argued that quality systems will pay for themselves by "doing it right the first time", preventing costly rework and scrap [15]. While ZDM has existed in theory for decades, it has not been possible in practice to implement successfully until more recently with the onset of new Industry 4.0 technologies, advanced data integration systems, and real-time computing capabilities. The objective of ZDM is

not necessarily to reach zero defects in the production process, but instead to ensure no outputs or products outside of specifications can reach the next step in a value chain or the customer [16]. This objective is achieved by detecting defects quickly in-line and correcting them through repair, prediction, and prevention so that the defects do not propagate in downstream processes [17].

ZDM strategies are aimed at gathering production and quality data from multiple sources and integrating them with information at different levels of the factory. The ZDM study most relevant to this thesis is a project called ForZDM, funded by the European Union's Horizon 2020 research and innovation program. The aim of the project was to "develop and demonstrate tools to support the rapid deployment of ZDM solutions in industry and design more competitive and robust multi-stage manufacturing systems" [18] The project defines several key layers to the ForZDM solution approach which will be explored and applied in subsequent chapters, and are defined in Table 2.2 below. The five essential components of the approach are a data collection system, and a data management platform, data analysis tools, process control capabilities, and inline product repair and compensation capabilities. A simplified reference architecture that depicts the flow of information between layers is also provided in Figure 2-4.

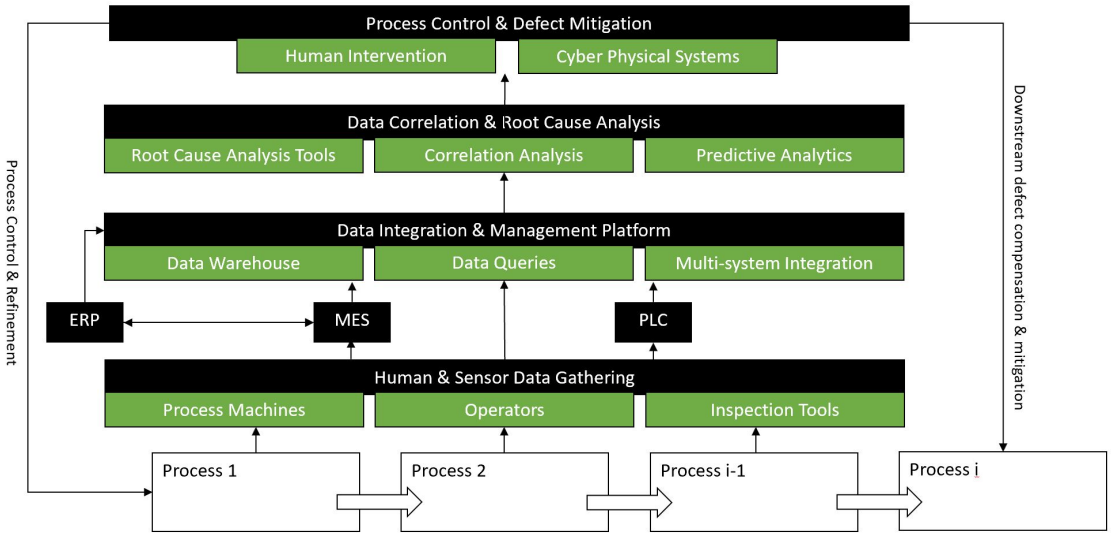

Figure 2-4: Zero Defect Manufacturing Reference Architecture, adapted from the ForZDM project

Solution Layer	**Description**
Data Acquisition System	This layer collects data from heterogeneous sources such as sensors, production planning systems, and manufacturing execution systems. In addition to automated data collection, human operator feedback is also collected in the form of structured (categorized) data and unstructured (free text) data.
Data Management Platform	The purpose of this layer is to structure and continuously update collected data in order to enable dynamic analysis on the product, process, and resource states.
Data Correlation and Root Cause Analysis Tools	These tools perform advanced data analytics and apply machine learning techniques, revealing defect correlations among product, process, and resource data at different process stages.
Process Control	Established process conditions must be monitored and the system must generate an alert if a deviation from those conditions occurs, which makes a defect more likely to appear. Process inputs must be adjusted accordingly to minimize disturbances.
Inline Product Repair and Downstream Compensation	When defects are detected immediately in-line, the product can be either reworked in-line before leaving the station or it can be corrected at a later station using feed-forward control by programming a downstream process to offset the original deviation.

Table 2.2: Solution Architecture Layers for ZDM Implementation

Chapter 3

EV Battery Manufacturing Processes

In order to reduce defects in a manufacturing process, it is important to first understand the subcomponents of the process that have potential to generate variation in the output of the process. Electric vehicle (EV) battery manufacturing is a multi-stage process, beginning with the production of individual lithium-ion battery cells, and ending with the assembly of multiple battery module assemblies into a battery pack. A simplified example of a battery pack assembly process is shown below in Figure 3-1.

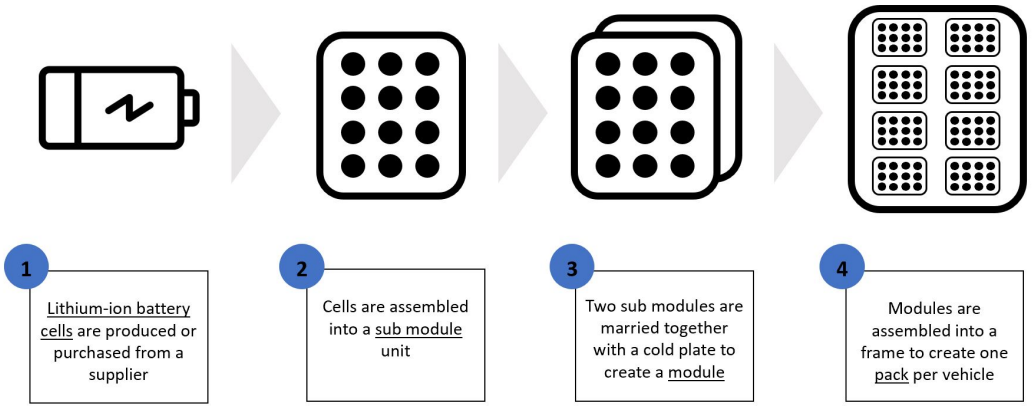

Figure 3-1: Simplified Electric Vehicle Battery Production Process Flow

First, battery cells are either manufactured onsite or purchased from a supplier. Second, cells along with other component parts are assembled into a sub module. Third, two sub modules are married to each other and additional components are added to form a complete battery module. Finally, multiple battery modules are

assembled in a frame to create a battery pack.

The energy applied in manufacturing processes is most commonly mechanical, thermal, chemical, or electrical [19]. The following sections describe several processes that may be involved in EV battery manufacturing, categorized by energy type. Also highlighted are potential sources of variation or defects that may be caused by these processes.

3.1 Mechanical Processes

Mechanical energy has the ability to transform material in several ways, including removal, joining, formation, and deformation of material. In battery module manufacturing, pressing and ultrasonic welding are two examples of mechanical processes that may be deployed.

Typically in a joining press process, one piece of material is set in a fixed position, while a pressure, stress, or force is applied to another piece of material to join it with the fixed piece. Successful pressing of two pieces of material together is dependent on both proper physical alignment of the two pieces and on the proper amount of force being applied to join the two pieces [20]. Improper alignment can lead to geometric nonconformity of the assembly, which may be exacerbated further in downstream processes. Too little press force may lead to instability or insufficient bonding of the assembly, and too much press force may lead to damage and unintended deformation of the assembly. A depiction of potential defects generated by the pressing process is provided in Figure 3-2 below.

There are several methods available for welding, including laser welding, arc welding, and ultrasonic welding. Ultrasonic welding is the local application of high-intensity energy generated by high-frequency mechanical ultrasonic vibrations in order to bond two work pieces are held together under pressure. This process produces a physical metallurgical bond without melting the base material [21]. The ultrasonic welder is an effective rework tool because it can be used on top of multiple failed laser welds, but the ultrasonic welder itself is still subject to variation such as misalignment,

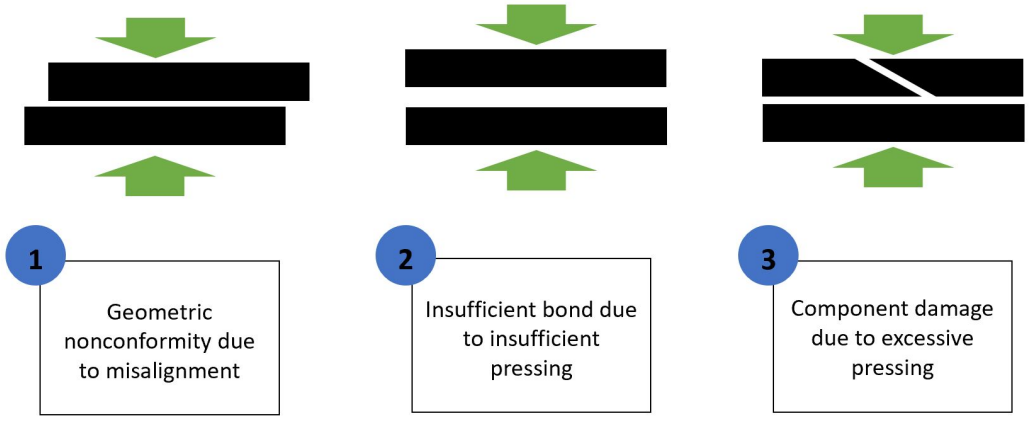

Figure 3-2: Common Press-Fit Defects [20]

overwelding, underwelding, and nonuniformity.

3.2 Thermal Processes

Thermal processes use the application of heat to transform material. Laser welding is one example of a thermal process which can be used in EV battery manufacturing to bond individual battery cells with a conductive material that can generate current across cells. In laser welding, a laser beam provides a concentrated heat source directed at the cavity between two metal pieces to be joined. A primary benefit of laser welding relative to other techniques such as arc welding is its ability to form deep, narrow welds with a smaller heat affected zone, reducing the risk of thermal distortions [22]. Despite its benefits, laser welding still has the potential to generate defects due to improper alignment, improper machine calibration, or material variations. In EV battery manufacturing, it is particularly of concern if one specific geographic area of a laser welding machine is not welding properly, because module specifications are not subject only to the total number of nonconforming welds per module, but also to the number of nonconforming welds per geographic section of each module.

3.3 Chemical Processes

Adhesives and potting are two materials commonly used in battery module manufacturing. Adhesives are used to bond various components of the subassembly to each other. Two examples of adhesives are ultra-violet (UV) adhesive, which requires exposure to UV light in order to properly cure after being applied [23], and two-component (2K) adhesive, which is made up of two parts that undergo a chemical reaction when mixed [24]. Both types have a limited curing window, after which the adhesive dries. The limited curing time resulting from the chemical properties of the adhesive makes parts vulnerable to variation and defects if they are not fully joined before the curing time expires. Additionally, 2K adhesive is sensitive to the ratio of each part of the mixture dispensed, creating an additional possible source of variation.

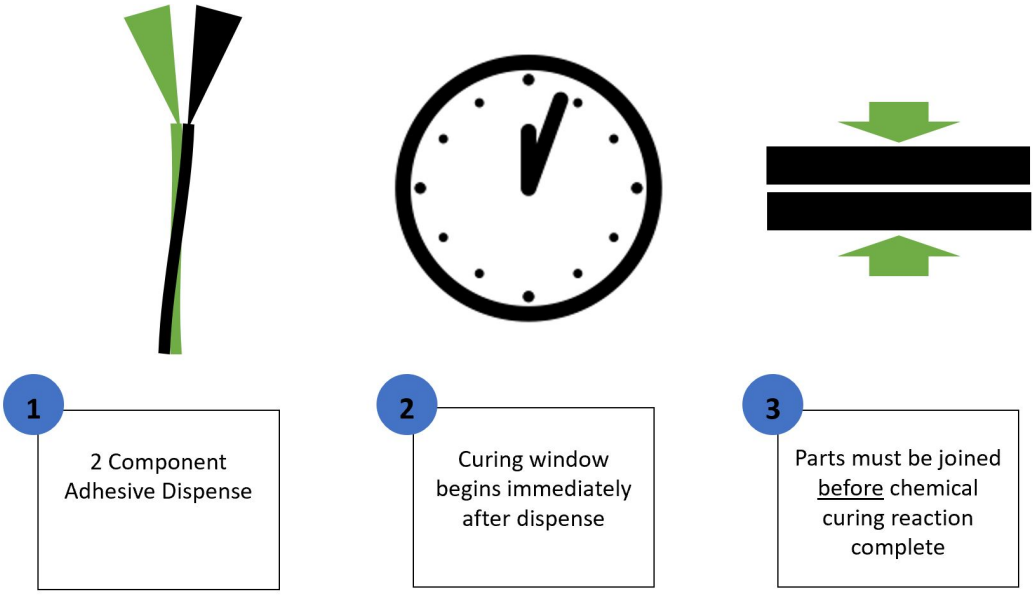

Figure 3-3: Time-Sensitive Curing Process Due to Chemical Reactions [24]

Chapter 4

Quality Data Measurement & Collection

The first step towards zero defect manufacturing is robust data collection. This chapter walks through which data must be measured and by what means it may be collected.

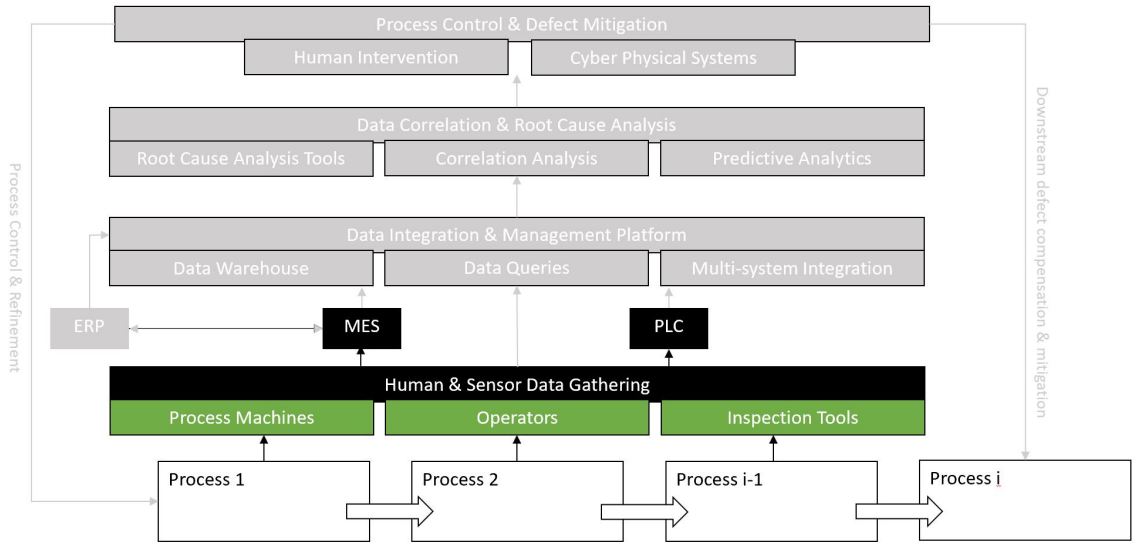

Figure 4-1: Data Gathering: Step 1 Towards Zero Defect Manufacturing

4.1 Key Performance Indicators

A key performance indicator (KPI) is a quantifiable measure of performance over time for a specific objective. The way a KPI is defined has a material impact on employee behavior, particularly if KPIs are tied to individual performance and compensation. Therefore, it is important for management to think carefully about what KPIs should be measured and reported in order to best meet stated business objectives. Some examples of KPIs commonly used in quality management are described in Table 4.1.

KPI	**Calculation**	**Description**
Defect Rate[25]	$\frac{\text{Number of units defective}}{\text{Number of Units Started}}$	The percentage of started units that are defective
Scrap Rate[26]	$\frac{\text{Number of units scrapped}}{\text{Number of Units Started}}$	The percentage of started units that are defective and cannot be reworked
Rework Rate[27]	$\frac{\text{Number of units reworked}}{\text{Number of Units Started}}$	The percentage of started units that are defective and are reworked
Defects per Unit[25]	$\frac{\text{Number of defects}}{\text{Number of Units Started}}$	The average number of defects per started unit
First Pass Yield [28]	$\frac{\text{Number of completed units without rework}}{\text{Number of Units Started}}$	The percentage of started units that are completed in the first pass production run without rework required
Time Spent in Rework[29]	$\sum_{i=1}^{t} \frac{\text{Reintro Datetime}_i - \text{Takeout Datetime}_i}{t}$	The average time it takes to rework reintroduce a unit after a defective unit is removed from the line

Table 4.1: Quality Improvement KPIs

It is important to keep in mind the dimension of time when calculating these metrics. There are two primary ways to measure most of these KPIs, by serial number or by time period. For explanatory purposes of this concept, we will use Scrap Rate as an example of a KPI we want to measure on January 1. In both measurement methodologies, our denominator (number of units started) will be a population of

units that started on the line on January 1 from midnight to 11:59:59 pm. If we use the serial number methodology, our numerator will represent how many of that exact population of units that started on that day were scrapped, regardless of when that defect was actually assigned. For example, if a unit was started at 11:58 pm on January 1 but was not scrapped until 12:10 am on January 2, the scrap would still be accounted for in the calculation for the January 1 scrap rate. In the time period methodology, the numerator would be measured as the population of units that were scrapped on January 1, regardless of when the unit started. So a unit that started on December 31 but was not scrapped until January 1 would be counted in the January 1 scrap rate. Depending on how data tables are defined, it is simpler in most cases to use the serial number methodology, given that criteria must be specified to define a specific population to be included in the denominator. The difference between the two methodologies should be relatively small under the following assumptions:

- The time span of study for the KPI is sufficiently long
- The production process is sufficiently short Scrap is typically identified immediately during production
- The distribution of operating hours are not skewed during the time span of study

If these criteria are not met, the serial number methodology may potentially underestimate the true scrap rate of the process. If it is not clear which methodology is more reliable, it may be useful to collect data using both methods and perform a comparison between the two. A difference in scrap rate measures between the two measures may reveal a significant delay in the processing of scrap material.

4.2 Subassembly State Data

The Manufacturing Execution System (MES) houses product and process data collected during production line processing. As soon as a unit starts on the production line, an "order" starts and generates a unique serial number. To calculate the KPIs described above, it is necessary to know the following about each order:

1. The time and the line at which an order started
2. A timestamp and description of all defects recorded for an order, if any
3. A timestamp of when the order was completed on the line
4. A timestamp of when the order was removed and reintroduced to the line, if applicable
5. A record of the current state of the order.

Order states should represent the physical state of a subassembly, as orders are essentially digital representations of the physical assets being produced. It is important that order state descriptions are mutually exclusive and collectively exhaustive.They should be mutually exclusive in the sense that order states should not overlap with one another. For example, for orders that are not currently on the production line, "Pending Disposition", "Pending Repair", and "Pending Reintroduction" are mutually exclusive states because it is explicit which stage of the rework process they are in, while "Offline" and "Rework" are not mutually exclusive. Orders that are offline may or may not be in a rework state. Order states should also all be collectively exhaustive in that all possible physical states are accounted for. While specific language should match as much as possible with the accepted nomenclature at a company, a proposed order state process flow is proposed in Figure 4-2 below.

4.3 Equipment Parameter Data

Equipment parameter data may include both the configurable parameters of a machine as well as the observed environmental parameters of the machine. Measurement and storage of this data is critical for root cause analysis, given that non-random variation in these parameters often have a direct effect on variation in production output. First, it is important to maintain a time-stamped change log of any machine parameter that is manipulated. This allows for a before and after analysis to compare the parameter values before and after the change to the product parameters before and after the

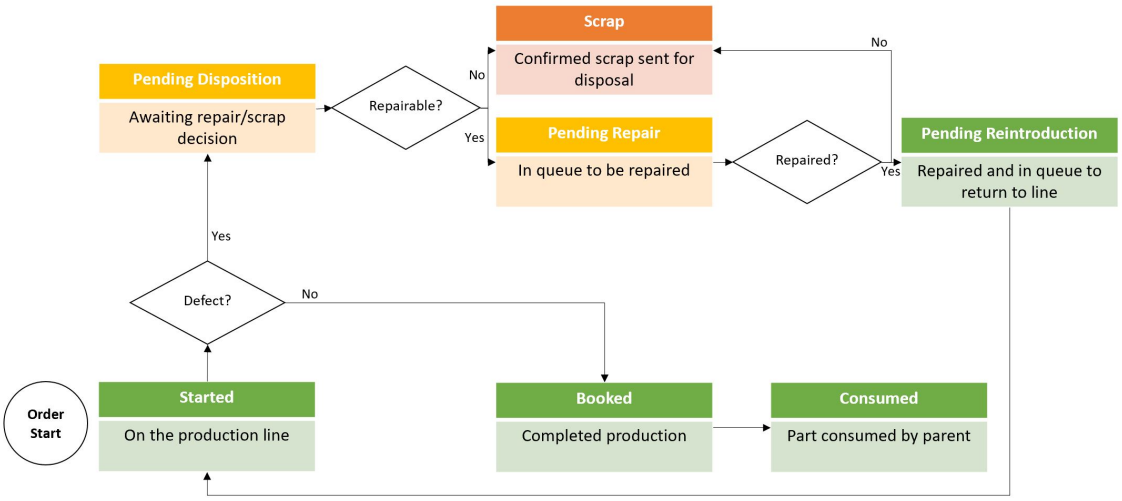

Figure 4-2: Subassembly Order State Flow

change. Additionally, the environmental conditions of the machine that may have an impact on product quality, such as temperature and humidity, should be measured periodically so that product characteristics relevant to each machine operation can be correlated with environmental variables.

4.4 Testing & Inspection Data

Testing and inspection are a significant cost of maintaining quality, but are essential to properly detect defects and prevent downstream defect propagation. There are several methods for detecting defects, subject to the specific application and the capabilities of the manufacturer. Three methods studied were computer vision, manual inspection, and destructive testing. The key characteristics of these methods are provided below in Figure 4-3, and each method is described in the subsections below.

4.4.1 Computer Vision

Computer vision is becoming a more widely used capability that "enables computers and systems to derive meaningful information from digital images, videos and other visual inputs — and take actions or make recommendations based on that information"

Method	Computer Vision	Manual Inspection	Destructive Testing
Detection Reliability	High	Moderate	Moderate
Technology Sophistication	Advanced	Basic	Variable
Set up cost	High	Moderate	Moderate
Labor cost	Low	High	Moderate
Material cost	Low	Low	High
Maintenance cost	Moderate	Low	Moderate

Figure 4-3: Comparative Analysis of Inspection Methods

[30]. In a manufacturing setting, computer vision technology can be implemented at several checkpoints throughout the production line to measure visually identifiable product characteristics at a 100% inspection rate. A picture of the work-in-process unit is captured on the line, and the computer vision model determines whether the unit is within specified criteria. Key advantages of using computer vision are that the images can detect variance not reliably detectable to the human eye, and reduced labor costs because of autonomous image processing. On the other hand, computer vision systems typically entail a large upfront investment. Additionally, the technology is fairly sophisticated, and if in-house talent cannot be acquired or developed to calibrate and improve vision models, the manufacturer may be dependent on contractors for continuous maintenance.

4.4.2 Manual Inspection

Manual inspection is used to collect data for characteristics that are not easily measured by machines or identifiable in images. An operator, for example, may inspect a unit at the end of the line to capture any defects not detected at other check points in the process. The operator may use either visual inspection or measurement tools, or a combination of both to complete the inspection. Drawbacks include high labor costs, impact to line speed, and potentially unreliable data. Accurate manual inspection is subject to proper training of all inspectors and proper calibration of any measurement

tools used to perform the inspection. Manual inspection may be 100% or selective. In a zero defect manufacturing where risk of defects can be predicted by process data, it may make sense to implement a selective manual inspection based on the defect risk of each individual unit.

4.4.3 Destructive Testing

In addition to automated and manual checkpoints throughout the production line to evaluate product quality, destructive testing may be required as an additional measure of assurance that products are being produced to stated specifications. For characteristics that cannot be explicitly measured by computer vision, tests, or human observation, destructive testing is used. Destructive testing implies that the tested units must be scrapped after testing, so the obvious disadvantage of this method is the lost material, labor, and line time spent to produce that unit. The negative impact of destructive testing can be minimized by:

1. Using units that are already assigned as scrap for destructive testing. The important thing to keep in mind with this approach is that defect that resulted in scrap assignment should not be associated with defect that the destructive test is trying to detect. In order to manage this process effectively, it is recommended to build a matrix of which scrap root causes are allowed to be used for which destructive tests. The scrap team should be familiar with this matrix and reserve scrapped units which are eligible for testing.

2. Optimizing the testing frequency. Required testing frequency will depend upon the expected probability of the defect the test is seeking to detect, as well as the desired confidence level that the test sample outcomes are representative of the production population outcomes.

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Chapter 5

Data Integration Platform

A data integration platform supports the zero defect manufacturing methodology by storing, organizing, and integrating multiple sources of data. Process, machine, quality, and cost data must be easily accessible from a unified location in order to perform advanced root cause and cost/benefit analyses. This chapter discusses some of the critical elements that make up a data integration platform, and it walks through one example of two data sources that create operational value when properly integrated.

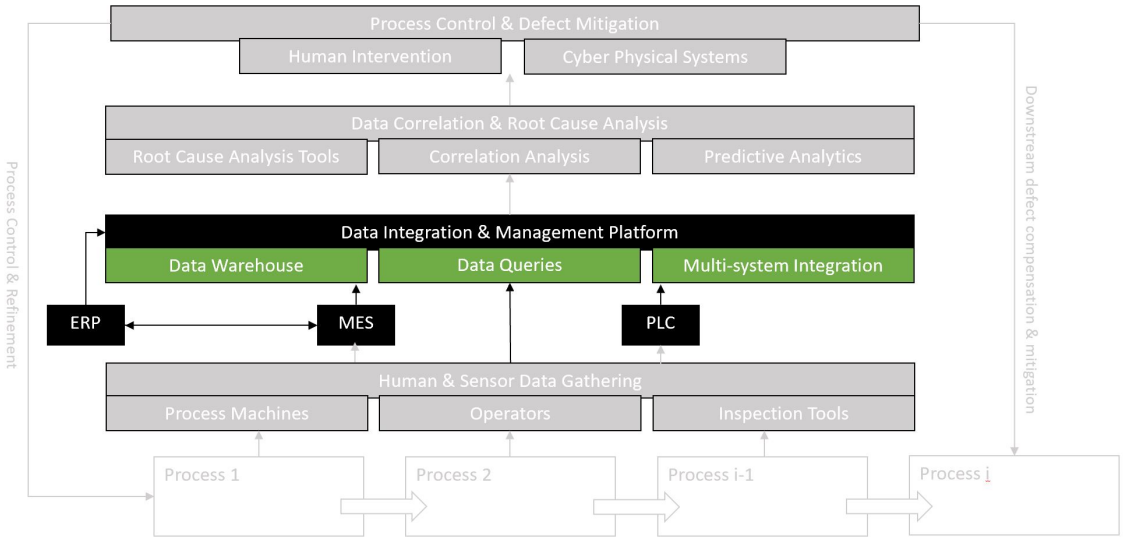

Figure 5-1: Data Integration: Step 2 Towards Zero Defect Manufacturing

5.1 Data Warehousing

A data warehouse is a database that is optimized for data retrieval to facilitate reporting and analysis [31]. For its reporting and analysis capabilities, a robust data warehousing solution is an essential component of an end-to-end quality management program. Today, common examples of cloud-based data warehouse solutions include Snowflake, Microsoft Azure, Amazon Redshift, and Google BigQuery. Based on observations noted throughout the project, three key considerations were found to be important in building and maintaining a data warehouse:

- **Frequency of data refresh:** In some settings it is important to have real-time to the minute or even to the second data. In other cases, using data that is stale by an hour or even a day does not have a significant impact on metric calculations or response behaviors. Detecting defects live on the line, for example, would require line data to be available for analysis immediately. On the other hand, measuring the historical monthly scrap rate over the past year would not be significantly impacted by the last hour's data. Because the frequency of data refresh from the source to the data warehouse takes up computational power, the decision on frequency should be tailored to the business use case, and may vary by source.

- **Length of history to store:** In the cloud era, data storage costs are relatively low, but not free. When designing a data warehouse, It should work with business users to determine how the data will be used. In most time series analyses, there is a trade-off between recency and robustness. The most recent data is likely most indicative of current and future system behavior. Excluding older historical data, however, may result in an inability to see relevant patterns and trends over time. Again, the decision of how long to keep operational data should depend on the potential analyses that will be performed.

- **Relational database design:** A data warehouse is typically structured as a relational database, which stores many tables that are related to each other

through key attributes. Serial number, for example, is a key attribute that may be used as unique identifier for an order data table. This serial number attribute would also appear in process run, defect, and rework tables. Careful thought in building the database is critical so that tables can be properly joined for more advanced analyses.

5.2 Queries and Dashboards

Queries are a means to retrieve data and link relevant pieces of disparate information together. While there are many variations in the market, SQL (Structured Query Language) forms the basis of most query packages. SQL serves as a powerful tool to combine and aggregate data. A typical basic query will include the following elements:

- **SELECT:** Define which attributes (columns) you want to see in your table.
- **FROM:** Define from which table in the data warehouse you want to pull data.
- **JOIN:** If applicable, define an additional table that you want to combine with the first table. Specify which attribute you want to match the tables with.
- **WHERE:** Define the conditions for which you want to filter your data. For example, you may be interested in a specific time period, a specific part name, or a specific set of machines to analyze.

Once queries are written, most data integration platforms will allow you to visualize several query results in a single dashboard. Each query makes up an individual tile, and the user can refresh data at the dashboard level to automatically update all tiles. The dashboard is an essential tool to translate data into insights into actions. During the project, dashboards were created for several purposes, including Pareto analysis, correlation analysis, and process control. Dashboards were reviewed during scrap reduction meetings to quickly identify top root cause contributors and to suggest possible corrective actions. One key takeaway from the dashboard development process is that separate dashboards should be created to cater to user needs. A managerial

dashboard, for example, may primarily display KPI trends and top issues across the shop, while a line engineer's dashboard might be made up of control charts and correlation analyses.

MES is the manufacturing execution system. This system documents the transformation of raw materials to finished goods at each step of the production line, and it is considered the source of truth for process and quality data. ERP is the Enterprise Resource Planning system. This system contains financial, order, and inventory data. A well-functioning manufacturing operation will integrate these systems so that the ERP system can send a signal to the MES to produce, and so that the MES can send consumption signals back to the ERP system to reduce component inventory and increase finished goods inventory. From a quality perspective, there are two important aspects to this integration:

1. **Scrap:** MES needs to provide ERP with an accurate count of consumed and scrapped material at the component level. For example, if a completed assembly is scrapped, which components (child parts) were scrapped and which were salvaged and available for re-consumption by another parent?

2. **Costs:** MES data reflects the count and proportion of defects generated on the line. In order to make an informed decision on whether or not to implement a costly solution to reduce defects, however, it is necessary to be able to integrate both cost and count data together in order to measure the financial impact of scrap and rework. MES should be sending defect/scrap/rework data, and ERP should be sending material cost and labor cost information to the data integration layer so that cost/benefit analyses can be performed.

An illustrative example in Figure 5-2 below proposes how consumption and scrap data might be captured by MES throughout a production process. The movement of component inventory from plant storage to line side bins, and any component rejections identified before process starts are managed directly in the ERP. Once a production order is initiated, however, MES houses all data necessary to accurately capture which parts were consumed, scrapped, and completed. Based on signals from

MES, ERP inventory will move from an available state to a work in progress (WIP) state. From a work in progress state, component inventory will move to a scrapped state if the component's sub module is scrapped and the component is not salvageable. If the sub module is completed, the component part WIP inventory is reduced and it's parent sub module part inventory is increased. This pattern continues as the sub module part is now considered a component part to build module inventory.

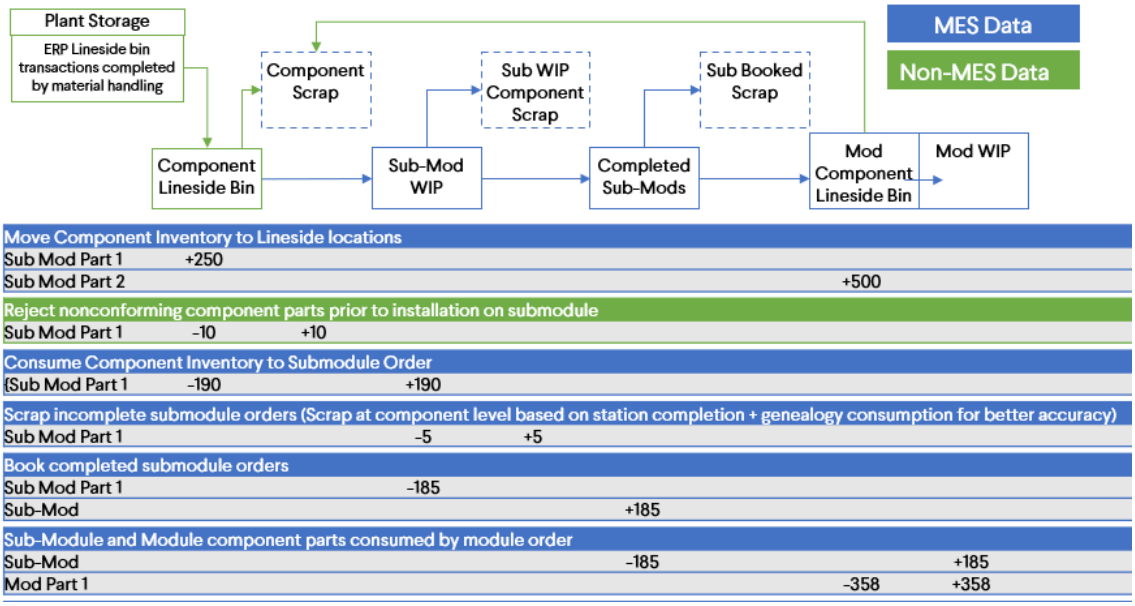

Figure 5-2: MES Integration to ERP: Consumption and Scrap Transactions

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Chapter 6

Root Cause Analysis

Once all quality-related data is acquired and accessible from a single source, the next step is to perform data analysis to determine the root cause of defect creation. At a high level defects can typically be attributed to process, equipment, operators, or product design. Without robust, centralized data analysis, however, it is not always immediately obvious which of the buckets the defect falls under. Analysis should be led by the quality team, but requires input from all representatives in the shop including engineering, operations, controls and maintenance teams. There are many different tools available to conduct root cause analyses, three of which will be discussed in this chapter: Pareto charts, correlation analyses, and predictive methods.

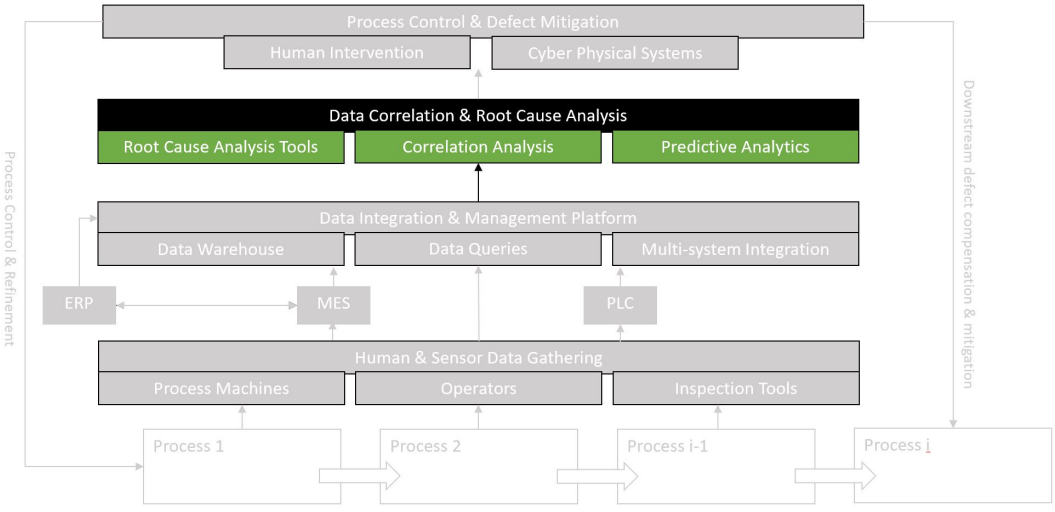

Figure 6-1: Root Cause Analysis: Step 3 Towards Zero Defect Manufacturing

6.1 Pareto Charts

A pareto chart is typically used in a quality setting to visually represent the most frequent or most impactful causes of defects and scrap. The name of the chart is derived from the Pareto principle, which asserts that 80% of the consequences or outcomes are generated by only 20% of the causes. Under this assumption, addressing the top subset of causes alleviates 80% of the problem. The pareto chart is displayed as a bar graph, with each bar representing either the frequency or cost of a particular root cause. The bars are ordered from greatest to smallest, so that it is easy to identify the top contributors that merit further attention. In building a pareto chart, one must consider the following factors [32]:

- **Categories:** Define each category used to group items. Categories should be mutually exclusive so that users are able to easily assign a category to a particular unit.
- **Measurement value:** If the cost impact of each category varies significantly, it may make more sense to use total dollar value rather than frequency as the key metric over frequency/count.
- **Time period:** More recent data is more representative of current system behavior, but considering a longer time period may make discrepancies between categories more obvious and less prone to outliers. For quality-related questions, a month, week, or day are reasonable time period selections depending upon the application.

An example of a pareto chart is shown in Figure 6-2 below, measuring the most frequent causes of scrap for one of the shop's production lines. As you can see, additional dimensions identified by color can be applied to differentiate multiple stages of the line, for example. Pareto analysis for each line is best to be kept separate to ensure accountability and actionability. Different managers oversee different lines, so it is important to provide each line management team with analysis specific to their scope of control. Additionally, a singular defect type across lines may manifest from

distinct root causes from each line, so combining analyses may lead problem solvers to apply a blanket solution that works for one line but not the other. A pareto is a valuable first line of inquiry to identify top issues. Once top issues are identified, additional qualitative analysis such as Five Whys and Fishbone diagrams can be developed to determine the root causes underlying top issues.

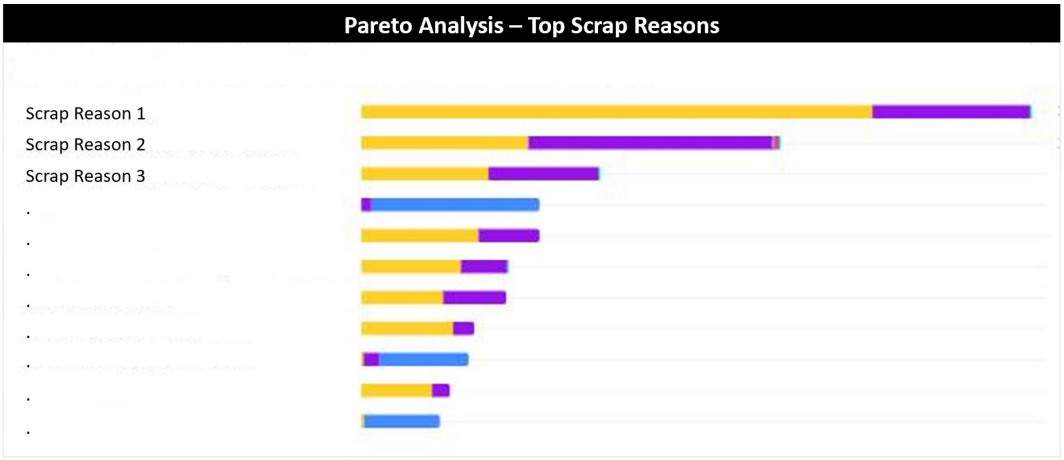

Figure 6-2: Pareto Chart of Scrap Causes

6.2 Correlation Analysis

Although correlation does not imply causation, correlation analysis is a useful tool to explore potential root causes for a defect. A correlation relates two or more variables and examines the relationship among them. As one variable increases, the correlation value indicates whether the other variable increases (positive correlation), decreases (negative correlation), or fluctuates randomly (no correlation).

Figure 6-3 shows an example of a scatter plot, a visual graph that plots one variable against another to evaluate their relationship to one another. On this graph, each point represents an individual unit. Two parameters, X and Y, were recorded. Additionally, data is available for whether each unit was scrapped (yellow) or was successfully completed (purple). This plot shows that the two parameters do not have a linear relationship. Parameter X appears to follow a close to normal distribution, while parameter Y follows a bimodal distribution (as confirmed by the histograms in

Figure 6-4). The bimodal distribution may be the result of two different machines or two different measurement tools being used on the same line, which could be an interesting line of investigation in itself. More notable, however, is that the points classified as yellow indicate scrap, which are all clustered at low values of parameter X. While not conclusive, this analysis would lead an engineer to suspect that a low value of parameter X leads to higher rates of scrap. The engineer could then take action to increase the equipment parameters or narrow the variance of parameter X so that low values appear less frequently.

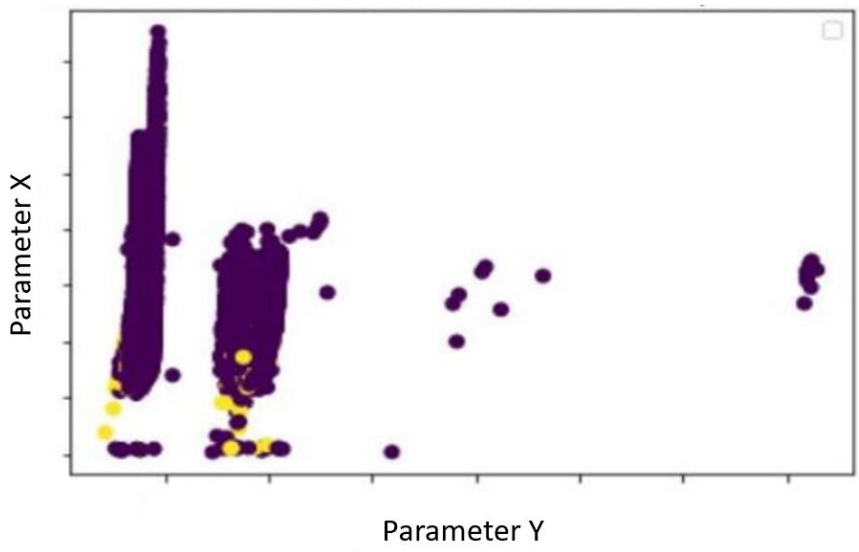

Figure 6-3: Correlation Analysis with Scatter Plot

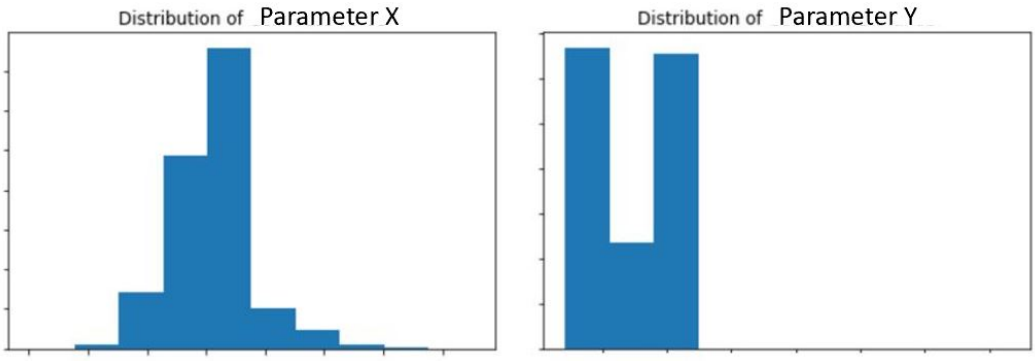

Figure 6-4: Frequency Distribution of Parameters X and Y

6.3 Predictive Methods

With robust data sets, historical attributes from previously produced units can be used to develop models that predict future attributes of new units being produced on the line. In quality, for example, one might want to predict a unit as being defective/non-defective, or as scrapped/completed based on many process parameters measured for each unit as it travels through the process. One application of this predictive method would be to flag units if they meet a certain threshold of risk for defects or scrap. Based on this risk output, selective manual inspection of the unit may be triggered, or, in more robust systems, downstream processes may be adjusted in real time to reverse the risk by changing machine parameters, parts, or line speed. Because risk can be naturally measured probabilistically, a logistic regression was chosen as the predictive method to explore for application.

In logistic regression, a model ingests numerical and categorical variables and predicts a categorical variable that has two possible outcomes. A logistic regression takes the following form:

$$P(Y=1) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\ldots\beta_k x_k)}}, \text{where}$$
$$Y = \text{categorical outcome}$$
$$x_i = \text{independent variables}$$
$$\beta_i = \text{model parameters}$$

In a manufacturing setting, independent variables, x_i, may include the following:

- Machine parameter data (e.g. x and y axis alignment settings)
- Environmental data (e.g. temperature)
- Time-based data (e.g. day of week)
- Inspection data (e.g. voltage test results)

The categorical variable measured in this specific application was order state (Scrap/Completed). After exploring correlations of several independent variables and testing statistical significance, the model identified variables X and Z as statistically

significant factors that influence the probability of a scrap outcome. Because there is attrition of units from the line throughout the process, it is necessary to only compare units which have reached the same station as each other. In this example, we only include data for units that have reached a particular station. If you try to compare scrapped units which fell out of the line before some of the measurements in the model were captured, the data may suggest an invalid effect that is being generated by null values for scrapped unit attributes.

Figure 6-5 below is a confusion matrix that describes the predictive accuracy of the regression. Actual values of a validation set are plotted on the y-axis (with 1 representing a scrap outcome), and predicted values are plotted on the x-axis.

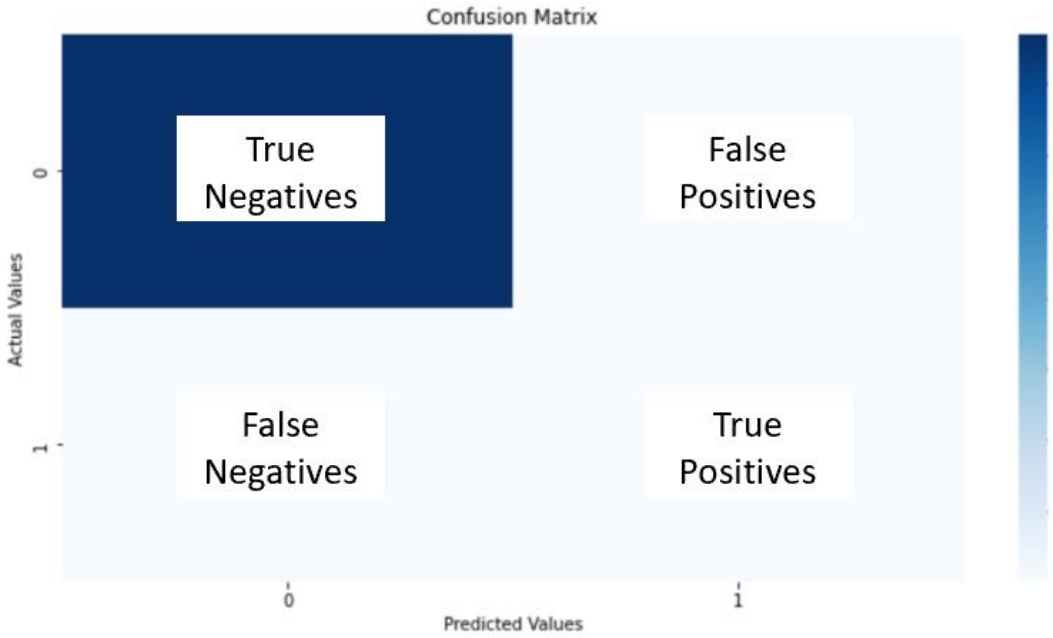

Figure 6-5: Confusion Matrix for Predicting Scrapped Units

- The top left corner represents the true negatives (the number of units that are actually completed which were predicted to be completed by the model based on the unit's attributes)

- The top right corner represents false positives (completed units which were incorrectly predicted by the model to be scrapped)

- The bottom right corner represents the true positives (the number of actually scrapped units that were predicted as scrap by the model)
- The bottom left corner represents the false negatives (the number of scrapped units that were predicted to be successfully completed)

Although accuracy in this model is high at 99%, this is largely due to heavy skewing of dependent data towards a "Completed" rather than a "Scrapped" outcome. Calculating specificity and sensitivity yield the results below. While the model predicts completed units (specificity) exceptionally well because of their large volume, the model is good but not as strong at predicting a scrap outcome (sensitivity).

$$\text{Specificity: True Negative Rate} = \frac{\text{True Negatives}}{\text{Actual Negatives}} = 0.997$$
$$\text{Sensitivity: True Positive Rate} = \frac{\text{True Positives}}{\text{Actual Positives}} = 0.762$$

While there are certainly opportunities for improvement and expansion of this predictive model, the application demonstrates the potential value it creates in guiding operational decisions. If an operator or quality team member is unsure of whether an offline unit should be assigned a scrap order state upon reviewing it visually, for example, with the model they would be able to look up the risk of scrap for that individual unit based on data collected on the line thus far.

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Chapter 7

Applications of Statistical Process Control

As referenced in Chapter 2, a process "in control" exhibits only common-cause, or random variation. Statistical process control is a methodology to identify signals that a process is out of control assignable cause variation, in which the process deviates from its expected output. Once a process is deemed to be in control, one must also confirm that the process is "capable". A process is determined to be capable when it produces output that the customer finds acceptable [33]. This chapter describes an application of control charts in order to demonstrate the benefits of these tools as part of a robust quality improvement program.

7.1 Control Charts

The most popular method for visualizing process control is a control chart, a graph that studies how a process changes over time. The control chart is intended to detect both shifts in the mean and changes in the variation of the data being measured. The specific type of control is dependent on the type of data and the sample size of the data being plotted [34]. A decision tree for determining the type of control chart to use is shown in Figure 7-1, which describes control chart options for both variable (continuous) and attribute (count) data.

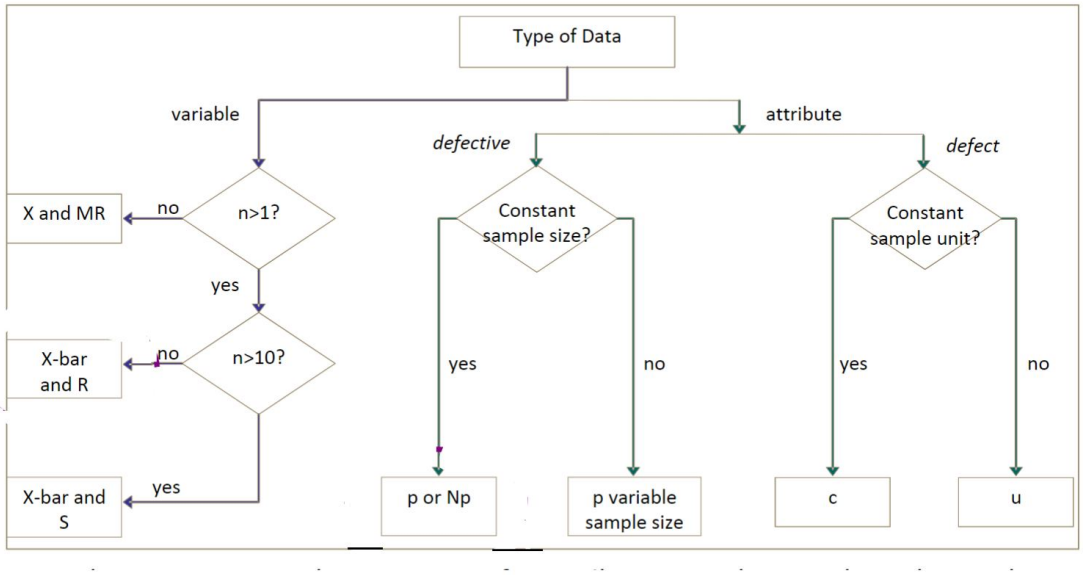

Figure 7-1: Statistical Process Control Chart Decision Tree [33]

When measuring a continuous variable, X-bar represents the average value for each sample. With a large sample size n per sample, it is possible to calculate the standard deviation per sample to measure expected variability, resulting in an X-bar and S chart. If sample sizes are smaller (generally when the cost of collecting data is significant), the range from the minimum to maximum values each sample are used as a measure of variation, resulting in an X-bar and R chart.

When measuring an attribute variable, either the count of defective units or the count of total defects can be measured. If a constant sample size is used, measurements in the control chart can be represented as an average count per sample (np and c charts). If the sample size of each sample varies, however, measurements in the control chart are represented as a proportion of inspected units (p and u charts). For charts using non-standard sample sizes, the upper and lower control limits for each sample are dynamic and are dependent on the size of the sample, n.

A control chart has three critical elements that capture both expected process behavior and real-time actual process behavior:

- **Center Line:** The historical mean of data
- **Upper and Lower Control Limits:** Three standard deviations above and

below the historical mean

- **Plotted Data:** Time-ordered, plotted points representing real-time collected data

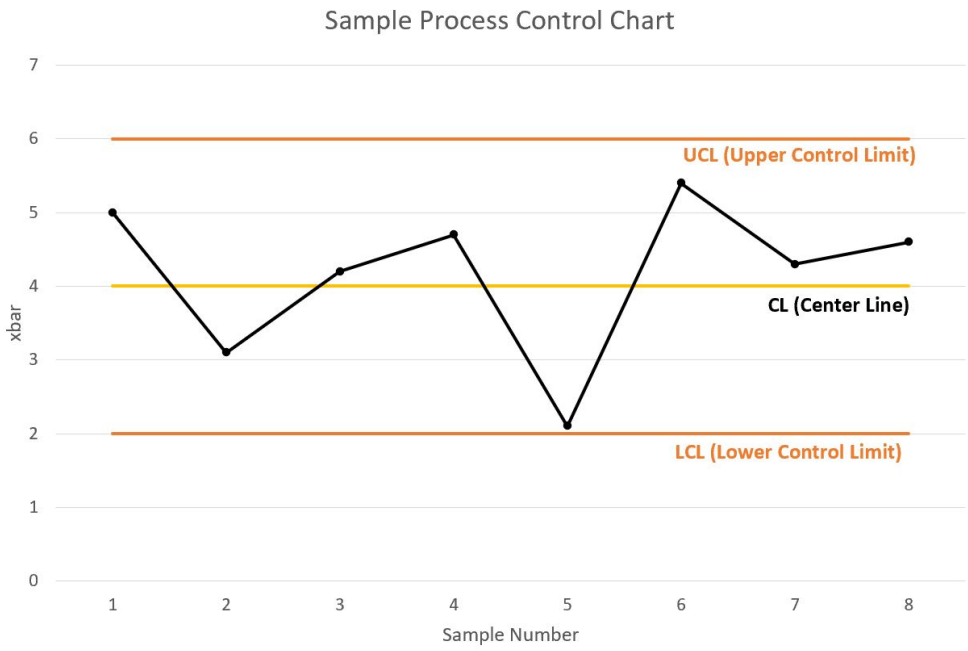

Figure 7-2: Sample Process Control Chart

7.1.1 Attribute Control Charts

Attribute data captured by control charts is assumed to be discrete. It may either be measured by the count of defective units, assumed to be binomial (e.g. Pass/Fail), or by the count of defects. An example of a p-chart, which is used for count of defective units, and a u-chart, which is used for count of defects, are provided below.

P-Chart

For defective unit count measurements, a p-chart is used rather than an np-chart when the sample size is not constant. For example, one may be measuring whether the defect rate each day is in control in a setting where the production rate is not constant each day. The p-chart measures the proportion of sampled units that are defective.

Because the only possible outcomes are Pass/Fail, Upper and Lower Control Limits are calculated using the binomial distribution. In a p-chart, you have the option to use a constant UCL and LCL using the average sample size or to use a variable UCL and LCL that changes dependent on each individual sample size. The following variables are relevant for construction of a p-chart (assumes constant control limits):

k = number of lots (number of points plotted on control chart)

n_i = sample size per lot i

np_i = number of defectives in each lot i

p_i = proportion of defectives in each lot i

$\bar{n} = \frac{\sum n_i}{k}$ = mean sample size

$\bar{p} = \frac{\sum np_i}{\sum n_i}$ = mean defective proportion

$UCL_p = \bar{p} + 3\sqrt{\frac{\bar{p}(1-\bar{p}}{\bar{n}}}$

$LCL_p = \bar{p} - 3\sqrt{\frac{\bar{p}(1-\bar{p}}{\bar{n}}}$

Given a data set of samples that includes the sample size and count of defective units, all of the above values can be calculated and plotted. Figure 7-3 provides an illustrative example of a p-chart, plotting the daily proportion of failed tests over a period of 30 days.

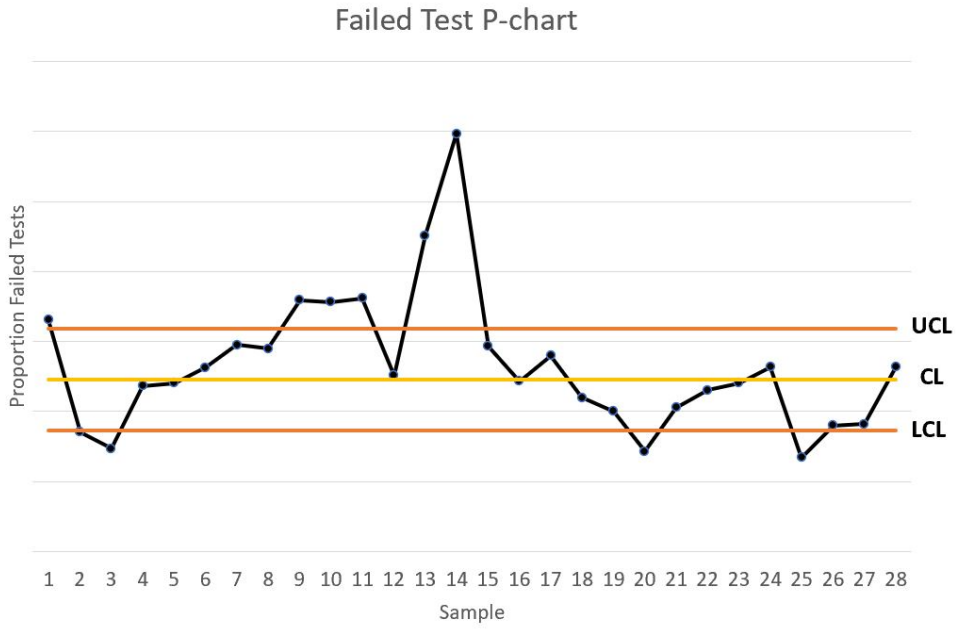

Figure 7-3: Failed Test P-Chart

U-Chart

For measurement of total defect counts rather than defective units, a u-chart is used when sample size is variable (a c-chart is used when sample size is constant). A u-chart calculates the number of total defects out of the number of inspected items. The u-chart assumes the occurrence of defects is estimated by the Poisson distribution. Again, the owner of the control chart has the option to use constant control limits by using an average sample size or to use variable control limits by using lot-specific sample size to calculate limits. While k and n have the same definition in a u-chart as a p-chart, the following expressions are introduced in the u-chart:

c_i = number of defects in each lot i

$u_i = \frac{c_i}{n_i}$

$\bar{u} = \frac{\sum c_i}{\sum n_i}$ = mean defects per unit

$UCL_u = \bar{u} + 3\sqrt{\frac{\bar{u}}{n_i}}$

$LCL_u = \bar{u} - 3\sqrt{\frac{\bar{u}}{n_i}}$

Given a data set of samples that includes the sample size and count of defects, all of the above values can be calculated and plotted. Figure 7-4 provides an example of a p-chart, plotting the daily number of defects A per unit over a period of 30 days.

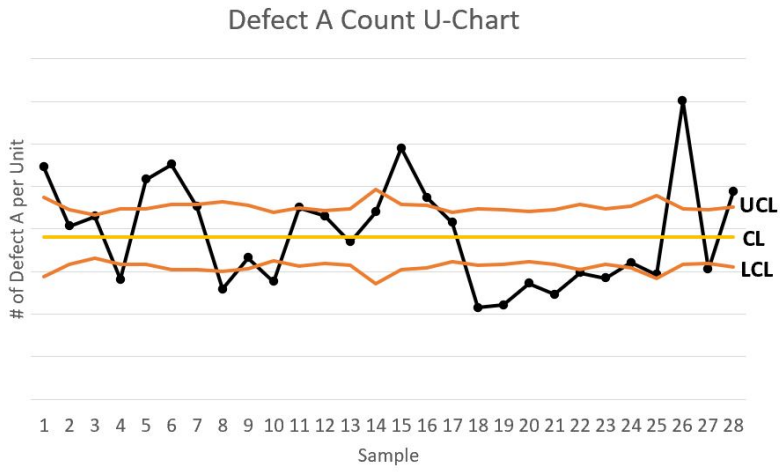

Figure 7-4: Defect A Count U-Chart

7.1.2 Variable Control Chart

Variable data captured in control charts are continuous, and samples are assumed to follow a normal distribution when the sample size is sufficiently large. The selection of specific chart type depends upon the sample size of lots. If sample size n is less than 10, an X-bar and R charts are used. X-bar is the mean of the variable being measured in each lot. The R chart shows the range of the variable; it measures the difference between the minimum and maximum values in each lot. If n is greater than 10, an X-bar and S chart are used. An S chart uses the standard deviation of each lot to measure the variation of the variable of interest.

X-Bar and S Chart

One example of a continuous variable that may be measured in battery module manufacturing is parameter X. Parameter X is subject to random variability, but it would be important to detect statistically significant movement away from the expected value. An X-bar and S chart can be created from sampling data to detect any changes in the process.

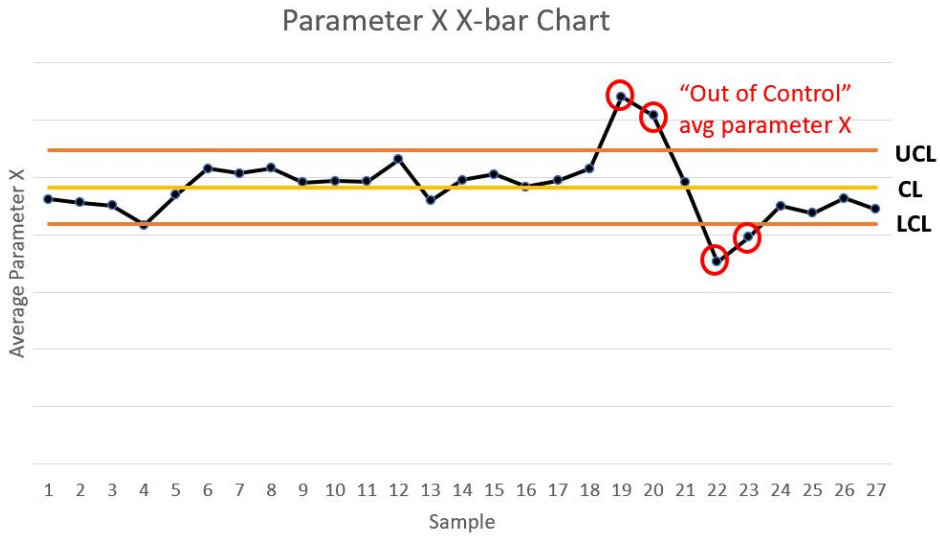

Figure 7-5: Parameter X Xbar-Chart

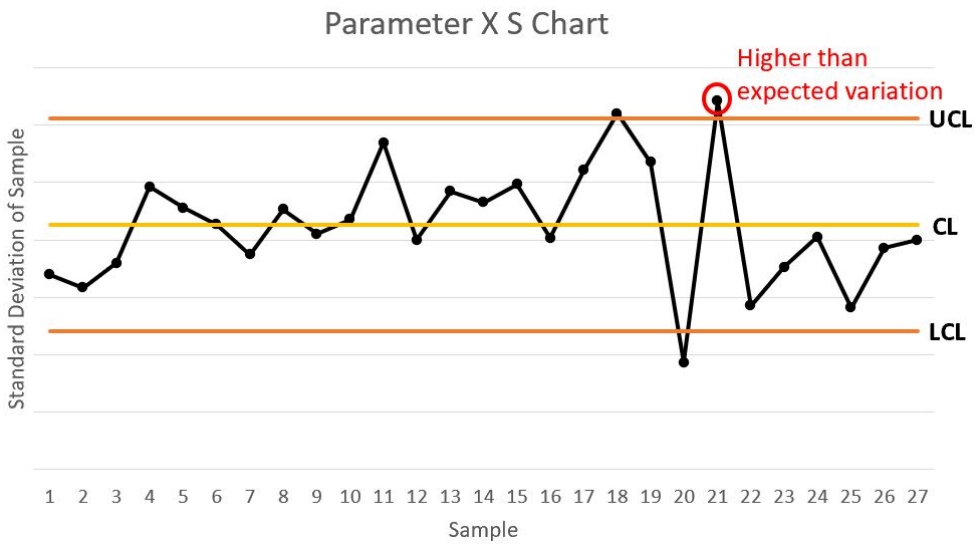

Figure 7-6: Parameter X S-Chart

7.2 Interpreting Control Charts

Control charts are used to measure process stability over time. The control chart allows the user to detect unexpected changes in the process. It also aids in comparing process performance before and after a process improvement is implemented to measure the improvement's effectiveness. A single point outside the LCL or the UCL is highly improbable (0.03%), indicating a process is out of control. We can also learn from trends in consecutive points, with a set of rules defined by DeVor et al, in order to identify statistically improbable events assuming only common cause variation is present [35]. Using an X-bar chart as an example, 2 of 3 consecutive points greater than 2 sigma from the mean, or 4 of 5 consecutive points greater than 1 sigma from the mean, suggest a process may be out of control. Other signals that the process is out of control are:

- Runs of 8 or more all above or all below the center line
- 6 or more points trending in a consistent direction
- 8 consecutive points outside 1 sigma (bimodal indication)

While the exact implementation will vary by software, this logic can be built into

the control charts and trigger a visual alert on the control chart when an out of control scenario occurs.

Chapter 8

Defect Prevention & Defect Propagation Mitigation

There are several routes of action to take once a process control problem is identified. Using the lean approach, management can use information from root cause analysis to decide the appropriate resolution for addressing a defect-generating process.

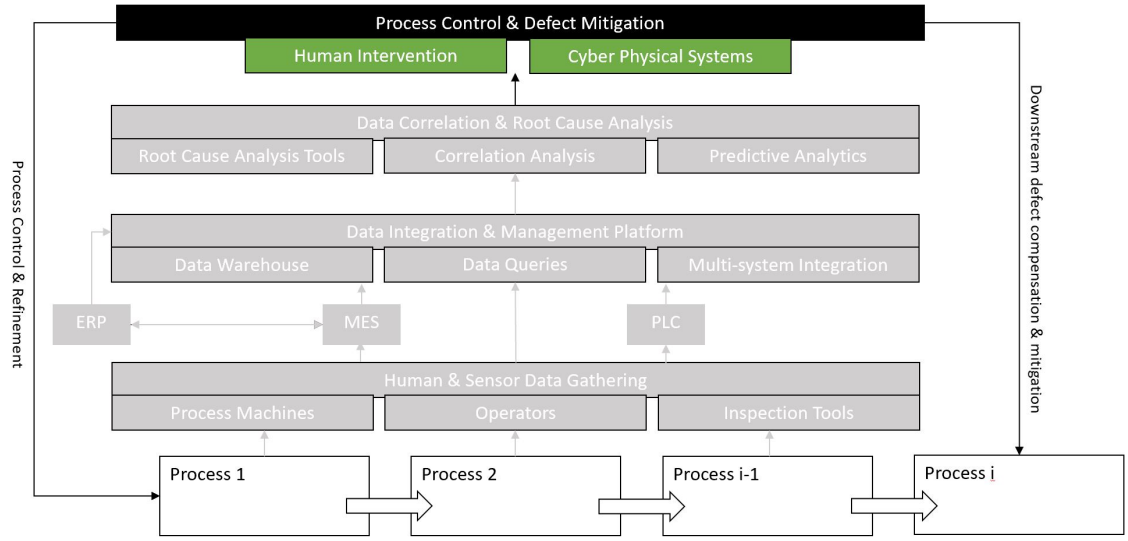

Figure 8-1: Process Control & Defect Mitigation: Step 4 Towards Zero Defect Manufacturing

This may involve both short-term workarounds that address potential defects in real-time, as well as long term solutions that eliminate the opportunity for defects to occur in a given process. In a more advanced manufacturing environment, processes may

even be able to compensate for upstream defects automatically using a combination of real-time process data and historical data analysis. This chapter primarily focuses on defect prevention rather than defect compensation, which will be reserved for future work. A comparison of several defect mitigation solutions is provided in Figure 8-2 below.

Method	Equipment Modification	Manual Recovery	Visual Alarms	Buffers / Conveyance	Design for Mfg
Implementation Cost	Low	Moderate	Moderate	High	High
Speed of Implementation	Fast	Fast	Moderate	Slow	Slow
Ongoing Maintenance	Moderate	Low	Low	Low	Low
Labor Requirements	Low	High	Moderate	Low	Low
Defect Mitigation Effectiveness	Moderate	Moderate	Moderate	Moderate	High

Figure 8-2: Cost and Operational Comparison of Defect Mitigation Solutions

8.1 Equipment Modification

Correlation and regression analysis results are useful in illuminating optimal machine parameters that minimize the frequency of defects. For example, if a correlation analysis suggests that a higher value of parameter X is correlated with a higher frequency of cracks, this is a signal that an engineer may want to tune parameter X of the machine downwards and document this parameter change. Once the machine parameter is adjusted, the engineer can monitor the effect on cracks, and also seek any potential negative effects of decreasing parameter X on other related characteristics.

In addition to equipment parameter adjustments, analysis may reveal that equipment maintenance or enhancements could potentially improve quality performance. Engineers can use quality data to identify malfunctioning parts and to develop a maintenance schedule based on performance trends. Additionally, they may identify

opportunities to enhance equipment. For example, if misalignment is determined to be a common root cause for defects, a fixture may be implemented on particular machines to auto-align components during machine processing. While parameter adjustments are typically fast and free to implement, maintenance and modifications of the machines themselves may be somewhat more time consuming and costly.

8.2 Manual Recovery

Even if there is no obvious or easy solution to quickly and permanently correct a defect-generating process, there may be temporary workarounds available to resolve the defect in-line without having to move the product to a rework station. Particularly for defects that are relatively infrequent, rather than implementing a complicated solution it may make sense to recover the part manually on the line. For example, if a process faults after being 95% complete, the process should be set up to allow for an operator to manually perform the remaining 5% of work on the line in order to allow for continued flow of materials. While this solution entails labor costs and requires training to effectively implement, it is also fast to implement and typically requires little technology investment. These characteristics make this solution an ideal candidate for infrequent defects that are not easily solvable by other technology or design methods.

8.3 Visual Alarms

One of the most notable uses of visual alarms or cues in an auto manufacturing setting is the andon cord. Pioneered as part of the Toyota Production System (TPS), the andon cord is pulled by an operator whenever a problem is encountered at a station. This tool alerts management that there is an issue requiring attention and stops the line if necessary in order to contain mistakes. In modern settings, alerts similar to an andon cord may be either triggered manually, or automatically by the production system itself.

Visual alarms are particularly useful for unmanned stations subject to possible delays or defects that may result in permanent scrap if not addressed through manual intervention in a time-effective manner. One relevant example in manufacturing is the process of adhesive application, pressing, and curing. As discussed in Chapter 3, adhesives have a limited curing window once dispensed. Additionally, once dried the adhesive cannot be easily removed from the component. In the event that a line becomes blocked, a component may have already had adhesive dispensed on it, but may not be able to reach the press machine prior to the curing expiration time. In this scenario, a visual alarm should be triggered on the line to alert an operator that action must be taken. The logic for the alarm would be driven by machine process data. Once the operator sees the alarm and reaches the station, they may either redirect the component to an offline manual press or wipe the adhesive from the component, given it has not yet dried. This solution can be implemented at relatively low cost, and eliminates the need for constant human monitoring when defects are relatively infrequent.

8.4 Buffers

A buffer is a buildup of work-in-process inventory between production stages intended to account for variation in the process. Typically, buffer space is optimized to minimize the chance that a downstream machine is starved and to minimize the risk of stranded capital from work-in-process inventory. It is important note that the choice of buffer size may also have an impact on the incidence and propagation of defects.

Returning to the example of adhesive dispense and press, let us consider the buffer between the dispense station and press station, and the buffer between the press station and the subsequent station. An illustrative example in Figure 8-3 below indicates how a smaller or larger buffer on either side of the press station may affect defect frequency in a process such as this. Before the press station, having a larger buffer increases the defect risk of units getting blocked in that buffer and adhesive drying out, if the press station or any station further downstream were to block movement

out of that buffer. After the press station, having more space available in the buffer before process i+2 gives the press station the opportunity to keep running and process the units which already have adhesive applied, in the event process i+2 and beyond becomes blocked. One option to consider in addition to the fixed size of the buffer is a flexible conveyance system, which can switch on to provide additional slots for pressed units as a detour to the primary conveyance buffer line only when required.

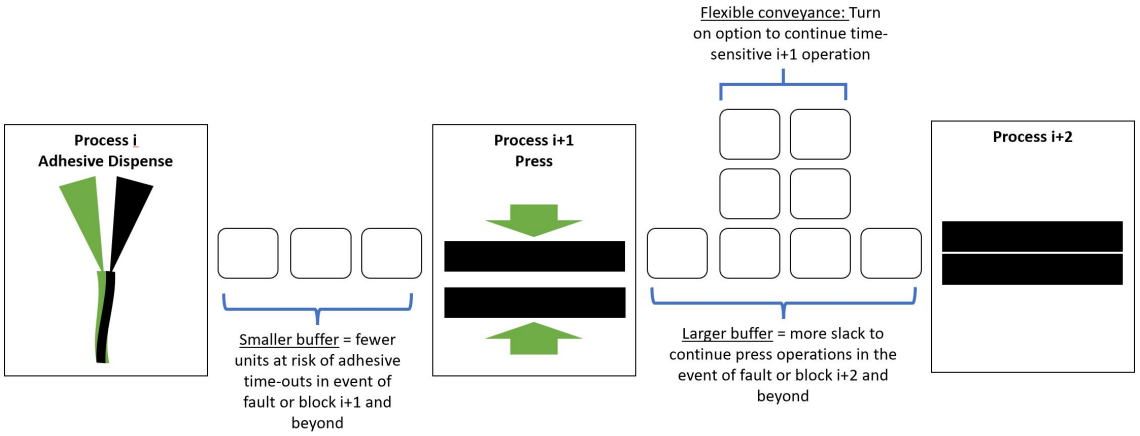

Figure 8-3: Effect of Buffer Size on Defect Risk

8.5 Design for Manufacturing

Design for manufacturing is the process of designing parts, components, and products for ease of manufacturing. The objective of design for manufacturing is to allow for maximal production output and minimal opportunity for defect generation. Of the solutions proposed, this solution requires the greatest investment and is the slowest to implement. It also, however, may have the biggest impact on production quality when implemented effectively. Particularly in a fast-growing manufacturing environment, it makes sense to invest in design for manufacturing early on before more significant capital investments are made. By taking lessons learned from low-speed validation production runs, new lines can be set up with product manufacturing modifications already incorporated.

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Chapter 9

Discussion

9.1 Zero Defect Manufacturing Framework

This thesis has validated that an adapted version of the ForZDM project zero defect manufacturing reference architecture is a valuable framework that can be used to build a more robust quality management process within a manufacturing organization. Key takeaways and methods to approach implementation of the five major pillars of the framework are summarized below:

1. **Data Gathering:** The volume and frequency of data collection is steadily increasing with the advent of new technologies such as IoT sensors and computer vision. Organizations must determine what data will be useful in performing analyses, and decide the most efficient means to capture that data, whether it be by an operator or machine.

2. **Data Integration:** Quality data must be logically organized and augmented with other sources of process and product data. Queries and dashboards allow business users to more easily extract and visualize relevant information.

3. **Root Cause Analysis:** A combination of both human expertise and computer models are required to hypothesize possible root causes of defects and to detect meaningful relationships amongst collected variables.

4. **Process Control:** Constant monitoring of measurable output parameters can reveal statistically significant shifts in the data, and can aid in measuring the effect of an implemented solution of production quality.

5. **Defect Mitigation:** Root cause analysis and process control can reveal data insights that translate into action. Defects can be reduced through both responsive and preventative methods.

9.2 Quality Improvement Results

Throughout the project, both qualitative and quantitative metrics were tracked to measure the effectiveness of the quality management program improvements.

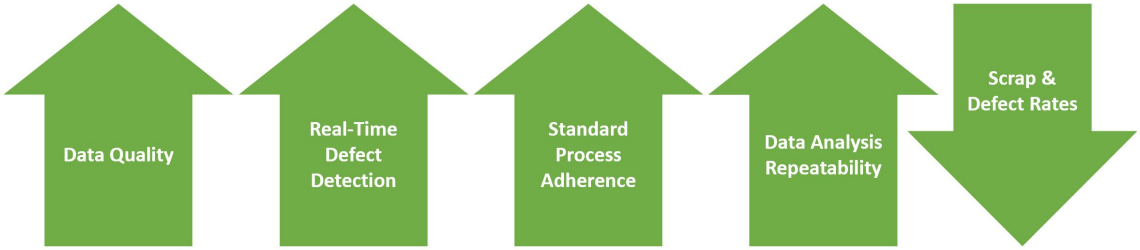

Figure 9-1: Effect of Project Implementation on Key Metrics

Data Quality

- Achieved stronger alignment across multiple data sources, such as the daily scrap count records in MES, ERP, and outbound shipping manifests.
- Defined mutually exclusive and collectively exhaustive categories for key data attributes, resulting in a more streamlined data management process.

Real-Time Defect Detection

- Introduced control charts to detect assignable cause variation in output parameters.
- Coordinated implementation of logic and alarms to stop the line or alert an operator live when a defect was detected, preventing downstream propagation.

Standard Process Adherence

- Documented process maps and step-by-step guides to clarify process ownership and to train team members on standard processes.
- Developed metrics and dashboards to measure process adherence for use by management to address gaps in a targeted fashion.

Data Analysis Repeatability

- Shifted the team's time investments from data generation and analysis to data interpretation and action planning.
- Leveraged the data integration platform to automatically refresh and update analysis output.

Scrap & Defect Rates

- The actions above, in addition to active project management and communication across teams, allowed the team to more efficiently recognize and prioritize solutions to address quality defects.
- Despite an increasing production rate and increasing material prices, scrap costs decreased from the project start date to the project end date as a result of the quality improvement program.

9.3 Implementation Challenges & Recommendations

Most people in the battery module manufacturing shop of Company A were open to changes to the existing process and to testing new processes with an iterative approach. Naturally, however, there were challenges in implementing quality solutions from both a technical and management perspective. Some of the key challenges and proposed actions to resolve said challenges are summarized in Table 9.1 below.

Challenge	**Recommendation**
Competing Priorities	Designate quality champions outside of the quality team. Incorporate quality metrics into both team and individual performance evaluation. Share key performance indicators to get leadership onboard with defining quality as a top priority.
Communication Channels	Create a cadence that gathers cross-functional teams to develop solutions that consider upstream and downstream effects. Use visualizations to communicate data more effectively. Develop a project management methodology to assign ownership across teams.
Technical Limitations	Clearly define and prioritize the set of technical requirements that must be met to implement solutions. Consider cost, urgency, and in-house capabilities to build a realistic road map of technology implementation.
Personal Performance Impact	Quantify and communicate the magnitude of impact that individuals' actions can have on plant performance. Achieve buy-in and hold line leads accountable to following process standards.

Table 9.1: Quality Improvement Program Challenges & Recommendations

Appendix A

Acronyms

- DMAIC - Define, Measure, Analyze, Improve, Control
- ERP - Enterprise Resource Planning
- EV - Electric Vehicles
- MES - Manufacturing Execution System
- SPC - Statistical Process Control
- TPS - Toyota Production System
- UV - Ultra Violet
- ZDM - Zero Defect Manufacturing
- 2K - Two Component

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