Data and Information Flow Improvements in Manufacturing Systems

by

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Abstract

The fourth industrial revolution, or Industry 4.0, is making its mark with a wave of efforts to digitize and digitalize data and information in manufacturing systems. Global efforts are being made to accelerate the adoption of advanced technologies in the manufacturing industry. Before Industry 4.0, continuous improvement efforts were focused on the efficient flow of physical products to shorten lead times, but that is no longer enough to remain viable in today's digital environment. Accurate and efficient data and information will be the difference between companies that remain viable and those that become extinct. There is a significant amount of ambiguity surrounding Industry 4.0, other similar terms, its technologies, and its benefits that have caused confusion throughout the manufacturing industry. However, it is clear that the costs of poorly designed data and information flows have yet to be understood, and the opportunities for improvement are untapped, eating up costs that could be minimized and/or eliminated. Purposeful design of interoperable data and information flows to achieve value creation and a complete digital thread are critical to organization competitiveness, now and in the future. Currently, there is not a way for manufacturers to identify and eliminate data and information wastes and evaluate the impact on their organizations.

This research begins to close this gap by uncovering, illuminating, and categorizing the non-value-added activities, or waste, in data and information flows in manufacturing systems. This is made possible by performing a deep dive into Lean literature to understand how Taiichi Ohno developed the 7 Wastes of the Toyota Production System (TPS) so that the success can be replicated in other domains, such as data and information flows. This work also presents the results

of a quantitative simulation analysis that depicts the negative impacts that data and information wastes can have on manufacturing production operations.

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List of Abbreviations

ABS	Agent-based Simulation
AI	Artificial Intelligence
ANSI	American National Standards Institute
AR	Augmented Reality
CAx	Computer-aided Technologies
CI	Confidence Interval
CIM	Computer-Integrated Manufacturing
CITI	Collaborative Institutional Training Initiative
COTS	Commercial off-the-shelf
DEMA	Data Element Mapping and Analysis
DES	Discrete-event Simulation
DMZ	Demilitarized Zone
DTG	Data-time Group
EDD	Earliest Due Date
ERP	Enterprise Resource Planning
FIFO	First In, First Out
FK	Foreign Key

IIoT	Industrial Internet of Things
I-O	Industrial and Organizational
IoT	Internet of Things
ISA	International Society of Automation
ISA-95	ANSI/ISA-95
IT	Information Technology
JUSE	Union of Japanese Science and Engineering
MBD	Model-based Definition
MBE	Model-based Enterprise
MBSE	Model-based Systems Engineering
MEP	Manufacturing Extension Partnership
MES	Manufacturing Execution System
MOM	Manufacturing Operations Management
MRP	Materials Requirements Planning
MxD	Manufacturing x Digital, pronounced Manufacturing times Digital
NAICS	North American Industry Classification System
NIS	Number in System
NIST	National Institute of Standards and Technology

OT	Operational Technology
PDF	Portable Document Format
PK	Primary Key
PLC	Programmable Logic Controller
PMI	Product Manufacturing Information
ROI	Return on Investment
RTU	Remote Terminal Unit
SCADA	Supervisory Control and Data Acquisition
SMMs	Small- and Medium-sized Manufacturers
TDP	Technical Data Package
TMC	Toyota Motor Company
TPS	Toyota Production System
TQC	Total Quality Control
TS&W	Toyoda Spinning and Weaving
URL	Uniform Resource Locator
VSM	Value Stream Mapping
WWII	World War II
2D	Two-dimensional

3D	Three-dimensional

Chapter 1 Introduction

1.1 Overview

Digitalization is here, and national imperatives are popping up across the globe to assist manufacturers in their Industry 4.0 initiatives [1]–[6]. Manufacturers must make the decision to join in on the movement or they will soon become extinct [7]. Manufacturers must go beyond digitizing their data, which means converting data into a digital format that can be read and interpreted by a computer; manufacturers will need to digitalize their data and information systems by continuously improving them and taking advantage of advanced technologies that enable connectivity and interoperability [8]. The purposeful design of interoperable data and information flows to achieve value creation and weave a complete digital thread are critical to organization competitiveness, now and in the future. There is unrealized profit hiding in the ineffective and inefficient data and information practices [9]. Some believe that the worldwide investments in digitalization could return a value in the trillions of dollars by 2025 [10].

Currently, there are a plethora of non-value-added activities, or wastes, that can be identified in the flow of manufacturing data and information [11]–[13], but there is not currently a way to properly identify and eliminate the wastes. This research aims to fill this gap by exploring how Taiichi Ohno, the father of the Toyota Production System (TPS) at Toyota Motor Company (TMC), successfully identified wastes in production flows, so that the same mental model can be applied to data and information flows. Ohno's mental model is then used to identify non-value-added activities that do not support the right data, in the right place, at the right time, and in the right form to inform optimal decision-making.

1.2 Aims and Objectives

There are several objectives this research aims to accomplish in the domain of data and information flow improvement in manufacturing systems. The successful completion of these objectives will contribute to the future of manufacturing continuous improvement efforts in a meaningful way.

The objectives of this research are:

1. Objective 1: Provide a thorough academic literature review that discloses the current state of improvement efforts in manufacturing data and information systems and identify the gap that this work fills.
2. Objective 2: Recreate the mental model that Taiichi Ohno utilized to develop the 7 Wastes of the TPS so that the mental model can be replicated in other domains, such as data and information flows.
3. Objective 3: Illuminate and categorize wastes in manufacturing data and information systems to demonstrate where improvements can be made.
4. Objective 4: Explain the interplay between data and information and the manufacturing plant floor and uncover the impact that data and information can have on manufacturing processes.
5. Objective 5: Provide a path forward for future research in the space of identifying and eliminating waste in manufacturing data and information systems so that future researchers can build upon the contributions of this dissertation.

1.3 Outline of the Dissertation

This dissertation is organized as follows: Chapter 2 provides a background and literature review. In Chapter 3, the problem statement is presented along with the research gaps that this dissertation fills, and the hypotheses for this research are provided. Chapters 4, 5, and 6 introduce the three main contributions of this research. Chapter 4 contains the exploration of the mental model utilized by Taiichi Ohno in the development and categorization of the 7 Wastes of the Toyota Production System (TPS) to be applied in other domains, such as data and information flows. Chapter 5 details the current challenges that manufacturers face with data and information flows and introduces categories of waste for identifying non-value-added activities in the flow of data and information in manufacturing systems. Chapter 6 details the relationship between data and information flows and the plant floor, revealing the impact that data and information wastes can have on manufacturing processes. Chapter 7 draws the dissertation to a close with conclusions and future work. Corresponding publications of this research can be found in Appendix A.

Chapter 2 Background and Literature Review

2.1 Introduction

The case for the creation of waste categories for data and information flow in manufacturing operations is built from the evidence of a need to digitally transform to benefit from the fourth industrial revolution and other continuous improvement efforts that have not yet been applied as data and information flow improvement methods. This section is segmented into two main sections: Background (Section 2.2) and Literature Review (Section 2.3). The Background serves to explain the necessary context information to understand previous continuous improvement efforts which include the development of waste categories and the 7 Wastes of the Toyota Production System (TPS). The Literature review aims to achieve one of the main objectives of this research, which is to identify the current state of data and information flows in manufacturing systems and reveal gaps in the research that need to be filled.

2.2 Background

The foundation of this research is on the identification and categorization of non-value-added activities or wastes. A description of classification and categorization is provided, and an explanation is given of the highly successful waste categories, the 7 Wastes of the Toyota Production System (TPS) that were developed at Toyota Motor Company (TMC) by Taiichi Ohno.

2.2.1 Categorization/Classification

Classification is a form of knowledge organization that combines entities with similar distinguishing attributes. It is used as a tool for innovation, to systematically investigate topics, develop ideas, and reduce complex issues into manageable parts. Decomposing a complex system into smaller homogenous categories assists in reducing complexity and making sense of the system and underlying performance issues. When classifying concepts, the resulting classifications are known as categories [14].

The human mind struggles to remember a multitude of details, but it can remember categories [15]. It is believed that our brains make subconscious mental categories to help us understand the world around us [16]. Forming categories by classifying entities based on their perceived relationships is one of our brain's most basic cognitive functions [17]. Therefore, it can be advantageous to group concepts into categories when trying to present new information that needs to be recalled and used later.

2.2.2 The 7 Wastes of the Toyota Production System (TPS)

The 7 Wastes of the TPS are an example of a set of categories that were formed from the observation of inefficient practices in the flow of manufacturing products for employees to easily recall and identify. Through many years of experience with continuous improvement by observing processes, Taiichi Ohno, the individual known as the father of the TPS, identified seven categories of wastes, shown in Table 1 [18], [19]. The TPS is built on the idea of reducing and eliminating all forms of non-value-added activities, or wastes, that impede the flow of value from raw material to finished goods [19], [20].

Value creation was the focus of TMC to sell more cars and make more profit. For TMC to achieve this goal, the customer must be pleased with the product they purchased. Any action that does not change the form or function of materials into a product that the customer is willing to pay for is classified as waste. Ohno defined waste as "the needless, repetitious movement that must be eliminated immediately" [19]. Shigeo Shingo, a colleague of Ohno's, defined waste as "any activity that does not contribute to operations" [21].

Table 1 Definitions of Ohno's 7 Wastes.

Waste Category	Definition
Overproduction	Producing a greater quantity of parts than required by the customer
Time on hand (waiting)	People or parts are delayed until a specific action occurs
Transportation	The unnecessary movement of people or parts between processes
Processing itself (over-processing)	Processing beyond the standard required by the customer
Stock on hand (inventory)	Excess of raw materials, work in progress, or finished goods
Movement (motion)	The movement of people, parts, or machines within a process or work cell
Defective products (defects)	The result of incorrectly producing the product to customer expectations the first time

The 7 Wastes are used by many organizations, not just manufacturers, in an attempt to reduce non-value-added activity, improve their systems, and reduce costs [22]. However, many fail to grasp the underlying logic that makes the 7 Wastes a successful approach [23]–[28]. Wastes are hardly ever identified within one category. Wastes can be classified into several categories but there is usually one that is the dominant category of non-value-added activity.

(1) *Overproduction*: Ohno described the waste of overproduction as TMC's "worst enemy" because it is a waste that helps hide other wastes [19]. Overproduction occurs when more product is being made than required by the customer. Overproduction can be seen between processes as a buildup of inventory. However, the waste of overproduction can easily be mistaken for work because workers are being utilized to produce products. The workers appear to be busy, but they are performing unnecessary work which is costly [19].

(2) *Time on hand* (*waiting*): The waste of waiting can be easy to identify if an operator is not performing work. However, waiting can be hidden if a worker begins to do other work during

the time they have on hand while waiting for their next task. If an operator has extra time on hand that is not utilized to perform value-added work, it should be considered waste [19].

(3) *Transportation*: The waste of transportation is the movement of product from one location to another without changing the product in any way. Fundamentally improving the layout of a facility can minimize or eliminate the need for transportation [21]. Transportation does not add value to the product, and therefore, it is unnecessarily costly.

(4) *Processing itself* (*over-processing*): The waste of processing itself, or over-processing, is excess actions that do not add value to the final product. Removing over-processing starts by asking "why we make a given product and use a given processing method" [21]; more efficient and cost-effective methods likely exist to produce the product.

(5) *Stock on hand* (*inventory*): According to Ohno, "the greatest waste of all is excess inventory" [19]. Excess inventory causes a ripple effect of waste creating more waste. When there is stock on hand, it must be handled, transported, and stored. This also causes a need for an increased number of workers, managers, and equipment. Simply having too much stock on hand quickly becomes costly. A business should "procure only what is needed when it is needed and in the amount needed" to avoid the waste of inventory, which also generates the waste of overproduction [19]. Inventory can also lead to a waste of defective products which is a costly loss [19].

(6) *Movement* (*motion*): The waste of movement or motion is defined as needless movement to perform a job or task. It is movement that does not add value to the process by "actually advancing the process toward completing the job" [19]. Just because a worker is moving, does not mean they are performing value-added work. Therefore, movements should be

categorized into those that add value and further the completion of the job and those that do not add value and are wasteful motions/movements. According to Ohno, "*Working* means that progress has been made, that a job is done with little waste and high efficiency" [19].

(7) *Defective products* (*defects*): The waste of defective products is mostly self-defined. It is wasteful to create products with qualities and characteristics that do not meet customer requirements or expectations. Products with defects should not continue down the production line; the line should stop, and the defective product should return to an earlier process. The waste of defects can lead to several other wastes because defects involve excess movement of the product to return it to a previous process (transportation), excess processing to correct the defect (over-processing), time on hand for the operators down the line that are waiting for the defective product to be fixed, and overproduction and scrap if the part cannot be fixed [19].

Like all of Ohno's actions at TMC to create the TPS, the creation of the 7 Wastes originated from need. TMC needed to remove excess manpower and repurpose it for more effective and efficient use. By utilizing the 7 Wastes to "trim excess capacity," TMC significantly increased its operating efficiency. According to Ohno, "eliminating waste must be a business's first objective" [19].

2.3 Literature Review

The following review of literature presents the current state of data and information flow issues and improvements in the manufacturing industry. A description of Industry 4.0 is used to set the stage for the need and urgency for digitalization in manufacturing. An explanation is then given of how Industry 4.0 is converging with former continuous improvement movements, such as Lean manufacturing. Previous work in the domain of data and information flow is presented to demonstrate the work that has already been completed and the needed future work. Previous work includes the formation of visualization techniques, such as mapping and simulation and metrics for data and information flows in manufacturing systems.

2.3.1 Industry 4.0

Manufacturing is currently undergoing a fourth industrial revolution, or Industry 4.0. The term "Industry 4.0" was first coined in Germany as "Industrie 4.0." The promotion of the term began in 2011 by three engineers: Henning Kagermann (physicist and one of the founders of SAP), Wolfgang Wahlster (professor of artificial intelligence (AI)), and Wold-Dieter Lukas (physicist and senior official at the German Federal Ministry of Education and Research) [29]. SAP, a leading provider of software for the management of business processes, described Industry 4.0 as the use of nine innovative technologies to "bridge the physical and digital worlds and make smart and autonomous systems possible:" (1) Big Data and AI analytics, (2) Horizontal and vertical integration, (3) Cloud computing, (4) Augmented reality (AR), (5) Industrial Internet of Things (iIoT), (6) Additive manufacturing and three-dimensional (3D) printing, (7) Autonomous robots, (8) Simulation and digital twins, and (9) Cybersecurity [30]. Many definitions are available for Industry 4.0, which adds to the ambiguity of the term and creates confusion throughout the manufacturing industry [31]–[34]. Most definitions agree that the fourth industrial revolution aims to increase automation and connectivity through the use of smart technologies.

To achieve the levels of automation and connectivity that Industry 4.0 requires, manufacturers must digitize and digitalize their data and information flows [35]. In manufacturing, the terms "digitization" and "digitalization" are often used interchangeably, but they are not the same [8]. Digitization is the computerization of analog data, turning analog data into binary zeros and ones so that it can be read and understood by a computer. Digitalization, on the other hand, is the continual improvement of the data's digitized form through the use of technologies that enable automation and connectivity [7], [35]–[40]. From these definitions, it can be noted that digitization is a prerequisite to digitalization. In other words, data cannot be digitalized without it first being digitized. However, to remain competitive in today's market, manufacturers cannot stop at simply digitizing their data and information flows. They must seek to digitally transform their operations and data and information systems [7]. The need to digitize and digitalize processes is not something of the future; it is happening now.

National initiatives to support manufacturers in their digital transformations are popping up all over the globe. Some of the most notable initiatives are South Korea's Creative Economy Initiatives [2], China's Made in China 2025 program [1], and the United Kingdom's National Adoption Programme [3]. South Korea launched demonstration factories to promote digital innovation to increase the adoption levels of tens of thousands of South Korean manufacturing companies [4]; China's program utilized direct subsidies to increase the adoption of digital technologies; and the United Kingdom put on a Manufacturing Made Smarter Challenge, a £30million competition to boost manufacturing productivity and agility. All of these initiatives have one main theme in common: accelerate the national adoption of digital manufacturing.

In the United States, the Hollings Manufacturing Extension Partnership (MEP) based at the National Institute of Standards and Technology (NIST) in Gaithersburg, Maryland is one of the leading efforts to accelerate the adoption of technologies in manufacturing. In 2021, the MEP interacted with 34,307 manufacturers through its public-private partnership with MEP centers across all 50 states and Puerto Rico. Their efforts resulted in $1.5 billion in cost savings and $14.4 billion in sales [5]. On a smaller scale, institutes like Manufacturing x Digital (MxD, pronounced

Manufacturing times Digital) are partnering with government, academia, and manufacturing to increase manufacturing productivity and strengthen the United States' manufacturing industry as a whole [6].

The benefits of digitalization are not expected to plateau any time soon. The opportunities and benefits are boundless with the potential being valued in the trillions of dollars [7], [10], [41]. A 2021 article states that the full potential of digital transformations could reach $100 trillion by 2025 [10]. Companies will see benefits such as new business opportunities, value co-creation (value created across company networks), increased innovation, heightened competitive advantage, increased resources and knowledge, and decreased costs [42]. It is also likely that there are benefits that have even been realized yet [7].

As mentioned earlier, there is a significant amount of ambiguity surrounding Industry 4.0 and what it entails. This is in part due to the number of terms that have arisen to describe it such as Digital Manufacturing, Digital Transformation, and Smart Manufacturing. Digital Manufacturing is a broader term to describe the aims of Industry 4.0. Though it has many definitions, for the most part, there is mutual agreement that digital manufacturing involves the application of digital technologies to plan and operate a manufacturing system that utilizes the right data, in the right place, and at the right time to perform optimal decision making [43], [44].

2.3.2 Industry 4.0 Adoption

The adoption of new technologies typically follows a set of five stages: (1) Knowledge, (2) Persuasion, (3) Decision, (4) Implementation, and (5) Confirmation (Figure 1) [45]. Based on mainstream media, it could be assumed that the majority of the industry is in the decision stage, where they are determining which technologies to implement. However, studies show that the majority of manufacturers are actually closer to the first stage, knowledge, where they are still learning what Industry 4.0 is and what technologies it entails [46].

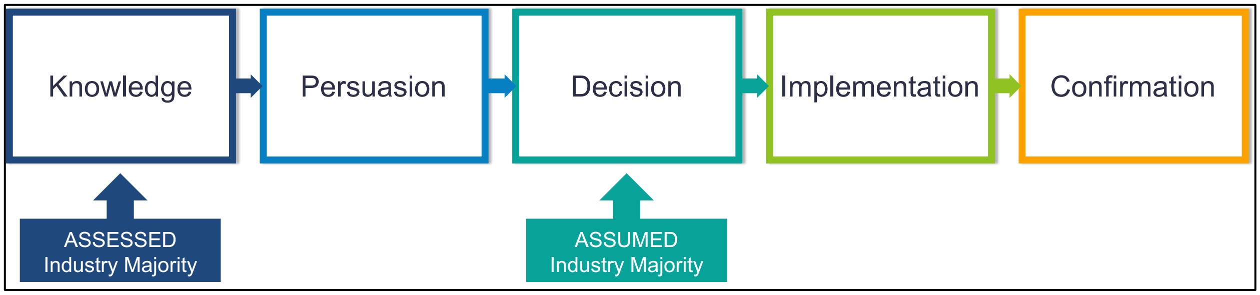


Figure 1 The 5 Stages of Technology Adoption [45], [47].

In 2019 and 2021 survey reports [48], [49], ToolsGroup studied the adoption stages of approximately 200 companies (Table 2). ToolsGroup used slightly different adoption stages than the five listed previously, but the stages are rather similar.

Table 2 ToolsGroup Industry Adoption Stages [48], [49].

		Adoption Stages					
		Not Pursuing	**Exploring**	**Evaluating**	**Gaining Organization-al Support**	**Executing**	**Reaping Benefits**
Year	**2019**	N/A	32%	26%	8%	27%	7%
	2021	10%	22%	17%	11%	28%	12%

When looking at the revenue of the respondents from the ToolsGroup reports, 64% and 59%, in 2019 and 2021 respectively, of the respondents maintain an annual revenue of over $100 million [48], [49]. Considering that small and medium-sized manufacturers (SMMs) make up over 90% of the United States supply chain with less than $100 million in annual sales and less than 500 employees [50], these percentages presented by ToolsGroup are likely skewed based on larger, higher revenue companies and not representative of the manufacturing industry as a whole. There is a widening gap between Small- and Medium-sized Manufacturers (SMMs) and large manufacturers that needs to be addressed if digitalization is to be fully integrated into the industrial base [46]. Reports from countries globally indicate that SMMs demonstrate a lack of awareness of the need for digitalization [51]–[56].

2.3.3 The Convergence of Industry 4.0 and Lean

A globally known and implemented method for identifying improvement opportunities in production systems is the Toyota Production System (TPS). The TPS began its formation with the TMC in the 1940s. 'Lean Manufacturing' (or 'Lean' for short) is the American term for the Toyota Production System (TPS). The term 'Lean' was first coined by John F. Krafcik in 1988 in his article, *Triumph of the Lean Production System* in the Sloan Management Review [57], [58].

Deloitte [59] and Bain [60] propose the idea of digital lean improving on traditional Lean. They explain how the implementation of Industry 4.0 technologies such as quality sensing & detection, factory asset intelligence, factory dynamic scheduling, augmented workforce, plant energy management, big data, Internet of Things (IoT), robotics, and analytics can enhance the identification and mitigation of the 7 Wastes of the TPS. These articles address the importance of introducing new technologies to improve upon traditional Lean by increasing the ability to identify and eliminate the 7 Wastes of the TPS; this can easily be confused with identifying and eliminating data and information wastes, but it is not the same. When discussing a digital lean environment, authors also mention that a key enabler is integrating Information Technology (IT) (technologies for information processing) and Operational Technology (OT) (hardware and software for equipment control) [61]–[64]. This demonstrates the lack of interoperability that exists in today's manufacturing systems. Before Industry 4.0, IT and OT were often viewed as separate entities, with little to no connectivity [59].

Another approach to converging Industry 4.0 and Lean has been identifying digital waste. Romero et al. define "digital waste" as "any non-value adding digital activity to women/men, materials, machines, method and measurements (5M) in the Digital Lean Enterprise" [64]. Researchers have taken various approaches to identify and define digital waste(s) with some authors grouping digital wastes [64], some converting the 7 Wastes of the TPS into their digital counterparts [13], and others creating new waste categories for data and information processes in manufacturing systems [11].

Romero et al. [64] categorized digital wastes into three groups: the elimination of physical waste (the 7 Wastes of the TPS), the avoidance of passive digital waste (missing digital opportunities), and the prevention of active digital wastes (the right amount of information is not provided at the right time to the right person, machine, or system for decision-making). In a follow-up article, Romero et al. [65] discussed the vicious cycle of three types of waste: muda (waste, including the 7 Wastes of the TPS), mura (unevenness), and muri (overburden) and how these wastes also exist in a digital environment, and an example was given of how digital wastes can lead to other digital wastes.

Roh et al. [13] propose wastes for data and information flows by converting the 7 Wastes of the TPS into their digital counterparts. The proposed definitions are shown in Table 3.

Table 3 Roh et al.'s Proposed Wastes for Data and Information [13].

Waste Category	Definition
Overproduction	Overproduction is the generation and the provision of too many and hence irrelevant information and data.
(Unnecessary) Motion	Unnecessary motion is the procedure of employees or IT systems to search for information and the need to combine them from different systems/sources.
Transporting	Transporting is the transmission process of information between different media, which can be wasteful, if not transferred on a direct path.
Waiting	Waiting is the time wasted to receive relevant information, e.g. download time from a server.
Extra processing	Extra processing is the needless (manual) editing of information.
(Unnecessary) Inventory	Unnecessary inventory is the saving of non-used and hence unrequired data and the saving in different forms/media, such as paper and on a server, for example for wasteful redundancy (double saving).
Defects	Defects in the context of information streams can be interpreted as incorrect, incomprehensible, or incomplete information transmissions.

Hicks et al. [12] studied information issues of ten organizations. The study resulted in 180 information issues that were summarized in 18 categories [11] and ultimately reduced to four, shown in Table 4.

- information exchange
- manual systems and data entry
- monitoring, control, and costing
- information flow from customers and/or sales
- functionality of information systems
- information storage
- numbering and traceability of machines, assemblies, and parts
- information availability and accessibility
- information identification, location, and organization

- information completeness and accuracy
- information duplication
- information currency
- end-user developed applications over commercial off-the-shelf (COTS) information systems
- paper systems over COTS information systems
- information systems use and maintenance
- information systems implementation and customization
- implementation and operation of quality systems
- information systems strategy and planning

Table 4 Hicks et al.'s Proposed Waste Categories for Data and Information [11].

Waste Category	Definition
Failure demand	This includes the resources and activities that are necessary to overcome a lack of information. This may include generating new information and/or acquiring additional information.
Flow demand	This concerns the time and resources spent trying to identify the information elements that need to flow.
Flow excess	This relates to the time and the resources that are necessary to overcome excessive information i.e. information overload.
Flawed flow	This includes the resources and activities that are necessary to correct or verify the information. It also includes the unnecessary or inappropriate activities that result from its use.

Each of these approaches shares a common theme of identifying ineffective and inefficient data and information flows in manufacturing systems with a Lean perspective. However, the approach of Romero et al. [64] did not define wastes that are easily identified; passive and active wastes are not waste categories that can be visualized, and visualization is a key component of waste identification. The approach by Roh et al. [13] built on the already developed 7 Wastes of the TPS. The waste categories can be used to identify wastes in data and information flows which is a positive outcome, but the approach did not consider creating waste categories that were derived from an understanding of the current issues in data and information flows. Roh et al. took the 7 Wastes of the TPS and changed their definitions to fit data and information wastes, but this is force-fitting wastes into categories that were not originally meant for data and information systems. Hicks et al. [12] began with an approach of identifying the current data and information issues in manufacturing, and the end result was four categories. Hicks et al.'s [12] approach has a similar issue to Romero et al.'s [64] approach- the categories are not easily identifiable; it is not clear how to identify failure demand, flow demand, flow excess, and flawed flow.

2.3.4 Visualizing Data and Information Flows

Manufacturers not only need a method to identify non-value-added activities, but they also need a way to visualize and communicate data and information flows. Authors have taken an approach to visualize data and information flows in manufacturing systems through mapping [13] and simulation [66], [67]. Making non-value-added activities, or wastes, visible was instrumental to Ohno's success in developing the 7 Wastes of the TPS [19]. Value Stream Mapping (VSM) is a mapping technique that has been used to identify and eliminate wastes in part production processes for decades [68]. A generic value stream map (Figure 2) includes two types of flows: (1) Information Flows and (2) Material Flows.

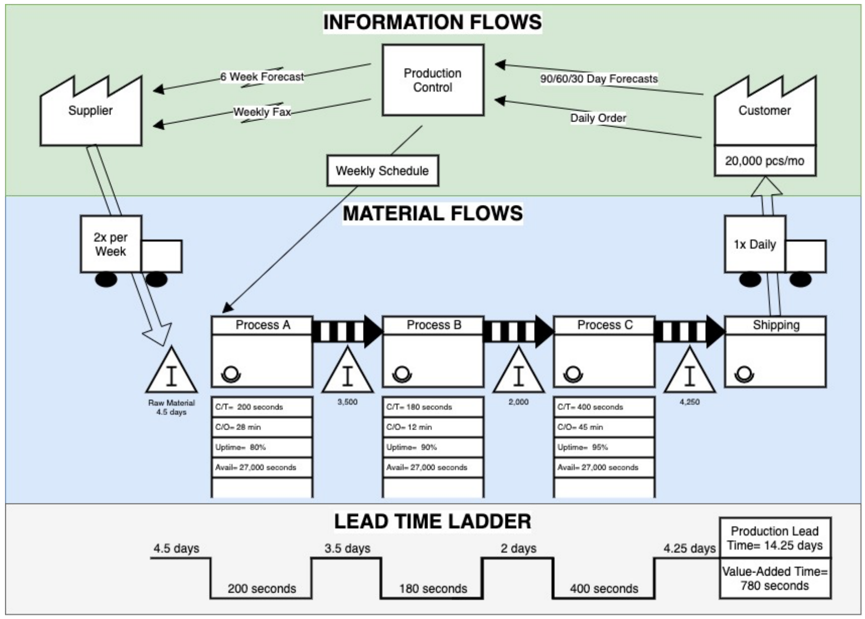


Figure 2 Generic Value Stream Map.

Though VSM has proven to be highly successful in visualizing and analyzing physical waste in manufacturing production systems, VSM does not provide enough transparency to elicit improvement opportunities in non-physical processes, such as data and information flow [13]. As shown in Figure 2, value stream maps present a high level of detail about material flows. However, the top half of the value stream map provides very little information about the data and information that supports production [66]. These data flows are drastically simplified and not reflective of reality in which data goes through time-consuming processes of being created, debated, modified, and delivered. The time and costs associated with these activities are not shown or considered in a value stream map. In addition, VSM does not address several indispensable data flows, such as work instructions, travelers/routers, authorizations/approvals, or machine code, to name a few, all of which go through multiple processes before reaching the operator on the plant floor. However, VSM can serve as a baseline for developing a new mapping approach specifically for data and information wastes. This is what Roh et al.'s [13] attempted with their creation of "Value Stream

Mapping 4.0", a proposed mapping technique for visualizing waste in data and information flows. However, this mapping technique loses connectivity with the material flows on the plant floor and therefore, loses the ability to understand the impact that data and information flows can have on plant floor operations.

Thiede et al. [69] present an approach to simulate information flows in support of digitalization and the increasing complexity of dynamic IT architectures. The simulation in the case study modeled information streams to machines in an electronics manufacturing plant. The authors state that it would be beneficial to also show the relationships between information flows, material flows, and energy flows; this was also just mentioned previously as a deficiency in Roh et al.'s data mapping technique [13]. The work of Thiede et al. was limited to the modeling of information flows to reduce complexity. Other articles stress the importance and difficulty of merging highly-detailed data and information flows with material flows into one mapping or simulation [66], [70].

2.3.5 Metrics for Data and Information Flows

Roh et al. propose metrics for data and information flows [13]. The authors present five performance indicators: (1) level of automation, (2) centrality index, (3) real-time capability index, (4) media disruption index, and (5) first pass yield of information. An explanation and equation are provided for each of the five performance indicators in Table 5 [13].

Each of the metrics is aligned with one of the 7 Wastes of the TPS, (1) level of automation with unnecessary motion, (2) centrality index also with unnecessary motion, (3) real-time capability index with transportation, (4) media disruption index also with transportation, and (5) first pass yield of information with defects. A performance indicator is not given for the other wastes: overproduction, waiting, over-processing, and inventory. The metrics are not tied to costs.

In developing the TPS, Ohno insisted that all actions and metrics must be tied to cost reduction because cost reduction is the ultimate goal when identifying and eliminating wastes [19].

Table 5 Roh et al.'s Proposed Metrics for Data and Information Flows [13].

Performance Indicator Equation	Explanation
(1) Level of automation $$la = \frac{\Sigma i_a}{\Sigma i_a + \Sigma i_{na}} = \frac{\Sigma i_a}{i}$$ where, la equals the level of automation, i_a, an automized information transfers i_{an}, a non-automized information transfer. Note, that the sum of i_a and i_{na} is the total number of information transfers i.	"The *level of automation* is defined as the ratio of the number of fully automated information transfers to the total number of information transfers."
(2) Centrality index $$ci = \frac{\Sigma i_c}{i}$$ where, ci equals the centrality index, i_c, information transfers pointing to a central IT-system i, the total number of information transfers.	"The new method defines the *centrality index* as the quotient of the information transfers to a central IT system and the total number of information transfers."
(3) Real-time capability index $$rtci = 1 - \frac{\Sigma i_{nr}}{i}$$ where, $rtci$ equals the real-time capability index, i_{nr}, non-real-time capable information transfers i, the total number of information transfers.	"The *real-time capability index* is defined as the quotient of the number of information transfers in real-time divided by the total number of information transfers."
(4) Media disruption index $$mdi = \frac{\Sigma i_{d\to p} + \Sigma i_{o\to p}}{i}$$ where, mdi equals the media disruption index, $i_{d\to p}$, information transfers from digital to paper-based $i_{o\to p}$, information transfers from oral to paper-based i, the total number of information transfers.	"*Media disruption index* is defined, based on Ref. [23], as the sum of information transfers with a transition from a digital medium to a paper-based and from oral to a paper-based medium, divided by the total number of information transfers."
(5) First pass yield index $$fpy_i = 1 - \frac{\Sigma i_q}{i}$$ where, fpy_i equals the first pass yield for information, i_q, information transfers where a query is needed i, the total number of information transfers.	"The *first pass yield of information*, i.e. the query quota, is defined as one minus the quotient of the amount of information transfers for which a query is needed, and the total amount of information transfers."

One paper was identified that formed metrics for contributors that affect the flow of data and information in manufacturing systems [70]. The metrics gauge the visibility of information, the visibility of the need for information, the feeling of empowerment by employees, communication barriers, the perception of risk, and human-to-human communication. The first three metrics listed are considered to be information flow promoters, while the last three are considered information flow inhibitors [70]. Once again, these metrics are not tied to costs or a return on investment (ROI) of implementing digital technologies or enabling digitalization. Therefore, it will be hard for manufacturers to utilize these metrics as a business case for digitalization. The metrics also are not tied to the impact of improved accuracy, efficiency, or effectiveness of data and information flow. This is an indicator that there is little understanding of the costs and effects of poorly designed information flows in manufacturing [9].

2.3.6 Other Advancements in the Field of Data and Information

Model-based Enterprise (MBE), Model-based Systems Engineering (MBSE), and Model-based Definition (MBD) are other terms that are often used when discussing data and information flow improvements in manufacturing systems. MBE and MBD refer to the translation of two-dimensional (2D) manually created drawings to 3D models in computer-aided design (CAD) software, which can eliminate the need for recreating models and information that were previously developed [8], [71]. An example of a 2D drawing and its corresponding 3D model is shown in Figure 3 with the 2D drawing on the left and the 3D model on the right [72]. The related data and information, called Product Manufacturing Information (PMI), for a part is contained and stored within its model.

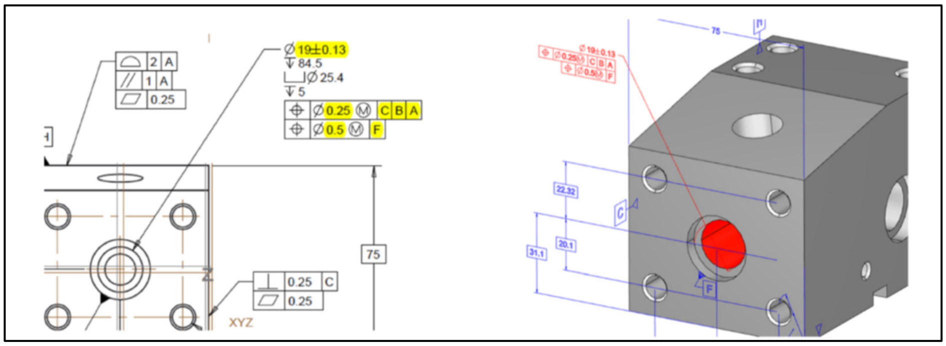


Figure 3 Example of 2D Drawing to 3D Model [72].

MBE supports the concept of a "digital thread." The term digital thread portrays the idea that data throughout a product's lifecycle (from its design to the finished part to its retirement) is connected so that data is traceable and easily accessible [72]. The Air Force Research Laboratory first used the term, "digital thread," in 2007 to describe a framework for the organization of data throughout the lifecycle of a product [73]. Achieving a digital thread and MBE requires that data that was once paper based be digitized because the data will be captured in a digital format.

Chapter 3 Problem Statement

3.1 Problem Statement

As a part of Industry 4.0, manufacturers are being compelled to digitally transform [7]. It will no longer be sufficient to digitize data by converting data into a digital format [35], [74]. Manufacturers must digitalize their data and information system by continuously improving connectivity and flow. Digitalization is not just something of the future; it is here now, and manufacturers must join the movement to remain viable in today's competitive market [7]. Manufacturers have mostly ignored data and information flow improvements while focusing on physical processes and the day-to-day tasks of getting products out the door. However, there is significant profit locked away in ineffective and inefficient exchange and flow of data and information [9]. The costs of data and information system inefficiency, wrapped up in overhead, are hidden and difficult to expose without a highly detailed breakdown of overhead costs, and even then, waste is not obvious. It is imperative in today's Industry 4.0 environment that this must change. Manufacturers will be unable to compete in the world marketplace and will soon be out of business if they do not digitally transform [7]. It is critical to understand where improvements can be made so that manufacturers can identify and eliminate their non-value-added activities, or wastes, in their data and information systems. A disciplined and structured approach for identifying and eliminating wastes in manufacturing data and information systems currently does not exist.

3.2 Research Gaps

The 7 Wastes of the TPS, a known and accepted method for identifying and eliminating wastes in manufacturing processes, is not applicable to other domains, such as data and information flows, and there is a lack of understanding behind the creation of the categories. Extensive research has been conducted on the application of the 7 Wastes, but a deep dive into how the 7 Wastes were created is necessary if their success is to be replicated in other domains. Secondly, attempts have been made to translate the 7 Wastes of the TPS into data and information wastes or digital wastes, but many of the current methods attempt to force fit each of the 7 Wastes of the TPS into digital counterparts, and the fit is questionable at best. By trying to simply use the same physical waste categories, an opportunity is missed to start from the ground up and follow Ohno's mental model to create wastes that are formed with the intention of identifying and eliminating data and information wastes. The current waste categories that have been made specifically for data and information flows lack the ability for manufacturing employees to easily identify and visualize the issues that are taking place. In a manufacturing environment, it is crucial to make wastes visible and easily identifiable so that the proper elimination methods can be deployed to eradicate the wastes.

3.3 Research Questions

This research aims to answer the following questions. The questions are organized by research objectives (as presented in Section 1.2).

- Objective 1:
  - What are the current and future states of data and information flow improvements in manufacturing systems?
- Objective 2:
  - What was Taiichi Ohno's mental model while identifying and categorizing wastes in the flow of manufacturing processes?

- Objective 3:
    - What are the data and information flows that are common amongst most manufacturing facilities?
    - What are the issues and challenges that manufacturers face with data and information flows?
    - What metrics could be utilized to evaluate the impact of ineffective and inefficient data and information flows in manufacturing systems?
- Objective 4:
    - How do data and information wastes manifest themselves in manufacturing operations?
    - What is the potential impact of data and information waste on manufacturing processes?
- Objective 5:
    - How can future researchers utilize the work presented in this dissertation to build upon the contributions of this work?

Chapter 4 A Generalized Framework for Continuous Improvement

4.1 Introduction

It is important to understand how to apply proven continuous improvement approaches to data and information flows in a manufacturing environment. The work performed by Taiichi Ohno in the development of the 7 Wastes of the TPS was critical to the overall success of the TPS. Categorization allows for the development of improvement tools that can be used to reduce entire classes of waste. Therefore, the first effort in this research is to understand how Ohno developed his classes of wastes so that a similar approach can be applied to data and information flows in the manufacturing setting. To achieve this goal, this research will deconstruct and analyze Ohno's mental model, utilize psychology tools for a novel approach to evaluating a manufacturing process improvement model, and create a generalized framework for identifying and eliminating physical and non-physical wastes in a system.

4.2 Background

To form Ohno's mental model for identifying and eliminating wastes in the manufacturing process flow, it is imperative to understand the environment in which it was developed, the history of the Toyota Motor Company (TMC), and Ohno's background. The history of the TMC provides insight into the sense of need that sparked the creation of the TPS. Ohno's background presents the context that enabled Ohno's efforts to envision and execute such a successful production system.

4.2.1 Toyota Motor Company (TMC) History

The timeline of the Toyota Motor Company (TMC) and Ohno's career at TMC are shown in Figure 4. In August of 1945, two years after Ohno started with TMC, Japan surrendered to the Allies to end World War II. The war was mostly responsible for the weakening of Japan's economy. With a devastated infrastructure, few raw materials, and little to no domestic demand, TMC had to find a way to become a profitable enterprise. In hindsight, Ohno believed the war's end marked a new beginning for TMC [19], [75].

Following the war, Kiichiro Toyoda, the President of TMC from 1941 to 1950, established the goal to "catch up with America in three years" [19], [76]. This became a rallying cry and mantra for TMC. However, in 1950, seven years after Ohno began working at TMC, Japan was still in a devastated economic state and lacked essential natural resources, leading to a labor dispute in 1950 with a layoff of a quarter of the total workforce and the resignation of President Toyoda. This state of turmoil left TMC with no choice but to find a different way to achieve its goals [19], [76], [77].

To survive in the early 1950s, TMC had to turn the production of cars into cash quickly [78]. Ohno firmly believed that every improvement originates from a need. The economic crisis created a widespread sense of need. Instead of being viewed as a crutch, the economy of Japan was considered an open door to widespread improvement opportunities, which would be crucial to economic turnaround [19].

In June of 1950, with increasing product demand due to the Korean War, a time of economic growth ensued that helped expand the Japanese automobile industry [19]. In support of South Korea, the U.S. Army Procurement Agency became a significant customer for TMC with a requirement for quick production with high quality. Ramping up production without the financial ability needed for this effort was a challenge that forced new and creative ways of thinking. Between 1945 and 1955 TMC increased annual production from 3,275 total units to 22,786 total units, a 595% increase [79]. With the new demand and financial support of the U.S. Army contracts, Ohno and TMC focused on continuous improvement in operations and created the culture behind the TPS.

BRIEF TIMELINE HISTORY

TOYOTA MOTOR COMPANY (TMC)		TAIICHI OHNO
	1932	Graduated from Nagoya Technical High School & Began Work at Toyota Spinning & Weaving (TS&W)
Beginning of WWII	1939	
Kiichiro Toyoda Becomes President of TMC	1941	
	1943	Began Work at TMC
End of WWII	1945	
The Union of Japanese Science and Engineering (JUSE) is Established	1946	
Kiichiro Toyoda Resigns from TMC, Japan Reaches Negative Net Worth, & Korean War Begins	1950	
Korean War Ends	1953	
	1954	Director at TMC
	1956	Visits General Motors and Ford
Rapid Economic Growth Begins	1959	
	1964	Managing Director at TMC
	1970	Senior Managing Director at TMC
Oil Crisis & Recession	1973	
Rapid Economic Growth Ends, State of Zero Growth	1974	
	1975	Executive Vice President at TMC
	1978	Retires from TMC

Figure 4 Timeline of Relevant Events.

In the 1960s, TMC's largest Japanese competitor was Nissan [80]. After Nissan received the Deming Prize in 1960, the highest honor for quality in Japan, TMC responded by implementing

Deming's Total Quality Control (TQC) approach in 1961 and received the Deming Prize in 1965 [81], [82]. TMC's efforts to compete on both the local and global scale demonstrate the organization's desire to become the world's most profitable automotive manufacturer.

Aside from economic factors, Japan's culture also influenced Ohno and enabled his success. Japan is historically a hierarchical society that creates many followers and few leaders. In Japanese culture, employees are team players that are hired as fixed assets and typically remain loyal to one company for their lifetime [83]. The Japanese culture allowed Ohno to form a learning and teaching culture at TMC. This learning culture is often noted as the reason TMC became so successful, and the lack of this learning culture is one of the reasons other companies do not successfully implement TMC's philosophy [24].

4.2.2 Taiichi Ohno Background

Ohno graduated from Nagoya Technical High School's mechanical technology program in the spring of 1932. It can be assumed that Ohno's mechanical technology education can be reflective of today's mechanical engineering focus at a high school or technical college level. Ohno did not pursue higher education by attending a college or university [19].

After high school, he began work at Toyoda Spinning and Weaving (TS&W). Ohno leveraged the knowledge gained at TS&W to identify shortcomings at TMC [19], [76]. While at TS&W, Ohno taught himself standard work and said later that his experience with standard work at TS&W laid the foundation for 35 years of work on the TPS [19]. TS&W is also where Ohno learned about autonomous systems and quality. TS&W was his primary source of industry experience and served as a pivotal point in his career [19].

When Ohno compared the TS&W system to automobile production, he was using what we term today as critical thinking skills. He noted that his work began by challenging the old system [19]. To make drastic improvements, Ohno had to think of new and creative approaches. Ohno lived by the mindset of "there is *always* another way," which will make TMC a more profitable company [21]. He strived to "avoid being entrapped by a single way of thinking" [19], [84]. He looked at every system with an eye for improvement and believed observation was the key to gaining insight into what is happening [19], [76].

From Ohno's experience with standard work, he learned the best way to improve a job is to be at the process. The importance of learning by seeing developed his "plant-first principle," in which the focus was on helping the operators do their jobs better through observation [19], [76]. Ohno viewed his employees as a set of eyes to identify ways to improve and reduce waste [23], [84]. According to Ohno, "people don't go to Toyota to 'work'; they go there to think" [85]. He did not simply provide solutions; he guided his employees by asking questions that would enhance their critical thinking skills. He wanted the operators to see the value of their work and show them they could improve their work. Ohno was known to show great support to plant floor employees but could be extremely hard on management. He made management responsible for encouraging employees to learn. He would scold his managers if they were not out on the floor, helping improve the operators' jobs [76].

Ohno had the drive to make improvements, and he did not give up. A quote from Ohno himself best describes the work ethic he fostered: "People got so tired of hearing me rant that they gave me a machining shop to try out my ideas" [76]. Ohno was eager to make changes to see if they resulted in cost reduction and improved productivity. He was a supporter of the scientific method, trial-and-error, and not waiting for a perfect solution. Ohno referred to this as "the mood to get things done". He urged others to match his work ethic [76].

Ohno's ideas for improvement did not come from just his own thinking. Ohno often borrowed ideas from other influential leaders of his time. The Union of Japanese Science and Engineering (JUSE) brought quality experts, Dr. W. Edwards Deming and Dr. Joseph M. Juran, to Japan in 1950 and 1954, respectively. Ohno was likely influenced by their teachings through the JUSE emphasis on quality and productivity improvement [78], [86]. Many parallels can be drawn between Ohno and Deming's works. Ohno and Deming shared the quality first idea of "doing it right the first time" [78]. Like Deming, Ohno made everyone responsible for improvement efforts. They also shared the concept that the employees on the plant floor are more important than management because they are the individuals adding value. It is also possible that Ohno's idea to eliminate waste came from Deming because Deming often used the word "waste" in his works. They also shared the idea that anything the consumer is not willing to pay for should be considered waste [19], [21], [78], [84].

When searching for improvement ideas, Ohno looked to the American automotive industry. Ohno first visited Ford, General Motors, and American supermarkets in 1956. He wanted to understand Ford's strategies and determine what was applicable for TMC, and what was not useful [19], [75]. It is also likely that Ohno found value in General Motors' focus to produce money, not cars [26], since TMC faced the requirement of turning products into cash quickly. However, he took General Motors' aim further by focusing on quality and cost reduction as a means to make money [19], [84], [87]. Ohno not only drew his ideas from the automobile industry, but also from how American supermarkets operated [88]. The supermarket method caught Ohno's attention in a 1954 report on how a Lockheed aircraft plant used the supermarket method to produce to customer demand. The supermarket method established Ohno's concepts of inventory management and overproduction, which are 2 of the 7 Wastes [19].

4.3 Methodology

The problem this research addresses is that of understanding the mental model behind the creation of the 7 Wastes of the TPS, which is not described in the literature. According to Senge [15], "'mental models' determine not only how we make sense of the world, but how we take action." The relationships between a mental model, one's behavior, and the result are shown in Figure 5 [89]. For Ohno, his mental model is not known, but the result is known (the creation of the 7 Wastes for manufacturing processes).

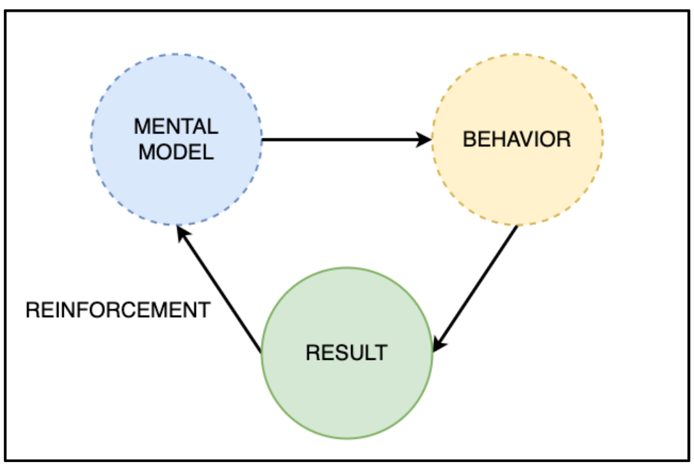


Figure 5 Relationships Between Mental Model, Behavior, and Result [89].

Other researchers, such as Thomas and Patterson [90], explained how they studied the mental models of individuals that led to their ultimate results. Thomas and Patterson also verify the usefulness of shared mental models. They mentioned benefits such as enhanced system understanding, improved communication between parties, and collaborative decision making and engineering of systems. Therefore, creating a mental model that can be shared by an organization is beneficial in a new system design. In the case for Ohno, having a mental model that can be used to identify and eliminate waste will assist in designing new data and information processes for manufacturing systems.

To recreate Ohno's mental model, it is important to identify and analyze Ohno's behavior and actions (results). For this analysis, researchers thoroughly studied the TPS, Lean literature, and Ohno's personal writings. Evaluation of primary sources such as content written by Ohno and those that knew Ohno in a work environment is of primary focus.

Kurt Lewin's equation for human behavior, Eq. (1)., which represents a person's psychological situation, provided validity by which inferences could be made about Ohno's behavior based on his environment and personal experiences. Lewin proposes that human behavior is a function of the person and their environment. Lewin stated that "One can hope to understand the forces that govern behavior only if one includes in the representation the whole psychological situation" [91]. By collecting events from Ohno's life, researchers can accurately observe the correlation between Ohno's actions and behavior.

$$B = f\,(P, E) \qquad \text{(Eq. 1)}$$

Where:
B represents human behavior,
P person, and
E environment.

In Eq. (1)., variables such as attitude, personality, and skills, are attributes of the person (P). A person's environmental variables (E) include workplace environment, culture, and economic state. Environmental variables tend to fluctuate often, impacting one's behavior. Lewin believed the relationships between personal and environmental variables affect the resulting human behavior [91]. Examples of personal and environmental variables specific to Ohno and his life experiences that were presented earlier are shown in Table 6. A list of key attributes such as attitude, personality traits, and skills (P) are shown in the first column of Table 6. A list of key attributes such as characteristics of the workplace, culture, and economic state (E) are shown in the second column of Table 6. Lewin's equation provides a guide for understanding how Ohno behaved and made decisions, which is related to his mental model as shown in Figure 5.

Researchers such as Hedberg et al. [92] have proposed utilizing an extended version of Lewin's equation to manage decisions for creativity, development, and change, which is similar to our goal of understanding Ohno's mental model for future change. Hedberg et al. [92] proposed $I = f(\sum P_i, E \in O)$ in which innovation (I) is a function of the personal variables (P) of the individuals (i) in the organization (O) and the environmental variables (E). This means that encouraging creativity at the personal level will support innovation at the organizational level. This applies to Ohno and the TMC. Ohno fostered creativity and encouraged others to join him in developing his innovative ideas and solutions. Ohno was an innovator that created a team of innovators. Hedberg et al. showed how Lewin's equation (personal and environmental variables) can help explain innovation.

While studying Ohno's life, researchers considered multiple psychology perspectives to ensure a complete analysis. Personality psychology was considered in determining the motivations and personality traits that made Ohno unique [93]. Social psychology placed attention on how Ohno behaved in a group setting, how his attitudes and beliefs were formed, and how he perceived his social environment [94]. An industrial-organizational (I-O) psychology perspective sought to understand Ohno's behavior in a workplace environment [95]. Each of these psychology perspectives provided insight into Ohno and helped in understanding his reasoning for identifying and classifying waste in a process.

Table 6 Personal and Environmental Variables that Formed Ohno's Behavior.

<table>
<tr><th>PERSON</th><th>ENVIRONMENT</th></tr>
<tr><td>a. Education- graduated from the mechanical technology department of Nagoya Technical High School [19]
b. Work at TS&W- taught himself standardization, learned about autonomous systems and quality, later compared TMC to his work at TS&W [19]
c. Mindset- challenged the old system [19], always believed there was a better method [21]
d. Thinking- utilized critical thinking and "logic escape" [19], [76], [84]
e. Learned by observation [19], [76]
f. Comparison of systems- compared seemingly unrelated systems to automobile production to derive improvement ideas (e.g. American supermarkets, the human body, baseball games) [19], [76], [88]
g. Likely influenced by the teachings of others- shared Deming's ideas of "doing it right the first time", eliminating waste (or anything the consumer is not willing to pay for) [78]
h. Treatment of others- treated plant floor employees with high regard [19], [76], but was known to be harsh on managers [76]
i. Personality- self-driven, strong work ethic, always in "the mood to get things done" [76]</td><td>j. World War II- weakened Japan's economic state, devastated infrastructure, few raw materials, little to no domestic demand [19], [75]
k. Goal-TMC President conveyed the goal to "catch up with America in three years" [19], [76]
l. 1950 Labor dispute- layoff of a quarter of the workforce, state of turmoil, no money, fewer people, high expectations [19], [76], [77]
m. Sense of need [19], [78], [84]
n. Korean War- sparked economic growth, ramped up production without the ability to purchase new equipment or hire new employees [19], [79]
o. Competition- TMC's largest competitor was Nissan. Nissan won the Deming Prize in 1960. TMC implemented Deming's TQC approach in 1961 and received the Deming Prize in 1965. [81], [82]
p. Japanese Culture- a hierarchical society in which employees are hired as fixed assets [83]</td></tr>
<tr><th colspan="2">BEHAVIOR</th></tr>
<tr><td colspan="2">1. Reducing and eliminating non-value-added activities, or wastes [19]
2. Categorized wastes into seven categories [18], [19]
3. Formed a learning and teaching culture [24]</td></tr>
</table>

A timeline of nearly 100 events was created to capture any event that may have influenced Ohno's life and his work. The timeline included historical events for TMC, shown in Figure 4 (36 events), historical events for Japan (11 major events), milestones in Ohno's life (13 events), and events in the lives of people that potentially influenced Ohno (21 events). Events from the timeline and personal and environmental variables from Table 6 were used to form a diagram of potential influences on Ohno, shown in Figure 6. Figure 4 and Figure 6 are reduced in complexity to emphasize important content. Figure 6 resembles a neural network and a process diagram. The connectivity between the circular elements represents the relationships between the influential factors in Ohno's life. The outputs are the characteristics of Ohno's work and the 7 Wastes of the TPS (the variable of interest).

To obtain the characteristics of Ohno's work, 15 primary sources that were written by Ohno, those who knew Ohno, and those who could have potentially influenced Ohno were collected. In the analysis, characteristics of Ohno's work that have influenced the identification of waste were documented. A total of 118 characteristics of Ohno's life were collected and grouped based on their similarities, resulting in 16 major influential elements and 20 characteristics of Ohno's work (Figure 6). Connections were identified and documented between the influential factors and characteristics of Ohno's work, resulting in the 7 Wastes. The characteristics that enabled Ohno to create the 7 Wastes were combined into eight elements that recreate Ohno's mental model.

Key elements of Ohno's personality and situation were determined by evaluating the common themes found in the literature. These themes were analyzed by asking two questions: (1) "Could this have enabled Ohno to identify and eliminate waste?" and (2) "If so, how?" This recursive analysis resulted in the discovery of eight specific elements of the mental model that led Ohno to strive for improving the Toyota system, resulting in the creation of the TPS.

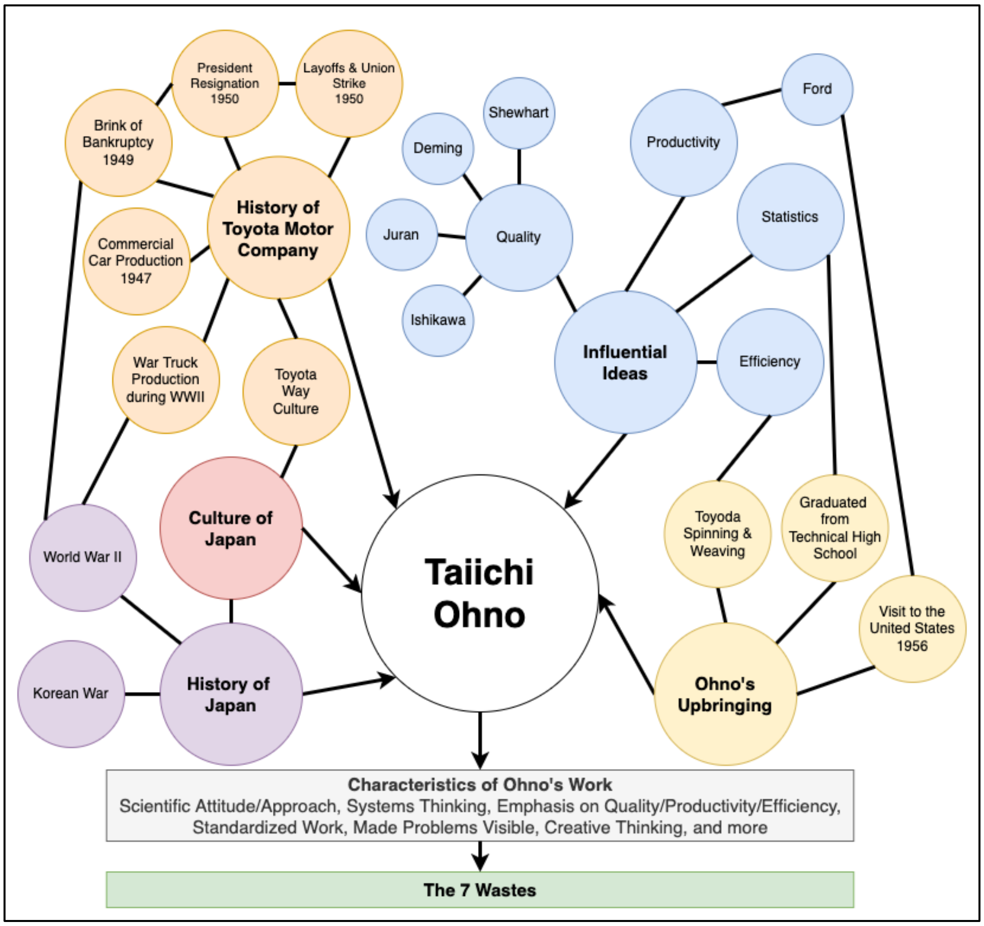


Figure 6 Influential Factors on Ohno's Life and Work.

4.4 Results

The eight elements of Ohno's mental model are presented removing references that are specific to TMC to form a generalized framework for identifying and eliminating waste in systems. This creation of Ohno's mental model serves as the basis of the framework presented in this research for identifying non-value-added activities in any domain. Without Ohno's mental model, it is not possible to fully grasp the philosophy behind the TPS and determine the principles that made Ohno's efforts successful.

Figure 7 depicts which attributes of Ohno's personality and environment impacted the eight elements of the resulting mental model. The italicized letters in the parentheses are the letters that correspond to the personal and environmental variables in Table 6. Ohno was as successful as he was in developing the 7 Wastes because of his personal and environmental variables. If you removed a combination of personal and/or environmental variables, the outcomes could have been different. For example, the Toyota Production System emerged solely out of necessity. The lack of resources and capital following WWII forced TMC to think critically and come up with new, more cost-effective production methods. It can be argued that Ohno's situation was the driving force behind everything that he did. The situation coupled with his background prepared him for the success that can be seen today as the TPS.

Descriptions of how Ohno's personal and environmental variables align with his mental model can be found below. Each of the eight components of Ohno's mental model are listed with the corresponding variable(s) that influenced the creation of each component.

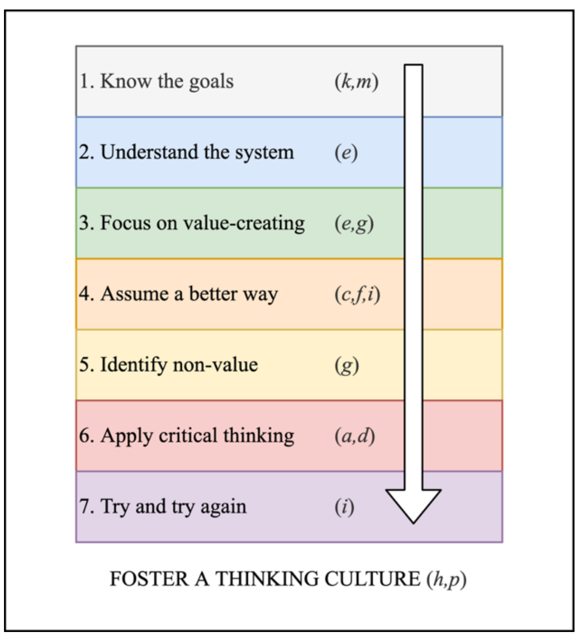


Figure 7 Attributes that Impacted Ohno's Mental Model.

4.4.1 Know the goals

Knowing the goals is most directly related to the goal and sense of need environmental variables (variables *k* and *m* from Table 6). Ohno's actions came from a clear understanding of the goals from both the TMC and customer perspectives. In 1945, two years after Ohno began working for TMC, Toyoda announced the goal to "catch up with America in three years" [19], [76]. Toyoda was able to motivate the organization towards improvement which provided the opportunity for Ohno to develop his continuous improvement mindset. Ohno stated that "cost reduction is the goal," and "all we are doing is looking at the timeline, from the moment the customer gives us an order to the point when we collect the cash. And we are reducing that timeline by removing the non-value-added wastes" [19]. These statements describe the tactics used to achieve the goal. The actual goal was to make money by turning products into cash quickly while maintaining high quality. This goal was also a subset of their broader aim to become the most profitable automobile manufacturer in the world. These goals were rather lofty for a company faced with a devastated economy and limited resources following World War II. Ohno understood the need and used that understanding to create a successful strategy for TMC [19].

4.4.2 Understand the system

Understanding the system is most directly related to Ohno's personal variable of learning by observation (variable *e* from Table 6). Ohno understood the system of manufacturing automobiles by spending time observing what was happening. Ohno believed the most valuable place to learn was the "gemba," which is Japanese for the real place in which the work happens. He knew this was the plant floor with the operators, and he is known for telling managers and engineers to go to the gemba to learn. Before making changes to a system, he stressed that you must first understand every detail of how the system works, including each of its components, their interactions, and where the value is created. Ohno expected managers to be able to answer all questions about the plant floor operations. If they were unable to answer a question, Ohno sent them back to the plant floor to find the answer. They were not supposed to return to him until they fully understood the purpose of each component of the system [76], [84].

4.4.3 Focus on value-creating resources

Focusing on value-creating resources is most directly related to the personal variables of thorough observation and the possible influence of Deming's teachings (variables *e* and *g* from Table 6). One of the fundamental motivations of the TPS is identifying and creating value. Value is defined by the customer [96]. Value-added activities are those that transform the product and add value from the customer's perspective. Activities that do not add value but are necessary should be minimized. Activities that are non-value-added and not necessary are wastes and should be eliminated. Emphasis should be placed on activities and resources that create value [97]. Ohno knew that the operators were the primary value-creating resource because they knew the system the best from performing the tasks. This knowledge enabled employees to also see their value and understand their role as a part of the system, which created an increase in the number of people searching for improvement opportunities.

4.4.4 Assume a better way

Assuming a better way is most directly related to the personal variable of constantly challenging systems, comparing systems, and Ohno's personality of being in "the mood to get things done" (variables *c*, *f*, and *i* from Table 6). Ohno believed there was always another way that would result in more profit for TMC. He looked at existing resources and systems as if they were unacceptable in their current state and thus had the opportunity for improvement [76]. Productivity improvements were not achieved by hiring more people or purchasing new equipment; he did not have the capital to do so. Instead, he focused on better utilizing the employees he already had through the elimination of waste. He searched for successful methods and then sought to make them more profitable [19].

4.4.5 Identify non-value

Identifying non-value is most directly related to the personal variable of being influenced by other teachings and the behavior of identifying wastes (variable *g* and behavior 1 from Table 6). There are three categories of activities. There are value-added, non-value-added, and non-value-added but necessary activities [97]. Ohno focused on eliminating waste or “muda,” which is Japanese for unnecessary or non-value-added activity. With an understanding that the customer determines value, Ohno identified actions that did not create the value the customer desired. Ohno sought to eliminate or reduce costs and increase profit. He looked for activities that did not occur in the right place, at the right time, in the right amount, or in the right form. He then categorized these unnecessary activities into seven categories, known as the 7 Wastes (Table 1) [19].

4.4.6 Apply critical thinking

Applying critical thinking is most directly related to Ohno’s personal variables of his education and methods of thinking (variables *a* and *d* from Table 6). Ohno was “fond of thinking about a problem over and over” to create a new and more profitable solution. Using his past experiences, Ohno sought out unique ways to improve systems. For example, he used his experience from TS&W to adapt standard work and the concept of autonomous systems to the TPS. He also analyzed unrelated systems to gather improvement ideas, such as applying American supermarket methods to the principle of producing automobiles to the rate of the customer pull. Ohno would not have been as successful without using ideas from systems outside of the automobile manufacturing industry [19].

4.4.7 Try and try again

Trying and trying again is most directly related to Ohno's self-driven personality (variable *i* from Table 6). As an advocate of trial-and-error methods, Ohno did not wait for the perfect solution. He motivated everyone to be in "the mood to get things done" by taking action and analyzing the outcomes quickly. He made sure to be quick to admit when he was wrong and fixed his mistakes promptly. His enthusiasm for improvement eventually gave him the opportunity to run a machine shop to try to prove that his ideas would be successful [76].

4.4.8 Foster a thinking culture

Fostering a thinking culture is most directly related to the way in which Ohno treated others and the Japanese culture, which Ohno utilized to create a teaching culture (variables *h* and *p* and behavior 3 from Table 6). The ability to learn and teach was instrumental in Ohno's success. He trained the workforce to view their jobs as roles to think, not simply to work. He refined his critical thinking skills while also developing those of his employees. By teaching the operators, Ohno was able to create a large number of problem solvers on a mission to eliminate non-value-added activities. The development of an inquisitive mindset helped employees find value in their work. This overarching element of Ohno's mental model is something he did throughout each of the previous steps. He fostered a thinking culture by encouraging others to view systems as an opportunity for improvement. Ohno thought of himself as a co-worker that helped the operators rather than a leader who enforced his ideas. He valued the employees and their contribution to the system, and he encouraged them to be engaged, fostering a mental model that included the principles of continuous improvement and respect for people [19], [76].

4.5 Discussion

Ohno's mental model serves as the basis for the identification and classification of physical wastes in a manufacturing system. The first four steps and the overarching thinking culture create a foundation for the identification of wastes in the system. The effort to eliminate waste begins in Step 5 by identifying non-value-added activities in the system. Understanding the goals of TMC and the customer, Ohno was able to recognize what actions support the goals of the organization. Understanding the system allowed him to determine which processes were essential because he understood the purpose that each activity served. By going to the gemba, he was able to perceive which activities added value.

Ohno recognized that non-value-added activities have a ripple effect. This ripple effect can cause one waste to be hidden within another, which creates difficulty in identifying root causes. A clear step-by-step mindset is essential to determine the underlying issues that create waste and the resulting inefficiencies. Ohno utilized a systematic mental model that allowed him to identify and classify the wastes of a manufacturing system successfully.

4.5.1 Creation of the Generalized Framework

Successfully eliminating waste in any system can be a difficult task. The 7 Waste classifications were created by Ohno for a manufacturing system, which is a physical system where waste can be observed. The 7 Wastes have been applied in many other domains besides manufacturing. However, not all 7 Wastes will be applicable, especially in a system that is not solely physical, and thus challenging to observe. For example, a digital system that involves the transfer of data and information does not have wastes that can be seen by the human eye. Waiting for data and information might be easy to find, but what about inventory, motion, or transportation? The 7 Wastes, as identified by Ohno and documented in the TPS, do not equally apply to all domains.

Because the 7 Wastes do not apply to all systems, utilizing the methods Ohno came up with in the development of the 7 Wastes of TPS is important so others can successfully define wastes in their systems.

The generalization of Ohno's mental model allows users to replicate the process of

Figure 8 Generalized Framework for Identifying and Eliminating Waste.

identifying, classifying, and eventually eliminating wastes in different domains. In this research, Ohno's thought processes were obtained and separated from any physical system ideology, creating a repeatable, disciplined, and iterative process for identifying and classifying waste in both physical and non-physical systems, shown in Figure 8. A guide for applying the framework follows:

1. Know the goals of the organization and the customer. The goals should be described so that all system participants easily understand them. A shared understanding of the goals ensures that everyone is working together toward the same purpose. The need should be felt, and the purpose should be clear. Do not neglect to consider the customer that receives the system's output. Strong emphasis should be placed on the customer's needs and wants. Consider that the customer may not always be a physical person, e.g., production data arriving at a scheduling system to form actionable information.

2. Understand the system and how its components interact. These components include but are not limited to inputs, outputs, enablers, and constraints. Determine which processes and/or activities add value by transforming the inputs to the desired output.

3. Focus on value-creating resources that produce the desired outcome. Emphasis should be placed on increasing the effectiveness of the resources that add value by transforming the inputs efficiently into the output. The primary purpose is to enhance and optimize the value-added components to increase value and make the identification of non-value-added wastes possible.

4. Assume a better way with an eye for improvement opportunities. This mindset is crucial to making continual improvements because it is where untapped improvement opportunities are identified.

5. Identify non-value features that do not optimally attain the desired outcome. Identify components of the system that are not in the right place, at the right time, in the right amount, or in the right form to attain the desired outcome and apply tools to eliminate these wastes.

6. Apply critical thinking to identify new and creative ideas. Do not limit opportunities by using conventional methods and problem-solving techniques, rather look at the activities from different perspectives. Think of new ways to eliminate the identified value inhibitors by creating new processes that most effectively utilize resources to attain the desired outcome.

7. Try and try again without waiting until the perfect solution is uncovered. Seek many small improvements instead of delaying action to find one big win. Define success by the increased ability to attain the goals of the business and customer.

Foster a thinking culture. Facilitate a thinking and learning culture in which all members of the organization understand the value of their work. This critical component of the generalized framework creates the environment in which the previous seven steps are practiced, improved, and celebrated.

Utilizing this framework can have many benefits that go beyond identifying waste in a system. This generalized framework can be used to create a continuous improvement mindset that provides a better approach to achieving organizational goals, determine who or what defines the success, and encourage new ways of achieving those goals. This generalized framework can be used to identify value-added and non-value-added activities by ensuring every component serves a purpose that supports the overarching goal(s). As Ohno would say, there is always a better way, and this generalized framework enables the finding of that better way.

4.6 Chapter Summary

Ohno had a clear purpose of making TMC profitable and a desire to ensure that TMC outperformed its competition. Today, the purpose and desire remain the same for manufacturing companies everywhere- to make money and outperform competitors. Applying tools without comprehending the underlying mental model will not lead to the improvements that companies and organizations seek. By deploying a culture of continuous improvement utilizing the generalized framework, organizations can create a model for systematic improvements and waste elimination that is tailored to their particular system. Forcing the application of TPS's 7 Wastes to domains that are not physical manufacturing production systems is ineffective and produces little benefit. However, the philosophy and mental model behind the creation of the 7 Wastes can be replicated for identifying the appropriate categories of wastes in many other domains.

In today's Smart Manufacturing environment, a framework such as the one presented in this work is crucial to manufacturing digitalization efforts. Currently, manufacturers have little to no guidance on how to digitally transform or decipher the difference between value-added and non-value-added data and information practices. The Generalized Framework for Identifying and Eliminating Waste can be leveraged for training and preparing an entire organization for a digital transformation. Doing so will form a culture that is equipped to identify inefficient and costly data and information flows, and in return, organizations can determine the right tools and software to eliminate these costly wastes.

The flow of manufacturing information that supports production is an improvement area that has already been identified as necessary by industry. The increasing complexity of production systems requires efficiency gains in non-physical components of systems, such as data and information flows [13], [35], [98]. Previous efforts have been made to adapt the 7 Wastes to apply to information streams [13], but the mental model used by Ohno in the creation of the 7 Wastes was not considered. The generalized framework proposed here is the missing link that is needed to successfully identify, categorize, and eliminate waste in non-physical systems.

An important use of the generalized framework is to develop waste categories focused on the flow of data and information in production systems. Doing so will show where to find the hidden costs of inaccurate and inefficient information in manufacturing systems. Being able to identify and eliminate non-physical waste in information systems that support manufacturing production will open a new domain of improvement opportunities for manufacturing. These efforts will support the digital transformation initiatives that are a part of the Industry 4.0 movement.

Chapter 5 Non-value-added Activities in Data and Information Flows

5.1 Introduction

By understanding and reproducing how Ohno identified, categorized, and eliminated waste at TMC, it is feasible to create categories for data and information wastes in manufacturing systems. Capturing and defining the data and information flows that are common amongst most manufacturing facilities is key to ensuring this work applies to all types of manufacturing companies. The challenges that manufacturers face with their data and information flows are captured and categorized to provide an overview of the current state of data and information issues in manufacturing systems. Waste categories for data and information flows are defined.

5.2 Background

To create categories of waste for data and information in manufacturing systems, it is essential to comprehend and define the data and information flows that are common amongst most manufacturing systems. The American National Standards Institute's (ANSI) International Society of Automation (ISA) standard for Enterprise-Control System Integration, ANSI/ISA-95 (or ISA-95 in short) accomplishes this by defining and mapping the data and information that commonly flow in manufacturing systems. A description of the Purdue Model is also provided, as it served as the basis of the formation of ISA-95. Then, the difference between the terms, "data" and "information," is distinguished and clarified.

5.2.1 Types of Data and Information in Manufacturing (ANSI/ISA-95 Standard)

ISA-95 [99] defines four pillars of data: (Pillar 1) Inventory; (Pillar 2) Production; (Pillar 3) Maintenance; and (Pillar 4) Quality. There are also five levels between which data and information can flow: (Level 0) the actual physical processes; (Level 1) sensing and manipulating the physical processes; (Level 2) monitoring and controlling physical processes; (Level 3) activities of the workflow, maintaining records, coordinating the processes; and (Level 4) business-related activities. Most manufacturers use enterprise systems to manage their data and information across a company [100]. Enterprise systems, such as Enterprise Resource Planning (ERP) and Manufacturing Execution System (MES), are commonly deployed by Levels 4 and 3, respectively (Figure 9) [101]. The physical processes on the plant floor, which are Levels 0-2 are controlled by the information provided by Level 3. Information that flows from Level 3 to 2 includes but is not limited to equipment and process-specific production rules, part drawings and models, work instructions, machine code, set-up and shutdown rules, part specifications, and work masters or routers.

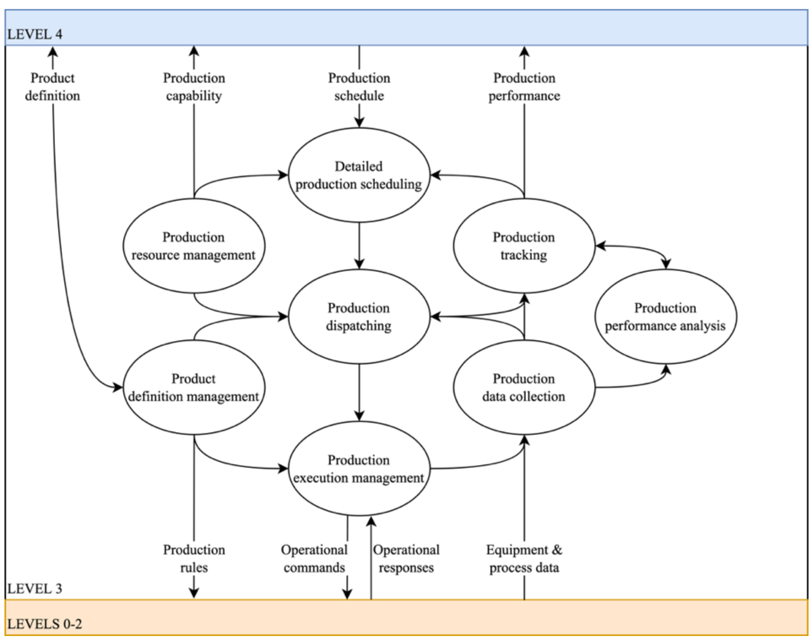


Figure 9 ISA-95 Level 3 of the Production Pillar [99].

Each of the arrows in the ISA-95 diagram represents an opportunity for data connectivity across the functions, which are represented by the ovals. ISA-95 shows how data should be connected within a manufacturing system. However, the simplicity of Figure 9 is far from reality. The arrows and functions are much more disjointed with several non-value-added activities. Multiple software packages attempt to address one or more of the functions shown in Figure 9 but many non-value-added activities remain that hinder interoperability. It is necessary to identify the non-value-added activities so that industry can begin to address and eliminate them.

Table 7 Activities Within Manufacturing Functions as Defined by ANSI/ISA-95 [99].

Function	Activities
Production Resource Management	Manage the information about resources (personnel, equipment, materials, and energy) that are required by production operations, and understand the relationships between the resources.
Product Definition Management	Manage and distribute information about the product and production rules (ex. work masters, manufacturing instructions, product structure diagrams, set-up/shutdown rules).
Detailed Production Scheduling	Uses the production schedule to determine the optimal use of resources to meet the production schedule requirements. Accounts for constraints and resource availability.
Production Dispatching	Manage production flow, dispatches equipment to personnel, schedules run times, sets operating targets, and sends job orders to work centers.
Production Execution Management	Create work directives from work masters for each job order, ensures correct resources are used, and confirm that the work meets the standards.
Production Tracking	Summarize and report info. on resources used (ex. equipment & personnel used, material consumed, material produced, costs, and performances analysis).
Production Data Collection	Gather, compile, and manage production data (ex. sensor readings, equipment statuses, event data, and operator-entered data).
Production Performance Analysis	Analyze and report performance information to business systems (ex. performance, cost, comparing runs to other runs, comparing runs to an optimal run, and suggests changes to process/procedures based on the analysis.

Activities of the workflow are depicted in Pillar 2, Level 3 of the ISA-95 model. Within Level 3 of the Production pillar, there are eight common functions of a manufacturing facility between which data flow (Figure 9): (1) Production Resource Management, (2) Product Definition Management, (3) Detailed Production Scheduling, (4) Production Dispatching, (5) Production Execution Management, (6) Production Tracking, (7) Production Data Collection, and (8) Production Performance Analysis. The functions provide the data elements that are needed for the planning and execution of production and the retrieval of data from the plant floor. The activities within each function are described in Table 7.

5.2.2 Purdue Model

The ISA-95 standard described in Section 5.2.1 was influenced by the Purdue Model of Computer-Integrated Manufacturing (CIM), known as the Purdue Model for short (Figure 10). The Purdue Model defines layers of hardware and software in manufacturing systems (Table 8). The Purdue Model is commonly used in security applications to define the separation of different layers of data in an Industrial Control System [102]. The following sections of this chapter will refer to several of the software systems that are listed in Table 8 and the data and information wastes that occur due to the interoperability of the various levels.

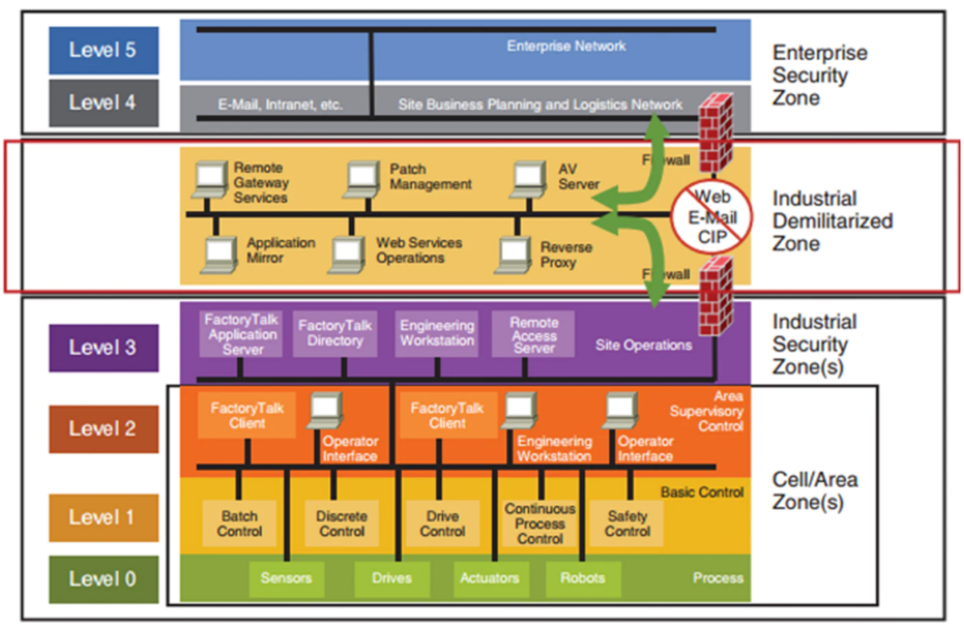


Figure 10 The Purdue Model [102].

Table 8 Levels of the Purdue Model [103].

Levels of the Purdue	Potential Elements in Each Level
Level 4/5: Enterprise Systems	Enterprise Resource Planning (ERP) systems
Level 3.5: Demilitarized Zone (DMZ)	Security systems- firewalls and proxies
Level 3: Manufacturing Operations Systems	Manufacturing Operations Management (MOM) systems, Manufacturing Execution Systems (MES), Data historians
Level 2: Control Systems	Supervisory Control and Data Acquisition (SCADA) software, Distributed Control Systems (DCSs), Human-Machine Interfaces (HMIs)
Level 1: Intelligent Devices	Programmable Logic Controllers (PLCs), Remote Terminal Units (RTUs)
Level 0: Physical Process	Sensors, actuators, machinery

5.3 Methodology

By understanding how Ohno created the original 7 Wastes of the TPS, the approach can be applied to other domains. To recreate the broad acceptance of the 7 Wastes of the TPS in another domain, equivalent principles behind the identification of waste must be used. Section 5.3.1 describes how Ohno's mental model was applied to data and information flows. Section 5.3.2 then explains how non-value-added activities were collected and documented to evaluate the gamut of wastes that are present in today's manufacturing data and information flows.

5.3.1 Ohno's Mental Model

Understanding Ohno's methodology behind the creation of the 7 Waste of the TPS was the first step in creating new waste categories for data and information flows. Ohno's methodology, his mental model, and a generalized form of his mental model were presented in Chapter 4. A simplified version of the Generalized Framework is presented in Figure 11. The following subsections explain how the Generalized Framework can be applied to the domain of manufacturing data and information flows.

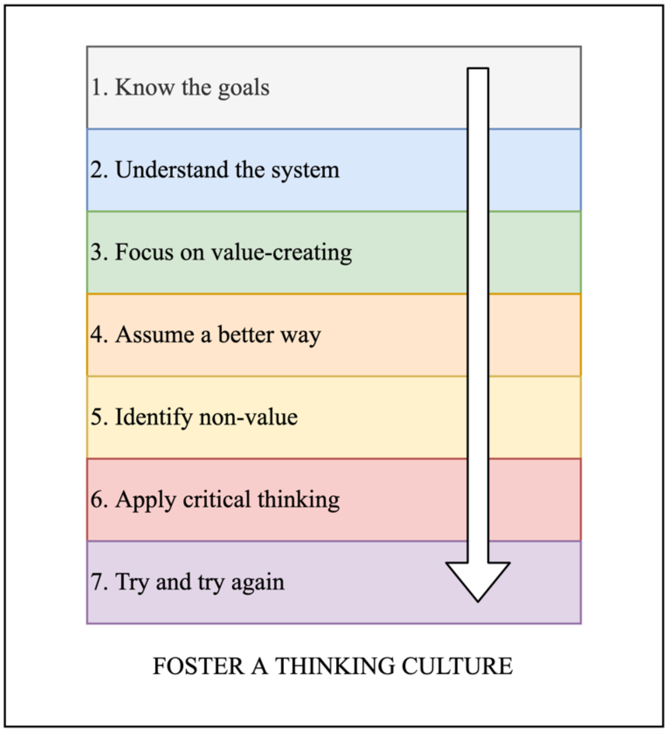


Figure 11 Generalized Framework for Identifying and Eliminating Waste [104].

5.3.1.1 Know the goals

Unless the organization is a not-for-profit or has a pure humanitarian focus, the ultimate goal in manufacturing is to generate profit by providing a product that meets the customer's expectations [105]. The data and information required for production should support the business goal (make money) and the customer goal (acquire a quality product). Data and information flows can inhibit both goals by incurring costs and causing unnecessary delays. The right data must arrive at the right place, at the right time, and in the right form to support the business and customer goals. Data and information flowing in this manner allow decisions to be optimized efficiently and effectively [104].

5.3.1.2 Understand the system

Understanding the entire manufacturing system and how components interact is essential. The traditional perspective focuses on the physical elements and how they interact and follow the product flow [68]. However, the non-physical components, such as data and information flows, are hidden, often forgotten, not analyzed, and not improved. Understanding how data is created, modified, delivered, consumed, and stored is critical to understanding the complex web of data and information flows. Data can serve as an input or output, and both must be acknowledged. It is also essential to understand the data required to perform manufacturing functions and the form or structure that the process requires. A portion of this is accomplished with ISA-95 by providing an ideal state of how data and information flows can be connected. However, one must also understand the intricacies of the current state of the data and information system to identify waste.

5.3.1.3 Focus on value-creating

Lean Manufacturing aims to maximize value by minimizing non-value-added activities [106]. When analyzing manufacturing processes, the value-creating resources add value to the product and support the goal. For data and information, focusing on value-creating resources will mean focusing on activities that support the goal of the right data, being in the right place, at the right time, and in the right form to inform the best possible decision [104]. Valuable data and information will differ across various roles in which individuals are trying to accomplish different yet related tasks [107]. Having multiple views of the same data may be necessary.

5.3.1.4 Assume a better way

Continuously improving in manufacturing requires a mindset that constantly assumes that operations can be performed in a better way. Ohno was a trailblazer for repeatedly looking at a seemingly well-established process as if it were a mess [108]. Viewing a process this way allows one to uncover activities that are not adding value. For data and information, this will mean looking at data and information flows as if they are a mess and assuming there must be a more efficient method. Data and information must go beyond digitization to digitalization to reap the highest benefits.

5.3.1.5 Identify non-value

Understanding the resources that create value provides the opportunity to identify resources that do not create value or support the goal. Lean Manufacturing practitioners use the 7 Wastes of the TPS to identify and categorize non-value-added activities, or waste, in manufacturing production systems for elimination or minimization [109]. Some have attempted to use the original list of 7 Wastes created by Ohno force fitting them with new definitions related to data and information flows [59], [110]. However, assuming that waste categories for physical part production flow will have an equivalent counterpart for data flow is not reasonable.

Creating waste classifications specifically for data and information flows provides better suited and understandable categories of waste to look for when studying the company's data and information flows. Without waste categories explicitly developed for data and information, manufacturers cannot easily differentiate non-value-added data flow from value-added data flow or determine which tools to employ to minimize or eliminate those wastes.

5.3.1.6 Apply critical thinking

After thoroughly evaluating and understanding the manufacturing system, critical thinking must be used to identify and develop improvement opportunities. Critical thinking takes an objective analysis of the system and couples it with the assumption that there is a better way to form new ideas on how the system performs. For data and information, this means fully understanding the data and information requirements, how the processes are currently executed, assuming the data can flow and be presented better, and actively thinking about ways to eliminate the non-value-added steps in the data and information processes.

5.3.1.7 Try and try again

When improving the physical flow of manufacturing processes, Ohno did not wait for the perfect solution or improvement to be uncovered [108]. He deliberately tried and tried again to find a better way. For data and information improvements, this will mean trying a new improvement idea and if it only provides an evolutionary improvement, or does not provide the expected results, try again. The recursive cycle of continuous improvement will always be relevant in today's competitive manufacturing marketplace.

5.3.1.8 Foster a thinking culture

Ohno captured everything he learned and shared it with his fellow manufacturing associates. He did not simply tell them about the new improvements; he taught them the reasoning behind the improvements. Ohno created an army of eyes searching for improvement opportunities [105], [108]. Similarly, significant effort must be made to disseminate the knowledge behind data and information flow improvements. Having classifications for data and information waste is a step in the right direction for training associates to regularly look for data and information flow improvement opportunities.

The seven steps and the 8th overarching component, fostering a thinking culture, of the Generalized Framework should be used in developing waste categories for data and information flows in manufacturing systems. Doing so replicates the process in which Ohno developed the 7 Wastes of the TPS, which proved to be highly successful in identifying and eliminating waste in manufacturing processes.

5.3.2 Industry Interviews

The Generalized Framework shown in Figure 8 has an overall theme of value creation and eliminating activities that inhibit value creation. For data and information flows, this is any action that hinders the right data from being in the right place, at the right time, and in the right form to make the best possible decision [104]. Step 5 of the framework calls for the identification of non-value-added activities. This study set out to identify non-value-added activities in manufacturing data and information flows by conducting industry interviews to identify, understand, and document issues with production data and information flows in manufacturing organizations. Discussions were held with manufacturers about their challenges with production data and information flows. All interviews were conducted via phone or video conferencing based on the participant's preference. The discussions were approximately one hour long. The interviewer took notes during the interviews. The interviews were not recorded or transcribed to provide anonymity.

Interviews were chosen because they allow for a semi-structured approach in which an interview guide can be used to ask uniform questions and allow for the responses from different interviews to be compared. It also permits asking additional questions if an insightful topic arises [111]. A survey would not have allowed this flexibility. A survey can capture unstructured data, but further questions cannot be asked when the participant's responses are anonymous.

Key informant sampling [111] was utilized to identify participants. This sampling method was chosen to target participants that are highly knowledgeable in their organization's data and information challenges. The target participant was a person who works closely with manufacturing operations and has in-depth knowledge of the data and information inputs and outputs. In manufacturing, these are typically management roles such as plant manager, general manager, operations manager, quality manager, planner, or scheduler.

The interview conversations were structured around two main questions: (1) What challenges do you face with data and information flows? and (2) How do you define success in data and information flows? The questions were open-ended, so the participants mentioned their foremost thoughts, revealing the most pressing challenges. If participants needed clarification on the first question, they were asked to provide examples of instances in which the right data was not in the right place, at the right time, or in the right form to make the best possible decision. If the participant could not provide further examples, the interviewer would ask about the following types of data/information: ERP, materials requirements planning (MRP), scheduling, inspection/quality, work instructions, MES, routers/travelers, models/drawings, and material certifications/approvals. The second question was open to the participant's interpretation to reveal if and how their organization thinks of successful data and information flows. The permission to perform the study by an institutional review board, training certificates for researchers, the recruitment email for participants, and questions to guide the interviews are in Appendices B-E.

5.4 Results

In this study, 32 interviews were conducted with participants from 22 companies. Of the companies that participated, five had multiple participants. The participant role, company size, and type of manufacturing demographics of the participants are shown in Figure 12-13. Participants represented roles in Operations (31%), Other (23%), Executive-level (19%), Engineering (15%), Quality (8%), and Planning (4%) (Figure 12). The "Other" group was created to aggregate small categories so as to not identify participants by their roles. Of the companies that participated, 64% of the companies were SMMs, having less than 500 employees [50], and 36% of companies were large manufacturers, having greater than 500 employees (Figure 13).

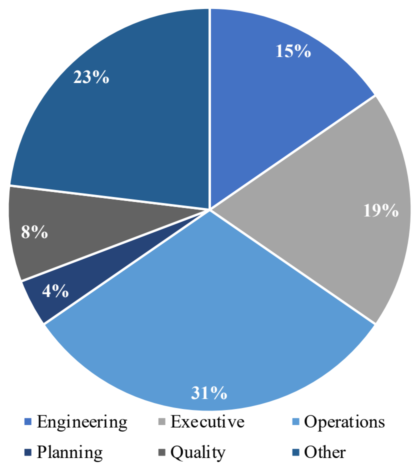


Figure 12 Roles of Participants.

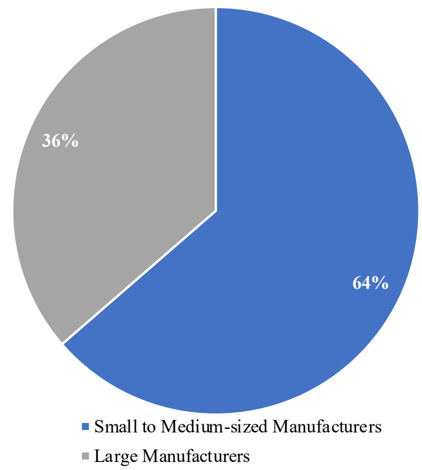


Figure 13 Company Size.

The North American Industry Classification System (NAICS) code for each company was used to classify the participants by type of manufacturing. The industries represented in the interviews were: Primary Metal & Fabricated Metal Product Manufacturing (28%); Transportation Equipment Manufacturing (24%); Miscellaneous Manufacturing (16%); Other (16%); Machinery Manufacturing (8%); and Plastics and Rubber Manufacturing (8%) (Figure 14). The "Other" group was created to aggregate small categories so that the manufacturing companies are not identifiable.

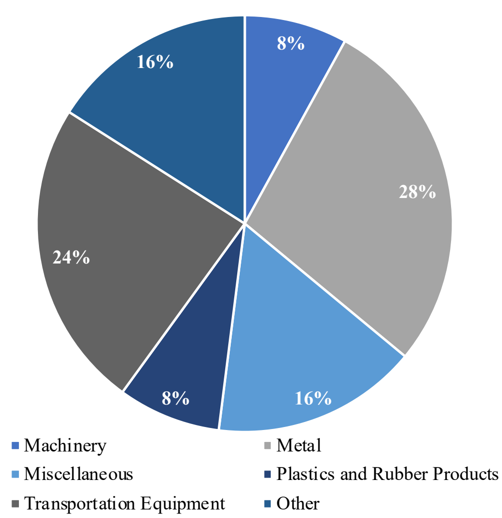


Figure 14 Type of Manufacturing.

The following subsections summarize the responses to the two main interview questions. Section 5.4.1 presents the challenges manufacturers face with their data and information flows. Section 5.4.2 summarizes how the participants defined success in the flow of data and information in manufacturing systems.

5.4.1 Challenges with Data and Information Flows

In this section, the participants' responses to the question "What challenges do you face with data and information flows?" are summarized. In the following subsections, the interview responses are grouped by the type of data and information the participants discussed.

5.4.1.1 General

It is apparent through the interview responses that communication issues are rampant across all types of manufacturing and amongst all levels of employment. One notable response was that "manufacturing fundamentally has a communication problem." This remark referred to the inefficient communication practices across manufacturing firms, from the plant floor to the executive suite. All participants mentioned inefficient, redundant, and back-and-forth communication practices. This indicates that communication issues are likely a widespread throughout manufacturing operations.

A large portion of overhead costs is allocated to employees' salaries for internal or supply chain communications, data reporting, and efforts to keep data and information up to date. A participant confirmed this statement by noting that they know their role could use significant efficiency improvements. The needed improvements are not enacted due to a focus on the day-to-day tasks at hand; this is the firefighting mindset of needing to focus on the issues at hand and not having the capacity to consider future improvement opportunities. The comments made by this participant support the proposition of this research that inaccurate and inefficient data and information practices are costly and often go unaddressed. However, the more significant issue may be a lack of perceived value of digitalization or the benefits that communication improvements can provide.

Incorrect, inconsistent, and incomplete data and information were broadly mentioned as common issues. The excessive amounts of data and information, particularly in reporting, were also mentioned by management-level participants. The problems with reporting were on two ends of the spectrum; some participants noted that reports include information that is not pertinent to their role, and others mentioned that customized reports could cause inconsistency amongst reports. It is evident that different roles need different views of the same data. However, the data source needs to be up to date and consistent for multiple views of the same data to be accomplished successfully.

Overall, the responses infer that data and information issues are widespread throughout manufacturing. Of the general comments about data and information in manufacturing, it became clear that there is no centralized or easily accessible source for data and information. The interviews also uncovered the importance of considering that "valuable data" will take on different meanings to individuals in various roles because they are trying to achieve related but somewhat different outcomes—the form and view of the data matter to the user. Therefore, non-value-added data and information will be defined differently by various users.

5.4.1.2 Enterprise Resource Planning

Interviews uncovered an overwhelming amount of disdain toward ERP software. The issues with ERP systems were multifaceted, including outdated and not user-friendly software, unorganized data or complicated search functions, homegrown software, and disconnected data and information. Many participants noted that their company's ERP system seems archaic due to the outdated interfaces and reports that are output in a form that is difficult to analyze, such as a portable document format (PDF). The ERP software can become a source of frustration if the user struggles to find the data they need to make informed decisions promptly. Several SMMs and large manufacturers have created homegrown ERP software to combat the costs and complexity of ERP software. In some cases, companies use a collection of files and spreadsheets that attempt to perform the functions of an ERP software suite. On the other hand, many large manufacturing participants with multiple plants or locations mentioned having non-similar ERP systems across the entire company. Having multiple ERP software providers can cause difficulty or inability to aggregate data for timely decision-making.

The value of having a centralized location for manufacturing information arguably outweighs the challenges ERP systems present. However, the most significant issue with ERP systems was the perception that data in an ERP system cannot be trusted. Almost every participant said that the data in their company's ERP system is wrong and prone to errors. ERP systems are designed to pull together disparate pieces of data from multiple sources. The data coming from many of the sources is often not up to date, resulting in a lack of trust in the data. Extracting data from one system and importing it to another can take time and manual intervention if the systems are not interoperable. Several respondents said the ERP system needs to be connected to the MRP module, but it is not. ERP is an evolution of MRP and MRP II. Since ERP systems typically have an integrated MRP component, the respondents likely meant that they desire to have their ERP system set up to consider material availability when scheduling production and that the ERP system is not correctly set up. ERP systems that have been properly configured and managed can allocate materials based on availability. Still, several respondents did not have this capability running or set up correctly, causing the ERP system to schedule production regardless of material availability. The leading cause of this issue was the data not being up to date to allocate supply to demand accurately.

Demand input and reporting for most respondents occur weekly while production happens in real-time daily, resulting in a significant lag in updating the needed data. In addition, most participants noted a missing feedback loop. From the production floor to the ERP system, meaning the ERP system does not keep track of planned vs. actual production. Combating the issue of outdated data is no easy task; for one company, a team has been tasked with evaluating all the data in their ERP system to remove data errors or "noise." Performing the evaluation is daunting and may only provide benefits until the data is outdated again. Therefore, standard methods must be in place to ensure that data is continuously updated and can be trusted.

The responses from the interviews reveal the vast frustration that ERP systems can cause. Most ERP systems are only correct and up to date on the day they begin running. After that, the data quickly becomes outdated and incorrect, resulting in a growing lack of trust. The inability to trust the data is a problem, but the root cause of the issue digs deeper into the data being outdated or incorrect. The data becoming outdated is most likely due to the ERP system not being set up with proper data feedback loops and a lack of connectivity between data sources that are needed as inputs for the ERP system [112]. Also, when data is manually entered into the ERP system, there is a high potential for data entry errors. The data entry procedures are commonly undocumented and unstructured or challenging to use. The task of manually entering data can be costly.

5.4.1.3 Scheduling

ERP software can create a schedule, however, few respondents use the schedule generated from the ERP software as is. The reasons for this varied: the ERP software does not take material availability into account, the ERP schedule is in a format that is difficult to understand, or it is not user-friendly, the ERP schedule is built off of incorrect lead times that cannot be trusted, the ERP schedule does not include after-market parts that cause high levels of variability, and the ERP schedule does not adjust based on production. These issues represent instances in which the right data is not in the right place, at the right time, and in the right form to make the best possible decision (in this case, an accurate schedule). Several participants use the schedule generated from the ERP system as a baseline to which they make changes. In contrast, others do not use their ERP software for scheduling even though it has the capability. The most common form of scheduling used by the participants was a spreadsheet.

Depending on the company's size, an individual or multiple persons work solely on scheduling functions. These scheduling tasks are often redundant and could be better performed by a computer. However, the lack of up-to-date and correct data in the ERP software presents a significant challenge in scheduling, whether the schedule is created by software or by manual intervention. Many participants described the back-and-forth communication between multiple departments that must take place to determine production capacity, resource availability, material availability, machine and tooling availability, machine code readiness, and authorization readiness. Back-and-forth communication can be difficult to track and document. It is an inefficient form of communication, and data and information can be lost or miscommunicated in translation.

Schedules are constantly changing in production environments. The manual intervention used to update schedules is time-consuming, an interruption to the flow of data, and happens at discrete points in time. Ideally, a continuous feedback loop would automatically update the production schedule. The interview responses illuminate the lack of connectivity between manufacturing functions (such as production resource management, product definition management, detailed production scheduling, production dispatching, production execution, etc.) that need to merge to create an accurate schedule at the right time.

5.4.1.4 Work Instructions and Manufacturing Execution Systems

Issues revolving around manufacturing work instructions included information that is not up to date, work instructions are seldom viewed by experienced operators, and disconnects between the work instructions and MES. It is common for work instructions to be paper-based and stored at the operator's workstation for future use. Other forms of work instructions include PowerPoint slides that are stored in a shared drive and can be pulled up by a uniform resource locator (URL) if needed, drawings that are used as work instructions, and work instructions that are printed, laminated, and posted at the operator's workstation.

Operators do not always refer to the work instructions, drawings, or specifications because they repeatedly perform the same or similar jobs. Familiarity with the work can lead to missing a change made to the product, leading to quality escapes. Work instructions that are not current can result in producing products to the wrong specifications, lost efficiency, and lost capacity.

Updating work instructions is a challenge that many participants noted. Work instructions are often stored in multiple locations and updated in one place but not another. For example, the work instructions may be updated in the ERP or MES software, but the new work instructions are not printed and delivered to the plant floor, causing a mismatch in information. The reasoning behind paper-based work instructions, as opposed to digital instructions, was that operators might not be computer savvy; this is indicative of a culture that is resistant to change, which is a more significant issue that needs to be addressed.

Several interviewees have an MES that is separate from the work instructions. For example, a company uses an MES for operators to sign off on completed tasks and specifications, but the work instructions are housed in different software that can be accessed through a URL in the MES. The MES contains many of the same steps as the work instructions, but the work instructions are typically more detailed and only used if needed. Many participants noted that their MES and work instructions are not connected or are poorly connected with other systems, such as the ERP and quality software.

Work instructions that are not digitized are prone to being outdated, causing the information used by the operator to be incorrect. Work instructions that are digitized and printed are liable to be mismatched and cause confusion about which version is correct. Printing and updating work instructions take time and can cause the work instructions to be incorrect and unavailable to the operator when needed. Work instructions are most likely not referred to due to the form in which they are displayed to the user, and it can be seen as a nuisance to view such detailed instructions. Of the respondents, the companies that use MES systems typically use them for logging job hours and status. However, this information is rarely correct or updated in real-time based on actual production because it requires an operator's manual interaction with the interface, which inherently causes a delay in the production status being updated.

5.4.1.5 Models/Drawings, Computer-aided technologies, and Technical Data Packages

A technical data package (TDP) is a set of information that a manufacturer receives from a customer about a part. The TDP typically includes the part design, configuration, performance requirements, and procedures [113]. The technical data may consist of 2D drawings, 3D models, notes or comments, and specifications. Because the information comes from many sources, it is common for TDPs to be incomplete, have conflicting information, or arrive in a non-standardized or inconsistent format, all of which were mentioned by participants in this study. Few companies trust the data in a TDP that comes from a customer. There is a fear of releasing jobs to the plant floor without first reviewing (and possibly reworking) all the TDP because of significant issues they have had in the past with incorrect data from TDPs. Several participants mentioned that there are jobs dedicated to ensuring that TDPs are checked for errors, missing information, and inconsistencies because they cannot trust any data from the customer.

Conflicting information is an error often found in TDPs, with the most common example being that drawings and models do not match. This requires the manufacturer to determine if the model or the drawing is correct, and then time is spent making the necessary changes to correct the data. Customers often use computer-aided technologies (cAx) to generate their models and drawings. The three most common issues with cAx mentioned by participants were difficulty verifying and validating models, interoperability issues from customers utilizing different cAx software, and loss of features or fidelity during model translation.

Configuration management of TDPs was also mentioned as a challenge. When a manufacturer receives a revision or engineering change, the TDP must be updated to ensure that only the most up-to-date and accurate information is used to manufacture the part. The respondents mentioned maintaining and keeping track of the changes in TDPs as a challenge. One change in a TDP can cause a cascading effect of other changes that need to be made to support the revision, but those changes are not always reflected throughout all necessary parts of the TDP and in the manufacturing of the part.

The respondents that produce classified products must protect TDPs and the models and drawings within the TDPs or risk a potential security breach. Moving this data with the appropriate level of security is challenging. Classified data on a network is a potential target for a security breach, so many companies are choosing to airgap their systems, which hinders the ability to flow data easily from the source of the data to the entities that are processing or using the data.

5.4.1.6 Production Data and Status

Real-time insight into the status of orders was an issue noted by all participants. Some manufacturers reported having real-time production status data, but most respondents utilized barcode scans or operator signoffs to update their operational statuses. Barcode scans have the potential to be near real-time if standard barcode scanning procedures are in place. However, these methods rely on manual intervention from an operator to update the status of an operation or order. As a result, manufacturers struggle to answer the question: "When is the customer going to receive their order?" For most respondents, answering this question requires iterative phone calls and emails between multiple internal departments to determine supply, resource, and scheduling constraints.

Another issue with production data is that many companies collect it, but there is a delay in receiving the data in a form that can be analyzed; Or worse, the data is stored and never analyzed. Experiencing a delay in receiving production data hinders the ability to take prompt corrective actions. Production issues, quality losses, and efficiency losses could have been prevented if the production data had been received and analyzed in near real-time. Production data must also be collected in a standardized way that is not prone to errors. Several participants mentioned that manual data entry is a common cause of data errors. In turn, the production statuses cannot be trusted due to incorrect data.

Possessing large datasets that are not used to their potential could indicate that the production data is being collected in a form that is not easy to analyze, understand, or enact change. More likely, the users do not understand how to utilize the large datasets they have collected, but they feel the need to collect large amounts of data and do not know why. Simply obtaining data for the sake of having it is not value-added; taking it and turning it into information to inform better decisions is value-added. The data may not appear to be value-added until it is in a form that can be understood and used to act. Valuable data is often overlooked because it is not visualized and presented effectively to decision-makers. It is also possible that the data is not used because it is not trusted. Systems must be in place to collect accurate data in a form that can be trusted.

5.4.2 Defining Success in Data and Information Flows

The interview's second question dealt with how the respondents define success in data and information flows. This question initially stumped several respondents, and they had to stop and contemplate their response, revealing that data and information flow improvements are not commonly considered and addressed in manufacturing. However, the answers provided valuable insight into the issues being faced by manufacturers.

The most common response in defining success in data and information was timely, fast, and accurate data. Manufacturers need readily available information. The desire to have timely data and information was driven by the need to provide the customer with the status of an order, an estimated or definitive delivery date, planned vs. actual man-hours and material used, and budget vs. actual production cost(s). One response described a desire to have a voice-activated system that could provide an answer instantaneously, essentially Alexa or Siri for manufacturing. The desire behind such a system is to obtain information quickly without exerting heroic effort in searching for an answer. There is a need for quick insight and visibility into any aspect of the manufacturing system.

The second most common response was that successful data and information flow is when data is presented in a manner that is valuable and useful, meaning it can be used to make sustainable improvements and inform better decision-making. One response was that data should be "given to the end-user in an actionable fashion." This participant sought to have the ability to view the data in its current form and, from that, be able to act. Manufacturers do not want to waste time, energy, or effort manually transforming data and making reports. They want to minimize the manual effort required to perform these data tasks so that they have readily available actionable information [114].

Success was defined as being able to have a direct link between manufacturing functions that is seamless and eliminates the need for an extensive number of emails and phone calls between departments. A participant provided an example of having the plant floor operations connected to the ERP system so that scheduling data is automatically updated based on actual production, indicating a disconnect between the production and planning systems in their current system. Manufacturers desire a centralized authoritative source for data with multiple views for various roles to enact different yet related value-added changes. This valuable insight must be considered when creating a tool to identify data waste.

Respondents that worked with classified data and information had different responses to the question of defining success in data and information flows. These responses spoke first and foremost about success being a flow in which no data is compromised, no integrity is lost in data transmission, and all safeguards are in place with no failures. In this case, a lack of connectivity between manufacturing functions could be a positive indicator of success. For example, for security purposes, there is a need to airgap information technology and operations technology so that no piece of data or information can be accessed through a network. Adherence to government policies and regulations necessitates a different definition of success in the flow, or lack of flow, of data and information. However, not losing data or its integrity would be a success for all types of data, not just sensitive data. Additionally, this extreme position infers that the organization is foregoing any competitive improvement from digitalization that can be gained from data and information technology improvement and connectivity in a trade-off with security, which is not a positive long-term growth strategy.

5.5 Discussion

This section explains how the interview responses contributed to the creation of 8 Wastes for Data and Information. Section 5.5.1 describes how the waste categories were formed from the interview responses. Section 5.5.2 introduces each of the 8 Wastes for Data and Information, and Section 5.5.3 expands on their application.

5.5.1 Creating the Waste Categories

Approximately 300 data and information issues were extracted from the interview responses and recorded in a spreadsheet. Similar responses that described the same type of issue were grouped together. The grouping process is shown in Figure 15. Natural groupings began to appear when sorting the challenges by their descriptions. The natural groupings resulted in 42 categories. The 42 categories were parsed over multiple iterations into fewer categories by a group of manufacturing experts. Each expert sorted the 42 categories individually and then compared their categories as a group, resulting in ten categories. For the final round of grouping, the ten categories underwent several iterations of regrouping and renaming by the team of experts, resulting in the 8 Wastes for Data and Information. These waste categories are presented in Section 5.5.2.

Fewer categories are desirable so that manufacturing associates can easily recall the categories, identify wastes, and methods of removal or minimization created and implemented. Multiple rounds of grouping took place to minimize the total number of categories (as shown in Figure 15). After two rounds of grouping, there were ten resulting categories, one being an "Other" category. The "Other" category consisted of issues that were not specifically data and information wastes, such as no responsibility for data and information, security hindering the flow of data and information, and lack of personnel or skills. Regrouping and renaming of the categories were conducted to eliminate the "Other" category. The final eight categories of this iterative and recursive process are presented as the 8 Wastes for Data and Information (Table 9).

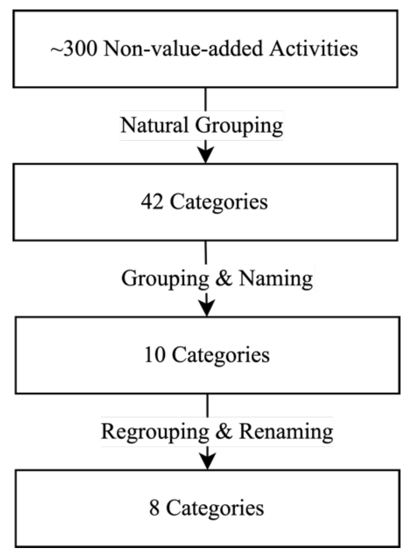


Figure 15 Waste Grouping Process.

5.5.2 The 8 Wastes for Data and Information

The resulting waste categories were Form, Excess, Error, Separation, Delay, Change, Manual Intervention, and Storage, defined in Table 9.

It is important to note that a data or information issue may fit into multiple waste categories. As with the 7 Wastes of the TPS, one waste can lead to other forms of waste, or numerous wastes may be present in one identified issue. Regardless of the chosen classification, identifying the waste is successful if the issue is identified and eliminated.

Table 9 Definitions of the 8 Wastes for Data and Information.

Waste Category	**Definition**
Form	A format of data or information that is suboptimal for use
Excess	A greater amount or volume of data or information than needed
Error	Incorrect, inaccurate, or incomplete data or information
Separation	Data or information that lacks connectivity in its flow
Delay	A stoppage in the flow of data or information
Change	The act of manipulating, modifying, or transforming data or information
Manual Intervention	Necessary intervention to initiate/continue the flow of data or information
Storage	The continued retaining of data that has no apparent purpose or requirement for preservation

5.5.2.1 Waste of Form

The Form category includes data and information that are not presented in a way to be efficiently utilized by the user. The user could be another software or someone who needs to interpret the data. The data or information may need to take on a different format, structure, or media to be user-friendly and interpretable. The form of the data or information either does not add value and is unnecessary or has the potential to add value but not in its current state. An example of the waste of Form could be machine-readable data being presented to humans for use, or human-readable data being presented to machines for use; either way, it is not suitable.

5.5.2.2 Waste of Excess

The Excess category includes data and information that are in an amount greater than necessary. Duplicates of data or information are considered a waste of Excess because the same information is stored in multiple locations, which can lead to inconsistent (waste of Form) or incorrect (waste of Error) data. One of the simplest examples of the waste of Excess is too much data or information. Presenting too much data to the user can cause them to skip over necessary details or become overwhelmed by all the data or information they feel they must review. A manufacturing example of the waste of Excess is generating a full MRP report for the operations manager instead of a tailored report that simply provides the information needed to determine operational status. In this example, it is possible to see the interconnectivity of these waste categories as more information was reported to the operations manager than necessary (waste of Excess) in a form that was not optimal for their use (waste of Form).

5.5.2.3 Waste of Error

The Error category includes data and information that are incorrect, inaccurate, or incomplete. If the data is not current, it is historical, not timely, and therefore of no real value for making decisions on current production. Data or information that is manually entered (waste of Manual Intervention) incorrectly with typos is inaccurate and contains errors. Data or information that loses fidelity from translation is incorrect. Information that is incomplete or not captured is also considered an error because data that should be available is not present. Waste of Error can also be found where data duplicates (waste of Excess) do not match. If the data does not match, at least one data source is outdated or incorrect. An example of the waste of Error is wrong lead times in the ERP system. The lead times were likely correct when they were entered but have since become outdated.

5.5.2.4 Waste of Separation

Separation includes data or information that is not connected in a thread-like flow but could reap benefits if connected in an interoperable fashion. This waste arguably is the most detrimental because it leads to several other wastes. Software programs from different vendors that do not allow interoperability due to the proprietary nature of their products cause delays, errors, and manual intervention. When data is separated and stored in multiple different locations, there is a need to aggregate the data for decision-making. Pulling data together from various sources can take time (waste of Delay) and manual effort (waste of Manual Intervention). It can also cause a need to modify the data (waste of Change) because it is not in the right form (waste of Form) for aggregation.

The waste of Separation can be identified where there is a lack of communication, poor communication, or back-and-forth communication. These are indicators that data is not in the right place, at the right time, or in the right form to inform the best possible decision. If data were readily available and centralized, the back-and-forth communication between manufacturing departments would no longer be necessary. An example of the waste of Separation is using ERP software for scheduling but using a spreadsheet for material allocation. The data is not connected, but a significant amount of time and effort could be saved if material allocation were integrated into the ERP system.

5.5.2.5 Waste of Delay

The Delay category includes data and information being moved or transferred from one place to another, either manually or automatically, which causes time delays and adds to the overall lead time in delivering the product to a customer. It can also be the result of unknown or overlapping responsibilities of personnel where needed data is not moved because it was not considered as part of the job responsibilities or the thought that someone else had taken care of the transmission. The waste of Delay is often seen on the receiving end of data and information. A user is waiting on data or information because of a delay that is likely from several other wastes such as Change or Manual Intervention. Delivering and transferring data belong to the waste of Delay because these actions take extra time. For example, an operator waiting for work instructions, a schedule, or approval, is experiencing the waste of Delay.

5.5.2.6 Waste of Change

The Change category includes data and information being manipulated, modified, or transformed, typically to fit another purpose or to be viewed/consumed differently by a user. The waste of Change encompasses any action in which the data takes on a new form. The data itself or how the data is presented has changed. It is prevalent in manufacturing for various users to view the same data differently because they are trying to accomplish different yet related goals. The action of putting the data in other formats is a waste of Change. The waste of Change can also tie into the waste of Form because the waste of Form often leads to a need to modify the data. Reviewing, verifying, and validating data also falls into the waste of Change because each action ensures that data modifications are unnecessary. Reformatting or creating different versions of a schedule for different users is an example of waste of change.

5.5.2.7 Waste of Manual Intervention

The Manual Intervention category encompasses all human interactions with data and information that interrupt the flow of data and information. However, the waste of Manual Intervention could also appear in a digital form. The actions of manually collecting, entering, and searching for data would be considered Manual Intervention because a human interface is utilized. Retrieving and extracting data also fall into this category because these actions are taken by a person or software when systems are not interoperable (waste of Separation). Manual Intervention will almost always cause the waste of Delay because of the time spent on the intervention. A typical example of the waste of Manual Intervention is an operator manually entering machine downtime reasons. Manually entering data is also susceptible to typos (waste of Error).

5.5.2.8 Waste of Storage

The Storage category includes data retained with no apparent purpose or requirement for preservation. An example is the continued purchase of storage space for data with little or no access, activity, or review. Storage of data for the sake of keeping the data is a non-value-added activity that is costly. The waste of Storage can be found where data and information are stored, but there is no plan to retrieve or analyze the data. Data or information is being collected, but it is not being used to inform better decision-making. The data may have the potential to be analyzed or used for actionable change, but it is not in its current state. Storing data and information can also cause a need for retrieval, which may take time (waste of Delay) and effort (waste of Manual Intervention).

5.5.3 Application of the 8 Wastes for Data and Information

The 8 Data and Information Wastes inhibit an organization's ability to effectively and efficiently make decisions related to production and operations, resulting in poor system performance. Figure 16 depicts how data and information wastes inhibit the right data and information from being in the right place, at the right time, and in the right form to make the best possible decision. Minimizing and eliminating the eight wastes supports data and information value creation. All data and information flows do not necessarily experience all the wastes presented in Figure 16. However, it is common for one data and information waste to lead to another or several wastes to be present within one data and information flow. Identifying waste so that it can be eliminated is the key. It is not necessary to classify waste into only one category. Having categories of waste provides a method for spotting the various types of waste that might be present in data and information systems and begin the generation of methods and tools to minimize or eliminate the waste.

Inputs commonly involved in data and information value creation or the hindrance of it include the six elements listed on the left side of Figure 16: hardware, software, methods, connectivity, and management. The hardware and software used can be a source in which data and information wastes can be identified. For manufacturing, the software would include the enterprise resource systems, and the hardware would consist of the equipment upon which the software can be found. Methods include any data and information methods, or practices, performed concerning data and information. Connectivity refers to how data and information are connected or not connected. For example, interfaces and places of disjointed connectivity are sources where waste can be found. Management explicitly refers to the management of data and information (in other words, how the data is handled and managed). It is also important to consider all users as inputs because users are those that see the direct impact of data and information waste. It is typical to view a user as a human, but in a digital environment, the user can also include a digital interface in which data must be interpreted in its expected/standardized form.

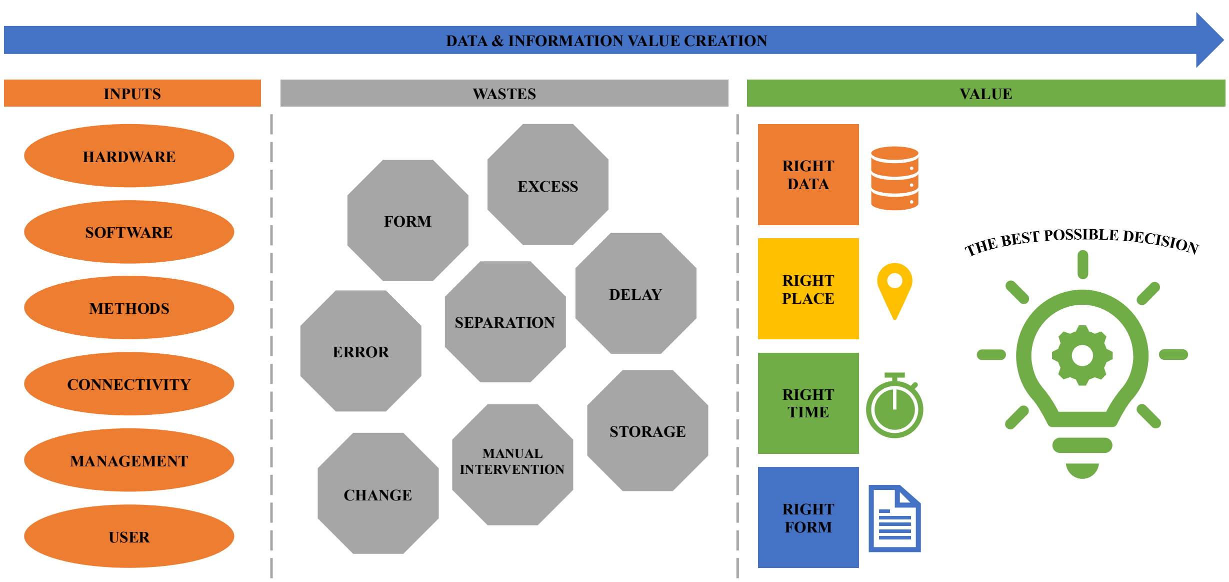


Figure 16 Data and Information Value Creation.

Much like the 7 Wastes of the TPS, it is envisioned that practitioners will utilize the 8 Wastes for Data and Information as a starting point to eliminate waste in data and information processes continuously. Searching for these 8 Data and Information Wastes will require that manufacturers start to understand the intricacies of their data and information flows entirely. Doing so will uncover the data and information practices that are value-added and non-value-added. Associates trained to identify the 8 Wastes for Data and Information can quickly identify improvement opportunities that can save time and money while increasing productivity and minimizing the previous effort spent on redundant data and information tasks that has been hidden in the overhead costs for years. Employees can repurpose their time to focus on forward-thinking and value-creating decisions. Identifying and eliminating data and information wastes will declutter data networks and generate data and information that is accurate, timely, and trusted.

Quantifying data and information wastes will assist in determining the time and costs associated with inaccurate and inefficient data and information practices. Tables 10-13 include metrics that should be considered when evaluating the impact of data and information wastes. Each metric is tied to value (right data, right place, right time, right form). Tying metrics to value ensures that non-value-added activities are identified for elimination, creating an environment that supports value creation. The 2nd-9th columns in Tables 10-13 indicate which waste categories are the most closely related to each metric. The 10th column of Tables 10-13 indicates if the metric should be minimized, maximized, or controlled, meaning that the metric needs to be observed over time. Controllable metrics are those that should not necessarily be minimized or maximized; a "good" value will vary from company to company and therefore "good" should be defined by the individual company. Most of these metrics can be converted to costs which is crucial in understanding the impact and importance of identifying and eliminating the non-value-added activities.

Each of these metrics should be measured with intent and purpose. It is not necessary to measure data and information flows for the simple sake of studying them. The outputs of these measurements should be used to enact change, understand the current state, and plan an improved future state in which the entire data and information system supports value creation. Before determining these metrics, one should foster a mindset of asking themselves, how do we measure for a purpose? Every organization should work to understand which metrics can increase return on investment in their system.

Table 10 presents metrics for “Right Data”. The amount of used data and unused data are metrics that should be controlled. The amount of data that a company collects will vary from company to company. Therefore, the amount of used and unused data will also vary. The time spent verifying and validating data is closely related six out of the eight waste categories. This reveals the significant amount of non-value-added activities that can occur in the quoting process when internal employees review TDPs for errors and inconsistencies and correct them. Time in error remediation can occur anywhere there is data that is incorrect and therefore must be corrected. The percentage of complete and accurate data can also be used in varying contexts. However, an example of using the metric would be to evaluate the incoming TDPs from customers. Having this metric should encourage customers to provide more complete and accurate data than before.

Table 10 Metrics for Data and Information Waste: Right Data.

	Waste Metric	Form	Excess	Error	Separation	Delay	Change	Manual Int.	Storage	Minimize (↓), Maximize (↑), or Control)	Definition	Unit
		Related Waste Categories										
RIGHT DATA	Amount of Used Data		X						X	**C**	Data used by software or human	Gigabytes, Megabytes, or Kilobytes
	Amount of Unused Data		X						X	**C**	Data not used by software or human	Gigabytes, Megabytes, or Kilobytes
	Time Verifying/Validating	X		X	X	X	X	X		↓	Time spent evaluating data/information to check for accuracy and completeness	Time
	Time in Error Remediation	X		X		X	X	X		↓	Time spent correcting data/information errors	Time
	Percentage of Complete/Accurate Data			X				X		↑	Percentage of incoming data that is complete and accurate	Percentage

Table 11 introduces metrics for "Right Place". All the metrics listed in Table 11 should be minimized. Data that is in the right place should not be found in disparate locations that would create the opportunity for mismatched and inconsistent data. If time is spent searching for data, it is not in the right place; therefore, time searching for data should be minimized. Transferring data from one location or software to another can be time consuming and costly and therefore should be minimized. Instances in which data is missing should also be minimized. A common example of this would be that an operator needs specific data to manufacture a part, but the operator does not have the data.

Table 11 Metrics for Data and Information Waste: Right Place.

	Waste Metric	Form	Excess	Error	Separation	Delay	Change	Manual Int.	Storage	Minimize (↓), Maximize (↑), or Control)	Definition	Unit
		Related Waste Categories										
RIGHT PLACE	Count of Disparate Locations	X	X		X					↓	Number of disparate locations in which the same data/information (and its other forms) is stored	Count
	Time Searching	X	X		X	X		X	X	↓	Time spent looking for the correct data/information	Time
	Count of Transfers	X			X			X		↓	Transmissions of the data/information from the point of creation or collection to the point of use or storage	Count
	Count of Instances of Missing Data	X		X	X					↓	Instances in which data/information is needed, but it is not present in its needed location	Count

Table 12 presents metrics for “Right Time”. Information lead time and time waiting should have a goal of minimization while time at rest and in use should be controlled by companies. The metrics of information lead time should be thought of in a similar manner to lead time for product flow. Each of the eight waste categories depict non-value-added activities that could impact the overall information lead time. Time waiting for data and information should always be minimized. However, this is not necessarily the case with time at rest and in use. Time at rest may be more meaningful to some companies than others. Data at rest is data that is not currently being used for actionable change and therefore could be costly in terms of storage. Time in use will also vary from company to company. An extended time in use could indicate that the data is not easy to interpret or its being evaluated for actionable change.

Table 12 Metrics for Data and Information Waste: Right Time.

		Related Waste Categories										
Waste Metric		**Form**	**Excess**	**Error**	**Separation**	**Delay**	**Change**	**Manual Int.**	**Storage**	**Minimize (↓), Maximize (↑), or Control)**	**Definition**	**Unit**
RIGHT TIME	Information Lead Time				X	X		X		↓	Time it takes from the point of data/information creation or collection to the point of use or storage	Time
	Time Waiting				X	X		X		↓	Time spent waiting on data/information	Time
	Time at Rest		X			X			X	**C**	Time data is at rest or not being used	Time
	Time in Use				X	X		X		**C**	Time data is being used by software or human	Time

Table 13 introduces metrics for "Right Form". The three metrics: time in manual intervention, count of manual interventions, and count of forms should all be minimized. Manual intervention is one of the eight wastes that should be mitigated. It is important to reduce the time spent in manual intervention and the occurrences of manual intervention to decrease the negative outcomes of the waste. Count of forms refers to the different formats that data or a dataset takes on during its lifecycle. While it may be positive to have several views of the data, it is not positive to have multiple forms and locations of the data because it creates opportunities for data inconsistencies.

Table 13 Metrics for Data and Information Waste: Right Form.

	Waste Metric	Form	Excess	Error	Separation	Delay	Change	Manual Int.	Storage	Minimize (↓), Maximize (↑), or Control)	Definition	Unit
		Related Waste Categories										
RIGHT FORM	Time in Manual Intervention	X				X	X	X		↓	Time spent to move data/information to the correct place or transform it into another form	Time
RIGHT FORM	Count of Manual Interventions	X		X	X			X		↓	Number of interventions that take place from the point of data/information creation or collection to the point of use or storage	Count
RIGHT FORM	Count of Forms	X	X					X		↓	Number of forms that data/information takes on from the point of data/information creation or collection to the point of use or storage	Count

5.6 Chapter Summary

In this study, interviews uncovered the vast amount of non-value-added activities that are present in today's manufacturing systems. This chapter presented eight waste categories to assist in the identification of non-value-added activities in the flow of data and information: (1) Form, (2) Excess, (3) Error, (4) Separation, (5) Delay, (6) Change, (7) Manual Intervention, and (8) Storage. These categories of waste are necessary to facilitate the creation of waste elimination solutions to achieve the value-added data and information flows that make manufacturers more competitive. Manufacturers can join the digitalization movement by using the eight categories presented in this chapter to start identifying wastes in their systems and then developing tools for minimizing and eliminating those wastes to develop optimized manufacturing information systems that improve organizational competitiveness.

Interviews revealed that manufacturers do not currently grasp what constitutes success in the flow of data and information. This chapter defined value in data and information as having the right data, in the right place, at the right time, and in the right form to inform the best possible decision. Metrics were also presented to quantify the impact of inefficient and inaccurate data and information practices.

Chapter 6 The Impact of Data and Information Wastes on the Manufacturing Plant Floor

6.1 Introduction

Now that the data and information wastes in manufacturing systems have been revealed (Chapter 5), it is prudent to evaluate the impact that the data and information wastes can have on manufacturing operations. This chapter answers the research questions: how do data and information wastes manifest themselves in manufacturing operations, and what is the potential impact of data and information waste on manufacturing processes? Answering these questions involved a quantitative analysis of data and information practices and plant operations. To form an abstraction and evaluate the manufacturing system, a simulation was created. The simulation discussed in this chapter demonstrates the impact of having and not having the right data, in the right place, at the right time, and in the right form to make the best possible decision.

6.2 Background

As mentioned across previous chapters, continuous improvement efforts in manufacturing are typically focused on the movement of product in plant operations and few efforts are focused on data and information flows that support the movement of product. Therefore, data and information wastes remain unanalyzed. Manufacturers need a method to visualize the effect that data and information wastes can have on operations. A common way to analyze manufacturing systems and isolate variables to assess their impact is through simulation. However, little literature can be found on simulation being used to simulate the interplay between data and information flows and product flows [66].

The eight data and information wastes identified in Chapter 5 are: (1) form, (2) excess, (3) error, (4) separation, (5) delay, (6) change, (7) manual intervention, and (8) storage. Many of these wastes happen before the information ever reaches the plant floor. For example, the if the work schedule is not in the correct form, manual intervention is required to make the necessary changes before the work schedule is delivered to the first operation. To provide another example, if there is an error in the work instructions or specifications, the error is likely created in within the business functions that happen before the issue arises on the plant floor, or worse, at the customer. Data and information wastes primarily manifest themselves on the plant floor in the form of data and information latency or errors. Whether the plant floor is waiting on information or if the information is wrong, serious issues can occur. A unique and novel simulation was created as a part of this research to demonstrate situations in which information causes delays.

6.3 Methodology

To better understand and evaluate data and information wastes in manufacturing systems, a simulation of an existing manufacturing system, a metal fabrication company, was developed using Simio simulation software. The company name and information are not shared due to confidentiality requirements. The company will be referred to as “The Company” in this study.

A discrete-event simulation (DES) approach was chosen over an agent-based simulation (ABS) approach because the DES approach allows the user to understand the state of the system at discrete points in time and to take an object-oriented approach [115]. An ABS approach would have focused on agents and how they interact with their environment and other agents; this was not the goal of the simulation. DES allows us to introduce delays and understand the impact on the overall manufacturing system. The interest is the impact on the manufacturing plant floor, not the data and information itself.

Section 6.3.1 describes the company's manufacturing system. Section 6.3.2 explains the input data collection and analysis that was performed for the simulation. Section 6.3.3 details how the simulation was developed. Section 6.3.4 discusses the assumptions and simplifications that were made during the model creation. Section 6.3.5 explains the verification and validation that were performed during the creation of the simulation. Section 6.3.6 describes the three simulation scenarios that were conducted to test the impact of data and information flows on manufacturing production systems.

6.3.1 System Definition

A high-level view of the company's manufacturing system is shown in Figure 17. Multiple customers send in order requests. If the order is accepted by the company, the order is added to the scheduling process. When it is time for the order to begin processing, the schedule is dispatched to the plant floor. A part router is matched up with the order on the plant floor. The part router contains printed information such as, but not limited to, a list of processes the part must undergo, 2D drawings, specifications, work instructions, quality documentation, and setup instructions for each operation. Each order consists of only one part type, and the router travels with the order. There are barcodes on the router that can be used to pull up a digital form of the information. The company is organized as a job shop in which orders follow different sequences that are defined by the order's process flow and work instructions.

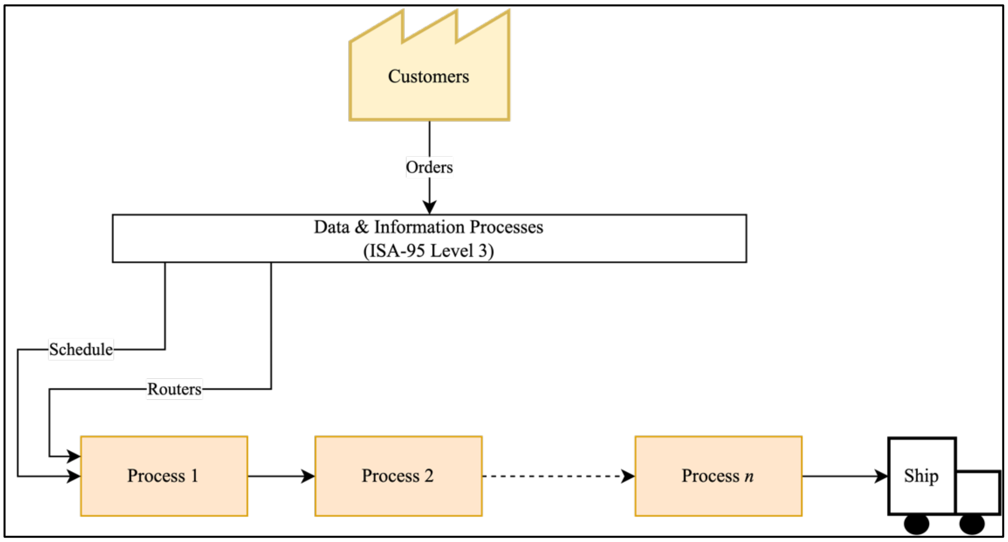


Figure 17 The Company's Manufacturing System.

There are many wastes that can be identified within the "Data & Information Processes" box that is shown in Figure 17, but the focus of this particular research is on the interplay between data and information and plant operations. For the company, data and information wastes can negatively affect the plant floor operations if there is a delay in receiving needed information such as the schedule or the part router or if the information is incorrect. For example, if any piece of information in the router is incorrect or if the digital information does not match the printed router, there is potential for an error to occur when processing a part, which can lead to costly defects, rework, and lost capacity.

6.3.2 Input Data Collection and Analysis

The company provided historical datasets to study the arrival of orders and the sequence that orders follow throughout the manufacturing system. The dataset included 39 weeks of order numbers, part numbers, operation codes, planned time at each operation, actual time at each operation, order arrival date, and order due date.

The company experienced an unusual influx of orders in January due to orders that were not accepted over the holidays. The daily number of order arrivals was not reflective of the company's typical order arrivals. The data was cleaned by performing an outlier test using Minitab, and outliers in the arrival data were removed. More information about the outlier test and a goodness of fit test data can be found in Appendix F. The arrival data and sequence data that were provided by the company were used as input data in the simulation. The company also provided work schedules with shift and break times to include in the simulation.

6.3.3 Building the Simulation

The simulation described in this section is a deterministic DES. A deterministic model was chosen because of the high level of data fidelity that was provided and because the complex manufacturing system could be represented through logical steps and processes. The simulation shows an abstraction of what happened in the real-world manufacturing operations. Making changes to the deterministic model allows the focus to be on the specific changes that are made to the model, and probability does not influence the results. The main drawback of a deterministic simulation is that the simulation will only reflect what actually occurred on the plant floor without including the randomization of incoming orders (which would be stochastic). A deterministic simulation was sufficient at this stage in the research because the company has a high level of volatility in their incoming orders, and a large dataset was provided which increased the complexity of the input data.

A baseline model of the simulation was developed so that various scenarios could be executed and analyzed against the baseline model. The baseline model consisted of 1 source, 19 servers, 1sink, and 1 model entity (Figure 18). For detailed notes on how the simulation was developed, see Appendix G.

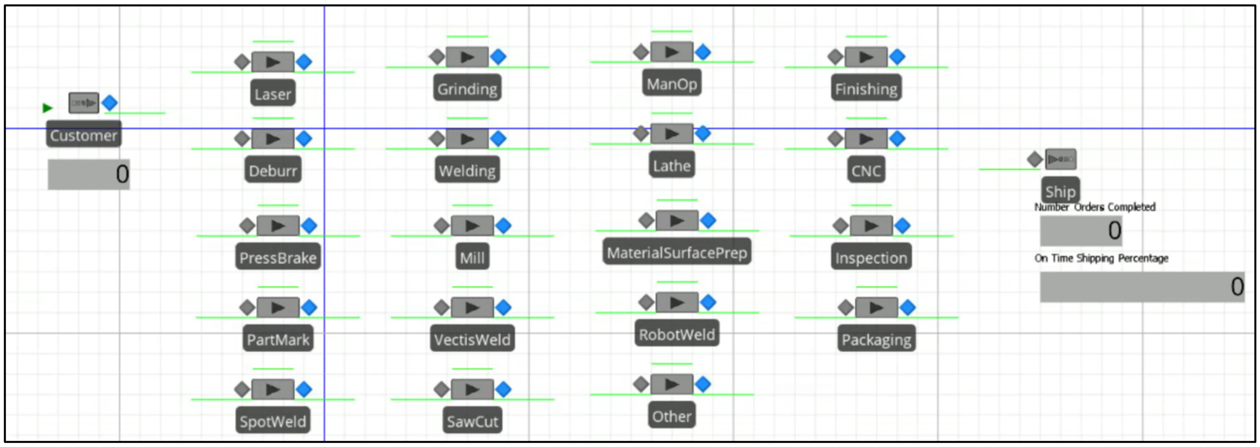


Figure 18 Baseline Model.

Two tables were created from the datasets: Arrivals and Sequence. The Arrivals and Sequence tables are relational tables that are connected through a Primary Key (PK), called Order ID, in the Arrivals table. Order ID is a Foreign Key (FK) in the Sequence table; in other words, the Sequence table references the Arrivals Table through the Order ID. The connection of the relational tables is shown in Figure 19. The columns in the Arrivals Table are Order ID, Mix, Estimated Time (Hours), Arrive Time Date-time Group (DTG), Completion DTG, Arrive Time (Hours), Completion Time (Hours), and Due Time (Hours). "Mix" is the percentage of each order type. In this case, the mix for each order had a value of one because each Order ID was unique and not repeated. DTG columns were created to ensure that the number of hours corresponded with the expected dates and times. The columns in the Sequence Table are Order ID, Sequence, Processing Time (pTime) (Hours), and Router Time (Minutes).

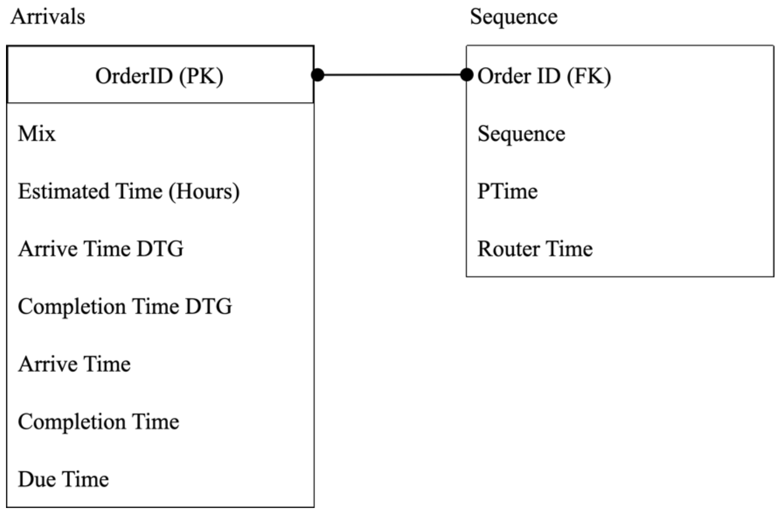


Figure 19 Relational Tables.

The source object, Customer, generates model entities, called Orders, based on the Arrival Table. From the Arrivals Table, each entity is assigned an Order ID, a total estimated time for processing (Estimated Time), an arrival time DTG (Arrive Time DTG), and a due time (Due Time). From the Sequence Table, each entity is assigned a list of operations based on its Order ID and processing times for each operation. The arrival time and due time are set when the entity enters the output buffer of the source object. The number of entities in the system, a variable called Number in System (NIS), is also calculated as entities enter the output buffer of the source object. The due time is calculated by adding the total estimated processing time to the arrival time and adding three days (or 72 hours) of queue time because the company typically adds time for queue waiting. Changes in output statistics such as on-time shipping percentage are more visible, and the impact of data and information issues can be studied more closely. Further constraining the due time reduces the likelihood of orders being on time.

The company's 19 operations are represented by servers in the simulation. The servers can be seen in Figure 18. The company does not run production on weekends, leaving only five days of production per week. Since the company does not run 24 hours, 7 days per week, work schedules were implemented at each server; doing so provides constraints on when the servers can run. The company's work schedules include two shifts that are approximately eight hours each with breaks. When the company is not producing, the servers stop running and switch to an off-shift mode. When servers are in an off-shift mode, they turn white (Figure 20). The laser operation is an exception to the work schedules because the laser can run 24 hours, 7 days per week, and the company runs the laser as parts arrive. Including work schedules was a necessary level of complexity to add to the simulation because servers spend approximately 50% of the time in an off-shift mode.

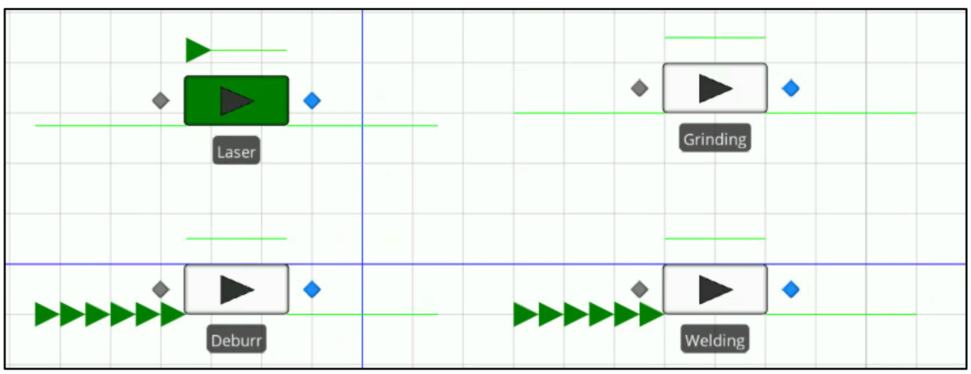


Figure 20 Off-shift Servers in White.

The sink object, called "Ship", is used to remove entities from the simulation when they are finished processing. Shipping does not have a processing time. The sink is used to decrement the NIS value and increment the number of completed orders. The sink also stores the completion time and completion time DTG for each completed order.

6.3.4 Assumptions and Simplifications

Assumptions and simplifications were used in the creation of the Simio model to reduce complexity and maintain a focus on identifying the impact of data and information wastes on the manufacturing plant floor. The assumptions and simplifications are listed below.

- **Holidays:** For simplification purposes, the simulation does not consider holidays. The company observes 10 holidays a year. Incorporating off-shift days for holidays adds unnecessary complexity to the simulation.
- **Laser:** To simplify the laser cutting operation, each order goes through the laser one order at a time. This does not account for the size, geometry, or thickness of the parts. It also does not consider the quantity of the parts and the possibility of using multiple sheets of metal for one order. Though these assumptions seem significant, they are not. If an order requires the laser operation, it is always the first operation. The laser is not a bottleneck; it can run 24 hours, 7 days per week. In the simulation, an order moves to the next process instead of waiting for the full metal sheet to finish with the laser process. This simplification significantly decreases the complexity of the simulation and removes the need for combiners and separators for the parts and would not add to the robustness of the study of data and information flow issues. It also removes the need to collect proprietary data that the company deems as sensitive information.
- **Material Handling:** One of the assumptions is that entities move from one operation to another in zero time. Therefore, the model is simplified by not considering material handling. In Simio, this is accomplished by setting the initial desired speed of the entities to infinity. Removing material handling is a reasonable assumption because orders spend

more time in the next process' queue as opposed to the output queue of the operation that it most recently completed.

- **Order Separation:** Parts within an order cannot be separated or go on various machines within one server object. Orders can only be processed on one machine. For example, if the deburr server has a capacity of two, two orders can be processed at the deburr server at one time. The ability to separate parts within an order would add significant complexity to the simulation by requiring combiners and separators and not add value to the analysis of data and information flow issues in the operations of the company.
- **Shipping:** When an order is finished processing, it enters the sink object, "Ship". The entity is no longer of interest when it enters the sink object. Therefore, shipping and preparation for shipping times are not considered in the simulation for simplification purposes. When operations are complete for an order, the order is considered complete.

6.3.5 Verification and Validation

Verification was conducted as an ongoing process as the simulation model was developed. Initially, the simulation only had 1 source, 1 server, 1 sink, and 1 model entity. The system utilized Poisson distributed interarrival times (M), exponentially distributed service times (M), and one server (1); this is denoted as an M/M/1 system. Queueing verification was used to determine if the outputs of the simulation equated to the M/M/1 queueing results. The equations for an M/M/1 system are shown in Table 14 [116].

After adding 18 more servers for a total of 19, a Jackson Network Excel template was used to verify the queueing results. A Jackson Network is used for analysis when there are multiple servers in a system or in other words, multiple nodes that entities can enter [117]. A Jackson Network defines the interarrival process of each server, the probabilities that an entity will go to other servers or return to the same server, and the probability that an entity will leave the system from its current server. The results of the Jackson Network model and the Simio model are shown and compared in Table 15 and Table 16. There was a less than 0.3% difference in the Jackson Network Model and the Simio model for all the server utilizations (Table 15) which was an accepted level of accuracy, indicating the model is running as intended [118]. The number of parts in the system and the overall throughput had very similar values when comparing the Jackson Network results to the Simio model (Table 16). The time orders spent in the system was not quite the same between the Jackson Network and the Simio model. However, the job shop layout and sequencing of orders accounts for the difference in the two values.

Table 14 M/M/c Queueing Results [116].

	M/M/1	
$p(0)$	$1-\rho$	Where: λ average arrival rate, μ average service rate, $\rho = \frac{\lambda}{c\mu}$ utilization factor, L expected number of customers at the workstation, W expected throughput time for an arbitrary customer, and q queue at the workstation.
L_q	$\frac{\rho^2}{1-\rho}$	
L	$\frac{\rho}{1-\rho}$	
W_q	$\frac{\rho}{\mu(1-\rho)}$	
W	$\frac{1}{\mu(1-\rho)}$	

Table 15 Jackson Network Queueing Verification: Utilization.

	Utilization									
	Laser	**Deburr**	**Part Mark**	**Press Brake**	**Machin-ing**	**Welding**	**Saw Cut**	**Lathe**	**Mill**	**Other**
Jackson Network	91.98%	91.98%	6.79%	35.22%	7.39%	9.25%	1.40%	0.39%	1.01%	7.80%
Simio	91.73%	91.78%	6.80%	35.22%	7.58%	9.14%	1.46%	0.37%	1.00%	7.92%
Difference	0.256%	0.206%	0.003%	0.008%	0.189%	0.115%	0.060%	0.028%	0.001%	0.127%

Table 16 Jackson Network Queueing Verification: Parts in System, Time in System, and Throughput.

	L (Parts in System)	W (Time in System)	Throughput (parts/hr)
Jackson Network	23.863	357.941	4.000
Simio	22.694	339.330	4.004
Difference	1.169	18.611	0.004

The creation of a Plan in the Simio Planning Tab was used for further verification purposes. The Plan included a Resource Plan and an Entity Workflow. The Resource Plan showed each of the servers, the orders being processed by each server, the capacity of each server (changes to zero during breaks), and constrained entities (the entities that cannot be processed because the server is full). The Resource Plan verified the capacity of each server was correct by displaying the number of orders being processed at any given time. The work schedules were verified by viewing the capacity changing to zero during off-shift times such as breaks and weekends. Figure 21 shows an example of the Resource Plan when deburr has a capacity of five. To the right of the deburr row, there are five colored rows representing there are five orders in the deburr server. To the right of the Capacity row, there are two colors that denote the capacity state of the server. White denotes a capacity of zero and the other color denotes a capacity of five. To the right of the Constrained Entities row, there are multiple rows of constrained entities that are in the queue of deburr waiting to be processed.

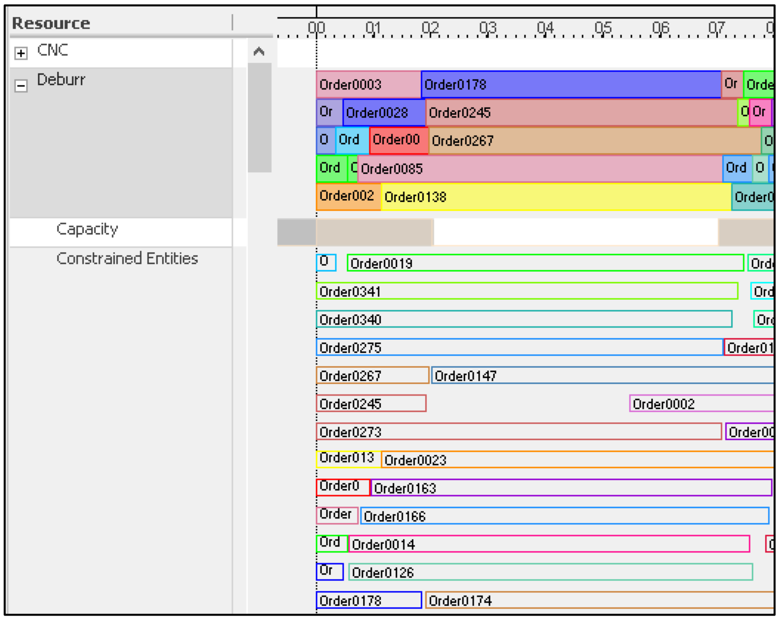


Figure 21 Example of Resource Plan.

The Entity Workflow verified that each order followed the sequence of operations as defined in the Sequence Table. The arrival times, processing times, and completion times were also verified by viewing the time at which the order arrived, the amount of time the order spent processing at each server, and the time that the order was completed; the values in the Entity Workflow were compared to the Arrivals Table to ensure that the values matched the expectation. For example, according to the Sequence Table, one of the orders should follow a sequence of spot weld, press brake, then ship, and according to the Arrivals Table, the order should arrive on Monday, April 11, 2022. As shown in Figure 22, the order went to spot weld, but the process was busy processing other orders. When spot weld became available, the order was processed and continued to the press brake operation. Therefore, the order followed its intended order of operations, and its sequence is verified. Figure 22 also shows that the order arrived on Monday, April 11, 2022, as intended. Therefore, the order arrived at its intended arrival time, and its arrival time is verified.

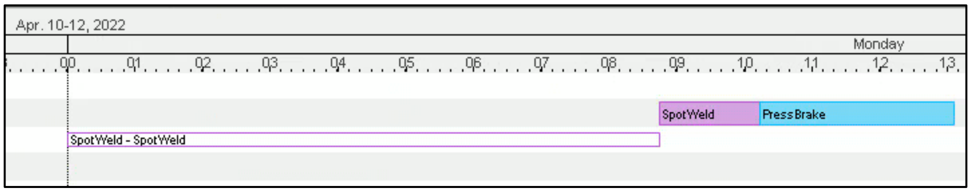


Figure 22 Example of Entity Workflow.

The most basic form of validation that was used was face validity. It was confirmed that the look of the model is reflective of the manufacturing operations. Each server in the simulation represents a group of machines that are of the same type which is similar to the layout of the manufacturing facility.

Status labels were created to track the number of entities that were created by the source object, the number of completed entities, and the on-time shipping percentage. The three status labels can be seen in Figure 18. When setting the simulation to run for a specific run length, the simulation accurately created the entities as specified. The on-time shipping percentage was also within 1% of the on-time shipping percentage that was actually achieved by the company.

A graph of the arriving entities was created to ensure that entities only arrive on weekdays since the company only pushes orders to their first process on weekdays. The iterative staircase pattern that can be seen in Figure 23 shows the spike of order arrivals on weekdays and no order arrivals on weekends.

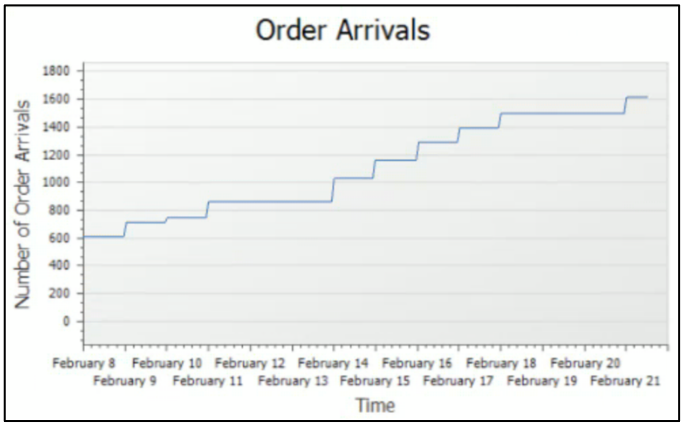


Figure 23 Graph of Entity Arrivals.

A graph of the number of entities in each server's queue was also created to ensure that the processing logic and server properties were properly implemented (Figure 24). Each colored line in Figure 24 represents the number of entities in a server's queue. As expected, the queues increased on weekdays and did not change on weekends. The queues deplete each day as the orders are processed.

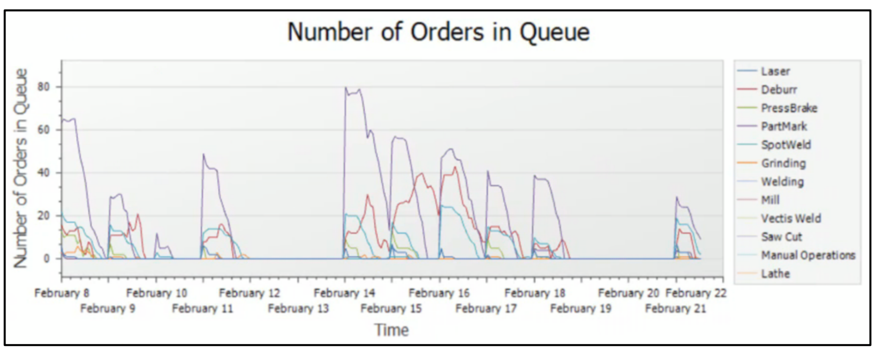


Figure 24 Graph of Number of Entities in Server Queues.

6.3.6 Simulation Scenarios

The methodologies behind the three simulation scenarios are explained in the following subsections.

6.3.6.1 Scenario 1

The first simulation scenario was created to compare three methodologies that can be utilized to run a manufacturing facility: (1) first in, first out (FIFO), (2) earliest due date (EDD), and (3) EDD at the first operation and FIFO at the following operations. A system that runs with a FIFO methodology does not use information such as due date or processing time to determine which order to process next. Instead, the order that is processed next is determined by the order in which work orders arrive in the queue. On the other hand, running a manufacturing plant with an EDD methodology requires that each operation's queue be ordered by due date. The operator is provided with due date information, and the operator determines the next work order to process based on the order that is due the soonest. A dispatch list is one way that operators can see the orders in their queue ordered by due date. The third methodology utilizes a combination of FIFO and EDD. Work orders start in EDD order, but as the work orders continue to subsequent operations, the work orders follow a FIFO pattern.

The first methodology, all FIFO, represents a manufacturing system that does not use information to guide their order of operations as the operation simply process orders in the sequence in which they arrive. The second methodology, all EDD, represents a manufacturing system that uses due date data to determine their order of operations; therefore, the efficiency of the data and information system has a significant impact on operational performance. The facility would need updating information on orders in each of the operations' queues to accomplish this methodology. The third methodology, a combination of FIFO and EDD, represents a manufacturing facility that deploys a schedule that follows EDD initially, but the data does not update as the manufacturing of orders progress.

Ranking Rule	First In First Out
Dynamic Selection Rule	None
▸ Transfer-In Time	0.0
Process Type	Specific Time
Processing Time	Sequence.PTime
Off Shift Rule	Suspend Processing

Figure 25 Scenario 1: FIFO Processing Logic.

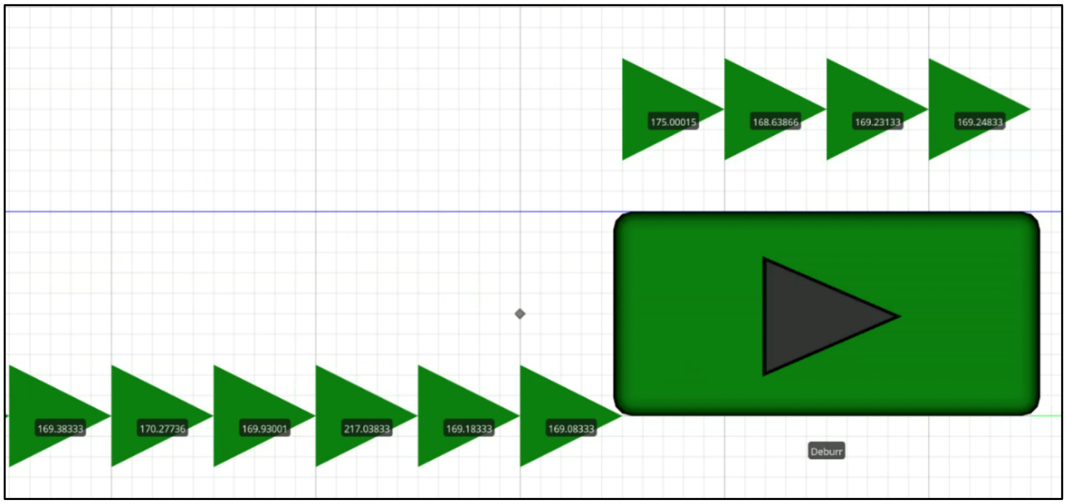
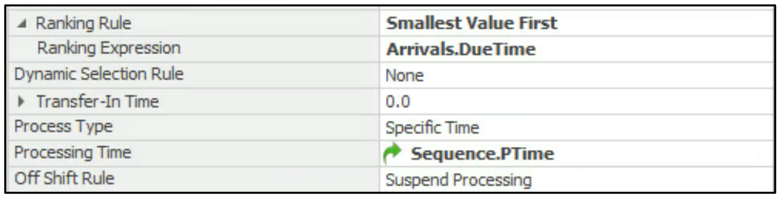


Figure 26 Scenario 1: Example of a FIFO Queue.

These three methodologies were built in the simulation using varying queue logic. All FIFO did not require any changes to the baseline simulation; this is because Simio automatically sets the servers to run in a FIFO manner (Figure 25). An example of a queue that is ordered with a FIFO methodology is shown in Figure 26. The values on each of the entities correspond to the "Due Time" of the order. For the second methodology, where all queues are ordered by EDD, changes were made to each of the servers so that the next order is selected by the EDD (or in Simio, smallest "Due Time" value from the Sequence Table). For the third methodology, only the Laser operation was changed from FIFO to EDD logic. The Simio logic for EDD is shown in Figure 27. An example of a queue that is ordered with an EDD methodology is shown in Figure 28. Notice the difference between FIFO and EDD ordered queues- the orders in the queue are ordered sequentially by their "Due Time" value in front of the server.



Ranking Rule	**Smallest Value First**
Ranking Expression	**Arrivals.DueTime**
Dynamic Selection Rule	None
Transfer-In Time	0.0
Process Type	Specific Time
Processing Time	**Sequence.PTime**
Off Shift Rule	Suspend Processing

Figure 27 Scenario 1: EDD Processing Logic.

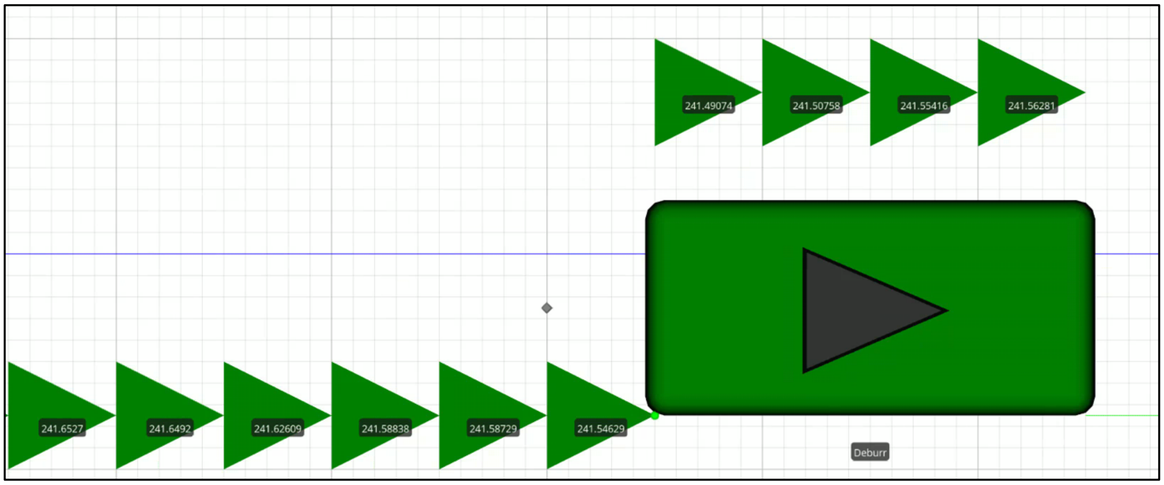


Figure 28 Scenario 1: Example of an EDD Queue.

6.3.6.2 Scenario 2

The 2nd Scenario was created to represent the impact of delays in receiving information on the plant floor. A sensitivity analysis was conducted by introducing information delays in plant operations. Information delays can come in many forms. Plant operations can experience delays in receiving information such as but not limited to, a schedule, work instructions, specifications, part geometry, drawings, models, routers, machine code, and authorizations. These pieces of information are referred to as production rules and operational commands in ISA-95 (described in Section 5.2.1). As shown in ISA-95 (Figure 9), it is common for production rules to come from a product definition function and for operational commands to come from a production execution management function. Therefore, it is easy for the two functions to lose synchronization, resulting in the operator experiencing a delay in receiving information, a mismatch in information, or not having the complete information that is needed to complete the task.

The information delay that is modeled in Scenario 2 is a part router being matched with its corresponding order. For the company, a part router is a packet of paper-based information that includes a list of processes that the order must go through, quality documents, part specifications, and part drawings. The router also has barcodes that can be used to pull up a digital form of the information. The routers are delivered by an individual to the operation; this is an example of the data and information waste of manual intervention. A manufacturing associate then matches the routers to their corresponding orders. For the company, this task can occur at the deburr, welding, or saw cut operations. Most of the orders go from the laser to the deburr operation, and therefore, the parts are not yet marked when arriving at the deburr station. Since the parts are not marked, grouping the parts by order and matching them with the correct router can be a difficult task.

A manufacturing system with no information delays has the right data, in the right place, at the right time, and in the right form to make the best possible decision. In other words, the information does not have a negative impact on the plant operations. However, this perfect information world is not realistic due to the information wastes that were identified in Chapter 5. Having minor or significant information delays is more realistic. Introducing a minor information delay allows us to see if the impact on the plant floor is minor also or if there are larger implications that cost time and money. A sensitivity analysis was used to test various values for the time it may take to match a router with its order.

In Simio, task sequences were added to the deburr, welding, and saw cut operations to account for the time that it takes for an order to be matched with its router (Figure 29). Matching the router with the order occurs before the processing at the deburr, welding, and saw cut operations (Figure 30). The sequence numbers default to increments of ten to indicate the order of task sequences. Matching a router with an order is conditional; it only occurs if the router time specified in the Sequence Table is greater than zero. If so, the processing time for the "Router" task sequence is equal to the router time that is specified in the Sequence Table. The "Processing" task sequence always occurs to account for the processing of the order at its current operation. The Auto Cancel Trigger is set to none to ensure that the "Processing" task sequence occurs even if the "Router" task sequence does not occur.

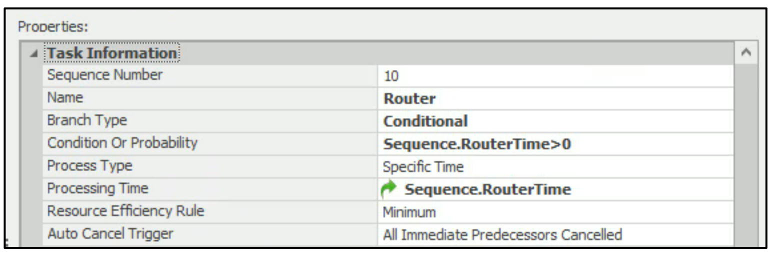


Figure 29 Scenario 2: Task Sequence for Matching Routers with Orders.

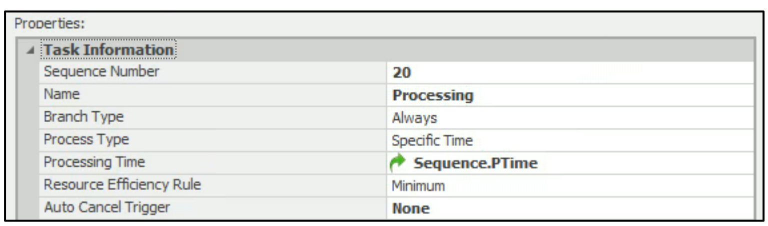


Figure 30 Scenario 2: Task Sequence for Processing Time at Stations with Router Matching.

The time that it takes to match a router with its corresponding order is defined in the Sequence Table. Randomly exponentially distributed times and deterministic times were used as input data for the router matching activity. Times of 1, 5, 10, 15, 20, 25, and 30 minutes are used to observe the implications of increasing the time that it takes to match each order with a router. Exponential and deterministic time values were used to determine if there was a significant difference in randomly distributed times versus deterministic time values.

6.3.6.3 Scenario 3

The company can accept priority orders because of their ability to order queues by EDD. Without the proper information structure, the company would have difficulty understanding its ability to accept a priority order, and the company would have little transparency into how priority orders affect other orders in the system.

The third simulation scenario builds on Scenario 1 and Scenario 2. It aims to understand the impact of priority orders. For the purposes of the simulation, priority orders are defined as orders that arrive with a due date that only allows for one day of queue time (24 hours) instead of three days of queue time (72 hours). This simulation scenario introduces priority orders in all EDD manufacturing environment (building on Scenario 1). The scenario also uses part router matching of five minutes per order (building on Scenario 2); five minutes was chosen because it is the typical time that it takes the company to collect the parts in an order and match the order with its corresponding part router.

To create priority orders in Simio, two servers were added to the system: a “NotPriority” server and a “Priority” server (Figure 31). Instead of orders going from the customer to their first operation, a specified percentage of the orders go to the “NotPriority” server and the rest of the orders go to the “Priority” server. The processing times at both servers are zero because there is no time associated with assigning an order a priority. To send the entities to their first operation, the output nodes at both servers have a routing logic of “By Sequence.”

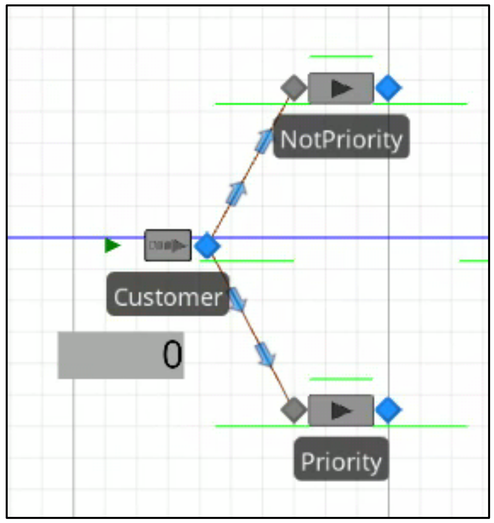


Figure 31 Scenario 3: Non-priority and Priority Servers.

When orders enter the "Priority" server, they are assigned a new due date (1st row in Figure 32), a new color (2nd row in Figure 32), and a priority value of one (3rd row in Figure 32). The new color of red is used to differentiate priority orders from non-priority orders (Figure 33). The priority value is binary: zero for non-priority and one for priority. This allows us to separate the simulation results by non-priority orders and priority orders. As shown in Figure 33, priority orders are correctly ordered before non-priority orders in the queue.

Figure 32 Scenario 3: Priority Server State Assignments.

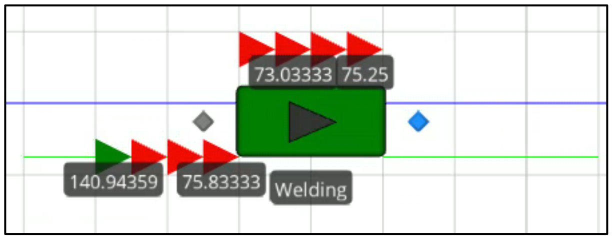


Figure 33 Scenario 3: Non-priority entities (green), Priority entities (red).

Several state assignments were added to the sink object to create the needed output statistics (Figure 34): total time priority orders spend in the system (5th row), total number of priority orders (6th row), total time non-priority orders spend in the system (7th row), and total number of non-priority order (8th row).

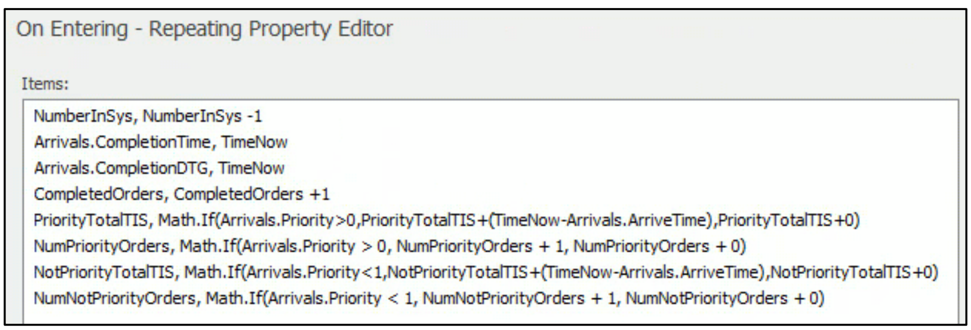


Figure 34 Scenario 3: Sink State Assignments.

An add-on process was also added to the sink object to create the needed output statistics (Figure 35). The first decide step determines if the order was completed on time or not (Figure 36). If so, the order moves to the second decide step. If not, the order completes the sink add-on process, and the entity is removed from the system. The second decide step determines if the order is a priority or not a priority (Figure 37). If the order is a priority, the total number of on time priority orders is increased by one (Figure 38). If the order is not a priority, the total number of on time non-priority orders is increased by one (Figure 39).

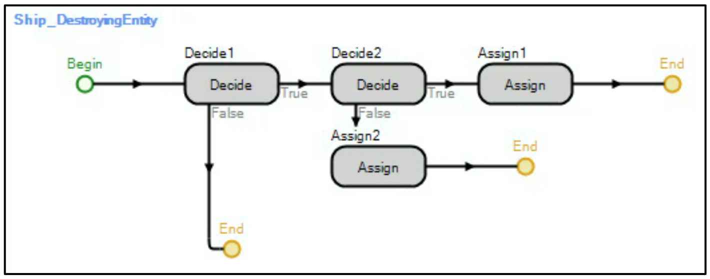


Figure 35 Scenario 3: Sink Add-on Process.

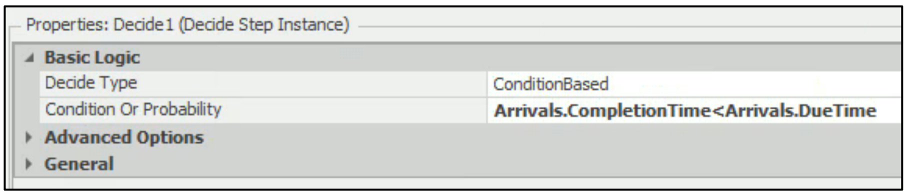


Figure 36 Scenario 3: Sink Add-on Process, 1st Decide Step.

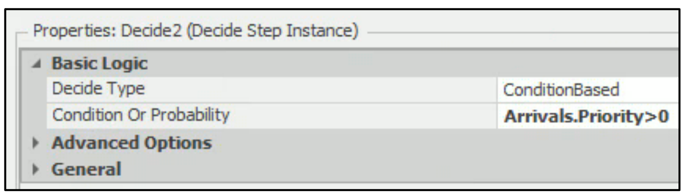


Figure 37 Scenario 3: Sink Add-on Process, 2nd Decide Step.

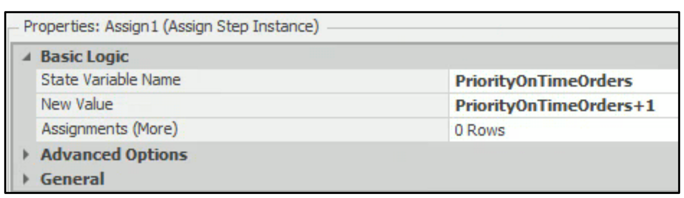


Figure 38 Scenario 3: Sink Add-on Process, 1st Assign Step.

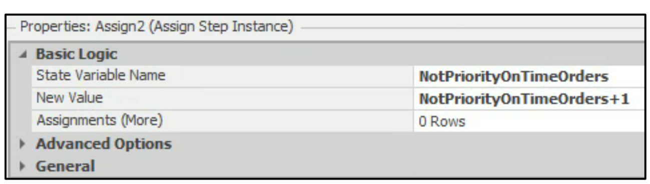


Figure 39 Scenario 3: Sink Add-on Process, 2nd Assign Step.

Four output statistic elements were added so that the simulation results would show the output statistic values: the average time in system for priority orders ("PriorityTISAverage" in Figure 40), the average time in system for non-priority orders ("NotPriorityTISAverage" in Figure 41), on time percentage for priority orders ("PriorityOnTimePercentage" in Figure 42), and on time percentage for non-priority orders ("NotPriorityOnTimePercentage" in Figure 43).

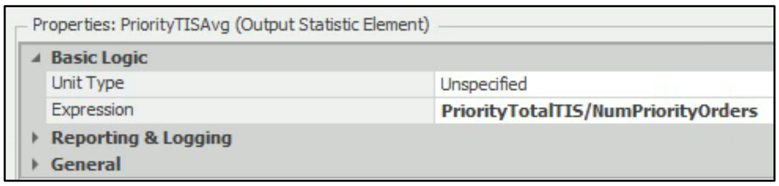


Figure 40 Scenario 3: Output Statistic- Average Time in System for Priority Orders.

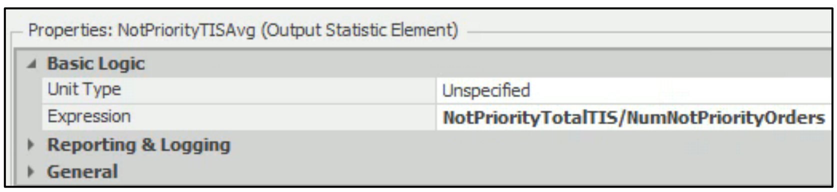


Figure 41 Scenario 3: Output Statistic- Average Time in System for Non-priority Orders.

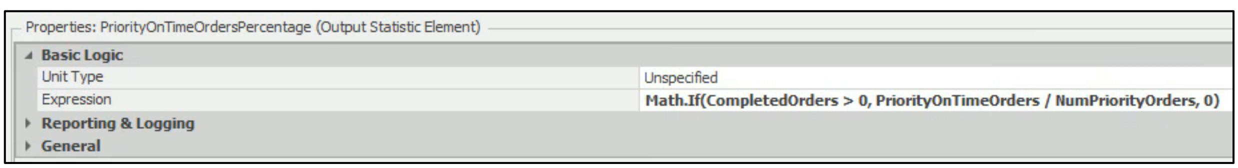


Figure 42 Scenario 3: Output Statistic- On Time Orders Percentage for Priority Orders.

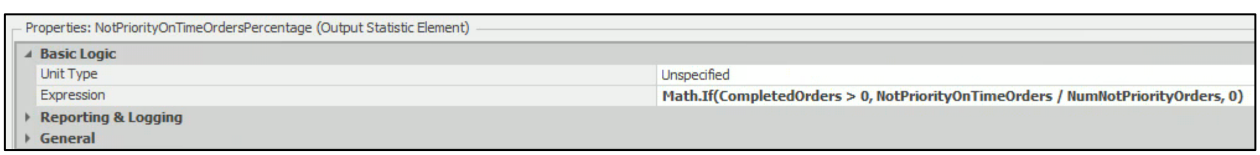


Figure 43 Scenario 3: Output Statistic- On Time Orders Percentage for Non-priority Orders.

6.4 Results

The results of the three simulation scenarios are explained in the following subsections.

6.4.1 Scenario 1 Results

The results of Scenario 1 demonstrate the positive and negative implications of running an all FIFO methodology, all EDD methodology, and an EDD at the laser operation strategy (Table 17). The output statistics for each of these methodologies are shown in the columns that are highlighted in grey, and comparisons of these methodologies are shown in the last three columns of Table 17.

For the average and maximum number of orders in the system and time the order spends in the system, a negative value indicates improvement. For the on time orders percentage and throughput, a positive value indicates improvement. However, for the company, delivering orders on time and having a higher on time orders percentage is more important than increasing throughput. Desirable values are highlighted in green. Output statistics that are not desirable are highlighted in red.

Table 17 Scenario 1 Results.

	Simulation Results			Percent Change		
	All FIFO	Laser EDD	All EDD	All FIFO vs. Laser EDD	Laser EDD vs. All EDD	All FIFO vs. All EDD
Average Number of Orders in System	60.2	58.7	49.2	-2.5%	-16.2%	-18.3%
Maximum Number of Orders in System	248.0	248.0	224.0	0.0%	-9.7%	-9.7%
On Time Orders Percentage	97.3%	97.5%	98.5%	0.2%	1.1%	1.3%
Average Order Time in System	19.5	19.0	16.0	-2.5%	-16.2%	-18.3%
Maximum Order Time in System	225.7	226.5	217.3	0.3%	-4.1%	-3.7%
Throughput (orders per weekday)	105.4	105.2	105.2	-0.2%	0.0%	-0.2%

Overall, the all EDD methodology resulted in the most favorable results. The all EDD methodology had the lowest average and maximum number of orders in the system and the lowest time orders spend in the system. All EDD also had the highest on time orders percentage. For the company, the decrease of less than 0.5% in throughput would not be a concern because the on time orders percentage is the preferred performance metric to gauge success.

6.4.2 Scenario 2 Results

The results of Scenario 2 demonstrate the negative impact that information delays can have on a manufacturing system (Table 18, Table 19). Scenario 2 builds on Scenario 1 by using the all EDD queue strategy for the baseline simulation. The following tables present a comparison of a system that organizes all its queues by EDD with no information delays due to automated router matching versus a system that organizes all queues by EDD with information delays due to manual router matching. The data presented in Table 18 is based upon randomly distributed exponential time values, and the data presented in Table 19 is based upon deterministic time values. The baseline column that is used for the percentage change calculations is highlighted in grey. Cells that are highlighted in red indicate a negative impact due to information delays. Cells that are not highlighted and are white indicate there is no significant impact due to information delays.

Table 18 Scenario 2 Results: Randomly Distributed (x) Minutes.

	Simulation Results All EDD vs. All EDD with Routers								**Percent Change All EDD vs. All EDD with Routers**						
	Randomly Distributed Exponential (x) Minutes								**Randomly Distributed Exponential (x) Minutes**						
	0 All EDD	**1**	**5**	**10**	**15**	**20**	**25**	**30**	**1**	**5**	**10**	**15**	**20**	**25**	**30**
Average Number of Orders in System	49.2	52.1	68.0	121.4	251.4	369.6	591.2	795.0	6.1%	38.4%	146.9%	411.4%	651.8%	1102.7%	1517.3%
Maximum Number of Orders in System	224.0	226.0	276.0	361.0	586.0	846.0	1144.0	1455.0	0.9%	23.2%	61.2%	161.6%	277.7%	410.7%	549.6%
On Time Orders Percentage	98.5%	98.4%	96.1%	87.8%	65.8%	61.4%	49.2%	42.1%	-0.1%	-2.4%	-10.9%	-33.2%	-37.6%	-50.1%	-57.3%
Average Order Time in System	16.0	16.9	22.0	38.7	77.4	112.8	178.3	238.4	6.0%	38.0%	142.5%	385.4%	607.2%	1018.0%	1394.6%
Maximum Order Time in System	217.3	217.5	217.6	234.6	331.4	407.3	561.9	682.0	0.1%	0.2%	8.0%	52.5%	87.5%	158.6%	213.9%
Throughput (orders per weekday)	105.2	105.2	105.0	104.2	99.6	96.3	92.7	89.6	0.0%	-0.1%	-0.9%	-5.3%	-8.4%	-11.8%	-14.7%

Table 19 Scenario 2 Results: Deterministic (x) Minutes.

	Simulation Results All EDD vs. All EDD with Routers								**Percent Change All EDD vs. All EDD with Routers**						
	Deterministic (x) Minutes								**Deterministic (x) Minutes**						
	0 All EDD	**1**	**5**	**10**	**15**	**20**	**25**	**30**	**1**	**5**	**10**	**15**	**20**	**25**	**30**
Average Number of Orders in System	49.2	52.0	67.6	119.9	248.7	373.2	584.6	793.5	5.9%	37.5%	143.9%	405.8%	659.1%	1089.2%	1514.3%
Maximum Number of Orders in System	224.0	226.0	275.0	360.0	590.0	853.0	1144.0	1456.0	0.9%	22.8%	60.7%	163.4%	280.8%	410.7%	550.0%
On Time Orders Percentage	98.5%	98.2%	96.1%	88.1%	65.8%	61.2%	49.9%	42.0%	-0.3%	-2.4%	-10.5%	-33.2%	-37.9%	-49.3%	-57.3%
Average Order Time in System	16.0	16.9	21.9	38.2	76.5	113.8	176.2	238.1	5.8%	37.1%	139.4%	379.4%	613.3%	1004.8%	1392.7%
Maximum Order Time in System	217.3	217.4	217.7	233.7	328.8	457.0	561.2	683.3	0.1%	0.2%	7.5%	51.3%	110.3%	158.3%	214.5%
Throughput (orders per weekday)	105.2	105.2	105.0	104.3	99.6	96.4	92.6	89.7	0.0%	-0.1%	-0.8%	-5.3%	-8.3%	-11.9%	-14.7%

For both randomly distributed router time values and deterministic router time values, all output statistics were impacted negatively due to information delays caused by router matching except throughput at a time value of 1 minute. Throughput did not experience a decrease of more than 5% until the router matching reached 15 minutes per order. The average number of orders in the system and the average time orders spend in the system were impacted the most by information delays. The maximum and average number of orders in the system are shown in Figure 44 and 46. The maximum and average time orders spent in the system are shown in Figure 46 and 48.

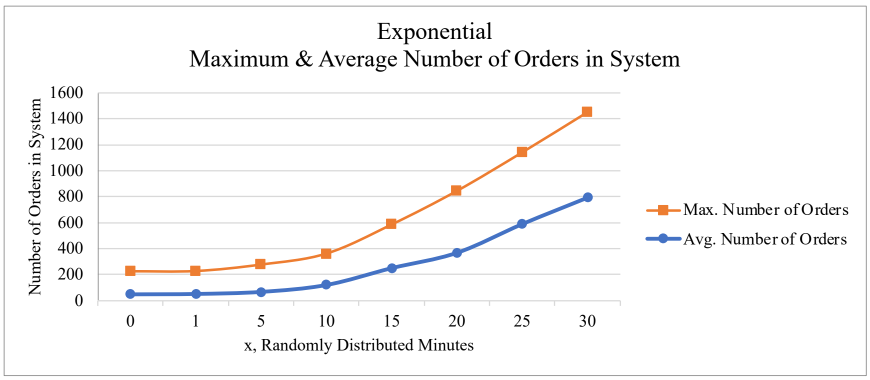


Figure 44 Scenario 2 Results: Exponential, Maximum & Average Number of Orders in System.

Figure 45 Scenario 2 Results: Deterministic, Maximum & Average Number of Orders in System.

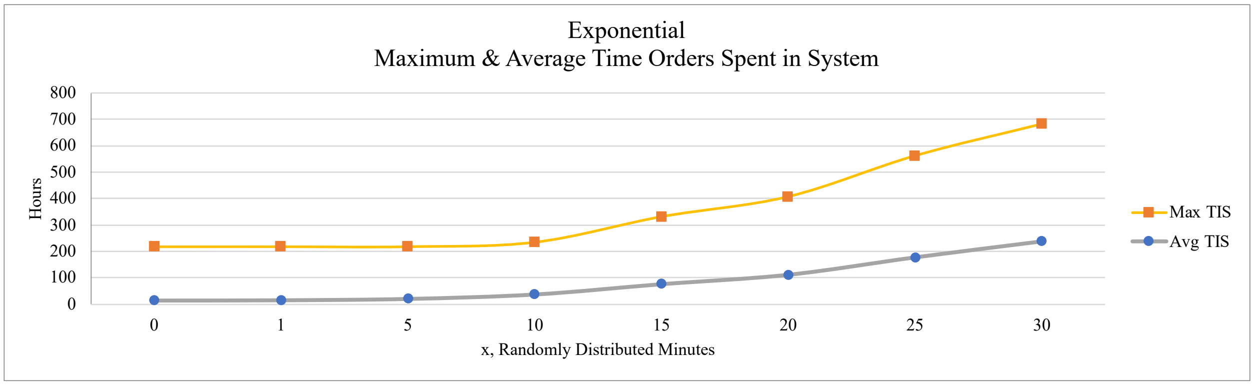


Figure 46 Scenario 2 Results: Exponential, Maximum & Average Time Orders Spent in System.

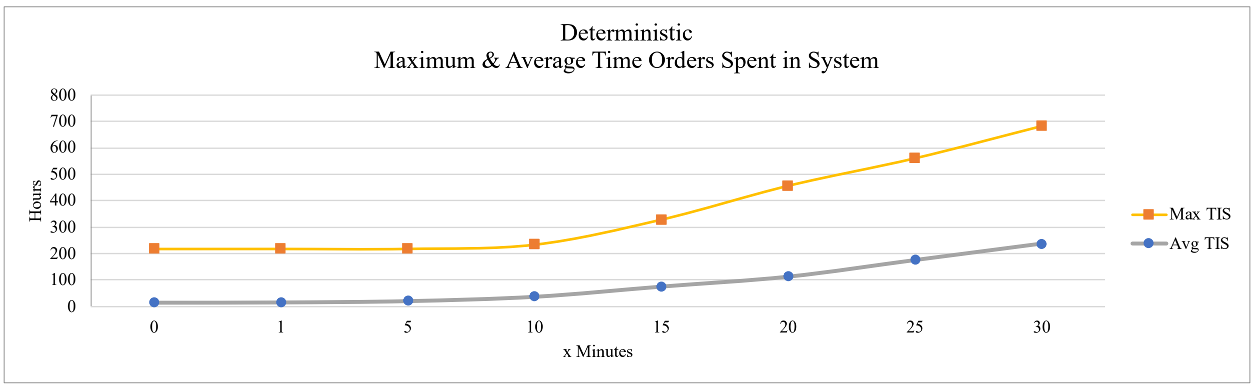


Figure 47 Scenario 2 Results: Deterministic, Maximum & Average Time Orders Spent in System.

The percentage of on time orders was also heavily impacted by information delays. Adding approximately 25 minutes to orders due to information delays reduces the on time orders percentage by nearly 50% (Table 18, Table 19). The following graphs show the decrease in on time orders percentage as the router matching time increases (Figure 48 and Figure 49).

6.4.3 Scenario 3 Results

The results of Scenario 3 demonstrate the implications of introducing priority orders (Table 20). Desirable results are highlighted in green, and results that are not desirable are highlighted in red. The baseline simulation results that were used for the percent change calculations are highlighted in grey. The term “Overall” in the results table is referring to all of the orders, both priority and non-priority orders combined.

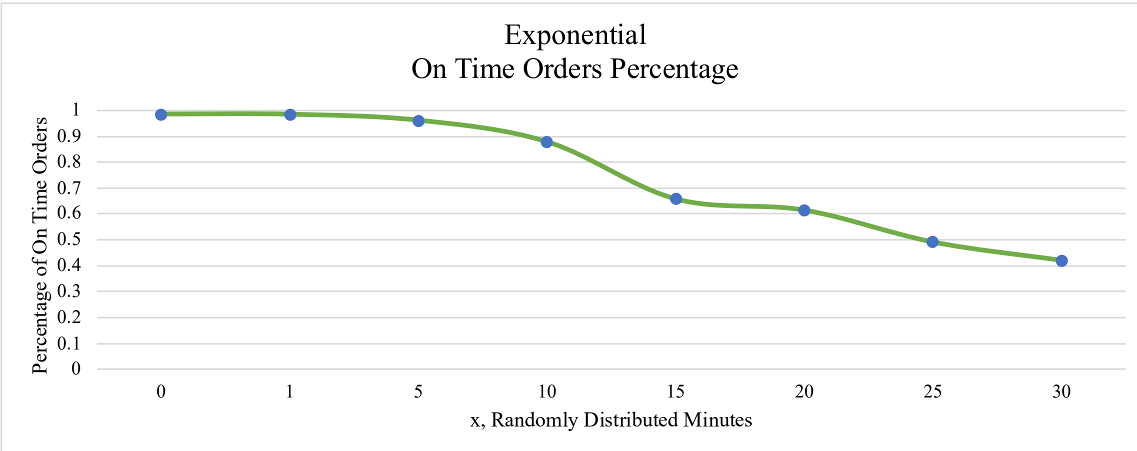


Figure 48 Scenario 2 Results: Exponential, On Time Orders Percentage.

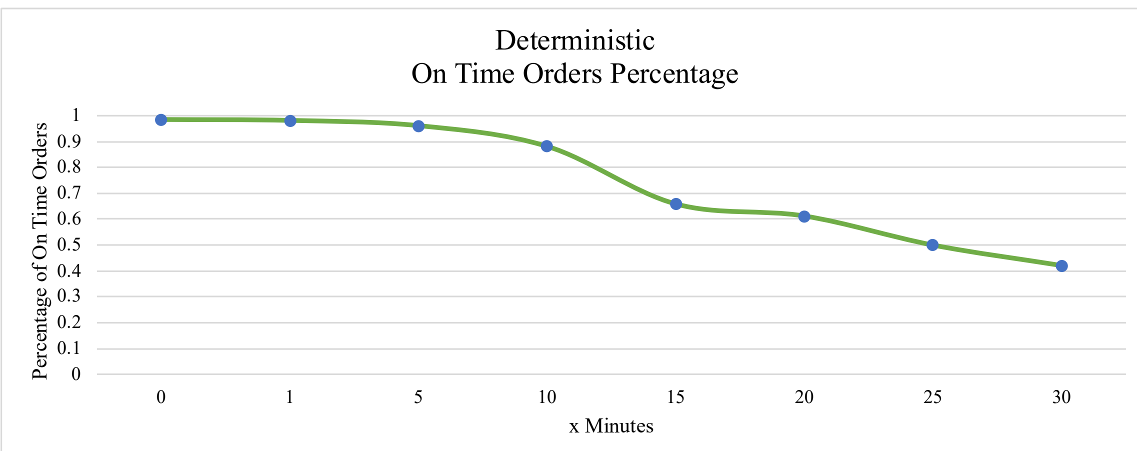


Figure 49 Scenario 2 Results: Deterministic, On Time Orders Percentage.

Table 20 Scenario 3 Results.

		Simulation Results with 5min. Router Matching				Percentage Change No Priority Orders vs. Priority Orders		
		Percentage of Priority Orders				Percentage of Priority Orders		
		0% (No Priority Orders)	5%	10%	15%	5%	10%	15%
Number of Orders in System	Overall Average	67.6	68.5	69.7	70.5	1.4%	3.2%	4.4%
	Overall Maximum	275.0	276.0	280.8	285.7	0.4%	2.1%	3.9%
Order Time in System	Overall Average	21.9	22.2	22.6	22.8	1.4%	3.2%	4.4%
	Overall Maximum	217.7	214.0	215.2	215.2	-1.7%	-1.2%	-1.1%
	Priority Orders Average	-	8.7	9.0	9.2	-	-	-
	Non-Priority Orders Average	-	21.1	22.2	23.2	-	-	-
Throughput (orders per weekday)	Overall	105.0	105.1	105.1	105.0	0.0%	0.0%	0.0%
On Time Percentage	Overall	96.1%	95.9%	95.5%	95.3%	-0.2%	-0.6%	-0.8%
	Priority Orders	-	97.8%	97.5%	97.4%	-	-	-
	Non-Priority Orders	-	95.8%	95.3%	95.0%	-	-	-

With 5%, 10%, and 15% of the arrivals being priority orders, the overall average (67.6 orders) and overall maximum (275.0 orders) number of orders in the system increased. The overall average time that orders spend in the system (21.9 hours) increased, but the overall maximum time that orders spend in the system (217.7 hours) decreased. No significant changes were seen in the overall throughput values.

The average time that priority orders spend in the system increased as the percentage of priority orders increased. The average time that non-priority orders spend in the system also increased as the percentage of priority orders increased. When comparing the overall average time that orders spend in the system (21.9 hours) to the time that non-priority orders spend in the system, the values are very similar; the non-priority orders saw an increase in the time they spend in the system at the 10% (22.2 hours) and 15% (23.2 hours) amount of priority orders.

The percentage of on time orders for priority orders and non-priority orders slightly decreased as the amount of priority orders increased. At the 5%, 10%, and 15% amount of priority orders, the on time percentage of priority orders was higher than the on time percentage of non-priority orders. The overall on time percentage of orders slightly decreased as the amount of priority orders increased. As expected, all on time percentages for priority orders were higher than the on time percentages for non-priority orders.

6.5 Discussion

The results of the first simulation scenario revealed the positive outcomes that can come from having the right data, in the right place, at the right time, and in the right form to make the best possible decision. Running a system with an all EDD strategy would require that the data maintain a continuous feedback loop to keep actual production data up to date. The company in this study has reaped tremendous benefits from transitioning to an information-centric business model that keeps data accurate so they can make critical business decisions in near real time.

From the simulation results for Scenario 1, benefits of an all EDD strategy included a reduction in the number of orders in the system, a reduction of time that orders spend in the system, and an increased percentage of on time orders. For a manufacturing company, having fewer orders in the system and orders spending less time in the system means less money tied up on the plant floor. Increasing the percentage of on time orders increases the trust the customer has in the supplier; having a nearly perfect on time shipping percentage for orders means that customers can trust that the supplier will provide their orders at the promised time. All EDD performed better than all FIFO and EDD at only the laser for almost all the tracked metrics. As expected on time orders percentage improved (increased) because queues are ordered by EDD, and therefore, orders spend less time in queue and are more likely to be shipped on time. This also means that the overall time in system will decrease which was found to be true from the simulation results.

Scenario 2 demonstrated the consequences of adding only a few minutes of information delays to each order. All time values from one to thirty minutes that are spent on matching part routers with their corresponding orders resulted in increases in the number of orders in the system, increases in the time orders spend in the system, and decreases in on time orders percentages. Increasing the overall number of orders in the system and increasing the time orders spend in the system also results in increased costs of material movement, warehousing, and orders that are tied up and reducing cash flow. The results of Scenario 2 uncovered the demise that information delays can inflict on a manufacturing facility. The negative outcomes of information delays should urge manufacturers to analyze potential areas were data and information may be causing unbeknownst ramifications.

The results of the third simulation scenario show how up to date data can be leveraged to send a priority order through the manufacturing facility. Priority orders were able to traverse the plant floor two and a half times faster than non-priority orders. Having the ability to prioritize orders is attractive to customers when choosing a supplier because customers need to know that their supplier can provide orders in a timely manner if the need to do so arises. Introducing priority orders did have negative implications on the overall percentage of on time orders. However, for the company, the benefits outweigh the consequence because having up to date information would allow the company to evaluate and communicate the effects of a priority order to the customer so that due dates of other orders can be adjusted if necessary. When transparency is increased between the customer and supplier, the customer can trust that the supplier will provide the orders that are needed when they are needed, and there is open communication about the effect of introducing priority orders. None of this would be possible without an information-centric business model that has accurate and up to date data that supports the manufacturing operations.

6.6 Chapter Summary

With today's efforts to digitize and digitalize data and information practices, manufacturers need to turn their attention to identifying data and information wastes, especially those that are manifesting themselves and causing negative ramification on the plant floor. Though the results in this chapter were for one company, the results should serve as a wakeup call for manufacturers and researchers alike to identify data and information wastes and create methods and technologies to eradicate the wastes. The company discussed in this chapter has reached their success by ensuring their data is accurate and up to date, which is the only way to make an information-centric business system work. The three simulation scenarios that were performed here are just the beginning of the simulation community evaluating the interplay between data and information flows and product flows.

Chapter 7 Conclusions and Future Work

This research unveiled the inaccuracies and inefficiencies that hinder manufacturers from having the right data, in the right place, at the right time, and in the right form to make the best possible decision. Former research efforts in the manufacturing domain have been mostly focused on improving product flow on the plant floor. However, manufacturing systems are composed of much more than product flow. Data and information systems are a large part of the overall manufacturing business, and yet, there are a few continuous improvement efforts that are focused on eliminating waste in data and information flows. This will soon change with the industry 4.0 initiatives that are happening across the globe. Manufacturers are faced with having to make drastic improvements to their data and information flows with little to no guidance. This dissertation lays the foundation for understanding and differentiating value-added and non-value-added activities in the data and information domain.

This research was built on Lean manufacturing principles that are commonly used for manufacturing system improvements. Lean literature is filled with methods and tools to further improvement efforts, but a significant gap was found in the literature. The methodology that Ohno used to develop the TPS, which is now known as Lean manufacturing, was not well-understood. This research began with a desire to discover how Ohno successfully identified and eliminated wastes in product flow so that the same level of success can be replicated in waste and data and information flows. After a deep dive into Ohno's writings and the writings of those that worked with him, Ohno's mental model was revealed. The mental model is a contribution to the Lean body of knowledge and a unique way of using I-O psychology to understand one's mindset in a work environment.

Ohno's mental model was then used to identify inaccuracies in inefficiencies in data and information flows in manufacturing. After conducting interviews across several manufacturing sectors, a plethora of wastes were revealed. When grouping the wastes, eight categories took shape: (1) form, (2) excess, (3) error, (4) separation, (5) delay, (6) change, (7) manual intervention, and (8) storage. Manufacturers can utilize these eight wastes to identify improvement opportunities in their data and information practices. These eight ways are intended to be used for waste identification, and the next step is waste elimination. Deploying the proper technologies to eliminate these wastes is only made possible with a thorough understanding of the root cause of the wastes. When one waste is found, several wastes are often found. The goal is not to properly categorize each waste; the goal is to identify what creates value in terms of data and information and use that value to drive business decisions. In this work, value in data and information flows is defined as having the right data, in the right place, at the right time, and in the right form to make the best possible decision.

After identifying data and information wastes in manufacturing systems, a quantitative analysis was performed to understand the interplay of data and information process and plant operations. It became clear that even adding only a few minutes of information latency to orders can cause a rippling effect of ramifications. Having an information-centric business model that aims to eliminate data and information wastes will be crucial to maintaining a competitive advantage. Manufacturers can use the simulation presented in this dissertation as an example of the importance of having up to date and accurate information that arrives in a timely manner to the plant floor.

This body of work will likely grow exponentially in the future. To further this research, investigators should begin adding to the conversation of data and information flow improvements.

There should be more effort on developing and publicizing the business case for digitalization so that manufacturers can become more familiar with the meaning and benefits of digitalization. SMMs that do not have the capital that larger manufacturers have, and they will need assistance in identifying the best ways to identify and eliminate their wastes. Manufacturers need to understand that spending large amounts of capital on new technologies is not always the answer. Creating value for the end-user should be of utmost importance when digitizing and digitalizing data and information. SMMs will want to see successful business cases with a substantial ROI. Doing so will require further quantitative analysis of how data and information flows impact manufacturing systems.

The examples of metrics for data and information wastes that were presented in Chapter 5 should be evaluated further by determining their applicability in multiple manufacturing facilities. Most of the metrics presented in Chapter 5 are output metrics. In future research, there should also be a focus on developing input metrics that evaluate the six inputs in Figure 16: hardware, software, methods, connectivity, management, and user. Input metrics will be useful in understanding where the wastes originate and not just the outcomes of having wastes in a system. For example, for hardware and software inputs, quantify system availability, and for the user input, quantify employee capacity, proficiency, and cross-training. These metrics will help manufacturers better understand the inputs that may increase non-value-added activities.

The simulation community can build on this research by making it more commonplace to evaluate data and information flows, not just product flows to understand the impact of data an information wastes on manufacturing operations. Three scenarios were presented in this work (Chapter 6), but more scenarios of data and information wastes should be developed and tested. The simulation presented in Chapter 6 should also be replicated and compared for other manufacturing facilities to understand how all manufacturers are affected by data and information wastes. The magnitude of the results will vary from company to company, but it is likely that data and information wastes have the potential to negatively affect all manufacturing companies.

The simulation work can also be furthered by analyzing stochastic order arrivals that have some level of variability as opposed to a deterministic simulation that was used in this work. Adding a probabilistic component by randomizing the order generation will add a layer of complexity that is more representative of what it is like receiving orders in a manufacturing system. The incoming orders can somewhat be predicted based on order history; however, the incoming stream of orders is not known.

It will also be of interest to analyze data and information practices that occur before the data and information reach the plant operations. There are several business practices such as scheduling and quoting that generate data and information for the plant floor. These practices are often lumped into overhead costs and not analyzed for continuous improvement purposes. Simulations could also be created to analyze these business practices for future improvement opportunities.

Data and information flow research is also headed in the direction of building new visual mapping tools that are made for capturing, mapping, and analyzing data and information flows. For example, Ledford and Patterson [119] have created a systematic methodology called "Data Element Mapping and Analysis" (DEMA). DEMA enables visibility to the individual data elements that drive a system as opposed to traditional visual mapping techniques that are only suitable for creating functional, document-centric views of data flows. DEMA focuses on the specific data elements within data vessels (documents), not just the documents themselves. Ledford and Patterson [119] have also found that most manufacturing data and information flows are nonstandard or undocumented. This reveals today's lack of knowledge and emphasis on data and information flows in manufacturing. The DEMA approach can be combined with the eight wastes for data and information presented in this dissertation to further this research area. Having a mapping tool such as DEMA can be used to visualize the occurrence of non-value-added activities or wastes in data and information flows.

Efforts of the future will no longer be focused on just digitization but also digitalization-continually improving data and information flows with advanced technologies. By using Ohno's mental model, we can assume there is a better way for not just product flow but also data and information flow. Identifying the eight wastes for data and information presented in this work and acting on them will improve data connectivity and interoperability. Documenting, mapping, and analyzing data and information flows in manufacturing will get us one step closer to realizing a true digital thread.

Manufacturers will no longer only design for product flows but also for data and information flows. Digitalization calls for data connectivity and interoperability. Today's systems are filled with non-value-added activities that could have been avoided if data and information systems were designed with value creation in mind: having the right data, in the right place, at the right time, and in the right form to make the best possible decision. It is likely that software providers will catch onto the current needs of manufacturers and rethink ERP and MES systems to better support a complete digital thread and an information-centric business model. Purposefully designing for data and information flows and eliminating non-value-added activities allows manufacturers to better control and visualize their operations to gain actionable insights.

In conclusion, manufacturers are on the brink of a new era of digitalization, and they must join in to remain competitive in today's marketplace. This research contributes to this area of study by building on the already successful Lean principles, creating eight wastes to identify data and information wastes, and demonstrating a way to create an abstraction of the data and information domain for analysis purposes.

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Appendices

Appendix A Corresponding Publications

The following list consists of publications that are associated with this research:

Published Journal Articles:

J1. Yarbrough, A.C., Harris, G.A., Purdy, G.T., Loyd, N. (2022). Developing Taiichi Ohno's Mental model for Waste Identification in Nontraditional Applications, The American Society of Mechanical Engineers (ASME) Open Journal of Engineering, 1:011017 (2022). https://doi.org/10.1115/1.4054037

J2. Yarbrough, A.C., Harris, G.A., and Purdy, G.T. (2022). Improving the Flow of Data and Information in Manufacturing, Manufacturing Letters, 32 (2022), 1-4. https://doi.org/10.1016/j.mfglet.2022.01.001

J3. Harris, G., Yarbrough, A., Abernathy, D., and Peters, C. (2019). Manufacturing Readiness for Digital Manufacturing, Manufacturing Letters, 22 (2019), 16-18. https://doi.org/10.1016/j.mfglet.2019.10.002

Journal Articles in Revision:

J4. Yarbrough, A.C., Harris, G.A., Purdy, G.T., and Loyd, N. (2022). Creating Value by Identifying and Eliminating Waste in Manufacturing Data and Information Flows. (In Revision, Reviewed by Journal of Operations Management)

Refereed Conference Proceedings:

C1. Evans, M., Yarbrough, A., Harris, G., and Purdy, G. (2021). A Simulation Testbed for the Evaluation of Product and Information Flows in a Manufacturing System. Proceedings of the IISE Annual Conference, 560-565.

C2. Yarbrough, A., Harris, G., Peters, C., and Purdy, G. (2020). The Digital Transformation Gap Widens Between OEMs and SMMs. Proceedings of the 11th Model-Based Enterprise Summit, 195-204. https://doi.org/10.6028/NIST.AMS.100-29

C3. Harris, G.A., Peters, C., Yarbrough, A., Estes, C., and Abernathy, D. (2019). Industry Readiness for Digital Manufacturing May Not Be as We Thought: Preliminary Findings of MxD Project 17-01-01. Proceedings of the 10th Model-Based Enterprise Summit, 110-116. https://doi.org/10.6028/NIST.AMS.100-24

Appendix B Institutional Review Board- Exemption Review Application

Auburn University Human Research Protection Program

EXEMPTION REVIEW APPLICATION

For information or help completing this form, contact: **THE OFFICE OF RESEARCH COMPLIANCE**
Phone: 334-844-5966 **Email:** IRBAdmin@auburn.edu

Submit completed application and supporting material as one attachment to IRBsubmit@auburn.edu.

1. PROJECT IDENTIFICATION **Today's Date** December 04, 2020

a. Project Title Production Data and Information Flows in Manufacturing

b. Principal Investigator Ashley Yarbrough Degree(s) Bachelors & Masters in Industrial & Systems Engineering
Rank/Title PhD Student Department/School Industrial & Systems Engineering
Phone Number 334-844-4340 (ISE Dept.) AU Email acy0004@auburn.edu

Faculty Principal Investigator (required if PI is a student) Greg Harris
Title Associate Professor Department/School Industrial & Systems Engineering
Phone Number 334-844-1407 (office) AU Email greg.harris@auburn.edu

Dept Head John Evans Department/School Industrial & Systems Engineering
Phone Number 334-844-1418 (office) AU Email evansjl@auburn.edu

c. Project Personnel (other PI) – Identify all individuals who will be involved with the conduct of the research and include their role on the project. Role may include design, recruitment, consent process, data collection, data analysis, and reporting. Attach a table if needed for additional personnel.

Personnel Name Ashley Yarbrough Degree (s) Bachelors & Masters in Industrial & Systems Engineering
Rank/Title PhD Student Department/School Industrial & Systems Engineering
Role Design interview instrument, recruit participants, consent process, data collection, data analysis, and reporting
AU affiliated? ☒ YES ☐ NO If no, name of home institution
Plan for IRB approval for non-AU affiliated personnel?

Personnel Name Greg Harris Degree (s) PhD in Industrial & Systems Engineering, P.E.
Rank/Title Associate Professor Department/School Industrial & Systems Engineering
Role Oversee research conducted by Principal Investigator, Ashley Yarbrough
AU affiliated? ☒ YES ☐ NO If no, name of home institution
Plan for IRB approval for non-AU affiliated personnel?

Personnel Name Degree (s)
Rank/Title Department/School
Role
AU affiliated? ☐ YES ☐ NO If no, name of home institution
Plan for IRB approval for non-AU affiliated personnel?

d. Training – Have all Key Personnel completed CITI human subjects training (including elective modules related to this research) within the last 3 years? YES ☑ NO ☐

Figure 50 Institutional Review Board- Exemption Review Application.

(Figure is continued on the following pages).

e. Funding source – Is this project funded by the investigator(s)? ☐ YES ☑ NO
Is this project funded by AU? ☐ YES ☑ NO If YES, identify source ___________________________
Is this project funded by an external sponsor? ☐ YES ■ No If YES, provide the name of the sponsor, type of sponsor (governmental, non-profit, corporate, other), and an identification number for theaward.
Name N/A ___________________________ Type ___________________________ Grant # ___________________________

f. List other AU IRB-approved research studies and/or IRB approvals from other institutions that are associated with this project.
N/A

2. Mark the category or categories below that describe the proposedresearch:

☐ 1. Research conducted in established or commonly accepted educational settings, involving normal educational practices. The research is not likely to adversely impact students' opportunity to learn or assessment of educators providing instruction. 104(d)(1)

■ 2. Research only includes interactions involving educational tests, surveys, interviews, public observation if at least ONE of the following criteria. (The research includes data collection only; may include visual or auditory recording; may NOT include intervention and only includes interactions). **Mark the applicable sub-category below (i, ii, or iii).** 104(d)(2)

■ (i) Recorded information cannot readily identify the participant (directlyorindirectly/linked);
OR

- surveys and interviews: no children;
- educational tests or observation of public behavior: can only include childrenwhen investigators do not participate in activities beingobserved.

☐ (ii) Any disclosures of responses outside would not reasonably place participant at risk; **OR**

☐ (iii) Information is recorded with identifiers or code linked to identifiers and IRB conducts limited review; no children. **Requires limited review by the IRB.***

☐ 3. Research involving Benign Behavioral Interventions (BBI)** through verbal, written responses (including data entryor audiovisual recording) from adult subjects who prospectively agree andONEof the following criteria is met. (This research does not include children and does not include medical interventions. Research cannot have deception unless the participant prospectively agrees that they will be unaware of or misled regarding the nature and purpose of the research)
Mark the applicable sub-category below (A, B, or C). 104(d)(3)(i)

☐ **(A)** Recorded information cannot readily identify the subject (directly or indirectly/linked); **OR**

☐ **(B)** Any disclosure of responses outside of the research would not reasonably placesubject at risk; **OR**

☐ **(C)** Information is recorded with identifiers and cannot have deception unless participant prospectively agrees. **Requires limited review by theIRB.***

☐ 4. Secondary research for which consent is not required: use of identifiable information or identifiable bio-specimen that have been or will be collected for some other 'primary' or 'initial' activity, if one ofthe following criteria is met. Allows retrospective and prospective secondary use. **Mark the applicable sub-category below (I, ii, iii, or iv).** 104(d)(4)

☐ (i) Biospecimens or information are publically available;

☐ (ii) Information recorded so subject cannot readily be identified, directlyorindirectly/linked; investigator does not contact subjects and will not re-identify thesubjects;OR

☐ (iii) Collection and analysis involving investigators use of identifiable health information when use is regulated by HIPAA “health care operations” or “research or “public health activities and purposes” (does not include biospecimens (only PHI and requires federal guidance on how to apply); OR

☐ (iv) Research information collected by or on behalf of federal government using government generated or collected information obtained for non-research activities.

☐ 5. Research and demonstration projects which are supported by a federal agency/department AND designed to study and which are designed to study, evaluate, or otherwise examine: (i) public benefit or service programs; (ii) procedures for obtaining benefits or services under those programs; (iii) possible changes in or alternatives to those programs or procedures; or (iv) possible changes in methods or levels of payment for benefits or services under those programs. (must be posted on a federal web site). 104(d)(5) (must be posted on a federal web site)

☐ 6. Taste and food quality evaluation and consumer acceptance studies, (i) if wholesome foods without additives are consumed or (ii) if a food is consumed that contains a food ingredient at or below the level and for a use found to be safe, or agricultural chemical or environmental contaminant at or below the level found to be safe, by the Food and Drug Administration or approved by the Environmental Protection Agency or the Food Safety and Inspection Service of the U.S. Department of Agriculture. The research does not involve prisoners as participants. 104(d)(6)

New exemption categories 7 and 8: Both categories 7 and 8 require Broad Consent. **(**Broad consent is a new type of informed consent provided under the Revised Common Rule pertaining to storage, maintenance, and secondary research with identifiable private information or identifiable biospecimens. Secondary research refers to research use of materials that are collected for either research studies distinct from the current secondary research proposal, or for materials that are collected for non-research purposes, such as materials that are left over from routine clinical diagnosis or treatments. Broad consent does not apply to research that collects information or biospecimens from individuals through direct interaction or intervention specifically for the purpose of the research.) **The Auburn University IRB has determined that as currently interpreted, Broad Consent is not feasible at Auburn and these 2 categories WILL NOT BE IMPLEMENTED at this time.**

****Limited IRB review*** **– the IRB Chairs or designated IRB reviewer reviews the protocol to ensure adequate provisions are in place to protect privacy and confidentiality.**

*****Category 3 – Benign Behavioral Interventions (BBI)*** **must be brief in duration, painless/harmless, not physically invasive, not likely to have a significant adverse lasting impact on participants, and it is unlikely participants will find the interventions offensive or embarrassing.**

3. PROJECT SUMMARY

a. Does the study target any special populations? (Mark applicable)

Minors (under 18 years of age)	☐ YES ☑ NO
Pregnant women, fetuses, or any products of conception	☐ YES ☑ NO
Prisoners or wards (unless incidental, not allowed for Exempt research)	☐ YES ☑ NO
Temporarily or permanently impaired	☐ YES ☑ NO

b. Does the research pose more than minimal risk to participants? ☐ YES ☑ NO

Minimal risk means that the probability and magnitude of harm or discomfort anticipated in the research are not greater in and of themselves than those ordinarily encountered in daily life or during the performance of routine physical or psychological examinations or test. 42 CFR 46.102(i)

c. Does the study involve any of the following?

Procedures subject to FDA regulations (drugs, devices, etc.)	☐ YES ☑ NO
Use of school records of identifiable students or information from instructors about specific students.	☐ YES ☑ NO
Protected health or medical information when there is a direct or Indirect link which could identify the participant.	☐ YES ☑ NO
Collection of sensitive aspects of the participant's own behavior, such as illegal conduct, drug use, sexual behavior or alcohol use.	☐ YES ☑ NO
Deception of participants	☐ YES ☑ NO

4. Briefly describe the proposed research, including purpose, participant population, recruitment process, consent process, research procedures and methodology.

The purpose of this research is to understand and document the issues with production data and information flows in manufacturing. I will be speaking with employees of Small and Medium-sized Manufacturers (SMMs) and Original Equipment Manufacturers (OEMs) about the challenges they face in developing a production schedule from customer orders, making changes to the schedule, and providing the operator with the information he/she needs to do their job. This research aims to understand why production data and information do not arrive in the right place, at the right time, in the right amount, and/or in the right form to make the best possible decision.

I will be talking to subject matter experts from the United States manufacturing industry. The target interviewee is someone who works closely with scheduling and has in-depth knowledge of manufacturing shop floor operations. A list of connections to manufacturing companies will be provided by Auburn University's Industrial & Systems Engineering Department. Potential interviewees will be sent an invitation to participate via email. The recruitment email will act as the information letter. Participants will indicate their consent by emailing Ashley Yarbrough to schedule an interview time.

5. Waivers

Check any waivers that apply and describe how the project meets the criteria for the waiver. Provide the rationale for the waiver request.

☐ **Waiver of Consent (Including existing de-identified data)**

☒ **Waiver of Documentation of Consent (Use of Information Letter)**

☐ **Waiver of Parental Permission**

All retrospective information will be de-identified.

The recruitment email will act as the information letter. Participants will indicate their consent by emailing Ashley Yarbrough to schedule an interview time.

6. Describe how participants/data/specimens will be selected. If applicable, include gender, race, and ethnicity of the participant population.

I will be talking to subject matter experts from the United States manufacturing industry. The target interviewee is someone who works closely with scheduling and has in-depth knowledge of manufacturing shop floor operations. A list of connections to manufacturing companies will be provided by Auburn University's Industrial & Systems Engineering Department.

7. **Does the research involve deception? ☐ YES ■ NO If YES, please provide the rationale for deception and describe the debriefing process.**

8. **Describe why none of the research procedures would cause a participant either physical or psychological discomfort or be perceived as discomfort above and beyond what the person would experience in daily life.**

   Participants will only participate on a voluntary basis. Participants may choose to decline to answer any question, end the interview, or choose not to participate at any time. The participant will be asked not to divulge any sensitive or confidential information.

9. **Describe the provisions to maintain confidentiality of data, including collection, transmission, and storage.**

   The demographic information that will be collected includes: Role/Title, Time in job, Time in role, Time at company, Department, Company size, Type of Materials produced, and Industry Type. During the interview, I will identify the methods used and issues associated with production information in manufacturing. All data and information presented in the resulting report will be anonymized and demographic information will only be reported in aggregate.
   The research study documents will be destroyed at the completion of this research effort.

10. **Describe the provisions included in the research to project the privacy interests of participants (e.g., others will not overhear conversations with potential participants, individuals will not be publicly identified or embarrassed).**

    The principal investigator will interview one participant at a time. Others will not overhear the conversations with potential participants. Demographic information will only be presented in aggregate in the resulting report. It will not be possible to identify participant or the particpant's company in the resulting report.

11. **Will the research involve interacting (communication or direct involvement) with participants? ■ YES ☐ NO If YES, describe the consent process and information to be presented to subjects. This includes identifying that the activities involve research; that participation is voluntary; describing the procedures to be performed; and the PI name and contact information.**

    Potential interviewees will be sent an invitation to participate via email. This invitation email will act as the information letter. Participants will indicate their consent by emailing the principal investigator to schedule an interview time.

12. **Additional Information and/or attachments.**

    In the space below, provide any additional information you believe may help the IRB review of the proposed research. If attachments are included, list the attachments below. Attachments may include recruitment materials, consent documents, site permissions, IRB approvals from other institutions, etc.

    Appendices:
    Consent Form
    Recruitment Email
    Questions to Guide the Interview Discussion
    Supporting Research References
    CITI Training Certificates for all Key Personnel

Principal Investigator's Signature Ashley C. Yarbrough Date 12/04/2020

If PI is a student,
Faculty Principal Investigator's Signature Gregory A. Harris, Ph.D., P.E. Digitally signed by Gregory A. Harris, Ph.D., P.E. Date: 2020.12.04 17:39:08 -06'00' Date 12/04/2020

Department Head's Signature ______ Date 12/4/20

AU Exemption Form Version 07.14.2020

Version Date (date document created): 12/04/2020

page __ of __

Appendix C CITI Training Certificates

CITI PROGRAM

Completion Date 04-Aug-2020
Expiration Date 04-Aug-2023
Record ID 37732187

This is to certify that:

Ashley Yarbrough

Has completed the following CITI Program course:

Not valid for renewal of certification through CME. Do not use for TransCelerate mutual recognition (see Completion Report).

IRB # 2 Social and Behavioral Emphasis - AU Personnel - Basic/Refresher (Curriculum Group)
IRB # 2 Social and Behavioral Emphasis - AU Personnel (Course Learner Group)
1 - Basic Course (Stage)

Under requirements set by:

Auburn University

CITI
Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?wc81d31e5-08db-4968-aa44-68c3054f20e0-37732187

CITI PROGRAM

Completion Date 08-Mar-2018
Expiration Date 07-Mar-2021
Record ID 26429315

This is to certify that:

Gregory Harris

Has completed the following CITI Program course:

IRB #1 Health Science Emphasis - AU Personnel - Basic/Refresher (Curriculum Group)
IRB #1 Health Science Emphasis - AU Personnel (Course Learner Group)
1 - Basic Course (Stage)

Under requirements set by:

Auburn University

CITI
Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?w15482480-66b7-4ddf-90c3-91f7938e242b-26429315

Figure 51 CITI Training Certificates.

Appendix D Recruitment Email

Hi *Name of Potential Participant*,
I am Ashley Yarbrough, a PhD student in the Department of Industrial & Systems Engineering at Auburn University. My research is conducted under the supervision of Associate Professor, Greg Harris, Ph.D., P.E. I would like to invite you to participate in my research study to better understand and document issues and challenges that are associated with data and information flows in manufacturing. I am talking with Small and Medium-sized Manufacturers (SMMs) and OEMs about the challenges they face in developing a production schedule from customer orders, making changes to the schedule, and providing the operator with the information he/she needs to do their job.

I am requesting a 30 min – 1 hr discussion via phone or web conference call with you, someone in your organization tasked with scheduling and work instructions, or someone knowledgeable in these topics. I understand the value of your time and will provide a list of topics prior to the interview and ensure that the interview time is of minimal impact to your organization. If you would like, we will provide you with the resulting publication at the conclusion of the study.

If you are interested in participating, please reply to this email, and we will arrange an interview time.

If you have questions, please contact me at ashley.yarbrough@auburn.edu or you may contact my advisor, Dr. Greg Harris, at greg.harris@auburn.edu.

The Auburn University Institutional Review Board has approved this document for use from __________ to __________. Protocol #__________ .

Thank you for your consideration,
Ashley Yarbrough
Auburn University | Industrial Engineering
Graduate Teaching & Research Assistant
Ashley.Yarbrough@auburn.edu

The Auburn University Institutional Review Board has approved this Document for use from
__10/16/2020__ to ____---------____
Protocol # ___20-435 EX 2010___

Figure 52 Recruitment Email.

Appendix E Questions to Guide the Interview Discussion

- ***How do you schedule customer orders?***
  - On a scale of one-to-five, with five being the hardest, how difficult is it to create a production schedule? Describe the reasoning for your answer.
  - Who does the scheduling (individual or committee)?
  - What tools are used (ERP, spreadsheet, whiteboard, etc.)?
  - How is the schedule communicated for people to follow?
  - How often does the process of scheduling take place?
  - How much employee time does creating a schedule take?
  - How do you determine the committed capacity of resources (equipment, material, and personnel)? Are multiple sources of information required/used to determine the committed capacity of resources?

- ***How are updates/changes*** (due to unanticipated events, change in customer orders, equipment unavailability, etc.) ***made to the schedule?***
  - On a scale of one-to-five, with five being the hardest, how difficult is it to change the production schedule? Describe the reasoning for your answer.
  - How often do updates/changes need to be made?
  - Who makes the updates/changes (individual or committee)?
  - Why do the updates/changes need to be made?
  - Is manual intervention required to update/change a schedule?
  - How much employee time does a typical update/change take?
  - How is actual production compared to planned production? Do you update production estimates based on any differences in actual and planned production?
  - How are other operations notified when an unanticipated event occurs?

- ***What information does the operator need to do his/her job?***
  - What pieces of information are required to begin production (job list, travelers/routers, work instructions, setup/changeover instructions, material certifications, etc.)?
  - How is the information presented to the operator? In what form (electronic, paper, etc.)?
  - What triggers the retrieval of these pieces of information?
  - How often is production delayed due to the operator waiting on a piece of information that he/she needs? When this takes place, how long is that wait time typically?

- ***Information Specific Questions***
  - Can you think of instances in which information is not:
    - In the right place?
    - At the right time?
    - In the right amount?

Figure 53 Questions to Guide the Interview Discussion.

Appendix F Data Analysis of the Company's Data

A Grubb's test for outliers was performed in Minitab to clean the company's dataset by removing outliers so that the outliers do not affect the results of the simulation. The null hypothesis was that all data values come from the same normal population, and the alternative hypothesis was that the smallest or largest data value is an outlier. The significance level for the test was 5%. There was one outlier in the arrival data that was removed before further analysis. The outlier is shown as the red data point on the right of the graph Figure 54. A second outlier test was performed to ensure that no outliers remained. The test resulted in zero outliers at the 5% level of significance.

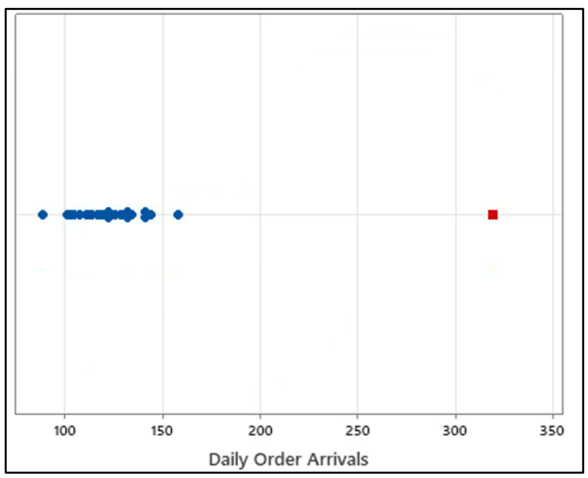

Figure 54 Outlier Plot of Arrivals.

After the outlier was removed, an Individual Distribution Identification test was applied to understand which statistical distribution the data most closely fits. Performing the individual distribution test was not used in the simulation discussed in this research. However, the test was performed to understand what distribution should be used for order arrivals if the simulation were stochastic as opposed to deterministic. A stochastic simulation was mentioned as potential future work.

The Individual Distribution Identification test revealed that the Lognormal distribution most accurately describes the data (Figure 55). The Lognormal distribution was chosen over other distributions due to it being the distribution with the highest p-value and therefore being the most statistically significant. (Note: The Box-Cox Transformation has the highest p-value in Figure 56, but it is not a representative distribution that can be used in Simio.) The results of the goodness of fit tests for each potential distribution are shown below (Figure 56).

For the Lognormal distribution, the goodness of fit test returned a p-value of 0.891 which indicated that the result was statistically significant with a Confidence Interval (CI) of 95%. The probability plot and goodness of fit test for the Lognormal distribution is shown in Figure 55. The points being inside the outer red boundaries and the points closely aligning to the middle red line indicate a good fit which is desirable when determining which distribution most closely fits the data. The parameters, μ and σ, that were calculated in the Individual Distribution Identification test can be used in future studies if using a randomly distributed interarrival process for orders.

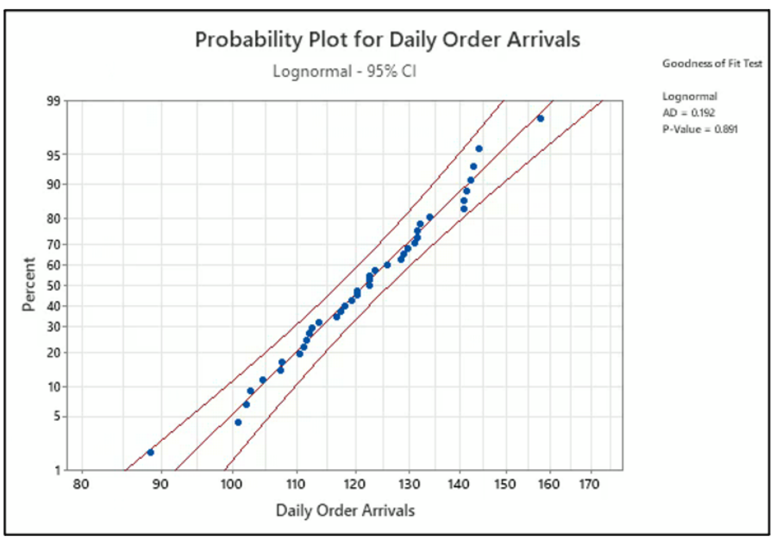

Figure 55 Probability Plot of the Arrival Data.

Goodness of Fit Test

Distribution	AD	P	LRT P
Normal	0.208	0.856	
Box-Cox Transformation	0.187	0.897	
Lognormal	0.192	0.891	
3-Parameter Lognormal	0.197	*	0.586
Exponential	14.014	<0.003	
2-Parameter Exponential	5.859	<0.010	0.000
Weibull	0.451	>0.250	
3-Parameter Weibull	0.206	>0.500	0.071
Smallest Extreme Value	0.715	0.058	
Largest Extreme Value	0.418	>0.250	
Gamma	0.191	>0.250	
3-Parameter Gamma	3.091	*	1.000
Logistic	0.250	>0.250	
Loglogistic	0.229	>0.250	
3-Parameter Loglogistic	0.233	*	0.771

Figure 56 Goodness of Fit Test.

Appendix G Detailed Simulation Building Notes

The following sections provide detailed information on how the simulation was built. In Simio, the properties that are changed by the user become bold text. Any properties that do not have bold text are inherent to Simio models.

E1. Entity

Orders are represented by entities in the simulation (Figure 57).

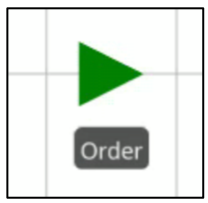

Figure 57 Entity: Order.

The properties of the "Order" entities are shown below (Figure 58). The travel speed is set to Infinity so that entities do not experience travel time. Entities move from one location to another in zero time. The display name is set to "Arrivals.OrderID" so that the OrderID is shown with each entity as the model runs. The OrderID is in the Arrivals Table. The dynamic label text is also set to "Arrivals.OrderID" so that the OrderID can be seen in the Planning Tab in Simio.

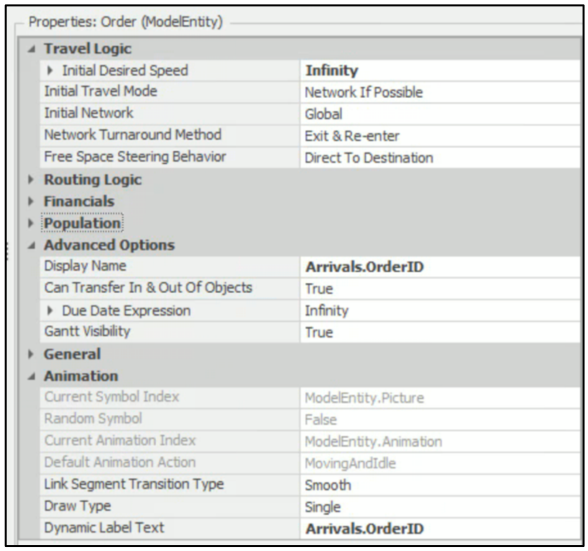

Figure 58 Entity: Properties.

E2. Source

The company's customers are represented by one source called "Customer" (Figure 59).

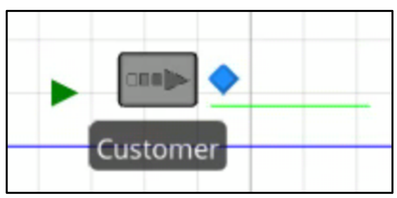

Figure 59 Source: Customer.

The properties of the source are shown in Figure 60. The source generates the "Order" entities. The source uses an arrival table called "Arrivals" to generate the entities at the times that are specified in the "ArriveTime" column of the "Arrivals" table.

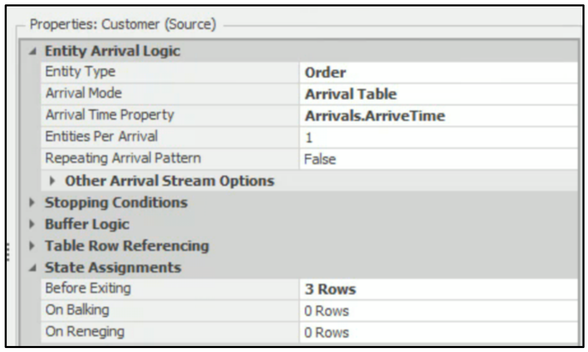

Figure 60 Source: Properties.

The source has three state assignments that occur before the entity exits the source (Figure 61). “NumberInSys” is used to calculate the total number of entities that are in the system. Before the entity leaves the source object, “NumberInSystem” is incremented by one. “Arrivals.ArriveTimeDTG” fills in the “ArriveTimeDTG” column in the “Arrivals” table. When each entity enters the system, it is assigned an arrival time of the current time. “Arrivals.DueTime” fills in the “DueTime” column of the “Arrivals” table. The “DueTime” is calculated by adding the arrival time, the total estimated time for the order, and three days’ of queue time. The units are in hours which is why there is a multiplication of 24 hours.

Figure 61 Source: State Assignments.

E3. Servers

The company’s operations are represented by 19 servers (Figure 62).

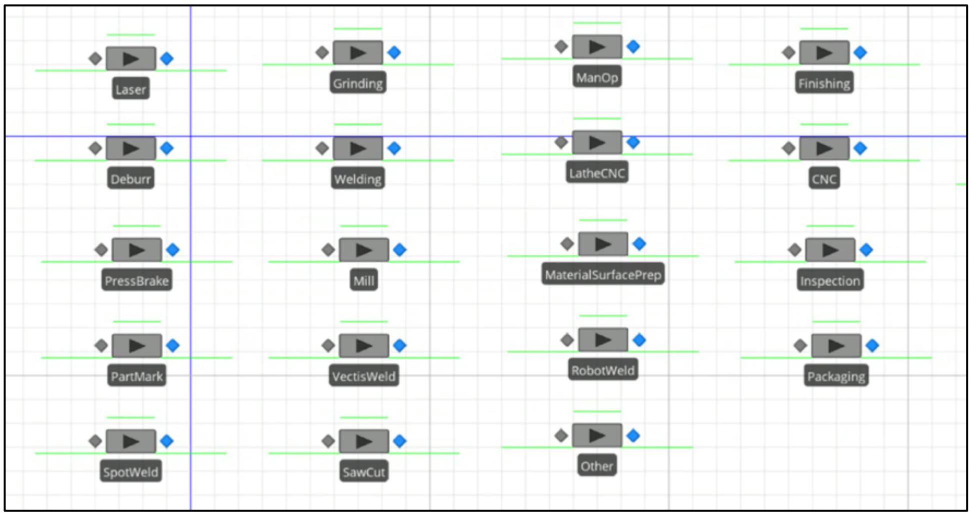

Figure 62 Servers.

All the servers have the same properties with the exception of the “Laser” server (Figure 63). The laser properties are shown in Figure 64. All the servers, except the laser, follow a work schedule. The work schedule tells the server when it should be available and when it should be off shift. The work schedules also define the capacity of each server. The servers reference the “PTime” column in the “Sequence” table to determine how long each order should spend processing. The log resource usage is set to “True” for all the servers so that their statuses can be logged and viewed in the Simio planning tab.

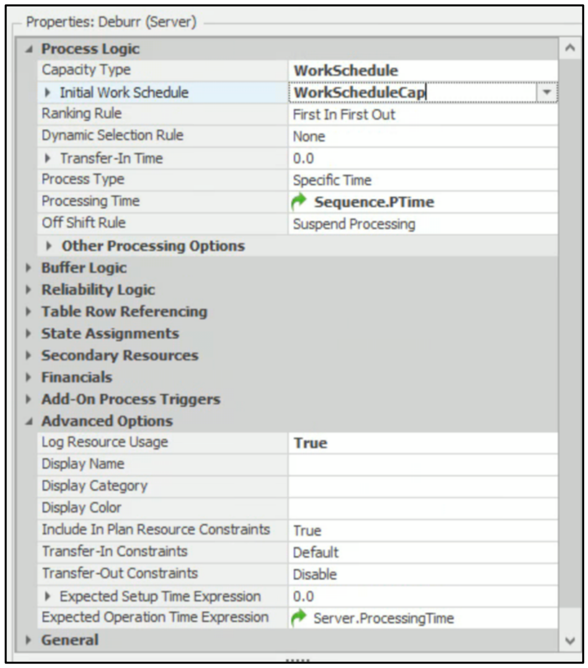

Figure 63 Servers (Except Laser): Properties.

The Laser can run 24 hours, 7 days per week. Because of this behavior, it does not need to follow a work schedule that specifies when the laser should be off-shift because the laser is never off-shift. The capacity of the laser is fixed. The capacity value is removed in Figure 64 due to privacy concerns.

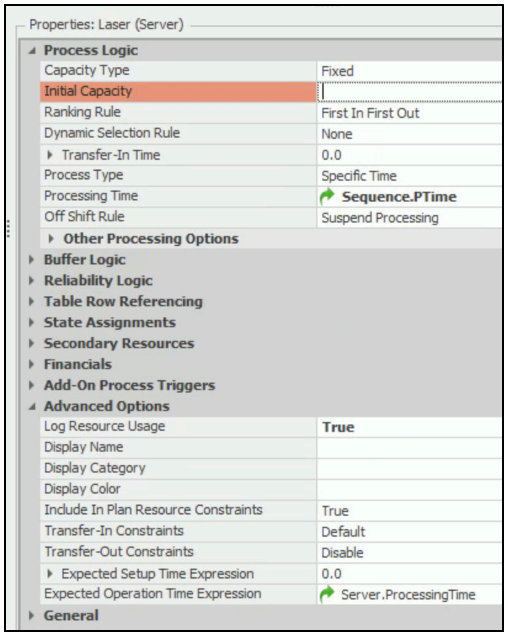

Figure 64 Server (Laser): Properties.

E4. Sink

“Order” entities leave the system through a sink object called “Ship” (Figure 65).

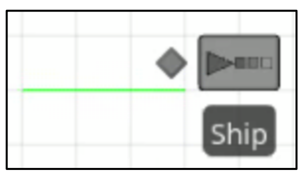

Figure 65 Sink: Ship.

“Ship” has four state assignments and one add-on process associated with it (Figure 66).

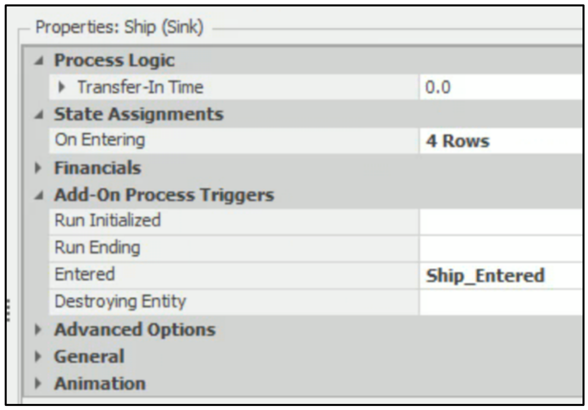

Figure 66 Sink: Properties.

The state assignments are shown in Figure 67. As mentioned earlier, “NumberInSys” is incremented at the source object. When an entity leaves the system, “NumberInSys” is decremented at the sink object. “Arrivals.CompletionTime” records the time that an entity leaves the system as the current time in the “Arrivals” table. The time is recorded in units of hours and as a DTG. “CompletedOrders” counts the total number of entities that have finished processing and were destroyed by the sink.

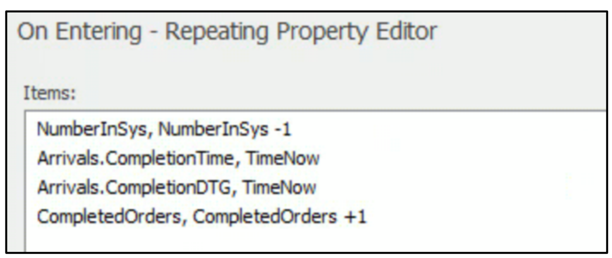

Figure 67 Sink: State Assignments.

“Ship” uses an add-on process to determine if orders were completed by their assigned due time (Figure 68). The add-on process begins when an entity enters the “Ship” sink. The add-on process contains two steps: Decide and Assign.

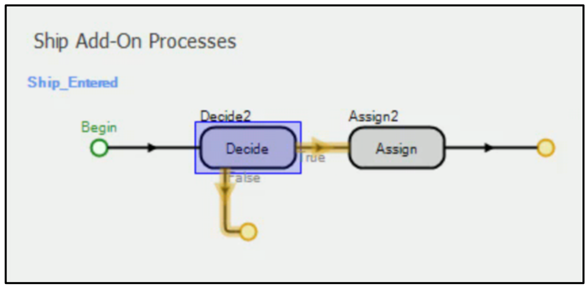

Figure 68 Sink: Add-On Process.

The Decide step is condition based (Figure 69). If the entity's "CompletionTime" is less the "DueTime" then the entity moves to the Assign step; this would mean that the order was completed on time.

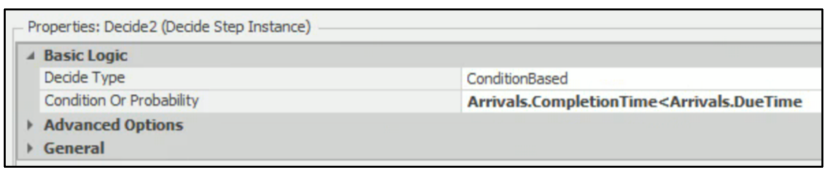

Figure 69 Sink: Add-On Process, Decide Step.

The Assign step used the state variable called "OnTimeOrders" to increment the total number of on time orders by one (Figure 70).

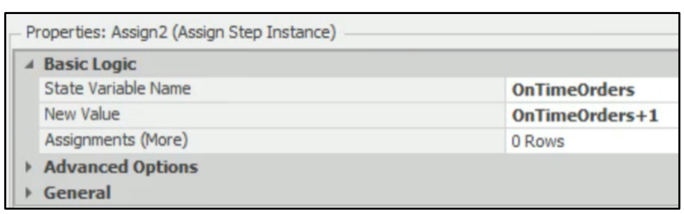

Figure 70 Sink Add-On Process, Assign Step.

E5. Output Nodes

There are output nodes after the source object and each server object (Figure 71).

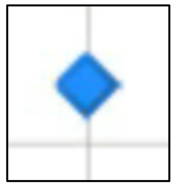

Figure 71 Output Nodes.

The output nodes are used to specify where an entity should travel next. The entity destination type is set to "By Sequence" so that entities follow their sequence that is specified in the "Sequence" table (Figure 72).

Properties: Output@Grinding (TransferNode)

Crossing Logic	
Initial Traveler Capacity	Infinity
Entry Ranking Rule	First In First Out
Routing Logic	
Outbound Travel Mode	Continue
Outbound Link Preference	Any
Outbound Link Rule	Shortest Path
Entity Destination Type	**By Sequence**
Transport Logic	
Ride On Transporter	Never

Figure 72 Output Nodes: Properties.

E6. State Statistic Element

The simulation uses one state statistic element to assist in the number in system calculation; it is called "NIS" (Figure 73).

State Statistic Elements	
NIS	State Statistic Element

Figure 73 State Statistic Element: NIS.

The state variable name that corresponds with the "NIS" state statistic element is "NumberInSys" (Figure 74). As mentioned previously, "NumberInSys" is incremented and decremented at the source and sink objects, respectively.

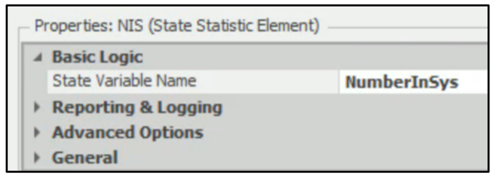

Figure 74 State Statistic Element (NIS): Properties.

E7. Output Statistic Element

The simulation uses one output statistic element to calculate the percentage of on time orders; it is called "OnTimeOrdersPercentage" (Figure 75).

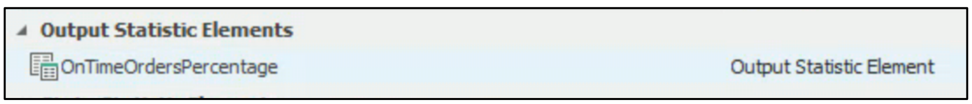

Figure 75 Output Statistic Element: OnTimeOrdersPercentage.

The output statistic is calculated by diving the number of on time orders by the total number of completed orders (Figure 76). The "OnTimeOrders" and "CompletedOrders" are calculated at the sink object.

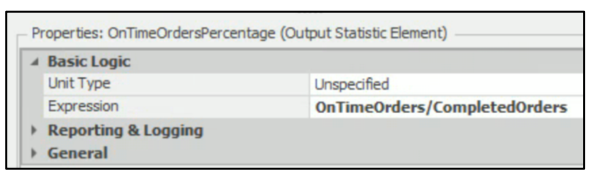

Figure 76 Output Statistic Element (OnTimeOrdersPercentage): Properties.

E8. Data Tables

There are two data tables that support the simulation model: the "Arrivals" table and the "Sequence" table (Figure 77).

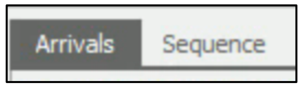

Figure 77 Data Tables: Arrivals and Sequence.

The “Arrivals” table has several columns: OrderID, Mix, EstimatedTime (Hours), ArriveTimeDTG, CompletionTimeDTG, CompletionTime, ArriveTime (Hours), and DueTime (Hours) (Figure 78, Table 21). The “Order ID” is the PK. At the far right of the table, there is also a Target Value that provides a shipment status of “Incomplete”, “OnTime”, or “Late” (Figure 79).

Figure 78 Arrivals Table Columns.

Table 21 Arrivals Table Columns.

Column Name	**Property Type**
Order ID	String Property
Mix	Real Property
EstimatedTime (Hours)	Real Property
ArriveTime (Hours)	Real Property
ArriveTimeDTG	Date Time State Variable
CompletionTimeDTG	Date Time State Variable
CompletionTime (Hours)	Real State Variable
DueTime (Hours)	Real State Variable

If the completion time is less than the due time, the completion time of the order is within bounds and considered “OnTime”. If the completion time is below the lower bound, the order is “Incomplete”. If the completion time is beyond the due time, the completion time is above the upper bound and “Late”.

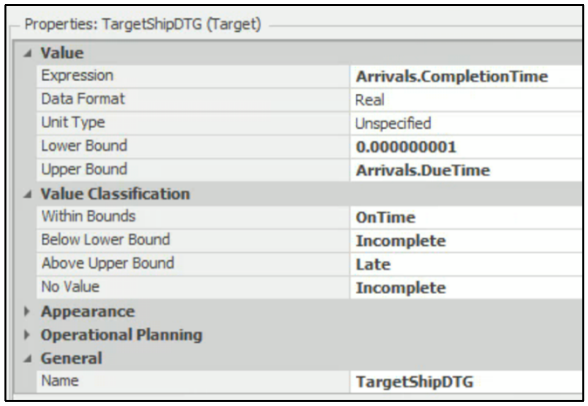

Figure 79 Arrivals Table: Target Ship Date.

The “Sequence” table has four columns: Order ID, Sequence, and PTime (Hours) (Figure 80, Table 22). The Order ID is a FK that is linked to the “Arrivals” table.

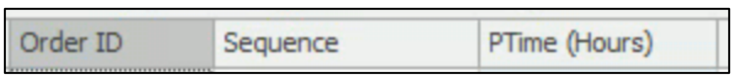

Figure 80 Sequence Table Columns.

Table 22 Sequence Table Columns.

Column Name	**Property Type**
Order ID	Foreign Key Property
Sequence	SequenceDestination Property
PTime (Hours)	Real Property

E9. Planning Tab

To use the Planning Tab in Simio, the user went to the model’s Run Tab, clicked “Advanced Options”, and then clicked “Enable Interactive Logging”. All the servers were selected, and their Advanced Options, Log Resource Usage properties were set to “True”.

E10. Dashboard Reports and Dispatching

Dr. Jeffrey Smith's Dashboard Reports from "INSY 6450 VM03 V02" were imported by going to the Results Tab, Dashboard Reports, Import. (The dashboards that are imported can be found at this link: https://jsmith.co/vm03-scheduling-type-job-shop-models/)