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Model for Prioritization of High Variation Elements in Discrete Production Systems

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I am submitting herewith a dissertation written by Bharadwaj Venkatesan entitled "Model for Prioritization of High Variation Elements in Discrete Production Systems." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Industrial Engineering.

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Abstract

The complexity of the modern manufacturing enterprise has led companies to look for techniques and methodologies for improving production performance. Lean manufacturing techniques have been applied in the US with varying degrees of success, and Theory of Constraints (TOC) has been used to emphasize the flow of production and identify performance improvement projects. One aspect of manufacturing for which there has been limited academic or industrial research till date is the impact of variation on production performance and the identification of improvement projects based on variation. This thesis develops a methodology to incorporate random and simultaneous occurrence of variability in a manufacturing facility, e.g., equipment failure, variabilities in the arrival time of raw materials and in-station processing time, to model system performance. Two measures of performance are developed corresponding to time and material. A prioritization algorithm is developed to utilize the "Coefficient of Variation" to identify a Bundle of High Variation Elements (BHVs) affecting the performance of a production system. The Bundled Variation-based Project Prioritization Model (BVPM) is a closed-loop model designed to provide decision makers with a list of projects to improve system performance while monitoring the implementation of projects.

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Chapter 1

Introduction

1.1 The Role of Variation in Impacting Throughput

The manufacturing sector employs metrics related to delivery, product quality, and cost. However, these performance measures are dependent on a production system's capacity and capability to produce, which in turn are reliant on the movement of material and performance of individual stations, equipment and personnel. Arrival and process-based performance determine the throughput of a system, and variations among any of these factors increase production cost while hindering the throughput of the system. Complex supply chains can be described as inter-connections among manufacturing facilities, suppliers, and customers, and any variation in the performance of a supplier facility can have a ripple effect on the performance of the supply chain via the so-called "bullwhip effect". One example of this is the disruption caused in the automotive industry as a result of the 8.9-magnitude earthquake that struck the northeast coast of Japan on March 11, 2011 (Canis, 2011; ElMaraghy et al., 2012). Japan is the world's second largest producer of automobiles, and many vehicle parts produced there are utilized by manufacturers across the world. Following the earthquake, a relatively small number of critical parts suppliers producing critical components for flash memory and paint could not meet their production commitments, resulting in global shortages that induced production stoppages in automotive manufacturers both at the local and international levels. The simultaneous stoppage of production was an important source of disruption in the supply chain. Although the above example is an extreme case, it provides an indication of the need for research into the use of variation for prioritizing improvements in manufacturing systems in which variations are considered simultaneously. Due to interdependent nature of complex manufacturing and supply chain systems, implementing a group (bundle) of improvement projects would reduce the impact of simultaneous variation in the production system.

Deming and Edwards (1982) maintain that “management is prediction, and variation reduces the accuracy of prediction”. As variation increases, the throughput of a production system is degraded, and maintaining system performance requires additional capacity, assets, and resources to compensate for the variation. Variation also hinders prediction of future system states by affecting the ability to identify root causes of negative system performance.

Figure 1.1 illustrates the multitude of factors that impact the throughput of a production system. Processing time at a station, setup time, wait time in queue, equipment availability, and equipment capacity are examples of the causes of variation in a production system. When there is a change in one element, such as the arrival rate of raw materials at one station in the production line, the throughput of the station is affected, which in turn affects the throughput of the next station propagating the effect of the variation through the production system. Similarly, the breakdown of equipment at one station will propagate the resulting variation to all other stations. However, an important factor that gets ignored but requires consideration is the simultaneous occurrence of different types of variation at each station, which would have a dynamic effect on the performance of the production system as a whole.

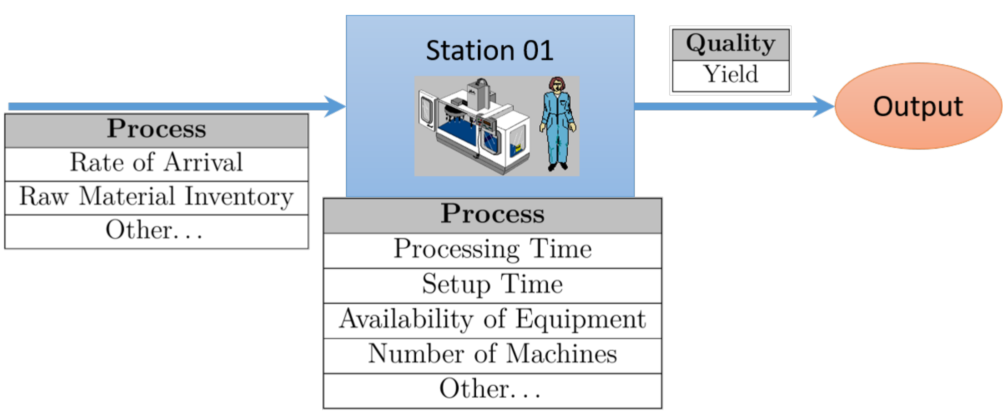

Figure 1.1: Variability in Manufacturing System

Sawhney (2015) compared the impact of variation on the throughputs of push and pull production systems. Increasing the variation was found to significantly increase lead times in a push production environment, although the effect of variation was mitigated in a pull environment. In such systems, manufacturing lines with raw material batching have lower throughput than single-piece production lines (Hopp and Spearman, 2011). As batching may allow different types of variation to affect the arrival rate of material to a station.

The frequency and duration of equipment breakdown have been found to have varying effects on the total output of a manufacturing system. In (Patti and Watson, 2010), the authors conclude that long-duration and low-frequency variations have a much more negative impact on the performance of a system than short-duration or high-frequency impacts. This suggests the need for a relative measure of variation to compare parameters affecting system performance. Hopp and Spearman (2011) propose the use of a 'Coefficient of Variation' (cv) as a measure of variability in manufacturing systems. Their proposed cv is a function of the absolute mean and variance of a parameter that is used to develop a metric to standardize comparison of variabilities in process times, inventory quantity and equipment breakdown.

According to Ikome et al. (2016), most of the academic research concentrates on the effects of independent disruptions while ignoring simultaneous disruptive events. The recent literature that does analyze the effect of simultaneous disruptions on production planning includes Katragjini et al. (2015), who analyze the effect of simultaneous disruptive events on production schedules. They conclude that random and simultaneous disruptions affect the overall performance of a manufacturing system by increasing factors such as material handling requirements and setup times.

Both industry and the existing academic literature utilize various performance metrics to measure the effect of disruptions in a manufacturing system. Throughput is a common measure that calculates the amount of finished product produced in a day. Little's Law (Little, 1961) states that throughput is a function of cycle time and inventory. Subburaman (2010) identifies categories of factors affecting throughput in terms of personnel, material, equipment and schedules. Karim and Arif-Uz-Zaman (2013) utilized efficiency and effectiveness performance metrics to prioritize lean strategies based on an efficiency metric calculated as the ratio of output value to input resource. Here the output value is a function of “Number of Outputs” and “Average Pitch Time”, while the input resource is a function of “Number of Workers” and “Total Allocated Time”. Neely et al. (1995) define *efficiency* as a measure of how economically a firm’s resources are utilized. Hopp and Spearman (2001) propose that the efficiency of a manufacturing facility can be defined specifically based on parameters such as cycle time, defining Cycle Time Efficiency as the ratio of Ideal Cycle Time to Average Cycle Time. In definitions of efficiency such as those discussed above, disruptions such as downtimes, wait times in the queue, and setup times are latently included in the data; consequently, the effect of disruptions on a system cannot be analyzed. With the explicit inclusion of variation information during data collection and computation of system performance, improvement projects can be selected based on the identification of root causes for disruptions in the system.

Parthiban and Goh (2011) developed a prioritization scheme to improve manufacturing performance through a model combining Quality Function Deployment (QFD) with an Analytic Hierarchy Process (AHP). They converted qualitative survey data to quantitative data using an Extended Brown-Gibson (EBG) model. Factors affecting production performance were evaluated through AHP, and existing processes were redesigned based on QFD results. Similarly, Subburaman (2010) utilized a modified Failure Mode Effects Analysis (FMEA) approach for prioritizing the causes of failure in implementing Lean Manufacturing practices. The author developed a qualitative methodology based on surveys of personnel to assess the progress of lean manufacturing methodologies in a facility.

Decision-making systems that are sufficiently integrated, dynamic, accurate, accessible, and visible to facilitate responsive manufacturing are still uncommon according to Nudurupati et al. (2011). The authors note that most PMSs are based on metrics that are historical and static and thus, not dynamic and insensitive to changes in a manufacturing system. This leads to insufficient scaling of PMSs with the size of manufacturing enterprise. Some PMSs are designed for small companies while Enterprise Resource Planning (ERP) system are intended for large companies and expensive for small enterprises. The non-scalable nature of existing PMSs leads to companies relying on different measurement systems and criteria to achieve the same production goals.

Traditionally, project selection for improvement of system performance is made based on suggestions from Lean, Six Sigma, and Theory of Constraints. The focus of Lean manufacturing is in the flow of production, while Six Sigma reduces variation through the elimination of defects. Theory of constraints concentrates on identifying bottleneck of a system based on criteria such as processing time of stations. These methodologies are independent applications as they have different goals. Therefore, the result would be a presentation of multiple improvement projects to decision makers without common criteria to compare their effect on system performance. Few PMSs have been designed to address the problem of information overload resulting from the scale of implementation (Sabeeh and Ismail, 2013), and there is a need on the part of decision makers for PMSs that can simplify the process of identifying improvement projects and estimated their effect on production performance.

1.2 Problem Statement

Variation is identified as a key factor impacting the throughput of a system. However, the use of variation to identify improvements in manufacturing based supply chains is not prevalent. Further, the role of bundling different types of variation has not been investigated as a basis for managing manufacturing systems. The focus of this research is to develop a Bundled Variation-based Project Prioritization Model (BVPM) to prioritize high levels of variation and their impact on performance of discrete manufacturing systems by the specific objectives of this research are:

1. Developing a scalable platform for managing productivity at station and facility level.
2. Developing a throughput based performance measurement system by,
    - developing metrics for Cycle Time and Inventory Efficiencies;
    - incorporating key sources of variation in the performance measurement system, and;
3. Developing an algorithm to,
    - prioritize different categories of variation within a system;

- bundle the relevant variations to enhance system performance;
- provide time-frame beyond which the Bundle of High Variation Elements (BHVs) result in degradation of system performance;

1.3 Key Contributions

The thesis develops a BVPM comprising two functionalities: Performance Measurement, and Prioritization Algorithm. The performance measurement system utilizes efficiency metrics to monitor the performance of a production system. The prioritization algorithm is applied to analyze system performance data, identify and prioritize BHVs in a system. It is important to note that BVPM is a closed-loop system in which improvement suggestions produced by the prioritization algorithm are to be utilized by decision makers to implement changes in the manufacturing line. Consequently, performance measures are recalculated, which leads to the identification of a new set of improvement suggestions.

Performance Measurement

BVPM utilizes two metrics to measure the performance of a manufacturing facility: Cycle Time Efficiency, and Inventory Efficiency. These metrics independently monitor the performance of each product in a manufacturing facility. Cycle time Efficiency indicates the deviation of the "Overall Cycle Time" of a manufacturing process in comparison to an "Raw Cycle Time" based on variations owing to downtime, setup time, arrival rates, and processing time. Similarly, Inventory Efficiency measures the deviation of "Overall Inventory" in a manufacturing process to an "Ideal Inventory" in the production line. These two efficiencies require the collection of station level data termed as Operational Metrics (OMs).

Prioritization Algorithm

Data from OMs and system efficiencies are utilized in the prioritization algorithm to identify the BHVs. The first step in this process is the prioritization of operational metrics based on their respective "Coefficients of Variation" (cvs). In this process, OMs for all stations in a system are considered in the ranking of the most critical variations impacting the two system performances. The second step utilizes stepwise regression to identify the most significant High Variation Elements (HVs) affecting system efficiency trends, resulting in the identification continuous improvement projects. The final step in the prioritization algorithm is the calculation of the time available to decision makers before the BHVs begin to cause significant reductions in system performance.

1.4 Model Validation

The BVPM is validated via a case study within a medium sized discrete manufacturing facility that produces automotive components. Validation process focuses on:

- Evaluating the data collected through on-site interviews and time studies.
- Calculating system performance metrics for a baseline model.
- Implementing prioritization algorithm of BVPM to identify the BHVs of the baseline model.
- Utilizing existing methodologies such as Theory of Constraints (TOC) to identify performance improvement projects for the baseline model.
- Comparing improvements in system performance gained through implementing BVPM with those obtained using the TOC model.

1.5 Structure of Dissertation

In the following four chapters, The **Bundled Variation based Project Prioritization Model (BVPM)** to monitor, improve, and sustain the productivity of a discrete manufacturing system is described. Chapter 2 looks at existing literature in the field of performance management, project selection and inclusion of variation in manufacturing systems. Chapter 3 elaborates on the theoretical structure of BVPM as a tool to measure system productivity and identify and prioritize HVs. Chapter 4 discusses the result of implementing BVPM in an existing production environment for the purpose of validating this research. The chapter provides a visualization and analysis of data generated by the BVPM from the perspective of decision-makers at a company going through the process of improving productivity. Chapter 5 summarizes the thesis and its contributions and suggests future research to improve BVPM for applications in other fields, including supply chain management and benchmarking.

Chapter 2

Literature Review

In a well-quoted study, Ghalayini et al. (1997) highlighted the need for newer performance measurement systems and methodologies that move away from traditional cost accounting-based systems. The remainder of this literature review will identify existing research and the technologies available to academicians and industry experts on the effect of variation in manufacturing and supply chain systems, prioritization, project selection and prediction algorithms. This review includes the following:

- Section 2.1 pertains to existing literature on effects of variation in measuring and monitoring manufacturing system performance.
- Section 2.2 presents existing prioritization and project selection methodologies.
- Section 2.3 presents existing predictive methodologies for improving manufacturing performance.
- Section 2.4 presents the calls for new capabilities in Performance Measurement Systems (PMSs) to include quantitative predictive process improvement methodologies.

2.1 Variation in Manufacturing and Supply Chain Systems

In the 1990s, industry began to use Overall Equipment Effectiveness (OEE) to measure and effectively maintain machine performance at optimum manufacturing capability Sherwin

(2000). This methodology was originally developed by Nakajima (1988), who cultivated practices for optimal equipment use. The original OEE was developed to address chronic disruptions that result in low utilization of equipment, and identified the six big loss categories of breakdown, waiting, minor stoppages, reduced speed, quality defects, and start-up losses (Nakajima, 1988). Efforts were also made to develop metrics to measure process effectiveness based on OEEs, although with limited success (Raja and Kannan, 2008) . The model they developed worked with a preset configuration comprising either a series or parallel system or a combination system. This paper adapts their performance metric of Overall Process Effectiveness (OPE), which is calculated in Equation 2.1, in which A_p is the availability of machines, P_p is the performance rate of machines, and Y_p is the yield of the process:

$$OPE = A_p \cdot P_p \cdot Y_p \tag{2.1}$$

Availability is calculated using Equation 2.2 in which MTBF is the mean time before failure and MTTR is the mean time to repair. Performance rate is calculated using Equation 2.3, in which n is the number of products produced per shift by a bottleneck process and t_s is the processing time per machine. Finally, the yield of a machine is calculated by Equation 2.4 in which input equivalent is the expected product at the end of a shift. The performance rate is calculated based solely on that of the machine with the smallest processing time.

$$A_p = \frac{MTBF}{MTBF + MTTR} \tag{2.2}$$

$$P_p = \frac{n \cdot t_s}{Actual\ Operating\ Time} \tag{2.3}$$

$$Y_p = \frac{Good\ Products}{Input\ Equivalent} \tag{2.4}$$

There have been several variations made to the original OEE to see if it can be used to identify potential areas of improvement and support lean initiatives. Some researchers have used a weighted OEE for measuring the performance of a production line. Raouf (1994); Wudhikarn et al. (2010) developed a weight-based OEE measure to challenge the assumption made by Nakajima (1988) that all elements of OEE are equally important. In the same vein, Overall Throughput Effectiveness (OTE) and Overall Cycle Time Effectiveness (OCE) have been developed in an attempt to expand the scope of OEE's implementation (Muthiah and Huang, 2007, 2008; Muthiah et al., 2008). These metrics use the standard set byNakajima (1988) to calculate effectiveness as a ratio of actual measurement to theoretical measurement. Here, actual measurements are computed by assuming that the production system is either series, parallel, assembly, or expansion (Muthiah and Huang, 2007) and are not compatible with a generalized manufacturing system. Although these methodologies included variation, they lack the scope and flexibility required for measuring and assessing real-world systems as they reflect combinations of solely series, parallel or assembly systems and not combinations across categories.

Patti and Watson (2010) analyzed the effect of variability in downtime on actual time lost in a serial production system. The authors considered two characteristics of equipment downtime: mean time before failure (frequency), and mean time to repair (duration). A given total downtime of equipment can be achieved by an infinite number of combinations of downtime and frequency. They tested three combinations of downtime and frequency (Table 2.1) in a simulation model and concluded that, for constant overall downtime, different downtime frequency/duration combinations have a different impact on system performance. Combinations with low frequency and long duration were found to have a much more negative impact on system performance than high-frequency and short-duration combinations. A company would have to increase its buffer inventory or capacity to alleviate the negative impact of downtime on system performance.

Table 2.1: Downtime Frequency/Duration Combinations Tested (Patti and Watson, 2010)

Model	**MTBF (hours)**	**# Events in 5500 hours**	**MTTF (mins)**	**Total Downtime**
Infrequent/long duration	11	500	66	33,000
Medium frequency/medium duration	5.5	1000	33	33,000
Frequent/short duration	2.75	2000	16.5	33,000

Katragjini et al. (2015) compared the performance of theoretical rescheduling algorithms with those of traditional repair routines utilized in production environments, stressing the importance of studying the effect of large numbers of simultaneous disruptions in production schedules. The authors considered job cancellations, processing time variations, sequence modifications, due date modifications, and weight variations by comparing the results of Local Search (LS) and Iterated Greedy (IG) methods with those of rule-based repair methods. The IG algorithm proved to be the most effective, followed by LS methods. In turn, both the IG and LS methods outperformed the rule-based repair methods for rescheduling while compensating for simultaneous disruptions in the production system.

Hopp and Spearman (2011) described the effect of rate of arrivals on throughput performance of a simple manufacturing system following three scenarios—Best Case, Worst Case, and Practical Worst Case - over a common processing time.

- The **Best Case** scenario presents a situation in which the arrival rate of raw material coincides with the processing time of the first station, resulting in no Work-in-Process (WIP) condition at stations and the highest throughput.
- The **Worst Case** scenario presents a situation in which raw material arrives in batches, resulting in a high WIP condition at each station and the lowest throughput.
- The **Practical Worst Case** (PWC) the rate of arrival of raw material varies between that of the Best and Worst Cases. The resulting throughput is between the Best and Worst Case results.

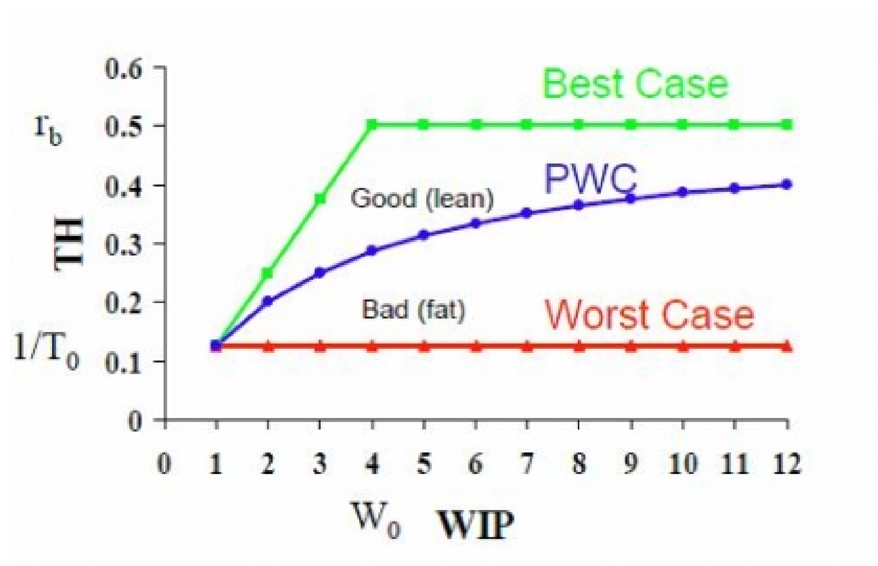

Figure 2.1: Trend of Throughput versus WIP (Hopp and Spearman, 2011)

2.2 Prioritization and Project Selection for Process Improvement

Improving performance of complex networks such as manufacturing and supply chain systems is a task requiring a combination of measurement and management. Alignment of management strategy with measurement and performance goals is essential to the success of improvement projects. Brown et al. (2007) suggest that Performance Measurement Systems (PMSs) should enable dialog and collaboration between upper management and operations management. This would help companies to manage their operations—an essential goal. The authors utilized case studies of manufacturing/assembly plants in the computer industry collected over the course of three years. They concluded that, performance can be either a financial or a non-financial measure, but manufacturing performance must be non-financial and encompass diverse areas such as new process technologies, developing new products, managing human resources, and supply chain management. In their study, they used commonly reported operational measures and only considered objective measures, as perceptive measures would have had higher bias and lower consistency. Through empirical analysis, they concluded that, in world-class plants, manufacturing strategy formed an important bridge that linked to business strategy and improved operational capabilities. They also found that such plants used expertise gained in one area of operations to enhance their overall manufacturing capabilities.

Dossi and Patelli (2010) attempted to determine the usefulness of financial and non-financial measures in multinational companies. They performed an extensive survey in the Italian subsidiaries of foreign enterprises and found that non-financial indicators in PMSs were positively associated with relative performance evaluation, interactive use of PMSs, subsidiary size, headquarters nationality, and subsidiary participation in the design of PMSs. Based on this, they suggested PMSs should broaden their scopes to improve strategy implementation and should be interactive to enhance global knowledge-sharing and learning. They found Strategic Performance Measurement Systems (SPMSs) to be useful in coordinating the disparate actions of entities within an organization and creating congruent goals through the improvement of communication, analysis, and evaluation of

Key Performance Indicators (KPIs). Although both financial and non-financial KPIs were considered, the authors primarily examined the influence of non-financial KPIs in enhancing organizational SPMS for enhancing the relationships between headquarters and subsidiaries. They found that non-financial indicators were more likely to be used in identifying best practices within cooperative relationships. They further examined the effect of non-financial indicators as means to primarily offset the limitations of financial indicators. Determining that non-financial indicators be more forward-looking, better at predicting future performance, and less subject to manipulation than financial indicators, they concluded that non-financial indicators should be used not only as a sophisticated method for monitoring but as a method for implementing a company's strategic goals.

The performance of a manufacturing system is determined by the flow of product and the variability in the system (Hopp and Spearman, 2011). Companies have utilized methodologies such as Lean Manufacturing, Six Sigma, and the Theory of Constraints to select projects for improving the performance of a manufacturing system. Lean manufacturing focuses on the flow of production and identifies improvement projects accordingly. Six Sigma concentrates on reduction in variation through the elimination of product defects. The Theory of Constraints is utilized to determine the bottleneck in a manufacturing system for criteria such as processing time at stations. As these three performance improvement methodologies are all designed to be implemented independent of each other, making any comparison among resulting improvement projects is untenable owing to a lack of commonality in metrics and criteria.

Traditionally, project selection techniques are categorized as either subjective or objective methodologies. The objective methods include Lean, Six Sigma, Total Quality Management, Kaizen events, and Statistical Quality Control while brainstorming, focus groups, interviews, customer visits, and experience fall under the category of subjective methods. Kirkham et al. (2014) statistically analyzed of a survey of 203 organizations to understand the nature of prioritization of operations improvement projects in the European manufacturing industry. They concluded that adoption of objective improvement methods increases through the implementation of improvement methodologies. Of the objective methods, Six Sigma was considered to be the most influential methodology.

2.2.1 Project Selection Methodologies

Project selection is a critical success factor in the continuous improvement of manufacturing enterprises (Su and Chou, 2008). According to Mittal et al. (2017), “Productivity is never an accident, it is always the result of a commitment to excellence, intelligent planning, and focused approach”. The authors developed a methodology for using “Shainin” and “Fuzzy Analytical Hierarchy” systems to enhance the productivity of a manufacturing system. The Shainin System is based on the use of data taken from daily maintained production sheets and simple calculations without the use of software and statistics. An advantage of this system is that the process is not disrupted while analysis for root causes proceeds. According to Shainin, “There is no space for subjective methods in serious problem solving”. The authors utilized various factors such as process and suspected source of variation (ssv) in developing their root cause analysis. Khalili-Damghani et al. (2014) developed a Decision Support System (DSS) to solve a sustainable multi-objective project selection problem applicable to financial data.

Kornfeld and Kara (2013) performed a survey of 74 practitioners to develop an understanding of the use of Lean and Six Sigma methodologies in project selection. They concluded that there is considerable dissatisfaction among practitioners in terms of project and portfolio selection. As subjective tools are used more widely than objective tools for project selection, practitioners sometimes make no connection between business and project selection strategy, reducing the likelihood of to the project achieving the desired impact. The critical step of linking business strategy to projects is skipped, leading to the selection of projects that do not create positive change in business operations.

In the late 1980s, General Motors invested $20 million to develop a new PMS to ensure employee focus on continuous improvement through teamwork in key business activities. They developed 62 measures that could be applied at various organizational levels (Figure 2.2), distinguishing between measures relating to results, e.g., quality and responsiveness and measures of process of strategy implementation.

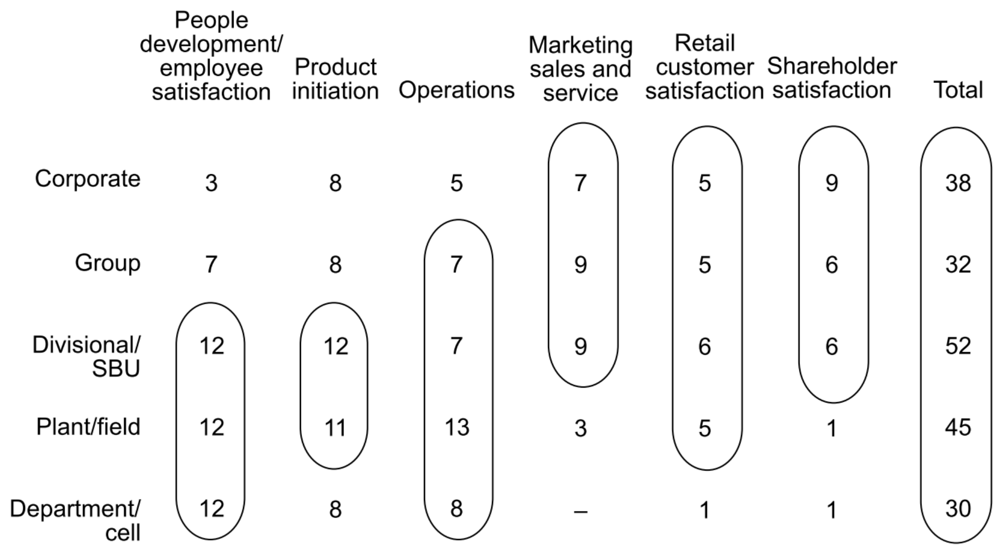

Figure 2.2: General Motors' integrated performance measurement system (Neely et al., 1995)

Since its introduction by Kaplan et al. (1996), Balanced Scorecard (BSC) has been one of the more successful methodologies for improvement and the achievement of company strategic goals. A company can define a specific set of measures, including financial, customer, internal business processes, and learning and growth (Dransfield et al., 1999), to understand overall organizational performance using BSC. Even though BSC has been popular both in industry and academia for assessing the health and performance of systems, it does not include a thorough empirical and operational level assessment procedure in its improvement methodology.

Panat* et al. (2014) described the application of Lean Six Sigma (LSS) in low-volume experimental manufacturing environments such as Intel's manufacturing R&D environment. They implemented LSS to systematically eliminate waste and improve Intel's existing configuration control during the development and ramp phases, resulting in a 60% reduction in idle time and non-value added activities in the production line.

Ray and Das (2010) proposed a methodology based on the analysis of performance data and the Balanced Scorecard tool to select the right projects for an organization. Their method employs metrics such as "Cost of Poor Quality", "Cost of Inventory", "Cost of Transportation", "Cost of Maintenance", and "Cost of Purchase" as organizational performance data.

Table 2.2: Balanced scorecard of Six Sigma project metrics (Ray and Das, 2010)

Effectiveness Measures	Efficiency Measures
Financial	*Internal business process*
1. Inventory turn ratio	1. Defects
2. Manufacturing cost per unit	2. Rework
3. Cost of poor quality	3. Yield
4. Transportation cost per unit	4. cycle time
5. Market share	5. Consumption variance
6. Turnover	6. Process capability
Customer	*Employee learning and growth*
1. Customer satisfaction	1. No. of Six Sigma projects
2. On-time delivery	2. Training effectiveness
3. Final product quality	3. No. of black belts
4. Development cycle time	4. Projects completed on time (%)
5. Response time to customer	5. Cultural change
6. Customer dissatisfaction	6. Safety

2.2.2 Prioritization and Root-Cause Analysis

Identification and prioritization of root causes have been applied as a maintenance process improvement tool in the manufacturing sector. The "Theory of Constraints" (TOC) is utilized as a technique to identify the constraint in a production system or equipment fleet. The simplified nature of TOC method has led to its application in a wide variety of fields, including manufacturing, healthcare, and software development. In TOC, the constraint in a system is identified for a specific criterion. For example, in a manufacturing system, the bottleneck process is identified by analyzing the throughput of the system and the utilization of stations. The station with the highest utilization is designated as the bottleneck of the production line. The disadvantage of TOC is that it is not a multi-criteria decision-making tool, as it is designed to work with one criterion and cannot compare results from multiple criteria. Costas et al. (2015) utilized TOC to identify the root causes of the Bullwhip effect in a supply chain, resulting in a significant decrease in the effect based on the implementation of their analysis.

Quality Function Deployment (QFD) is a method that has been used by industry for manufacturing process improvement. Using this technique, a relationship between the "voice of the customer" and design, engineering, manufacturing, and production processes is developed to ensure that products meet the needs of the customers. Although it is a very useful technique, it lacks an internal process improvement methodology based on the company's manufacturing metrics that can also provide improvement suggestions. Parthiban and Goh (2011) suggest a model using AHP and QFD to integrate performance measurement with improvement. Performance measures they propose using include operating cost per employee, cost of goods sold per inventory, rejection ratio, capacity utilization, and customer surveys.

Resurreccion and Santos (2011) used a Dynamic Inoperability Input-Output Model (DIIM) to identify critical sectors using economic loss and inoperability as minimization criteria. They developed a Dynamic Cross Prioritization Plot (DCPP) to prioritize and identify critical sectors for inventory-based solutions. Their research was based on a modified version of Cross Prioritization Plot (CPP) developed by Gokey et al. (2009), which was used by decision-makers from the Virginia Department of Transportation for allotment of a bridge maintenance budget based on economic and maintenance criteria.

Bayraktar et al. (2013) used a Structural Equation Model (SEM)-based methodology to prioritize factors affecting a retailer's supply chain performance. Using a simulation of a two-level supply chain with linear demand and seasonal swings under various operating conditions, they explored the relationships between the bullwhip effect, lead time, forecast accuracy, seasonality, service levels, and retailer performance. They found several strong causal links, for example, between forecast inaccuracy and bullwhip ratio. Also, the desired service level was found to be strongly related to a retailer's fraction of no-stock-out cycles and fill rate.

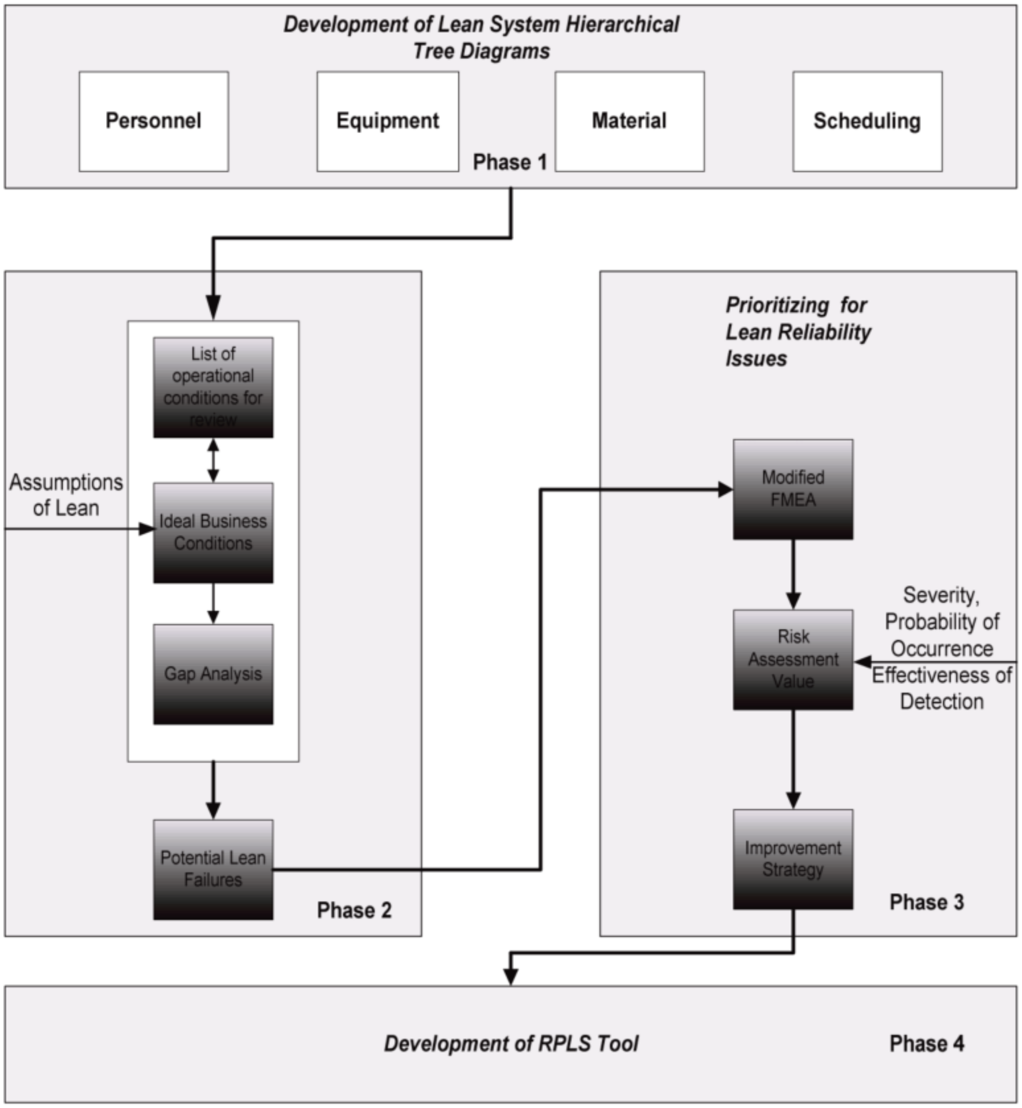

Figure 2.3: Road Map for Risk Prioritization of Lean Systems (RPLS) (Sawhney et al., 2010; Subburaman, 2010)

Sawhney et al. (2010) and Subburaman (2010) developed a performance measurement system for benchmarking the reliability of lean production systems Figure 2.3. To develop their model, they used the Risk Assessment Value (RAV) and Analytical Hierarchy Process (AHP) measures to develop a modified Failure Mode Effects Analysis (FMEA) approach to measuring and prioritizing risk in a lean philosophy-implemented production system. Their result represented an improvement on FMEA's Risk Priority Number (RPN) in that RAV places a greater emphasis on a lean practitioner's competence to increase a system's ability to detect and manage lean failures. Equation 2.5 gives the derivation of RAV, where, where

O is the probability of occurrence of an actual business condition, S is the severity of its potential effects, and D is the effectiveness of detection to control its root cause.

$$RAV = \frac{O \cdot S}{D} \tag{2.5}$$

Parthiban and Goh (2011) developed a model that uses an Analytic Hierarchy Process (AHP) to identify the current performance of an organization using a combination of qualitative and quantitative dimensions of manufacturing performance measurement. They also developed a method for improving a manufacturing system based on the results of their previous model based on Quality Function Deployment (QFD).

Ibrahim and Chassapis (2016) noted a lack of quantitative models to prioritize "key characteristics" and quantify their risk of variation. The authors presented a model to prioritize and quantify future variations arising from possible deviations of design parameters from their nominal values as a means of assessing the related risk of variation.

2.3 Predictive Methods in PMSs

Existing literature utilizes some predictive methods for forecasting through the use of lagging measurements with the goal of suggesting process improvement opportunities. W. Edwards Deming famously stated that "If I could reduce my message to management to just a few words, I'd say it all has to do with reducing variation". Reducing variation in a production line reduces variability in performance, resulting in a better fit for statistical modeling; hence, "management is prediction".

Lee et al. (2013) performed a comprehensive review of existing predictive manufacturing systems. Concentrating on the "Internet of Things" and "Big Data" as they are applied to manufacturing enterprises, they reiterated the necessity of using the right approach and tools to converting data into useful and actionable information. Under the correct supposition that "Data is not useful unless it is processed in a way that provides context and meaning that can be understood by the right personnel", they built a conceptual framework for a predictive manufacturing system that utilizes large quantities of data and through the application of predictive analytics systems such as Watchdog Agent®, which uses algorithms in the categories of signal processing and feature extraction, health assessment, performance prediction, and fault diagnosis that can be integrated into a company's ERP systems for visualization.

Ding et al. (2013) developed a data-driven methodology for KPI prediction and diagnosis to improve performance. Applying the Left Coprime Factorization (LCF) of processes, they developed efficient prediction algorithms for application in a hot strip mill. Luo et al. (2015) used neural networks for the prediction of equipment maintenance schedules, employing a two-stage maintenance framework to predict degradation in industrial applications. To forecast degradation, they applied regression analysis methodology. Wei et al. (2013) implemented a model for predicting useful life and anticipated performance for a class of multi-sensor dynamic systems subject to possible degradation. In addition to the studies described above, there have been a number of efforts to develop prediction algorithms with respect to the reliability of equipment.

One of the restrictions on PMS performance is the continuous and never-ending need to collection data, which creates constraints on the methodology parameters such as near- or complete automation and speed of execution, two essential characteristics in developing a method for prediction in a PMS. One example of this is a PMS that collects data and assesses the state of a system with a data collection frequency of 10 minutes, i.e., a new data point for prediction is created every 10 minutes, which requires that the analysis is adjusted accordingly. This speed can only be useful if the prediction method were fast enough to suggest improvement opportunities before collection of the next data point, thus ensuring that the prediction model does not lag too far behind the measurement metrics.

2.4 Calls for New PMS Capabilities

Most of the original PMSs designed in the late 1970s and early 1980s were based on financial indicators that were lagging in nature, e.g., weekly and monthly reports. The lag creates a delay in providing information to decision-makers. The 1990s represented the peak of activity in the development of new performance measurement metrics and systems. A reality of modern manufacturing is the concept of extended enterprise and inter-organizational PMS (Jagdev and Browne, 1998). Starting as early as 1999, PMSs have been criticized for their inability to keep up with globalization and the emergence of new manufacturing centers in emerging markets such as Brazil, Russia, India, and China. This trend, along with the formation of enterprises established across vast territories and nations, has forced researchers to move away from the traditional view of manufacturing companies with clear boundaries and limited relationships with other businesses while focusing solely on internal metrics and practices (Browne and Zhang, 1999).

According to Beamon (1999), in developing performance measurement systems it is necessary to ask the right questions, including what should be measured, how should multiple individual measures be integrated into the measurement system, how often should measurements occur, and how and when should measures re-evaluated.

Operational PMSs must additionally perform four critical functions according to Olsen and Ward (2006):

- Document historical performance
- Indicate current state of production system compared to company strategy
- Predict future performance
- Motivate action

Yeniyurt (2003) identifies numerous methodologies developed in two primary streams: traditional finance-based PMSs, and non-finance-based PMSs. The author recognizes the lack of research into developing PMSs for global industry as well as the lack of proactive and forward-looking methodologies to complement the existing purely retrospective methods.

When analyzing performance, qualitative measures such as “good”, “fair”, and “poor” do not carry any intrinsic value to assess system performance, as these represent a human interpretation of the state of the system and are often based on arbitrary metrics. Numerical performance measures such as the Likert scale fall into the same trap as qualitative measures by producing vague performance measures. This opens the door for the development of a quantitatively driven performance measurement system designed from the ground up to measure, monitor, and suggest improvements to a system.

One of the main weaknesses of current PMSs is the lack of systems based on strong empirical foundations. The authors have also suggested that more empirical research is needed in the fields of performance measurement (Nudurupati et al., 2011). Until recently, most PMSs have been designed primarily based on case studies and survey methods and not on rigorous empirical methodologies. To address this issue, Herzog et al. (2009) developed an empirical methodology for analyzing linkages between manufacturing strategy, benchmarking, performance measurement (PM), and business process re-engineering (BPR).

Nudurupati et al. (2011) suggest that Management Information Systems (MISs) are essential in implementing PMSs. Neely et al. (1995) identify reasons for implementing PMSs including performance monitoring, identification of areas that are in need of attention, enhancing motivation, improving communications, and strengthening accountability.

Many inadequacies of existing performance metrics and systems have been identified but have not been fixed completely, including the following:

- Traditional accounting measures are not adequate for strategic planning and decision making (Kaplan and Norton, 2005).
- They are historical in nature (Ittner and Larcker, 1998).
- They lack the predictive element needed for analysis and improvement (Ittner and Larcker, 1998).
- Such measures do not provide sufficient information for identifying and understanding root causes (Ittner and Larcker, 1998).
- There are too many measures, with the need for a short set of measures covering a broader range of content (Frigo and Krumwiede, 2000; Kaplan and Norton, 2005).
- Traditional metrics do not aggregate from operational to strategic levels (Frigo and Krumwiede, 2000; Kaplan and Norton, 2005).

Performance Measurement Systems in Supply Chain Management

In the past decade, globalization, the increasingly competitive nature of the industry, and an enhanced customer orientation have increased interest in the understanding of supply chain concepts (Gunasekaran et al., 2001). However, there is a major discrepancy between perception and reality in terms of how well supply chains have been implemented and sustained. Deloitte Consulting reported that, although 91% of North American manufacturers viewed supply chains as necessary and critical to organizational success, only 2% considered their supply chain as "world class" (Thomas, 1999). Given this discrepancy, there has been a call for new research into developing performance measures that would enable all players in a supply chain to quantify progress and growth (Chen and Paulraj, 2004). Organizational performance measurement and metrics from a supply chain perspective have received a good deal of attention from the researcher and practitioner communities (Gunasekaran et al., 2004). Shepherd and Günter (2011) pointed out the dearth of literature regarding PMSs in the supply chain framework. They provided a comprehensive list of performance measures and also evaluated various systems designed to assess the performance of supply chains.

Supply chains have traditionally used a combination of cost and customer responsiveness to measure productivity performance. Customer responsiveness is typically measured in lead time, stock-out probability, and fill rate. Single supply chain measures have also been suggested and used in some cases but have been found to be non-inclusive in nature when trying to measure all relevant aspects of a supply chain. Over the years, many papers have recommended against the use of cost as a single measure of performance (Lee and Billington, 1992; Maskell, 1991), as operational metrics such as rework are masked under a cost performance measurement system.

Gunasekaran et al. (2004) suggested that supply chain performance measurement can be separated into six categories:

1. Metrics for order planning
2. Metrics for evaluating supply link
3. Measures and metrics at production level
4. Metrics for evaluating delivery link
5. Measures for customer service and satisfaction
6. Supply chain and logistics cost

Continuous improvement has been considered to be a tool for enhancing core competitiveness by firms in a supply chain. Unfortunately, use of this method has failed to produce the performance measures and metrics needed to integrate supply chains and maximize utilization. As pointed out by Lee and Billington (1992), assessment of overall supply chains through consistent measures and metrics is essential. If companies in a supply chain seek to achieve goals independently and not as a cohesive unit, the overall efficiency of the supply chain will not be optimized. Another important aspect of a performance measurement system is its robustness and resiliency to manipulation by entities in the supply chain (Schroeder et al., 1986).

2.5 Conclusion

Based on the preceding analysis of the literature on performance measurement systems, it has been identified that extensive work has been done in the fields of measurement and improvement of performance, but the globalization of manufacturing in the last decade has forced industry and academia to rethink the usefulness of traditional measures and systems. The literature suggests that some preliminary research has gone into the development of performance management and performance improvement methodologies based on empirical models and quantitative performance measures with the flexibility to help both small and large enterprises flourish in the modern manufacturing environment.

Many studies have noted that the present performance measurement landscape has been dominated by metrics and measurement systems that use financial indicators to monitor system health and process improvement. Although useful, such systems do not provide an accurate picture of the health of a production system, as has been pointed out by various researchers over the last two decades. Many studies have also noted the need for more quantitative and non-financial measurement and system assessment metrics.

There are some famous examples of performance management systems over the years, including General Motors' integrated performance measurement system and the Balanced Scorecard tool. Although these have been useful to a certain extent, all have flaws such as a lack of quantitative measures inclusion. Overall equipment effectiveness (OEE) is a measurement system that uses quantitative measures and variation to assess the productivity of a machine. Although attempts have been made to expand OEE to encompass entire production lines or factories, the results have been mixed. Identification and prioritization of root causes for performance degradation in manufacturing systems have not been a major goal of research into PMSs. Although there are various existing predictive algorithms in the field of reliability, these have not transitioned into systems operational performance prediction. This dissertation will develop a new PMS that utilizes quantitative measurement metrics as the basis for a comprehensive system that helps companies attain continuous improvement. Hopp and Spearman (2011) will be used as a foundation for development of this system.

Table 2.3 lists relevant literature in categories pertaining to the present dissertation. The table shows early interest in the effect of variation in equipment maintenance and simple production processes. It also shows renewed interest in prioritization and predictive methodologies for process improvement in manufacturing and supply chain systems. Table 2.4 shows a trend toward the development of more comprehensive and modern PMSs through the use of quantitative methods and reduced reliance on financial metrics for system analysis. It is of note that recent publications are assessing sophisticated algorithms to reduce data overload on managers.

Table 2.3: Relevant Categories of Literature for Present Dissertation

Categories	Author	Year	Industry
Variation in Manufacturing and Supply Chain Systems	Nakajima S.	1988	Manufacturing
	W. J. Hopp and M. L. Spearman	2011	Manufacturing
	Kaplan R.	1996	Manufacturing
	Raja N. and Kannan S.	2008	Manufacturing
Prioritization and Project Selection Methods	Ray, S. and Das, P	2010	Manufacturing
	Sawhney, R., Subburaman, K., Sonntag, C., Rao, P. R. V., and Capizzi, C.	2010	Manufacturing
	Resurreccion J. and Santos J.	2011	Supply Chain
	Bayraktar, E., Sari, K., Tatoglu, E., and Zaim, S.	2013	Supply Chain
Predictive Methods	Lee, J., Lapira, E., Bagheri, B., and Kao, H.-a.	2013	Manufacturing
	Ding, S. X., Yin, S., Peng, K., Hao, H., and Shen, B.	2013	Manufacturing
	Luo, M., Yan, H.-C., Hu, B., Zhou, J.-H., and Pang, C. K.	2015	Manufacturing

Table 2.4: Relevant Methodologies of Literature for Present Dissertation

Author	Year	Industry	Methodology
D. P. Keegan, R. G. Eiler and C. R. Jones	1989	General	Financial and Non-Financial
A. M. Ghalayini, J. S. Noble and T. J. Crowe	1997	Manufacturing	Literature Review
A. Lockamy III	1998	Supply Chain	Normative
D. Sherwin	2000	Manufacturing	Overall Equipment Effectiveness
L. Berrah and V. Clivillé	2007	Supply Chain	Analytic Hierarchy Process
K. Muthiah and S. Huang	2007	Manufacturing	Overall Throughput Effectiveness
N. V. Herzog, S. Tonchia and A. Polajnar	2009	Business Processes	Empirical
R. Wudhikaran, C. Smithikul and W. Manopiniwes	2010	Manufacturing	Overall Equipment Effectiveness
P. Parthiban and M. Goh	2011	Manufacturing	Analytic Hierarchy Process and Quality Function Deployment
W. J. Hopp and M. L. Spearman	2011	Manufacturing	Empirical
M. Godinho Filho and R. Uzsoy	2011	Manufacturing	System Dynamics

Chapter 3

Methodology

Lead Time (LT) is the time between placement of order and delivery of product to a customer. Cycle Time (CyT) is the time taken to transform raw material into finished product. The dynamic between Lead Time and Cycle Time characterizes the ability of a company to deliver product to customers. If,

- $CyT > LT$, cannot provide high-level on-time deliveries to a customer.
- $CyT = LT$, no buffer to allow for production related issues resulting in a delay of order delivery.
- $CyT < LT$, additional capacity to enhance customer expectations.

Multiple strategies can be utilized to improve the output of a system. Three primary strategies (or any combination thereof) for selecting projects that enhance the capacity of a system as measured by throughput are; designing system flow, reducing variation in the system, and reducing disruptions to the system. These strategies are not independent allowing for the possibility of development of integrated methods. The objective for companies is to maintain and improve the third scenario, $CyT < LT$.

This chapter illustrates a novel method for prioritizing and selecting a set of improvement projects based on bundling of different types of variation in a discrete manufacturing system. The uniqueness of this approach is that project selection is based on variations in the system, unlike other approaches. Further, the concept of bundling variation has not been tested as a means for selecting projects to enhance system throughput. This research is divided into five distinct segments: **Framework of Methodology, Metric System Development, Data Evaluation and Bundled Variation based Prioritization Algorithm.**

- Section 3.1 presents the conceptual framework for the Bundled Variation based Projection Prioritization Model (BVPM).
- Section 3.2 articulates the assumptions and scope of this dissertation.
- Section 3.3 details the development of efficiency based metric system for monitoring the throughput based on variation in the system. Specifically, Inventory efficiency and Cycle Time efficiency based metric system.
- Section 3.4 methods for the identification of non-conforming and incomplete data.
- Section 3.5 presents an algorithm to prioritize and bundle High Variation Elements (HVs) in a system.

3.1 Framework of Methodology

BVPM prioritizes HVs in a discrete manufacturing system based on key operational performance metrics. A manufacturing system can be generalized as "a network of stations performing tasks with the objective of converting raw material into finished product". As shown in Figure 3.1, the methodology is divided into four segments:

- **Assumptions and Scope:** The type of manufacturing systems covered in BVPM is presented. The key assumptions for development and implementation of BVPM are also presented.
- **Variation-Driven Efficiency Metric Development:** Quantitative performance metrics are developed to measure efficiency in the utilization of available Cycle Time, and Inventory. A hierarchy of metrics is developed to identify metrics for data collection, i.e., operational metrics (OMs).
- **Data Evaluation:** Completeness of data is evaluated, and a simulation model is suggested to fill in incomplete data. Event-based data are converted to time series data for the calculation of the efficiency metrics of a production system.

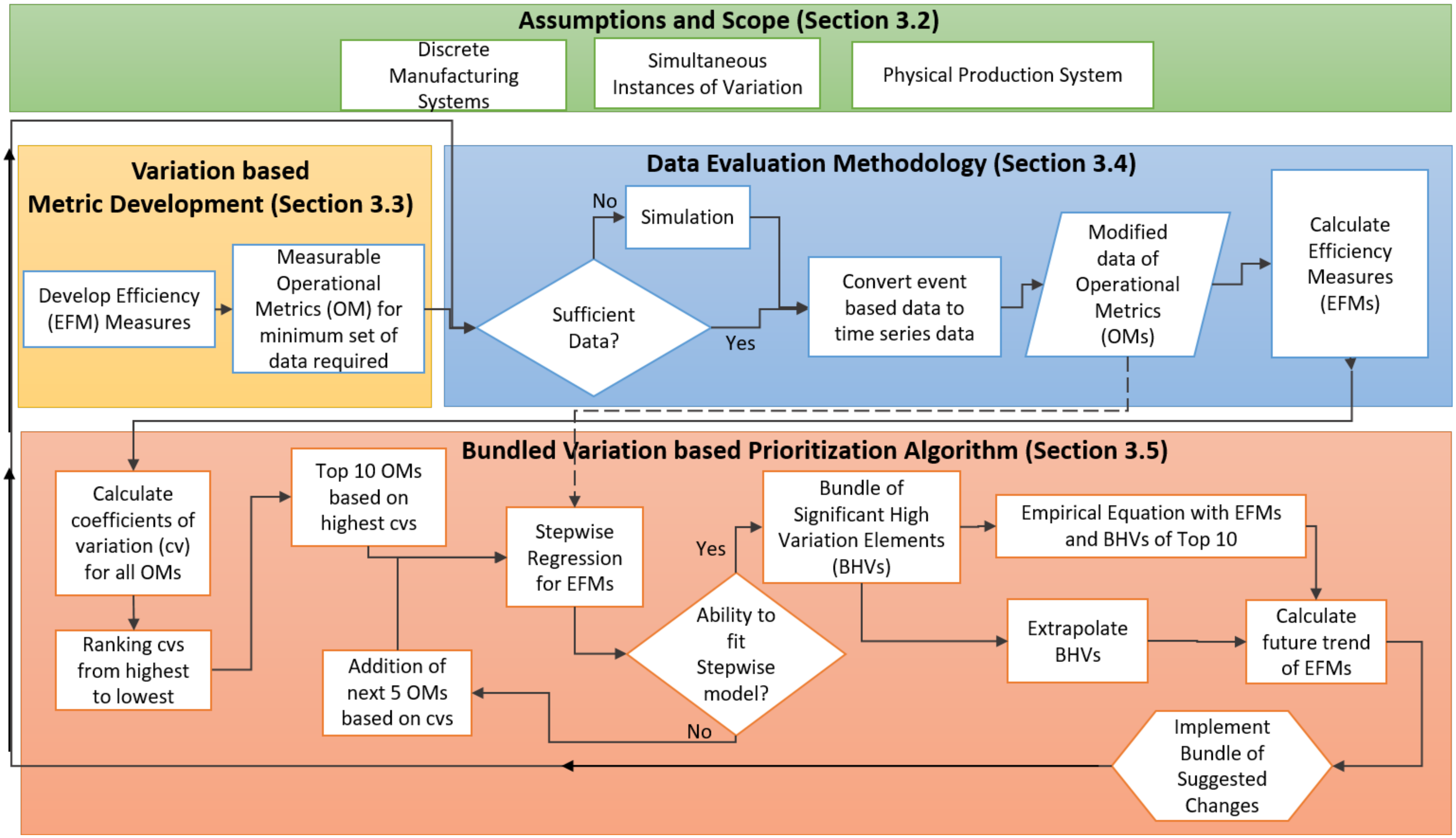

Figure 3.1: Framework of Methodology for Bundled Variation Based Project Prioritization Model (BVPM)

- **Bundled Variation based Prioritization Algorithm:** Coefficients of Variation of OMs are calculated to rank the most varying elements in the production system (for all stations). Regression analyses of the HVs and the system efficiency metrics are performed to identify a Bundle of High Variation Elements (BHVs). The effect of the BHVs on future trend of system efficiencies is calculated. Based on the identified BHVs, changes in the production system are performed to improve performance.

3.2 Assumptions and Scope of BVPM

This thesis focuses on quantitative methodologies to measure the performance of discrete production systems. Its scope covers the measurement of productivity at each station, production line, and facilities. BVPM is designed to monitor the parts of the production system in direct contact with the product: equipment, stations, and material handling.

3.2.1 Variability in a Manufacturing System

To measure the effect of variation on the performance of a manufacturing system, BVPM considers various sources of variation at each station. The key measures utilized in this study are presented in Figure 3.2. They are separated into three categories: Inbound, Process and Quality.

- Inbound Variability (IV) focuses on the arrival of raw material at a station and the time spent in queue before processing at the station. It includes variabilities in the rate of arrival, material amount, and queue time of raw material at each station in the manufacturing system.
- Process Variability (PV) centers on the transformation of raw material at a station. Variabilities in processing time, setup time and availability of equipment are considered under PV.
- Quality Variability (OV) covers variations in yield of a station.

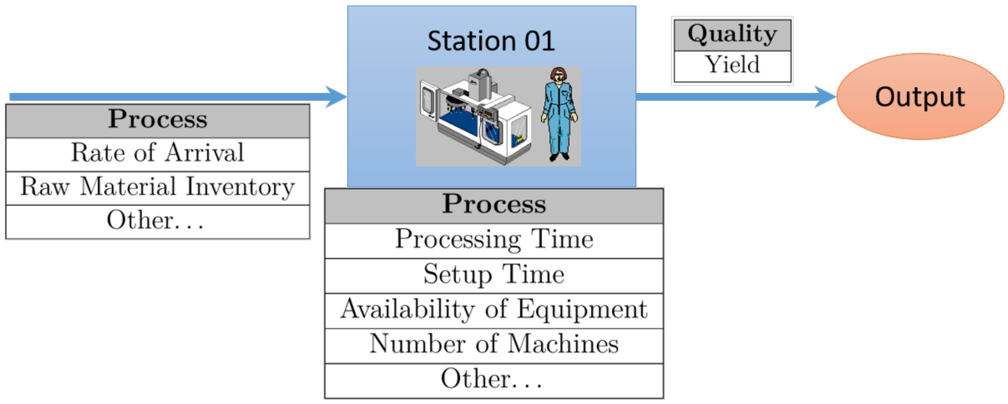

Figure 3.2: Variability in Manufacturing System

By including variability in the measurement metrics for the three segments of each station, the performance metrics represent a realistic representation of the performance of the system. The productivity of a station and variation in output is a function of Inbound, Process, and Quality parameters.

$$Output = f(Inbound,\ Process,\ Quality)$$

Therefore, as the number of stations increases, the effect of a variation in one station element has an increasing ripple effect on downstream stations. Incorporating variability through data collection and calculation of system efficiency ensures that variability is considered in project selection. This study considers the simultaneous occurrence of variations in the three segments of stations in a manufacturing system.

3.3 Metric Development

The Throughput (TH) of a manufacturing process is the amount of product passing through a system. Little's Law (Little, 1961) states that throughput is a function of Cycle Time (CyT) and Work-in-Process (WIP) inventory:

$$TH = \frac{WIP}{CyT} \tag{3.1}$$

The disadvantage of exclusively using Throughput as a metric to measure the performance of a system is loss of information. For example, a production line with long CyT and low

WIP will have the same throughput as a line with short CyT and high WIP. Similarly, decreasing both CyT and WIP will result in the same Throughput as results from increasing both. Hopp and Spearman (2001) developed two efficiency metrics: Cycle Time Efficiency and Inventory Efficiency. This dissertation presents modified formulations for Cycle Time Efficiency and Inventory Efficiency to utilize station level data to compute performance of a discrete manufacturing system.

3.3.1 Cycle Time Efficiency

"Cycle Time" in a manufacturing environment refers to the cumulative time incurred by a product from beginning to the end of the production process. Hopp and Spearman (2001) developed a formulation for Cycle Time Efficiency as shown in Equation 3.2.

$$E_{CT} = \frac{T_o}{CT} \tag{3.2}$$

where T_o = Raw Cycle Time not including detractors

CT = Actual Cycle Time of a product line

The formulation for calculating the Actual Cycle Time at a station, CT, as developed by Hopp and Spearman (2011) is a summation of two components: Mean Time Spent in Queue and Effective Processing Time (Equation 3.3). This formulation does not distinguish stations with batching of raw material and stations without batching of raw material. Time spent by material waiting to be batched before processing at station induces variation in process time at a station. For example, a large batch size of arriving material would increase variation in the cycle time of the product if the station capacity is smaller than size of batch, leading to reduced efficiency in the production line.

$$CT = CT_q + t_e \tag{3.3}$$

where CT_q = Mean Time spent in queue

t_e = Effective Processing Time

Cycle Time Efficiency developed in this dissertation is a modified version of Equation 3.2. Processing time, wait time and setup time are measured at each station while move times are measured between stations. Each of these categories impacts Cycle Time of the system. Variation has an adverse impact on the system as it can impact every category. The proposed Cycle Time Efficiency metric has the advantage of computing system level efficiency based on components (stations, equipment, and material) of the system.

Figure 3.3 presents the Hierarchy of Metrics (HOM) associated with the deconstruction of Cycle Time Efficiency, η_{CT}, to its base measurement metrics. The base measurement metrics are the smallest non-divisible metrics in the HOM (e.g. Raw Process Time and Setup Time at a station). There are several key developments in the HOM. First, it can analyze information from the shop floor (station level) level and imbibe it into the computation of performance of the system. Second, variation is integrated into the formulation and categorized either as Inbound Variability (IV), Process Variability (PV) or Quality Variability (QV) as presented by Figure 3.2. The base measurement metrics are categorized under IV, PV and QV. They are utilized in the Variation based Bundled Prioritization Algorithm in Section 3.5 to identify the bundle of high variation elements.

"System level" metrics shown in Figure 3.3 are developed specifically for BVPM. While "Station level" metrics are utilized from existing literature (Hopp and Spearman, 2011). Equation 3.4 defines the Cycle Time Efficiency of product j at the system level. The formulation includes all stations associated with transformation of product j from raw material to finished product:

$$\eta_{CT}(j) = \frac{T_o(j)}{OCT(j)} \tag{3.4}$$

where j = Product manufactured in the system

$T_o(j)$ = Raw Cycle Time of product j

$OCT(j)$ = Overall Cycle Time of product j

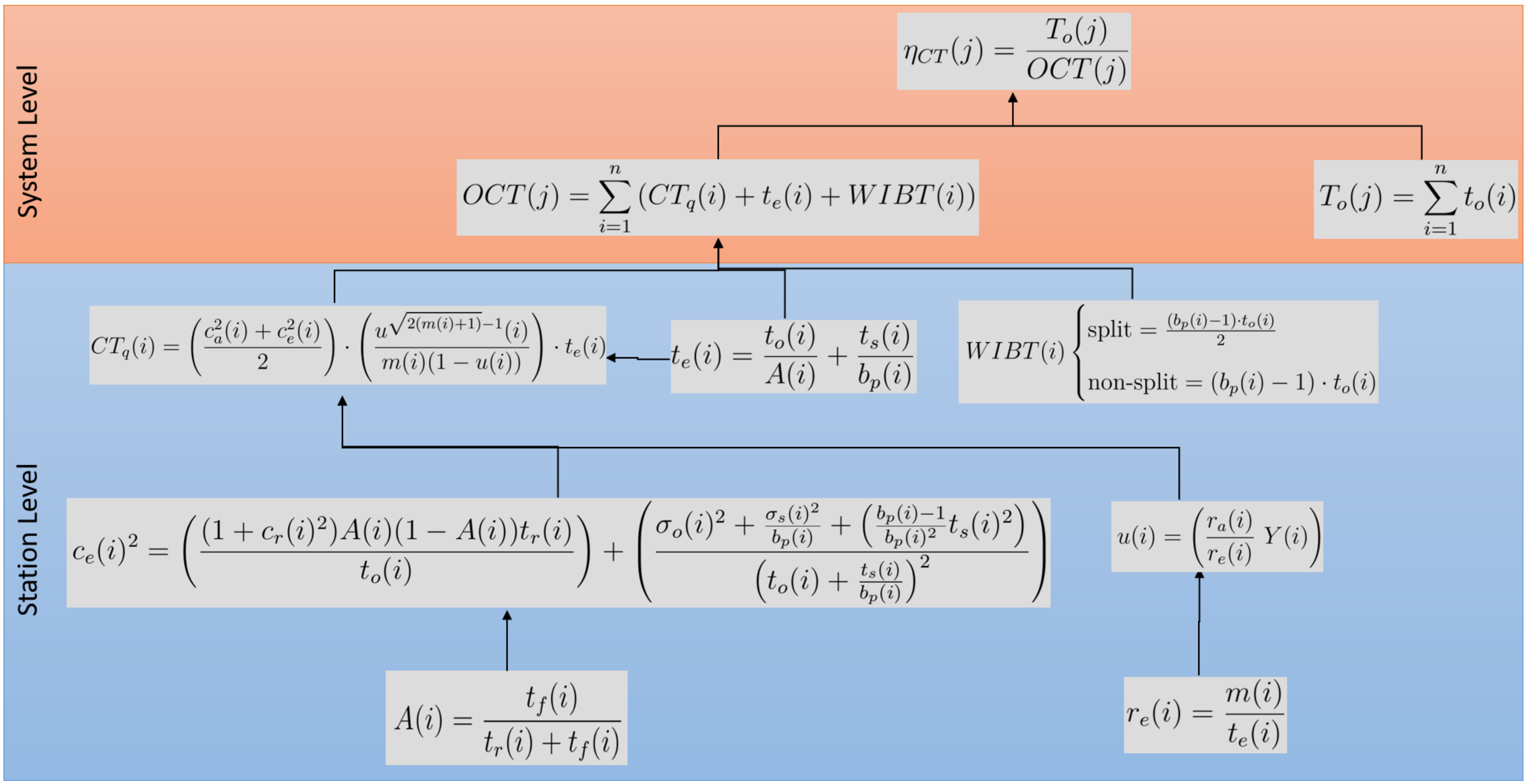

Figure 3.3: Hierarchy of Metrics for Cycle Time Efficiency (η_{CT})

The Raw Cycle Time, $T_o(j)$, of a product is the fastest possible cycle time to manufacture the product. It is calculated based on the summation of Raw Process Time at each station of production as presented by the Equation 3.5 below. This does not include setup time, wait time and move time. Variation in performance of human operator and wear-and-tear of equipment cause changes in processing time at a station. Therefore, Raw Process Time is classified under Process Variability (PV) as shown in Table 3.1.

$$T_o(j) = \sum_{i=1}^{n} t_o(i) \tag{3.5}$$

where j = Product manufactured in system

i = Process location of product j

n = Number of stations in production line

$t_o(i)$ = Raw Process time at station i

Table 3.1: Variability included in $T_o(j)$

Inbound	**Process**	**Quality**
	$t_o(i)$	

This dissertation considers three distinct occurrences at each station: arrival of material, material wait in queue, and processing of material. These steps are repeated in the manufacturing line to transform raw material into finished product. Under this station segmentation scheme, the Overall Cycle Time (Equation 3.6) becomes a function of Wait Time of material in queue, $CT_q(i)$, the Effective Processing Time at the station, $t_e(i)$, and the Wait-in-Batch to be processed at the station, $WIBT(i)$.

The Wait-in-Batch Time at a station, $WIBT(i)$, is calculated based on Equation 3.7. A "Split" occurs when a batch of material is split and processed individually at the station and "Nonsplit" indicates when the entire batch is processed simultaneously at station i.

$$OCT(j) = \sum_{i=1}^{n} (CT_q(i) + t_e(i) + WIBT(i)) \tag{3.6}$$

where j = Product manufactured in system

i = Station location of product j

n = Number of stations in production line

$CT_q(i)$ = Wait Time in queue

$t_e(i)$ = Effective Processing Time

$WIBT(i)$ = Wait-in-Batch at station i

Table 3.2 presents the classification of the two non-divisible components of $WIBT(i)$. Batch size, $b_p(i)$, of a product affects the incoming flow of material to a station, therefore is classified as Inbound Variability (IV). As mentioned previously, $t_o(i)$ is classified as Process Variability (PV).

$$WIBT(i) \begin{cases} \text{split} = \frac{(b_p(i)-1)\cdot t_o(i)}{2} \\ \text{non-split} = (b_p(i)-1)\cdot t_o(i) \end{cases} \tag{3.7}$$

Table 3.2: Variability included in $WIBT(i)$

Inbound	**Process**	**Quality**
$b_p(i)$	$t_o(i)$	

Hopp and Spearman (2011) present the Wait Time in Queue consisting of three components: Variation, Utilization, and Time ($CT_q(i) = V \cdot U \cdot T$). BVPM utilizes this formulation, as presented in Equation 3.8. For readability, the HOM for Variation component is first described, followed by the Utilization component and finally the Time component.

The number of parallel machines, $m(i)$, at a station is the only non-divisible component in $CT_q(i)$.

$$CT_q(i) = \left(\frac{c_a^2(i) + c_e^2(i)}{2}\right) \cdot \left(\frac{u^{\sqrt{2(m(i)+1)}-1}(i)}{m(i)(1-u(i))}\right) \cdot t_e(i) \tag{3.8}$$

where $c_a(i)$ = Coefficient of Variation of Arrivals at station i

$c_e(i)$ = Coefficient of Variation of Effective Processing Time

$u(i)$ = Instantaneous Utilization of station i

$m(i)$ = Number of parallel machines at station i

$t_e(i)$ = Effective Processing Time of station i

Variation in the number of available parallel machines at a station affect production capacity of the station. Therefore, $m(i)$ is classified as Process Variability (PV), as presented by Table 3.3.

Table 3.3: Variability included in $CT_q(i)$

Inbound	**Process**	**Quality**
	$m(i)$	

The Variation component of $CT_q(i)$ is a function of the Coefficient of Variation of Rate of Arrival, c_a, and the Coefficient of Variation of Effective Processing Time, $c_e(i)$. The formulation for $c_a(i)$ is given by Equation 3.9, where both $\sigma_a(i)$ and $\mu_a(i)$ are calculated from Rate of Arrival ($r_a(i)$) of material at a station. As changes in $r_a(i)$ affect incoming material at a station, it is classified under Inbound Variability as shown in Table 3.4.

$$c_a(i) = \frac{\sigma_a(i)}{\mu_a(i)} \tag{3.9}$$

where $\sigma_a(i)$ = Standard deviation of rate of arrivals r_a at station i

$\mu_a(i)$ = Mean of rate of arrivals r_a at station i

Table 3.4: Variability included in $c_a(i)$

Inbound	Process	Quality
$r_a(i)$		

The Coefficient of Variation of Effective Processing Time, $c_e(i)$, includes two components of variation: preemptive outages (availability of the station), and non-preemptive outages (setup time and batch size of raw material) as presented in Equation 3.10. Hopp and Spearman (2011) developed two formulations for the Coefficient of Variation of Effective Processing Time, $t_e(i)$, one accounting for preemptive outages and other for non-preemptive outages. This dissertation combines the two components to calculate the Coefficient of Variation of Effective Processing Time, $c_e(i)$ (Equation 3.10).

$$c_e^2(i) = \left(\frac{(1 + c_r^2(i)) \cdot A(i) \cdot (1 - A(i)) \cdot t_r(i)}{t_o(i)} \right) + \left(\frac{\sigma_o^2(i) + \frac{\sigma_s^2(i)}{b_p(i)} + \left(\frac{b_p(i)-1}{b_p^2(i)} t_s^2(i) \right)}{\left(t_o(i) + \frac{t_s(i)}{b_p(i)} \right)^2} \right) \tag{3.10}$$

where $c_r(i)$ = Coefficient of Variation of Mean Time to Repair $t_r(i)$

$A(i)$ = Availability of station i

$t_r(i)$ = Mean Time to Repair at station i

$t_o(i)$ = Raw Process Time at station i

$\sigma_o(i)$ = Standard deviation of Raw Process Time $t_o(i)$ at station i

$\sigma_s(i)$ = Standard deviation of Setup Time $t_s(i)$ at station i

$b_p(i)$ = Batch size of product at station i

The formulation for $c_e(i)$ consists of non-divisible components as presented in Table 3.5. Changes in Batch Size ($b_p(i)$) of the product affects incoming material at a station. Therefore, $b_p(i)$ is classified under Inbound Variability. Variation in Setup Time ($t_s(i)$), Repair Time ($t_r(i)$) and Raw Process Time ($t_o(i)$) are classified under Process Variability.

Table 3.5: Variability included in $c_e(i)$

Inbound	**Process**	**Quality**
$b_p(i)$	$t_o(i)$	
	$t_r(i)$	
	$t_s(i)$	

The Availability of a station (as required in Equation 3.10) is a function of Mean Time to Failure and Mean Time to Repair (Equation 3.11). Changes in both parameters affect equipment utilized at a station and are classified under Process Variability (Table 3.6).

$$A(i) = \frac{t_f(i)}{t_r(i) + t_f(i)} \tag{3.11}$$

where $t_f(i) =$ Mean time to failure

$t_r(i) =$ Mean time to repair

Table 3.6: Variability included in $A(i)$

Inbound	**Process**	**Quality**
	$t_f(i)$	
	$t_r(i)$	

The Utilization component of Wait Time in Queue, $CT_q(i)$, from Equation 3.8 is a function of Instantaneous Utilization of station, $u(i)$, and Number of parallel machines assigned to a station, $m(i)$. Equation 3.12 represents the Instantaneous Utilization of station i. Variation in $r_a(i)$ affects the incoming flow of material to a station and variation in $Y(i)$ has an impact on the quality and outgoing flow of material (Table 3.7).

Table 3.7: Variability included in $u(i)$

Inbound	**Process**	**Quality**
$r_a(i)$		$Y(i)$

$$u(i) = \left(\frac{r_a(i)}{r_e(i)} \; Y(i) \right) \tag{3.12}$$

where $r_a(i)$ = Rate of Arrival of material at station i

$r_e(i)$ = Effective Rate of Production at station i

$Y(i)$ = Yield of station i

The Effective Rate of Production, $r_e(i)$, for station i (Equation 3.13), is a function of the number of parallel machines assigned to the station, $m(i)$, and the Effective Processing Time, $t_e(i)$, of the station. The number of parallel machines is classified under Process Variability (PV), as a change in the number of machines will affect the time taken to process a product.

$$r_e(i) = \frac{m(i)}{t_e(i)} \tag{3.13}$$

where $m(i)$ = Number of parallel machines assigned to station i

$t_e(i)$ = Effective Processing Time of station i

Table 3.8: Variability included in $r_e(i)$

Inbound	**Process**	**Quality**
	$m(i)$	

The Effective Processing Time, $t_e(i)$ (Equation 3.14) of material at station i includes the Raw Process Time and excess time owing to breakdowns, repairs, and setups as a combination of expected and unexpected variation affecting the processing time of a product. Hopp and Spearman (2011) present the Effective Processing Time of a station for preemptive and non-preemptive outages in separate formulations. Preemptive outages are dependent on the availability of the station and its effect on the expected product processing time, which are classified as Process Variability (PV). Non-preemptive outages include variability induced by setups for equipment classified as PV and the batch size of raw material classified as IV. It is noteworthy that variation in processing time resulting from equipment failure is included in the calculation of Availability of Station $A(i)$. $t_e(i)$ is also the final component to compute Actual Cycle Time of the product, $CT(j)$, and Wait Time in Queue of a station, $CT_q(i)$.

$$t_e(i) = \frac{t_o(i)}{A(i)} + \frac{t_s(i)}{b_p(i)} \tag{3.14}$$

$$\text{where } A(i) = \text{Availability of station } i$$

$$t_s(i) = \text{Setup time}$$

$$b_p(i) = \text{Batch size of product at station } i$$

There are three non-divisible parameters in the formulation for $t_e(i)$. Variation in Batch size of a product affects incoming material at a station while variation in Raw Process Time and Setup Time affect station operation (Table 3.9).

Table 3.9: Variability included in $t_e(i)$

Inbound	**Process**	**Quality**
$b_p(i)$	$t_o(i)$	
	$t_s(i)$	

In conclusion, Cycle Time Efficiency of a product j is de-constructed in a HOM (Figure 3.3) to the base measurement metrics. The non-divisible parameters identified in the HOM are combined to form the base measurement metrics in Section 3.3.3.

3.3.2 Inventory Efficiency

The "Inventory" in a manufacturing environment refers to all states of a physical entity from raw material to finished goods. Inventory Efficiency is designed to measure the utilization of available inventory in a production line. Hopp and Spearman (2001) developed a formulation for Inventory Efficiency (Equation 3.15). According to the authors, Ideal Inventory is a function of the average throughput of a station, $TH(i)$, and the ideal rate of production of the station, $r^*(i)$. Actual inventory is a function of the Work-in-Process (WIP) in the line, the Finished Goods Inventory (FGI), and the Raw Material Inventory (RMI) at each station in the production line.

$$E_{inv} = \frac{\sum_i \frac{TH(i)}{r^*(i)}}{RMI + WIP + FGI} \tag{3.15}$$

The authors measure inventory at three points in the system: raw material warehouse, production line, and finished goods warehouse. The WIP is the average amount of inventory in the production line not taking into account changes in inventory throughout the day. The WIP at each station in a production line is included under the combined WIP of the production line and not considered individually. A station's ability to process multiple parts in not accounted in the formulation. In such situations, low utilization of a station's capacity to processes multiple parts could cause disruptions in the production line.

In this dissertation, Inventory Efficiency is defined as a function of Ideal Inventory and Overall Work-in-Process in a production line (Equation 3.16).

$$\eta_{INV}(j) = \frac{I_o(j)}{OI(j)} \tag{3.16}$$

where $I_o(j)$ = Ideal Inventory in production line j not including detractors

$OI(j)$ = Overall Work-in-Process in production line j

Based on Theory of Constraints (TOC), the "Bottleneck Station" dictates the performance of the production line. Ideal Inventory of the production line is a function of Rate of Production of bottleneck station and Raw Cycle Time of the production line (Equation 3.17). $r_b(j)$ is computed based on Raw Process Time of bottleneck process. Variation in $r_b(j)$ and $t_o(i)$ is caused by changes in operator performance and wear-and-tear of equipment. Both are classified under Process Variability (Table 3.10).

$$I_o(j) = r_b(j) \cdot T_o(j) \tag{3.17}$$

where $r_b(j)$ = Rate of Production of bottleneck station of production line j

$T_o(j)$ = Raw Cycle Time of production j

Table 3.10: Variability included in $I_o(j)$

Inbound	Process	Quality
	$t_o(i)$	

Inventory at a station exists in two states: inventory in a station i that is being processed, and inventory waiting in queue at station i before being processed. Overall Work-in-Process Inventory at each station is a function of the Inventory Waiting in Queue to be processed, $WIP_q(i)$, and the WIP at a station being processed, $WIP(i)$:

$$OI_j = \sum_{i=1}^{n}(WIP(i) + WIP_q(i)) \tag{3.18}$$

where i = Station location of product j

n = Number of processes in the production line

$WIP(i)$ = WIP in station i

$WIP_q(i)$ = WIP waiting in queue at station i

The Work-in-Process at a station, $WIP(i)$, is the amount of raw material being processed in the station. It depends on the Instantaneous Capacity of the machines at the station, $C_m(i)$, and the number of parallel machines $m(i)$ assigned to each station. Instantaneous Capacity and number of parallel machines are non-divisible components of $WIP(i)$. Variation in both result in variation in performance of a station, therefore, they are classified under Process Variability.

$$WIP(i) = m(i) \cdot C_m(i) \tag{3.19}$$

where $m(i)$ = Number of parallel machines at station i

$C_m(i)$ = Instantaneous Capacity of station i

Table 3.11: Variability included in $WIP(j)$

Inbound	Process	Quality
	$m(i)$	
	$C_m(i)$	

The Work-in-Process waiting in queue $WIP_q(i)$ is a function of Cycle Time in Queue $CT_q(i)$ and the Throughput of Queue of the station. The Throughput of Queue at a station is the Rate of Arrival $r_a(i)$ of material at the station. Variation in Rate of Arrival of material affects the flow of incoming material at a station. Therefore, it is classified under Inbound Variability (Table 3.12).

$$WIP_q(i) = CT_q(i) \cdot r_a(i) \tag{3.20}$$

$$\text{where } CT_q(i) = \text{Wait time in queue at station } i$$

$$r_a(i) = \text{Rate of Arrival of material at station } i$$

Table 3.12: Variability included in $WIP_q(j)$

Inbound	Process	Quality
$r_a(i)$		

The formulation for $CT_q(i)$ presented in Equation 3.8 during the development of the Cycle Time Efficiency. The rest of HOM for Inventory Efficiency (η_{INV}) as presented Figure 3.4 is similar to that for Cycle Time Efficiency (η_{CT}).

3.3.3 Identifying Metrics for Data Collection

In the previous section, Efficiency Measures (EFMs) were developed to measure the productivity of a system in terms of Cycle Time and Inventory. Figures 3.3, and 3.4 show the Hierarchy of Metrics (HOM) for the EFMs. The non-divisible metrics in HOMs of η_{CT} and η_{INV} are identified as base measurement metrics (Table 3.13).

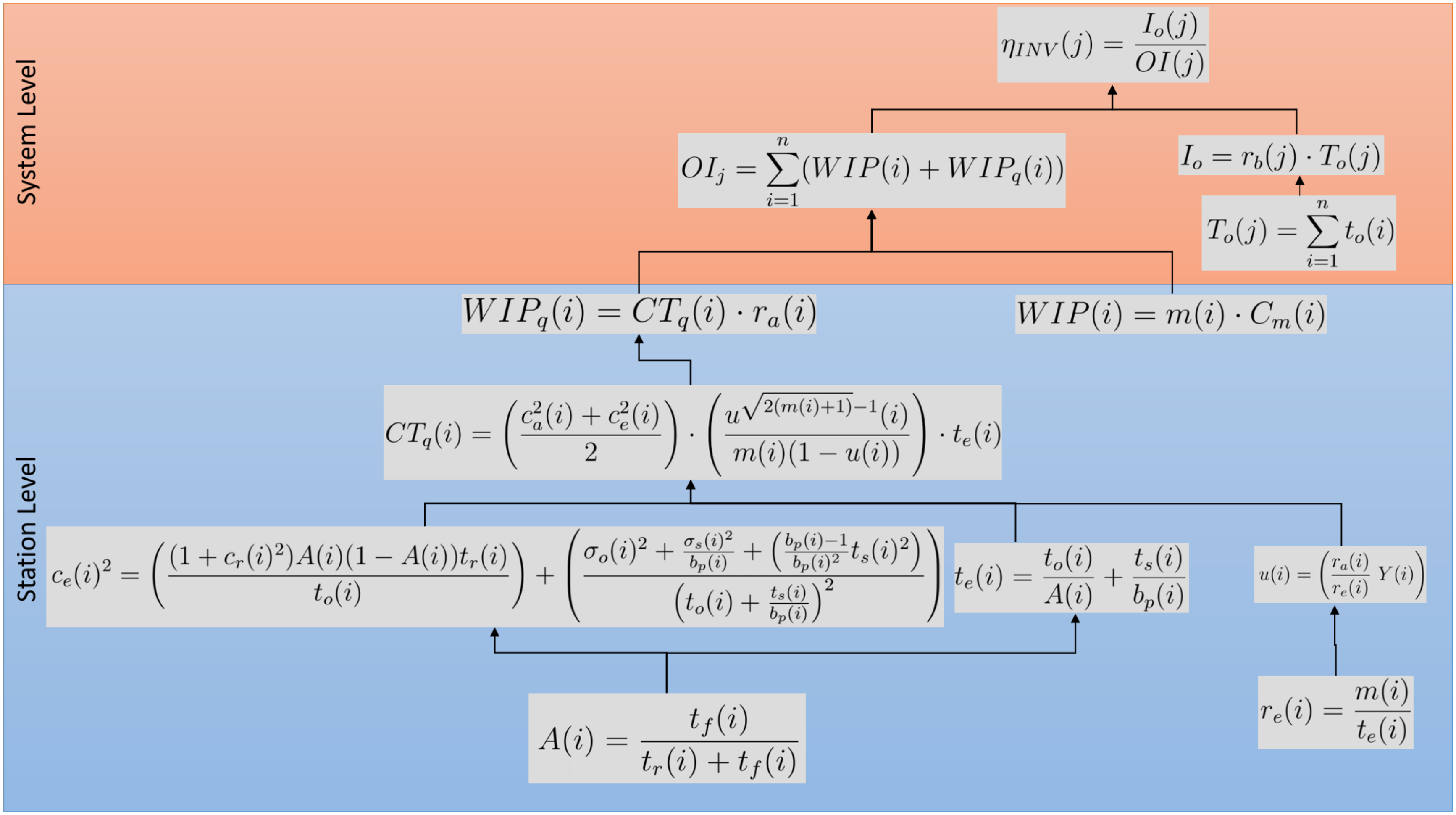

Figure 3.4: Hierarchy of Metrics for Inventory Efficiency (η_{INV})

In this dissertation, the base measurement metrics are termed as Operational Metrics (OM). These data collection parameters are divided into three sections: Inbound, Process and Quality.

Table 3.13: Operational Metrics for BVPM

Station Segment	Metric	Definitions
Inbound	$r_a(i)$	Rate of Arrivals at station i
	$RI(i)$	Instantaneous Raw Material Inventory at station i
	$b_p(i)$	Batch Size of product j at station i
Process	$t_o(i)$	Raw Process Time (no downtimes, setups, etc.)
	$t_s(i)$	Setup Time at station i
	$C_m(i)$	Instantaneous Capacity of station i
	$t_r(i)$	Mean Time to Repair at station i
	$t_f(i)$	Mean Time to Failure at station i
	$m(i)$	Number of parallel machines assigned to station i
Quality	$Y(i)$	Yield of station i

There are two formats for collecting OM data: event-based and time-series. Event-based data represent a sequence of events with corresponding times of occurrence. Time-series data are a series of discrete-time data consisting of consecutive equally spaced points in time. All OMs are required to have te same number of data points. For example, to calculate η_{CT} for a production line for 30 days (i.e., 30 data points at one point per day), all OMs should also have 30 data points for 30 days. The EFMs cannot be calculated if there is an inconsistency in the number and format of OM data. Therefore, the OMs identified for BVPM are required to be in a time-series format to calculate and monitor η_{CT} and η_{INV} of a production line.

3.4 Data Evaluation Methodology

This section presents a standardized methodology (Figure 3.5) evaluate data collected at a company to calculate EFMs in the Bundled Variation based Project Prioritization Model

(BVPM). BVPM streamlines and addresses problems arising from incomplete collection of data. The data evaluation methodology of BVPM is divided into two parts: Completeness and Format. Completeness section presents methodologies to augment incomplete data. Format section presents methods to modify the format of nonconforming data to meet the specifications of BVPM.

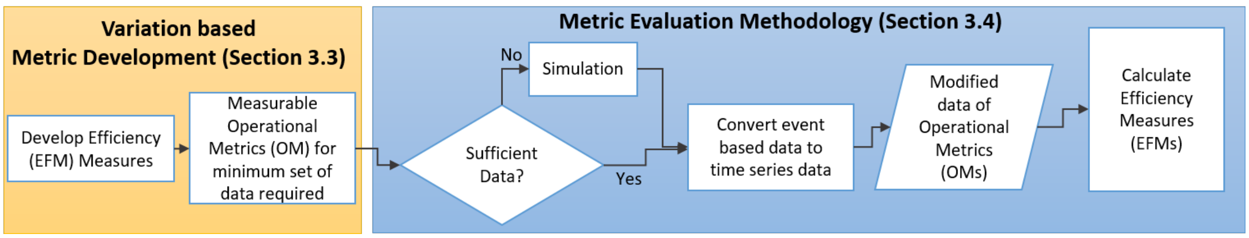

Figure 3.5: Framework for Data Evaluation Methodology

3.4.1 Data Evaluation: Completeness

The Operational Metrics (OMs) listed in Table 3.13 are required for calculating the EFMs of a production system. However, situations arise where OM data cannot be collected. For example, it may not be possible to measure the Rate of Arrival of raw material at each station in a production system. To compensate for such instances, BVPM utilizes a discrete event simulation model as a substitute to generate required OM data.

A discrete event simulation model is a representation of an existing manufacturing system with some approximations. Simulations have been used to model existing systems for testing new manufacturing techniques and methodologies. Spedding and Sun (1999) used simulation to estimate Activity Based Costing (ABC) on a printed circuit board (PCB) manufacturing line. They conducted a case study to evaluate their simulation model and noted that "Without the flexibility of a computer simulation model, the number of combinations and testing variations required by ABC would be extremely time consuming and costly, making implementation difficult". Robinson et al. (2012) demonstrated how discrete event simulation can be used to monitor and enhance the implementation of lean techniques in the healthcare industry. Discrete event simulation can be used to model manufacturing, healthcare, supply chain, and other systems to diagnose problems, test performance improvements, and evaluate investments. Patti and Watson (2010) used simulation to measure the effect of downtime on system performance. They simulated a serial production line to test the theory that the same overall downtime can be achieved by both long-duration, low-frequency and small-duration, high-frequency variation. As a simulation model, they used a representation of a production line and calculated the throughput of the system to make a comparison between the two scenarios, and concluded that the adverse effect of the former on a system is much greater than that of the latter.

In this dissertation, a simulation model of a production facility is utilized to fill incomplete and inconsistent data. In a discrete event simulation (DES) model, a manufacturing system is modeled as a sequence of events. Each event defines a specific change in the state of the system at a specific time. Correspondingly, data obtained as a result of DES models are in event-based format. The data should be converted to time-series format to be utilized in BVPM to calculate the efficiencies of a production system.

3.4.2 Data Evaluation: Format

The EFMs developed in Section 3.3 are calculated at evenly spaced intervals of time. For each station in a production system, event-based data should be modified to fit the requirements of BVPM (i.e., they should be changed to time-series data). The time series data of OMs and EFMs must also have the same frequencies. Among OMs, not all metrics in the event-based format will have data points at evenly spaced intervals. For example, the Processing Time at a station will have more data points than Mean Time to Failure, as there are more instances of material being processed at a station than the failure of equipment. A Target Frequency (TF) suitable to the facility of intended application should be identified as the basis for modification of OM data to a common number of time-series data points. For example, if a company measures the performance (such as Throughput) of their manufacturing systems on a daily basis, they would likely choose a TF of one day for their EFMs and OMs. In the modification of event-based OM data to a common number of time series data points, two situations need to be addressed:

- The frequency of occurrence in the OM data is higher than the TF (e.g., the Rate of Arrival of raw material occurs approximately every one minute).

- The frequency of occurrence in OM the data is lower than the TF (e.g., equipment failure occurring once every six months).

When the frequency of data points is higher than the TF, it is modified using the formulation in Equation 3.21 to match the TF (e.g., hour, day, or week). For OMs measured at each of the m stations in a system for time 1 to n, if the frequency of data is higher than required, a moving average is calculated. The resulting data points for the OMs of the production line will be in a time-series format, facilitating the continuous calculation of EFMs.

$$Q_{T_l} = \frac{\sum_{k=0}^{N} q_k \cdot \delta_k}{\sum_{k=0}^{N} \delta_k} \tag{3.21}$$

$$\delta_k = \begin{cases} 1 & \text{if } T_{l-1} \leq t_k \leq T_l, \\ 0 & \text{if } T_{l-1} \geq t_k \text{ or } t_k \geq T_l. \end{cases} \tag{3.22}$$

where $l \geq 1$

$Q_{T_l} =$ Mean of given period (between T_{l-1} and T_l)

$T_l =$ Time of calculation (TF)

$q_k =$ Value of data point in the sample (i.e., "value" column from Table 4.2)

$t_k =$ Time values of the data points in the sample

When the frequency of collected data is lower than TF, as is the case with metrics such as Mean Time to Failure, the previous data point is carried over until the occurrence of a failure event. When a new failure event occurs, the average of the two data points (Mean Time to Failure) is imputed until the next occurrence.

3.5 Prioritization Algorithm for High Variation Elements

The prioritization algorithm in BVPM is designed to identify and prioritize High Variation Elements (HVs) in a production system. This study utilizes coefficient of variation and stepwise linear regression to identify the principal variables, i.e., a bundle of significant HVs (Figure 3.6). The Coefficient of Variation is applied to Operational Metric (OM) data to rank the HVs in a system. Stepwise linear regression is used to identify the bundle of significant HVs affecting the trends of EFMs starting from the top-ranked HVs. Curve fitting extrapolation is applied to the bundle of significant HVs to forecast their effect on the EFMs of the production system.

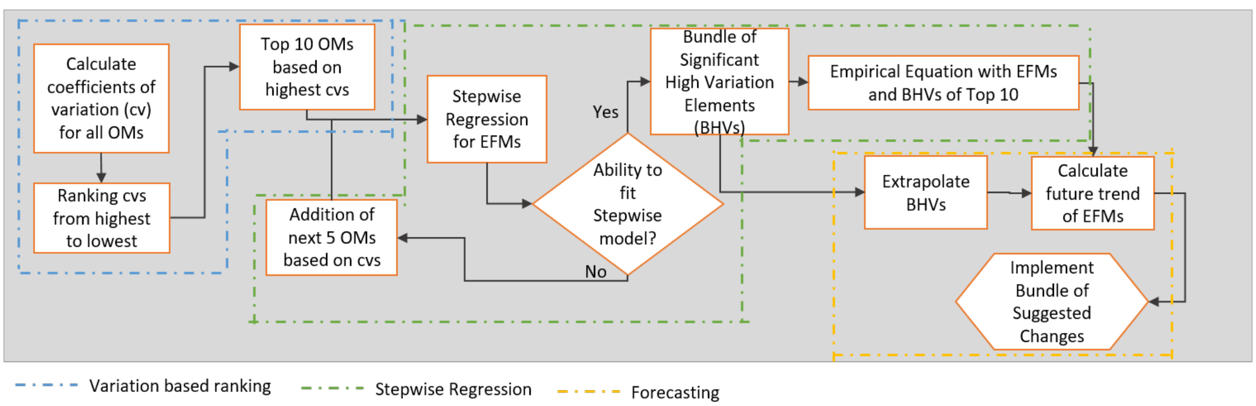

Figure 3.6: Prioritization Algorithm for Identifying Bundle of High Variation Elements

3.5.1 Variation based Ranking of High Variation Elements

The term "Variation" is used to describe the change in factors as diverse as process time, arrival rate, inventory quantity, and machine breakdown. This results in difficulties when the prioritization of factors affects entire production systems. For example, the absolute mean of process times are very low compared to the absolute means of equipment failure rate, and therefore these cannot be compared without a metric-standardized analysis of variation. Hopp and Spearman (2011) proposed the use of the Coefficient of Variation as a method to quantify and analyze variability. The Coefficient of Variation (cv) of a parameter measures the variation in the data relative to its mean. It is formulated as the ratio of the standard deviation and the mean ($cv = \frac{\sigma}{\mu}$) of the data. Hopp and Spearman (2011) presented the effects of variation in manufacturing systems and proposed utilization of cv to categorize low, medium, and high variation. Taking this further, Patti and Watson (2010) conducted a study to measure the impact of low, medium, and high cvs on the performance of a system and concluded that factors causing higher cvs in a system had a more negative impact on system performance.

In this thesis, cv is used as a standardizing factor for comparing metrics of all stations in the production system. It is calculated for the Key Operational Metrics (KOMs) for all stations in a production line; the KOMs are a subset of the OMs that include parameters aligned with company specific requirements (Table 3.14). For example, if a company does not utilize parallel machines in its stations, $m(i)$ is eliminated. Similarly, if batching of product is not performed in the production system, $b_p(i)$ is removed from OMs. The reduced number of variables, aid in accuracy and analysis of statistical modeling. KOMs for all stations are ranked from most to least varying based on the corresponding cv. The KOMs of stations related to the top 10 cvs are termed as High Variation Elements (HVs).

Table 3.14: Key Operational Metrics for Performance Improvement

Station Segment	Metric	Definitions
Inbound	$r_a(i)$	Rate of Arrivals at station i
	$RI(i)$	Instantaneous Raw Material Inventory at station i
	$b_p(i)$	Batch Size of product j at station i
Process	$t_o(i)$	Raw Process Time (no downtimes, setups, etc.)
	$t_s(i)$	Setup Time at station i
	$C_m(i)$	Instantaneous Capacity of station i
	$t_r(i)$	Mean Time to Repair at station i
	$t_f(i)$	Mean Time to Failure at station i
	$m(i)$	Number of parallel machines assigned to station i
Quality	$Y(i)$	Yield of station i

3.5.2 Identifying Significant High Variation Elements

The HVs, as determined by their *cv*s are representative of the amount of variation in a production system. BVPM utilizes stepwise linear regression (Step-r) to analyze the relationship between HVs and the Efficiency Metrics (EFMs). The two important inferences that can be made from the results of Step-r are the regression function and the significant independent variables. In this case, the regression function represents the empirical relationship between the EFMs and HVs. Meanwhile, the significant independent variables are a subset of HVs describing the trends of η_{CT} or η_{INV}. These are the variables most affecting the performance of the system as measured by the EFMs and are termed as significant HVs in BVPM.

Step-r is a semi-automatic process in which a regression model is constructed by adding or removing variables based on the t-statistics of their estimated coefficients. A cut-off t-statistic (P-value) is used to eliminate parameters (HVs) not significant in describing the trend in the EFMs (this statistic is generally set to 0.05). The resulting model will consist of significant variables that can describe the trend in the efficiency metrics. If the ten HVs do not yield a model, BVPM will use HVs corresponding to top fifteen cvs to identify Significant HVs. A formulation for the regression equation identified by Step-r is shown in Equation 3.23:

$$\eta_{CT} \; or \; \eta_{INV} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \ldots + \beta_n x_n \tag{3.23}$$

where $x_1 \ldots x_n$ are HVs in the production system

$\beta_1 \ldots \beta_n$ are coefficients indicating

the effect of HVs on the trend of EFMs

n is number of HVs identified as "significant"

Some points to note in interpreting the results of stepwise linear regression are as follows:

- The signs of coefficients ($\beta_1 \ldots \beta_n$) indicate the impact of significant HVs on η_{CT} or η_{INV}.

- A p-value of less than 0.05 indicates that a selected HV significantly affects the trend of EFMs. This value is used as a cut-off to eliminate parameters not significant to the present round of regression analysis.

Bundling of Significant High Variation Elements

Selecting a project to improve the performance of a manufacturing system is the goal of Lean Manufacturing and the Theory of Constraints. However, existing techniques cannot account for interdependency if there are simultaneous occurrences of variation in the three station segments (Inbound, Process, and Quality) in a manufacturing system. A production line comprises a network of stations, each having a specific task in the process of transformation of raw material to finished goods. The performance of each station is dependent on the adjacent station, i.e., each station affects the next. Thus, there is an intercorrelation of data between stations; in statistical analysis, this phenomenon is called multicollinearity, in which the correlation of two or more variables means that a linear equation can be used to predict one value from the other. As a result of collinearity, the interpretation of individual significant variables' impact on overall system efficiencies cannot be considered. Instead, the entire set of significant variables can be deemed to impact the system as a group (Dormann et al., 2013). The group of significant HVs suggested by the prioritization algorithm of BVPM is called the Bundle of High Variation Elements (BHVs). The BHVs are intended to help decision-makers identify the set of projects leading to a reduction in the impact of variation and improvement of system performance.

Note that BVPM will result in two BHVs, each corresponding to Cycle Time Efficiency and Inventory Efficiency. The best set of HVs for a production system is identified based on two criteria:

- The predicted effect of the BHVs on respective system efficiencies. For example, if no predicted change in system efficiency the corresponding BHVs is not selected.
- Throughput estimates are calculated from the simulated production system after implementation of each set of BHVs. The BHVs providing the largest improvement in estimated throughput are selected for implementation.

3.5.3 Forecasting the Effect of BHVs and Implementing Changes

Forecasting utilizes historical data to predict future trends of a parameter. In this study, forecasting is used to estimate the effect of BHVs on the future trend of EFMs. Curve-fitting techniques are employed in statistical models with applications in a variety of fields. Farahat and Talaat (2010) and Jain et al. (2012) utilized curve fitting in short-term load forecasting for electrical systems. In curve fitting methodology, a mathematical function (curve) is fitted to a series of data points. Curves generated by polynomial or rational functions are utilized in this study.

The formulation for a fitted Polynomial Function (PF) is shown in Equation 3.24. The response variable y is an HV included in the BHVs identified by stepwise linear regression. Examples of polynomial functions include a line (one-degree polynomial) and a quadratic function (two-degree polynomial). PFs provide moderate flexibility in developing the shapes of curves used for fitting data. Based on existing literature, higher order polynomials (with degrees greater than seven) are not recommended as they exhibit high variation in the trend of extrapolated data points.

$$y = \sum_{i=1}^{n+1} p_i \cdot x^{n+1-i} \tag{3.24}$$

where y is a significant HV

n is intended degree of polynomial function

A Rational Function (RF) is the ratio of two polynomial functions. Polynomial functions in the numerator and denominator of a RF are identified based on separate intended equation degrees. In the existing literature, RFs are known for their ability to generate an extremely wide range of shapes for fitting data. Their extrapolated data points are more stable in the higher orders when compared to those obtained from PFs. RFs are restricted to fifth-degree functions owing to the increased complexity in the interpretation of resulting empirical formulations. Equation 3.25 shows the formulation for an RF.

$$y = \frac{\sum_{i=1}^{n+1} p_i \cdot x^{n+1-i}}{x^m + \sum_{i=1}^{m} q_i \cdot x^{m-1}} \tag{3.25}$$

where y is a significant HV

n is intended degree of polynomial of the numerator

m is intended degree of polynomial of the denominator

The Estimated Time Before Impact (ETBI) of a Bundle of High Variation Elements (BHVs) is calculated based on the regression function resulting from step-r of EFMs. ETBI is applied when the BHVs lead to the degradation of the efficiency metrics of the production line. In choosing whether to use PFs or RFs, the former are often recommended due to comparatively simple interpretation. However, as noted above, higher-order PFs can result in extrapolations with wide prediction intervals, and therefore lower-order (below five) RFs are recommended in place of higher-order PFs in the existing literature for the stable prediction of extrapolations. The data points resulting from extrapolation of either a PF or RF are applied to the regression function formulation based on Equation 3.23 to estimate the future trend in EFMs and to calculate the time until BHVs result in degradation in efficiency of a production line. In combination with BHVs, the ETBI is intended to provide decision-makers with suggestions for performance improvement projects.

Implementing Changes based on BHVs

The BVPM is designed to aid decision makers to monitor the efficiency metrics of a production line and determine a set of improvement projects representing one cycle in the closed loop of data recalculation performed by BVPM. After the suggested changes are implemented, the EFMs are recalculated. A change in performance of the system can be visualized by calculating the Cycle Time Efficiency and the Inventory Efficiency. The resulting new dataset represents a new state of the production system. The prioritization algorithm results in the identification of a new set of BHVs affecting the trend of EFMs. This feedback loop of data and implementation of suggested changes results in the continuous reduction of the impact of variation and improvement of system performance.

Chapter 4

Validation via Case Study

This chapter presents a validation of the Bundled Variation based Prioritization Model (BVPM) through the use of a case study, specifically, a discrete manufacturing line producing components for the automobile industry. The validation process comprises the following steps:

- In Section 4.1, a description of the cellular manufacturing line is presented, and associated data are collected to develop standardized metrics.
- In Section 4.2, the data are assessed with a simulation model utilized as necessary to develop all required data for the BVPM. The resulting data are converted from an event-based to a time series format.
- In Section 4.3, the efficiency measures of the production system are calculated. These results include the baseline model for a comparison between improvement projects based on BVPM and improvement projects based on concepts of Theory of Constraints (TOC).
- In Section 4.4, the prioritization algorithm is applied to the time series data of Operational Metrics (OMs) and Efficiency Metrics (EFMs) to prioritize High Variation Elements (HVs). Variation in the BVPM formulation is identified using the Coefficient of Variation (cv). A Bundle of High Variation Elements (BHVs) affecting the system performance is identified, and its impact on the future state of the system is assessed.

The EFMs are computed after implementation of projects selected by the prioritization algorithm of BVPM to assess the impact of BHVs.

- In Section 4.5, validation of the BVPM algorithm is performed by comparing system performance resulting from implementation of BHVs to Theory of Constraints.

4.1 Process Description

The case study was performed in coordination with an automotive components manufacturer. The company has a diverse product portfolio, as it supplies to major automotive manufacturers. The manufacturing facility is segmented into manufacturing cells based on product families. The majority of products manufactured by the company are produced in high volumes and over short durations (short-run production). The product considered for validation is produced during two months each year; for this case study, the product is designated Pro01. It is fabricated from a pre-packaged kit comprising eight individual components provided by a supplier. The manufacturing cell (Figure 4.1) is designed to assemble and weld 150 finished products in one eight-hour shift per day.

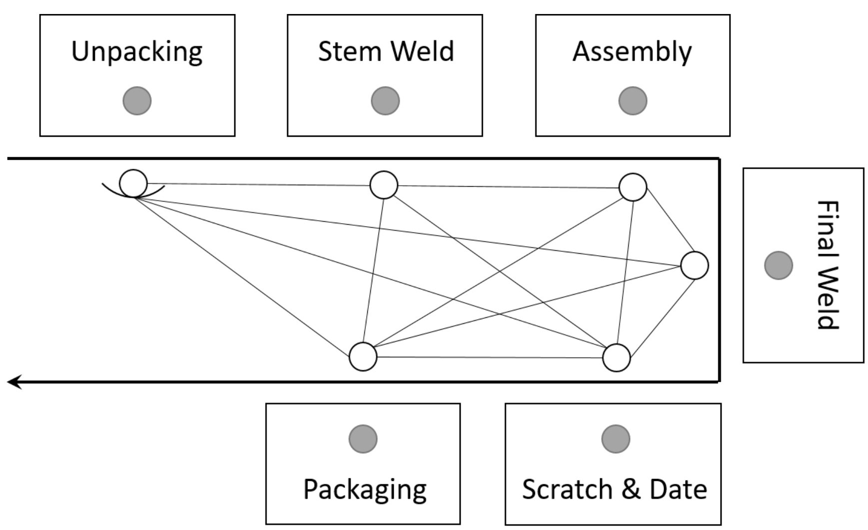

Figure 4.1: Design of Pro01 Manufacturing Cell

The Pro01 manufacturing cell involves six steps in which raw material are transformed into the finished product (Figure 4.2). The steps are described as follows:

1. **Unpacking:** The eight components required for Pro01 assembly are separated by one operator from a kit provided by the supplier. The kit is located in a box beside the station. The operator picks one kit and unpacks it, taking one minute to do so. The number of kits an operator is required to disassemble, and frequency of picking kits is not standardized. After disassembling the kits, the operator moves to the next station.

2. **Stem Weld:** An operator picks up two components from the disassembled kit (stem and base) and places them in a welding machine. The welding operation is automated and runs for 1.25 minutes and is performed on all disassembled kits before moving to next station. The Setup Time for the machine is 10 minutes and is done at the beginning of a production run. According to company personnel, breakdowns of the welding machine are rare and have not occurred in the previous year. After approximately 500 hours of continuous operation, the weld tip is changed, taking 10 minutes of the operator's time (maintenance personnel are not required).

3. **Assembly:** The remaining components of the disassembled kit are assembled along with the stem welded component by one operator on a bench and then arranged for welding. The assembly process takes 0.167 minutes. The number of kits an operator is required to assemble before moving to the next station is not standardized.

4. **Final Weld:** An operator places parts assembled in the previous step in a welding machine. The welding operation is performed by the machine and is automated. After completion, the operator places a sensor to check for leaks in the weld. Leak testing is done for each part. Together, welding and leak testing for each part take two minutes. A Setup Time of 0.77 minutes is required at the beginning of a production run. After approximately 500 hours of continuous operation, the weld tip is changed, taking 10 minutes of the operator's time.

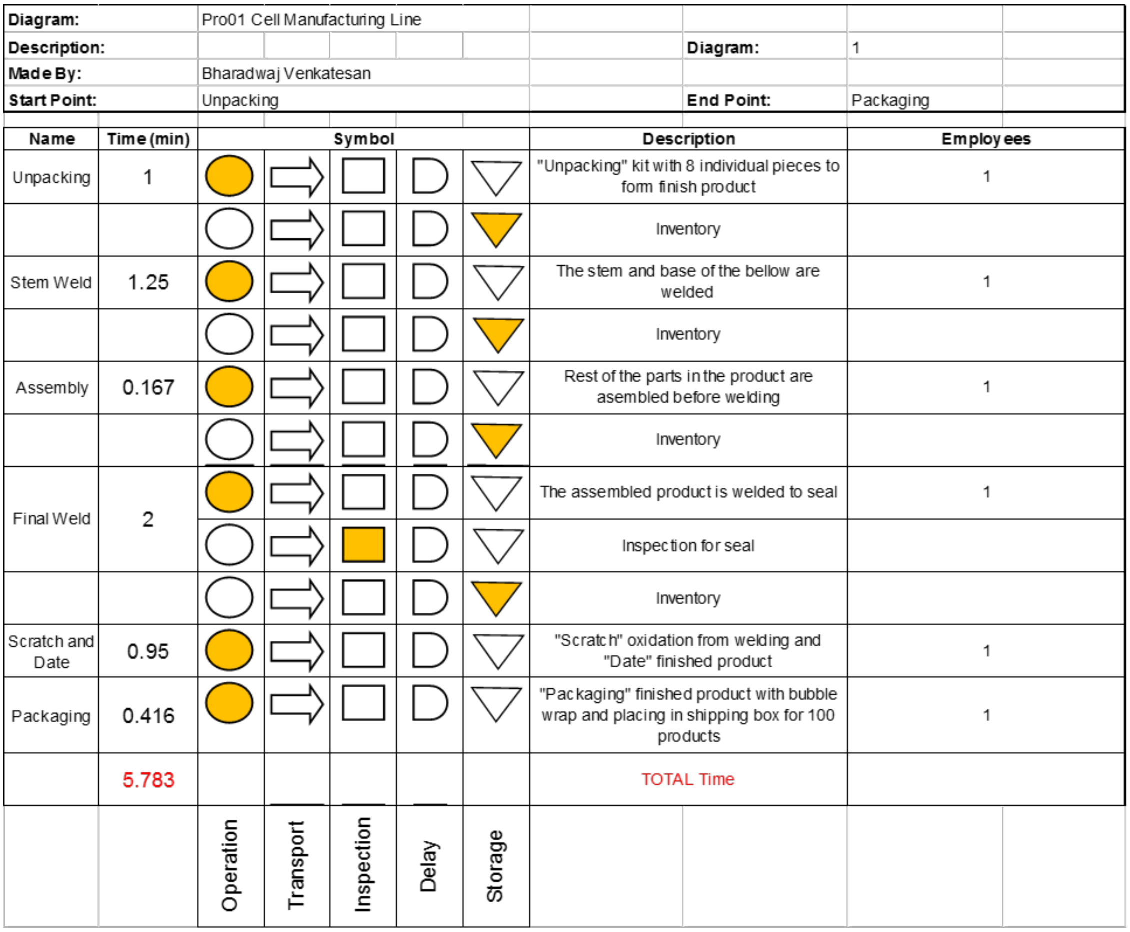

Figure 4.2: Production Flow of Pro01 Manufacturing Cell

5. **Scratch & Date:** An operator scrubs each unit to remove oxidation that may have formed during the welding process. This is done by placing the part against a moving brush to scratch and remove residue. The operator visually inspects each part and, once it is assessed to be clean, a part number and date of manufacture is stamped on the part. The entire procedure is performed in 0.95 minutes. The date stamp is changed at the beginning of each day, taking five seconds.

6. **Packaging:** The finished product is visually inspected for physical defects by an operator, packed in bubble wrap, and placed in a shipping box. The shipping box can hold 100 finished products. The packaging procedure takes 0.416 minutes.

Data Collection

During on-site visits, two operators were assigned to the manufacturing cell to increase Throughput and achieve promised delivery dates. Each operator was responsible for different stations; thus, the case study was performed based on a two-person operation. The following mechanisms were utilized to collect data:

- Interviews of company personnel were conducted to assess the present state of the Pro01 manufacturing cell; the production manager of the plant and operators of Pro01 manufacturing cell were interviewed. According to the production manager, an existing bulk manufacturing order of 6,000 units is estimated to require two months of production. The standard operating procedures at each station were assessed through the interviews of the operators.
- Historical data on equipment maintenance were utilized to calculate Mean Time to Failure and Mean Time to Repair owing to the non-occurrence of equipment breakdown during the on-site visits. The Yield of the equipment was also obtained from historical data.
- During the on-site time studies, metrics such as Processing Time at each station, Batch Size of the product, and Setup Time of equipment were obtained.
- Metrics such as Rate of Arrival of raw material and Instantaneous Raw Material Inventory at each station could not be collected using the above techniques. A simulation model was therefore developed to fill in missing data. The following section (Section 4.2.1) will elaborate the utilization of the simulation model.

4.2 Data Evaluation for BVPM

The BVPM algorithm prescribes evaluating and modifying collected data in two steps: data completeness, and formatting. Figure 4.3 illustrates the process of data evaluation.

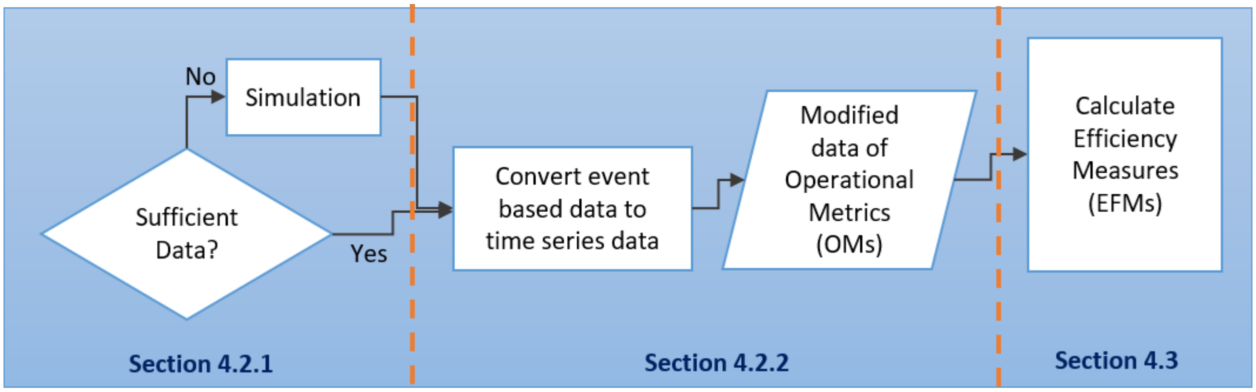

Figure 4.3: Framework for Data Evaluation (Section 4.2)

4.2.1 Data Evaluation: Completeness

Table 4.1 lists the Operational Metrics (OMs) required for calculating the efficiency metrics of the Pro01 manufacturing cell. The column "Data from Company" lists the data obtained from personnel interviews, historical data, and time studies. The Rate of Arrival (r_a) of material, Instantaneous Raw Material Inventory (RI) and Instantaneous Capacity (C_m) of each station were not obtained during the data collection visits.

A discrete event simulation model of the Pro01 manufacturing cell was developed in ProModel simulation software using data obtained from the company to fill in missing information ($r_a(i)$, $RI(i)$, and $C_m(i)$). The simulation model was designed under the assumption of two operators working in the Pro01 cell to deliver an order size of 6,000 units. Because the simulation model started with no inventory in the system, a "Warm-up Period" was introduced to account for the initial transient state of the simulation. The "Warm-up Period" of the Pro01 manufacturing cell was run for four days. The simulation model discards all variable data before renewing for the rest of the replication.

4.2.2 Data Evaluation: Format

The data obtained from the simulation model were in event-based, rather than time series, format. In an event-based format, the time of occurrence of an event is recorded along with the value of the variable; by contrast, the amplitude of the variable in a time series format is recorded at equal time intervals.

Table 4.1: Operational Metrics (OMs) data obtained from company and complementary data obtained through simulation

Station Segment	Metric	Definitions	Data from Company	Data from Simulation
Inbound	$r_a(i)$	Rate of Arrivals at station i		✓
	$RI(i)$	Instantaneous Raw Material Inventory at station i		✓
	$b_p(i)$	Batch Size of product j at station i	✓	
Process	$t_o(i)$	Raw Process Time (no downtimes, setups, etc.)	✓	
	$t_s(i)$	Setup Time at station i	✓	
	$C_m(i)$	Instantaneous Capacity of station i		✓
	$t_r(i)$	Mean Time to Repair at station i	✓	
	$t_f(i)$	Mean Time to Failure at station i	✓	
	$m(i)$	Number of parallel machines assigned to station i	✓	
Quality	$Y(i)$	Yield of station i	✓	

During the interviews, production personnel stated that internal performance metrics such as Throughput were calculated daily. They indicated a preference for BVPM to calculate efficiency metrics at the same frequency. Conversion of data from an event-based to a time series format was performed based on a Target Frequency (TF) of one day, i.e., all OMs were sampled at a frequency of one day, and efficiency metrics were calculated every day.

When converting data from event-based to time series format, two situations are encountered: the metrics have frequencies higher or lower than the TF. For example, Instantaneous Raw Material Inventory is collected at a frequency higher than one day, while Mean Time to Failure occurs once every few months. It would not be possible to calculate the latter efficiency metric for days in which there is no failure of equipment. Efficiency measures can be calculated if data points for all input metrics exist for all days. To alleviate errors occurring during the calculation of efficiency metrics, the collected data were either smoothed for variables with more than one data point for each day (higher than TF) or imputation of variables for which there was no data point in a given day (lower than TF).

Table 4.2 shows a variable measured at a frequency greater than TF. When event-based data are at a frequency higher than TF, Equation 4.1 can be utilized to calculate the average for each day. For example, all event-based data points from day 0 to day 1 are counted towards a time series data point for day 1. Similarly, all data points from day 6 to day 7 (i.e., 6.0048, 6.1789, 6.3517, etc.) are counted toward day 7. The average of all events corresponding to day 7 of Instantaneous Raw Material Inventory at the Assembly station was calculated and assigned to the time series data point of day 7 of Assembly station. Table 4.2 shows a part of the Instantaneous Raw Material Inventory data for day 7 at the Assembly station, corresponding to an average of 0.5 units/day (Equation 4.3). The shaded area in Table 4.3 shows day 7 for Instantaneous Raw Material Inventory of the Assembly station and data converted from event-based to time series format to obtain a daily average raw material inventory.

$$Q_{T_l} = \frac{\sum_{k=0}^{N} q_k \cdot \delta_k}{\sum_{k=0}^{N} \delta_k} \tag{4.1}$$

$$\delta_k = \begin{cases} 1 & \text{if } T_{l-1} \leq t_k \leq T_l, \\ 0 & \text{if } T_{l-1} \geq t_k \text{ or } t_k \geq T_l. \end{cases} \tag{4.2}$$

where $l \geq 1$

$Q_{T_l} =$ mean value of given period of time

$T_l =$ present time (days)

$q_k =$ value of data point in the sample (i.e., "value" column from Table 4.2)

t_k time values of the data points in the sample

$$\begin{aligned} RI(Assembly)\ for\ day\ 7 &= \frac{(1+0+1+0+1+0+\ldots)\cdot(1)}{1+1+1+1+\ldots} \\ &= 0.500\ units \end{aligned} \tag{4.3}$$

Table 4.2: Event-based data of Raw Material Inventory $RI(i)$ from simulation model for day 7 of Assembly Station in units

Time (day)	**Value (RI)**	**Time (day)**	**Value (RI)**	**Time (day)**	**Value (RI)**	**Time (day)**	**Value (RI)**	**Time (day)**	**Value (RI)**	**Time (day)**	**Value (RI)**
6.0048	1	6.1789	1	6.3517	1	6.5256	1	6.6989	1	6.8723	1
6.0051	0	6.1792	0	6.3520	0	6.5259	0	6.6991	0	6.8726	0
6.0119	1	6.1858	1	6.3586	1	6.5325	1	6.7058	1	6.8792	1
6.0121	0	6.1859	0	6.3588	0	6.5328	0	6.7060	0	6.8794	0
6.0185	1	6.1924	1	6.3659	1	6.5395	1	6.7131	1	6.8859	1
6.0188	0	6.1927	0	6.3662	0	6.5398	0	6.7133	0	6.8861	0
6.0254	1	6.1995	1	6.3729	1	6.5461	1	6.7199	1	6.8933	1
6.0257	0	6.1998	0	6.3731	0	6.5464	0	6.7201	0	6.8936	0
6.0325	1	6.2063	1	6.3796	1	6.5535	1	6.7272	1	6.8999	1
6.0328	0	6.2066	0	6.3799	0	6.5538	0	6.7274	0	6.9001	0
6.0397	1	6.2131	1	6.3865	1	6.5604	1	6.7339	1	6.9070	1
6.0399	0	6.2134	0	6.3868	0	6.5606	0	6.7342	0	6.9073	0
6.0463	1	6.2199	1	6.3932	1	6.5671	1	6.7407	1	6.9143	1
6.0465	0	6.2201	0	6.3935	0	6.5674	0	6.7409	0	6.9145	0
6.0532	1	6.2267	1	6.4005	1	6.5741	1	6.7477	1	6.9212	1
6.0535	0	6.2269	0	6.4008	0	6.5743	0	6.7479	0	6.9215	0
6.0599	1	6.2341	1	6.4075	1	6.5809	1	6.7546	1	6.9284	1
6.0602	0	6.2342	0	6.4077	0	6.5812	0	6.7548	0	6.9287	0
6.0668	1	6.2410	1	6.4143	1	6.5878	1	6.7613	1	6.9353	1
6.0671	0	6.2413	0	6.4146	0	6.5881	0	6.7615	0	6.9355	0
6.0742	1	6.2478	1	6.4213	1	6.5947	1	6.7679	1	6.9424	1
6.0745	0	6.2480	0	6.4216	0	6.5950	0	6.7681	0	6.9426	0
6.0809	1	6.2546	1	6.4285	1	6.6015	1	6.7749	1	6.9495	1
6.0812	0	6.2548	0	6.4287	0	6.6017	0	6.7751	0	6.9498	0
6.0880	1	6.2615	1	6.4352	1	6.6087	1	6.7815	1	6.9566	1
6.0882	0	6.2618	0	6.4354	0	6.6090	0	6.7818	0	6.9568	0
6.0950	1	6.2687	1	6.4423	1	6.6156	1	6.7888	1	6.9632	1
6.0953	0	6.2690	0	6.4425	0	6.6158	0	6.7890	0	6.9634	0
6.1018	1	6.2756	1	6.4492	1	6.6221	1	6.7957	1	6.9701	1
6.1020	0	6.2758	0	6.4494	0	6.6224	0	6.7960	0	6.9703	0
6.1088	1	6.2825	1	6.4565	1	6.6292	1	6.8029	1	6.9770	1
6.1091	0	6.2828	0	6.4567	0	6.6294	0	6.8032	0	6.9773	0
6.1157	1	6.2896	1	6.4635	1	6.6365	1	6.8098	1	6.9842	1
6.1160	0	6.2898	0	6.4637	0	6.6367	0	6.8100	0	6.9844	0
6.1225	1	6.2966	1	6.4704	1	6.6432	1	6.8165	1	6.9907	1
6.1228	0	6.2968	0	6.4706	0	6.6435	0	6.8167	0	6.9909	0
6.1297	1	6.3032	1	6.4774	1	6.6497	1	6.8235	1	6.9979	1
6.1299	0	6.3035	0	6.4776	0	6.6500	0	6.8237	0	6.9981	0
6.1366	1	6.3102	1	6.4841	1	6.6570	1	6.8303	1		
6.1368	0	6.3105	0	6.4843	0	6.6573	0	6.8305	0		
6.1440	1	6.3169	1	6.4909	1	6.6640	1	6.8372	1		
6.1443	0	6.3172	0	6.4911	0	6.6642	0	6.8375	0		
6.1509	1	6.3238	1	6.4979	1	6.6709	1	6.8443	1		
6.1510	0	6.3241	0	6.4982	0	6.6711	0	6.8446	0		
6.1581	1	6.3309	1	6.5050	1	6.6780	1	6.8514	1		
6.1583	0	6.3311	0	6.5052	0	6.6782	0	6.8516	0		
6.1650	1	6.3380	1	6.5121	1	6.6848	1	6.8584	1		
6.1652	0	6.3382	0	6.5124	0	6.6851	0	6.8586	0		
6.1718	1	6.3447	1	6.5191	1	6.6920	1	6.8653	1		
6.1721	0	6.3450	0	6.5194	0	6.6922	0	6.8654	0		

Table 4.3: Time series data of Instantaneous Raw Material Inventory $RI(i)$ in units for each day

A partial table upto Day 13 is presented here for brevity. The complete table is included in the Appendix (Table B.1)

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.498	0.498	0.498	0.500	0.500	0.498
6	0.500	0.500	0.500	0.500	0.500	0.500
7	0.500	0.500	0.500	0.498	0.502	0.500
8	0.500	0.500	0.500	0.502	0.498	0.500
9	0.500	0.500	0.500	0.500	0.500	0.500
10	0.500	0.500	0.500	0.500	0.500	0.500
11	0.500	0.500	0.500	0.498	0.502	0.500
12	0.500	0.500	0.500	0.500	0.498	0.500
13	0.500	0.500	0.500	0.500	0.502	0.500

For instance, when the frequency of collected data was lower than a day, as was the case for the Mean time to Failure of equipment, the previous data point was carried over until the occurrence of a failure event. When a new failure event occurred, the average of the two failure rates was utilized to calculate the new Mean Time to Failure.

4.3 Baseline Model: Calculating Efficiency Measures of Production Line

In the previous section, data smoothing or imputation (i.e., carrying over of data) was applied to Operational Metrics (OMs) obtained from the simulation model. The event-based data were converted to a time series format as prescribed by BVPM. Note that days 1 to 4 in the simulation model are considered to be a "Warm-up Period", and therefore all OM data in the case study are considered to start from day 5 as data collected during the "Warm-up Period" were discarded. Similarly, the Efficiency Metrics and Throughput of the system are computed from day 5 to the end of the simulation (day 42 for the baseline model).

The time series data of OMs is utilized to calculate the Efficiency Metrics (EFMs) of the Cycle Time and Inventory. Figure 4.4 shows the equations corresponding to Cycle Time Efficiency ($\eta_{CT}(j)$) of the examined process,where j is the designation for the Pro01 manufacturing cell and i is the station in the cell. All expressions containing i in the left-hand variable are computed for each station, while all expressions containing j in the left-hand variable are calculated for the entire Pro01 manufacturing cell.

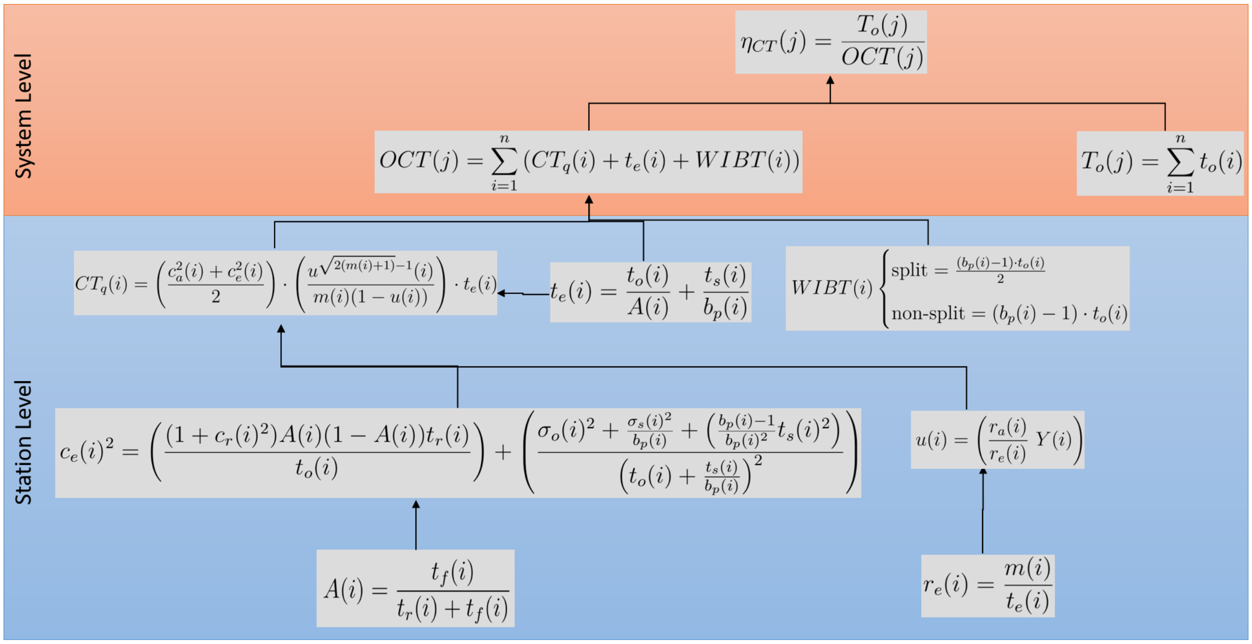

Figure 4.4: Hierarchy of Metrics for Cycle Time Efficiency

Note: Day 7 at the Assembly station ($i = 3$) is used here to guide the reader through the progression of calculations. This example illustrates the computation of intermediate metrics leading up to calculation of EFMs for the Pro01 manufacturing cell. The station is represented in each table as a colored cell. For example, in Table 4.4 the Raw Process Time on day 7 at the Assembly station is 0.169 minutes.

4.3.1 Cycle Time Efficiency

The computation of Cycle Time Efficiency ($\eta_{CT}(j)$) is divided into three steps as shown in Figure 4.4:

1. Calculating the Coefficient of Variation for Effective Processing Time ($c_e(i)$) for each station in the production line;

2. Calculating the Wait Time in Queue ($CT_q(i)$) at each station in the production line, and;
3. Calculating Overall Cycle Time ($OCT(j)$) for the production line.

Coefficient of Variation of Effective Processing Time ($c_e(i)$)

Calculation of the Coefficient of Variation for Effective Processing Time starts with the Availability for all stations (Equation 4.4). Owing to the low frequency of equipment failure (around once very six months), there are no failure or repair events during the 38 days of the simulation. Therefore, the availability of all machines in the cell is 1 (100 percent).

$$A(i) = \frac{t_f(i)}{t_r(i) + t_f(i)} \tag{4.4}$$

$$\text{where } t_f(i) = \text{Mean Time to Failure}$$

$$t_r(i) = \text{Mean Time to Repair}$$

The Coefficient of Variation of the Mean Time to Repair $c_r(i) = 0$ and there is no Mean Time to Failure ($t_r(i)$). The first part of the Cycle Time Efficiency expression is zero, as the Availability for all stations is 1 (i.e., 100%) during the 38 days of the simulation model run. The second part of the equation for ($c_e(i)$) is a function of the Variance of Raw Process Time ($\sigma_o^2(i)$), the Variance of Setup Time ($\sigma_s^2(i)$), the Batch Size of Product ($b_p(i)$), the Raw Process Time ($t_o(i)$) and the Setup Time ($t_s(i)$). The variance terms $\sigma_o^2(i)$ and $\sigma_s^2(i)$ are calculated from $t_o(i)$, and $t_s(i)$, respectively. Including all terms in the equation, $c_e(i)$ is computed, as shown in Equation 4.5, to be 0.174 on day 7 at the Assembly Station. The results for rest of stations is shown in Table 4.5.

$$\begin{aligned}
c_e^2(i) &= \left(\frac{(1 + c_r^2(i)) \cdot A(i) \cdot (1 - A(i)) \cdot t_r(i)}{t_o(i)}\right) + \left(\frac{\sigma_o^2(i) + \frac{\sigma_s^2(i)}{b_p(i)} + \left(\frac{b_p(i)-1}{b_p^2(i)} t_s^2(i)\right)}{\left(t_o(i) + \frac{t_s(i)}{b_p(i)}\right)^2}\right) \\
&= \left(\frac{(1 + 0^2) \cdot 1 \cdot (1 - 1) \cdot 0}{0.169}\right) + \left(\frac{(0.418 \cdot 0.169)^2 + \frac{0^2}{1} + \left(\frac{1-1}{1^2} \cdot 0^2\right)}{\left(0.169 + \frac{0}{1}\right)^2}\right) \\
&= 0.174 \text{ on day 7 at Assembly Station}
\end{aligned} \tag{4.5}$$

The Raw Process Time ($t_o(i)$) for all stations is shown in Table 4.4. The value for the Assembly station on day 7 is 0.169 minutes. The Setup Time ($t_s(i)$) for Assembly station on day 7 is 0 minutes, as there is no change of product in the Pro01 manufacturing cell. One unit of product is operated on at any given time in each station, resulting in a Size of Batch at each station $b_p = 1$. Therefore, the Coefficient of Variation for Effective Processing Time $c_e(i)$ of the Assembly station on day 7 is 0.174 (Equation 4.5).

Table 4.4: Raw Process time $t_o(i)$ in minutes

A partial table upto Day 13 is presented here for brevity. The complete table is included in the Appendix (Table B.2a)

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.995	1.261	0.174	2.011	0.953	0.423
6	1.005	1.248	0.161	1.983	0.939	0.418
7	1.002	1.265	0.169	2.000	0.945	0.420
8	0.999	1.233	0.171	2.007	0.953	0.414
9	0.999	1.246	0.168	1.995	0.955	0.417
10	1.003	1.243	0.160	1.986	0.954	0.413
11	0.999	1.277	0.167	1.975	0.948	0.415
12	0.997	1.270	0.162	2.006	0.941	0.413
13	1.000	1.252	0.166	1.995	0.945	0.412

Table 4.5: Coefficient of Variation of Effective Processing Time $c_e(i)$

A partial table upto Day 13 is presented here for brevity. The complete table is included in the Appendix (Table B.2b)

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	3.998	0.107	0.127	2.219	0.113	0.114
6	1.999	0.108	0.150	2.806	0.121	0.123
7	1.333	0.110	0.174	2.918	0.130	0.132
8	0.999	0.111	0.199	2.839	0.138	0.142
9	0.800	0.112	0.225	2.680	0.146	0.151
10	0.666	0.113	0.253	2.495	0.153	0.161
11	0.571	0.115	0.281	2.311	0.161	0.170
12	0.500	0.116	0.311	2.137	0.169	0.179
13	0.444	0.116	0.342	1.973	0.177	0.189

Waiting Time in Queue ($CT_q(i)$)

To compute the Waiting Time in Queue four variables must be calculated: the Coefficient of Variation of Rate of Arrivals ($c_a(i)$), Coefficient of Variation of Effective Processing Time ($c_e(i)$), Utilization and Effective Processing Time ($t_e(i)$). $c_e(i)$ was previously calculated and c_a is calculated from the standard deviation of the Rate of Arrival ($r_a(i)$) for each station. The Effective Processing Time ($t_e(i)$) for each station in the Pro01 manufacturing cell is calculated using Equation 4.6. As previously mentioned, $A(i)$ is 1 for the entire simulation run of 38 days. Similarly, Setup Time, Raw Process Time, and Batch Size are reused from the calculations for the Coefficient of Variation for Effective Processing Time. The results for Effective Processing Time are shown in Table 4.6; the value for the Assembly station is 0.169 minutes during day 7.

$$\begin{aligned} t_e(i) &= \frac{t_o(i)}{A(i)} + \frac{t_s(i)}{b_p(i)} \\ &= \frac{0.169}{1} + \frac{0}{1} \\ &= 0.169 \text{ minutes on day 7 at Assembly Station} \end{aligned} \tag{4.6}$$

Table 4.6: Effective Processing Time $t_e(i)$ in minutes

A partial table upto Day 13 is presented here for brevity. The complete table is included in the Appendix (Table B.3)

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.995	1.263	0.174	2.011	0.954	0.423
6	1.005	1.250	0.161	1.983	0.939	0.418
7	1.002	1.267	0.169	2.001	0.945	0.420
8	0.999	1.235	0.172	2.007	0.953	0.414
9	0.999	1.248	0.169	1.995	0.955	0.417
10	1.003	1.245	0.160	1.986	0.954	0.413
11	1.000	1.279	0.167	1.975	0.948	0.416
12	0.997	1.272	0.162	2.007	0.941	0.413
13	1.000	1.255	0.166	1.995	0.945	0.412

The Instantaneous Utilization of a station is calculated from the Effective Processing Time, Rate of Arrivals and Effective Rate of Production ($r_e(i)$). $r_e(i)$ is calculated using

Equation 4.7, in which $m(i)$ represents the number of parallel machines assigned to a step in the production system. There are no parallel machines at stations in the Pro01 manufacturing cell therefore, $m(i) = 1$. The Effective Rate of Production for each station is shown in Table 4.7. Using the Effective Processing Time of 0.169 minutes for day 7 at the Assembly station, the Effective Rate of Production is calculated to be 5.921 units/min.

$$\begin{aligned} r_e(i) &= \frac{m(i)}{t_e(i)} \\ &= \frac{1}{0.169} \\ &= 5.921 \text{ units/min on day 7 at Assembly Station} \end{aligned} \tag{4.7}$$

The Instantaneous Utilization of a station is calculated by Equation 4.8 using data from the Rate of Arrival $r_a(i)$, Effective Rate of Production $r_e(i)$, and Yield $Y(i)$ of the station. For the Pro01 manufacturing cell, the Yield is set at 0.95 in the simulation model for all stations based on historical information gathered from the company. The Rate of Arrival from Table 4.8 and the Effective Rate of Production from Table 4.7 are used to calculate the Instantaneous Utilization of stations (Table 4.9). With a Rate of Arrival on day 7 for the Assembly station of 0.026 units/day and corresponding Effective Production Rate of 5.921 units/day, the Instantaneous Utilization is 0.004.

$$\begin{aligned} u(i) &= \left(\frac{r_a(i)}{r_e(i)} Y(i)\right) \\ &= \left(\frac{0.026}{5.921} \cdot 0.95\right) \\ &= 0.004 \text{ on day 7 at Assembly Station} \end{aligned} \tag{4.8}$$

Based on the computed Coefficient of Variation for Rate of Arrivals, Coefficient of Variation of Effective Processing Time, Instantaneous Utilization, and Effective Processing Time, the Waiting Time in Queue for the product at all stations in the Pro01 manufacturing cell is computed, with the results listed in Table 4.10.

Table 4.7: Effective Rate of Production $r_e(i)$ in units/min

A partial table upto Day 13 is presented here for brevity. The complete table is included in the Appendix (Table B.4)

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	1.005	0.792	5.737	0.497	1.049	2.365
6	0.995	0.800	6.199	0.504	1.065	2.390
7	0.998	0.789	5.921	0.500	1.058	2.379
8	1.001	0.810	5.825	0.498	1.050	2.414
9	1.001	0.801	5.932	0.501	1.047	2.395
10	0.997	0.803	6.241	0.503	1.048	2.422
11	1.000	0.782	5.977	0.506	1.055	2.406
12	1.003	0.786	6.156	0.498	1.062	2.421
13	1.000	0.797	6.015	0.501	1.058	2.428

Table 4.8: Rate of Arrivals of Inventory $r_a(i)$ in units/min

A partial table upto Day 13 is presented here for brevity. The complete table is included in the Appendix (Table B.5a)

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.036	0.036	0.036	0.036	0.036	0.036
6	0.030	0.030	0.030	0.030	0.030	0.030
7	0.026	0.026	0.026	0.026	0.026	0.026
8	0.022	0.022	0.022	0.022	0.022	0.022
9	0.020	0.020	0.020	0.020	0.020	0.020
10	0.018	0.018	0.018	0.018	0.018	0.018
11	0.016	0.016	0.016	0.016	0.016	0.016
12	0.014	0.014	0.014	0.014	0.014	0.014
13	0.013	0.013	0.013	0.013	0.013	0.013

On day 7 at the Assembly station, $c_e(i)$ is 0.174, $u(i)$ is 0.004, and $t_e(i)$ is 0.169 minutes, resulting in a Waiting Time in Queue for the product of 0.000256 minutes.

$$\begin{aligned} CT_q(i) &= \left(\frac{c_a^2(i) + c_e^2(i)}{2}\right) \cdot \left(\frac{u^{\sqrt{2(m(i)+1)}-1}(i)}{m(i)(1-u(i))}\right) \cdot t_e(i) \\ &= \left(\frac{0.8397^2 + 0.174^2}{2}\right) \cdot \left(\frac{0.004^{\sqrt{2(1+1)}-1}}{1 \cdot (1-0.004)}\right) \cdot 0.169 \\ &= 0.000256 \text{ minutes on day 7 at Assembly Station} \end{aligned} \tag{4.9}$$

Table 4.9: Instantaneous Utilization of Station $u(i)$

A partial table upto Day 13 is presented here for brevity. The complete table is included in the Appendix (Table B.5b)

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.034	0.044	0.006	0.070	0.033	0.015
6	0.029	0.036	0.005	0.057	0.027	0.012
7	0.024	0.031	0.004	0.049	0.023	0.010
8	0.021	0.026	0.004	0.042	0.020	0.009
9	0.019	0.023	0.003	0.037	0.018	0.008
10	0.017	0.021	0.003	0.033	0.016	0.007
11	0.015	0.019	0.003	0.030	0.014	0.006
12	0.014	0.018	0.002	0.028	0.013	0.006
13	0.013	0.016	0.002	0.025	0.012	0.005

Table 4.10: Wait Time in Queue CT_q in minutes (Table B.6)

A partial table upto Day 13 is presented here for brevity. The complete table is included in the Appendix (Table B.6)

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.355	0.021	0.0004	0.423	0.012	0.0023
6	0.090	0.017	0.0003	0.515	0.009	0.0018
7	0.040	0.014	0.0003	0.472	0.008	0.0016
8	0.022	0.012	0.0002	0.389	0.007	0.0013
9	0.014	0.011	0.0002	0.303	0.006	0.0012
10	0.010	0.009	0.0002	0.236	0.006	0.0010
11	0.008	0.009	0.0002	0.183	0.005	0.0010
12	0.006	0.008	0.0001	0.150	0.005	0.0009
13	0.005	0.007	0.0001	0.119	0.004	0.0008

Calculating Cycle Time Efficiency $\eta_{CT}(j)$ of Production System

Finally, the Cycle Time Efficiency of the system is computed using Equation 4.10. This factor is the ratio of the Raw Process Time and the Actual Process Time cell. The Raw Process Time for the Pro01 manufacturing cell is a function of all Raw Process Times for all stations. The Actual Process Time is a function of Wait Time in Queue ($CT_q(i)$), Effective Processing Time ($t_e(i)$), and Wait Time in Batch ($WIBT(i)$). For the Pro01 manufacturing cell, there is no batching of parts during the production process, so the Wait Time in Batch of product Pro01 $WIBT(i) = 0$. Figure 4.5 shows the trend of $\eta_{CT}(j)$ over the course of the simulation (days 5 to 42).

$$\eta_{CT}(j) = \frac{\sum_{i=1}^{n} t_o(i)}{\sum_{i=1}^{n} (CT_q(i) + t_e(i) + WIBT(i))}$$
$$= 0.9149 \text{ on day 7 in the Pro01 manufacturing cell} \tag{4.10}$$

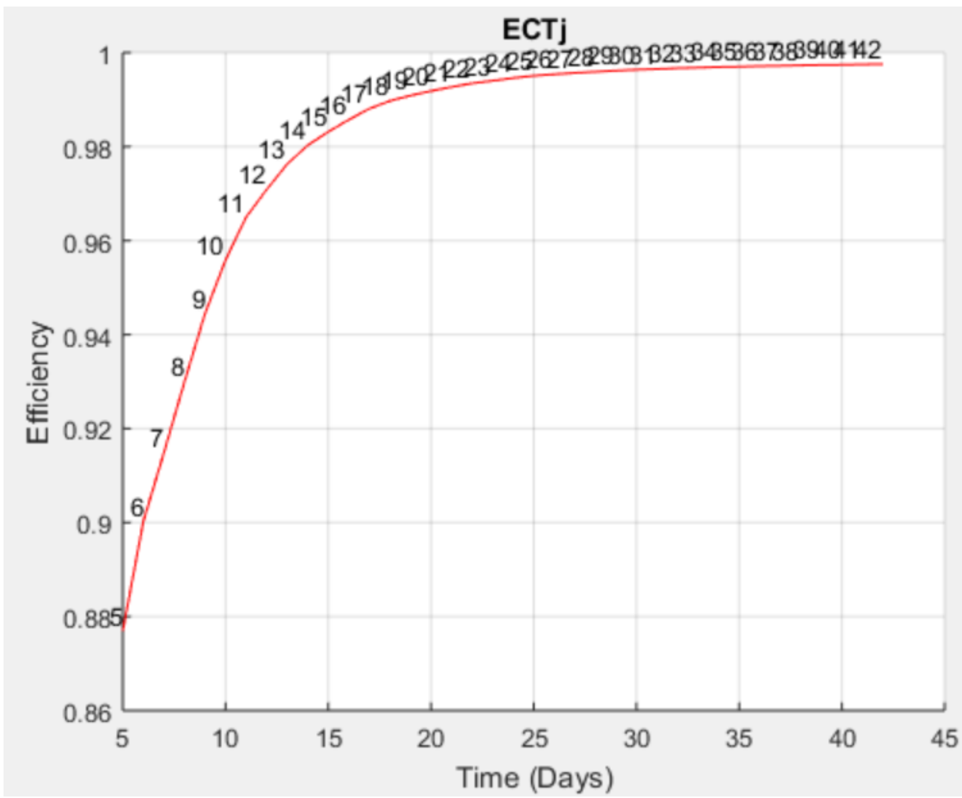

Figure 4.5: Calculating the Cycle Time Efficiency ($\eta_{CT}(j)$) of the Pro01 Manufacturing Cell (Table B.7)

Note that data collected for the first four days by the simulation model were discarded from analysis to account for the "Warm-up Period", which was implemented to mitigate the extreme variation in $\eta_{CT}(j)$ caused by the lack of work-in-process (inventory) at start-up not saturating the manufacturing cell. The value of $\eta_{CT}(j)$ increases from 87% to 99% over the course of 38 days (day 5 to 42) of production.

4.3.2 Inventory Efficiency

The Inventory Efficiency of the Pro01 manufacturing cell is calculated using Equation 4.11. This factor is the ratio of Ideal Inventory in the manufacturing cell and the Actual Inventory. Ideal Inventory is a function of Raw Process Time ($\sum_{i=1}^{n} t_o(i)$) and Rate of Production of the Bottleneck Station ($r_b(j)$). The bottleneck is the station with the highest utilization and the longest processing time; for the Pro01 manufacturing cell, it is the Final Weld station. To confirm the choice of bottleneck station, BVPM was used to calculate the Inventory Efficiency with each station assigned as a bottleneck, with the iteration resulting in the lowest efficiency then identified as the true bottleneck.

The Actual Inventory is a function of Work-in-Process ($WIP(i)$) and the Work-in-Process in Queue ($WIP_q(i)$) at each station in the system. The structure of equations to calculate Inventory Efficiency are shown in Figure 4.6.

$$\eta_{INV}(j) = \frac{r_b(j) \cdot \sum_{i=1}^{n} t_o(i)}{\sum_{i=1}^{n}(WIP(i) + WIP_q(i))} \tag{4.11}$$

The Work-in-Process Inventory $WIP(i)$ at a station is calculated using Equation 4.12. In the Pro01 line, there are no parallel machines; therefore, $m(i) = 1$ and the Instantaneous Capacity ($C_m(i)$) of the station is 0.999 units on day 7 at the Assembly Station, resulting in a $WIP(i)$ of 0.999 on day 7 at the Assembly station. Results for rest of the stations are shown in Table 4.11.

$$\begin{aligned} WIP(i) &= m(i) \cdot C_m(i) \\ &= 1 \cdot 0.999 \\ &= 0.999 \text{ units on day 7 at Assembly Station} \end{aligned} \tag{4.12}$$

The other part of the expression for Actual Inventory is Work-in-Process in Queue at each station ($WIP_q(i)$), which is a function of the Wait Time in Queue ($CT_q(i)$) and Rate of Arrival ($r_a(i)$) at the station. $CT_q(i)$ was measured in the calculation of Cycle Time Efficiency, and the Rate of Arrival is also available; therefore, as seen from Figure 4.7, $\eta_{INV}(j)$ is nearly constant at approximately 48.2% from days 5 to 42. For reasons mentioned previously, the first four days of data are excluded in the measurement of Inventory Efficiency, so only data from day 5 to 42 are considered in the analysis.

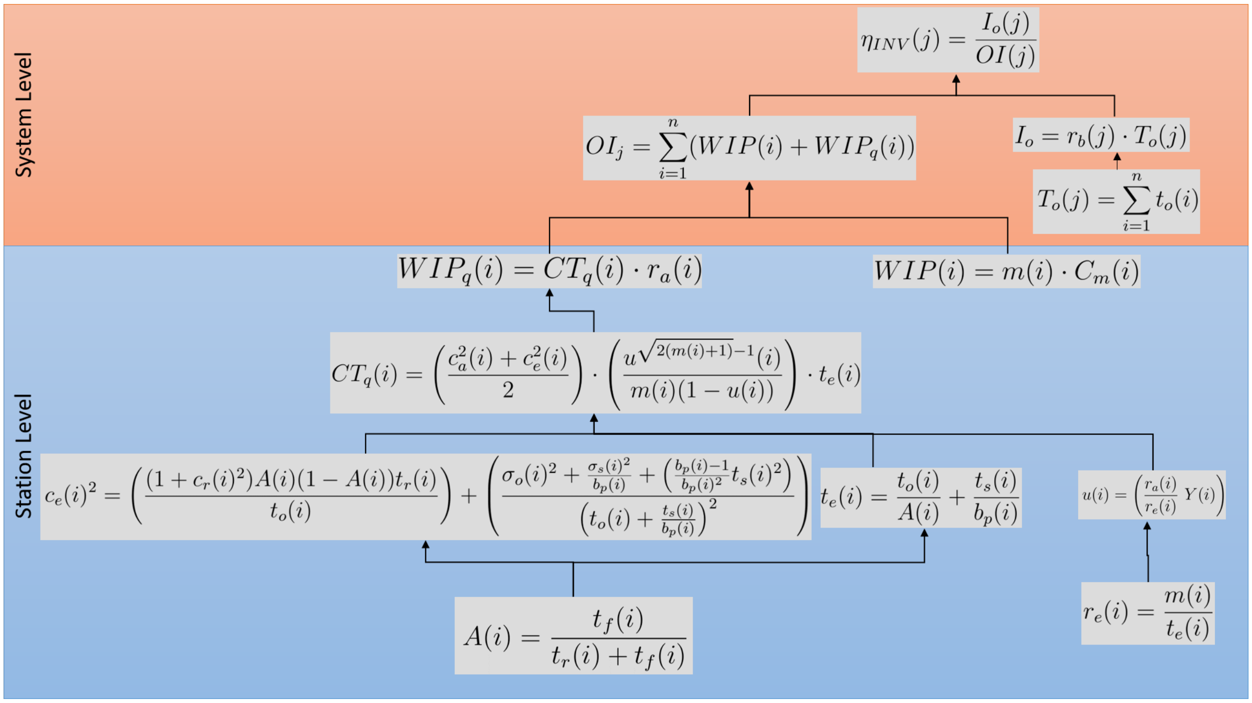

Figure 4.6: Structure of Equations used to Calculate Inventory Efficiency

Table 4.11: Instantaneous Capacity of station

A partial table upto Day 13 is presented here for brevity. The complete table is included in the Appendix (Table B.8)

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	1.000	0.998	0.998	0.998	0.998	0.998
6	1.000	0.999	0.999	0.999	0.999	0.999
7	1.000	0.999	0.999	0.999	0.999	0.999
8	1.000	0.999	0.999	0.999	0.999	0.999
9	1.000	0.999	0.999	0.999	0.999	0.999
10	1.000	0.999	0.999	0.999	0.999	0.999
11	1.000	0.999	0.999	0.999	0.999	0.999
12	1.000	0.999	0.999	0.999	0.999	0.999
13	1.000	0.999	0.999	0.999	0.999	0.999

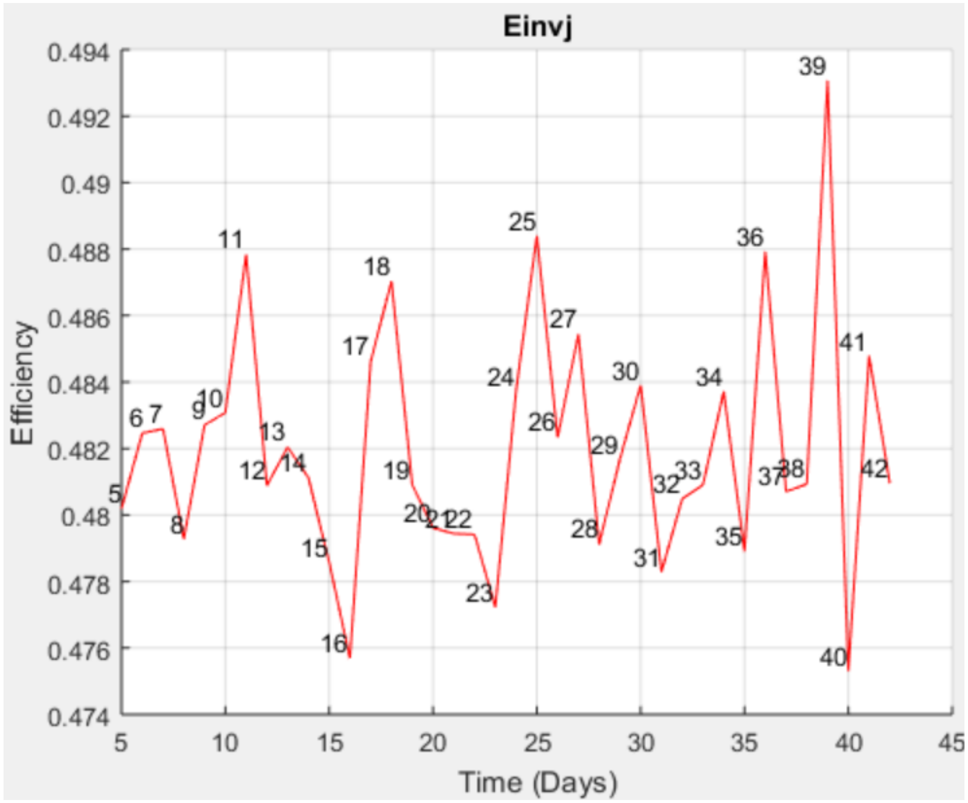

Figure 4.7: Calculating Inventory Efficiency $\eta_{INV}(j)$ of Pro01 Production Line (Table B.9)

4.4 Prioritization Model: Project Selection Utilizing Variation

The goal of the prioritization algorithm is to identify the Bundle of High Variation Elements (BHVs) affecting Pro01 manufacturing cell's productivity and to estimate the time available before they degrade system performance. Coefficients of variation (cv) of all Operational Metrics (OMs) are calculated. Stepwise regression is then used to identify the most significant High Variation Elements (HVs). Extrapolating the values of BHVs yields an estimate of time available to the company before degradation of system efficiencies, which can aid the company in developing strategies to reduce the impact of HVs.

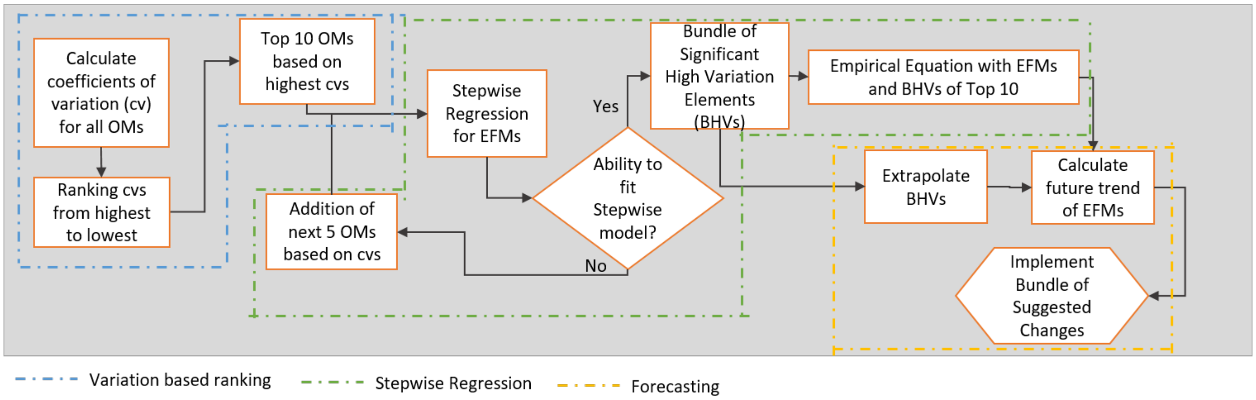

Figure 4.8: Framework of Prioritization Algorithm

4.4.1 Identifying Most Varying Elements in System

Key Operational Metrics (KOMs), a subset of the OMs. The Pro01 production line does not utilize parallel machines for the six stations, and there is no defined batch size for material in the production line. Therefore, $m(i)$ and $b_p(i)$ are eliminated from OMs to form the KOMs. The KOMs are used to identify the most varying elements in the system. However, many of the KOMs cannot be compared owing to non-uniformity of units. For example, the unit of Rate of Arrival is "units/day", while that of Raw Material Inventory is "units". Therefore, the Coefficient of Variation (cv) is used by the prioritization algorithm to standardize the KOMs for comparison and sorting of the most varying HVs in the system.

Table 4.12: Key Operational Metrics (KOMs) for Identifying Variability in a System

Station Segment	Metric	Definitions
Inbound	$r_a(i)$	Rate of Arrivals at station i
	$RI(i)$	Instantaneous Raw Material Inventory at station i
Process	$t_o(i)$	Raw Process Time (no downtime, setup time, etc.)
	$t_s(i)$	Setup Time at station i
	$C_m(i)$	Instantaneous Capacity of station i
	$t_r(i)$	Mean Time to Repair at station i
	$t_f(i)$	Mean Time to Failure at station i
Quality	$Y(i)$	Yield of station i

The top ten highest cvs in the Pro01 manufacturing cell over the course of the simulation run (Days 5 to 42) are listed below (from $x1$ to $x10$). Table 4.13 shows the corresponding data for these operational metrics. Here, $UP = Unpacking$, $SW = Stem\ Weld$, $AS = Assembly$, $FW = Final\ Weld$, $S\&D = Scratch\ \&\ Date$ and $P = Packaging$.

$x1 = r_a$ @Unpacking

$x2 = r_a$ @Stem Weld

$x3 = r_a$ @Scratch & Date

$x4 = r_a$ @Packaging

$x5 = r_a$ @Assembly

$x6 = r_a$ @Final Weld

$x7 = t_o$ @Assembly

$x8 = t_o$ @Packaging

$x9 = t_o$ @Stem Weld

$x10 = t_o$ @Final Weld

Table 4.13: Top ten High Variation Elements (HVs) of the Pro01 line based on Coefficient of Variation

A partial table upto Day 13 is presented here for brevity. The complete table is included in the Appendix (Table B.10)

Days	r_a **@UP**	r_a **@SW**	r_a **@S&D**	r_a **@P**	r_a **@AS**	r_a **@FW**	t_o **@AS**	RI **@P**	t_o **@SW**	t_o **@FW**
5	0.036	0.036	0.036	0.036	0.036	0.036	0.174	0.423	1.261	2.011
6	0.030	0.030	0.030	0.030	0.030	0.030	0.161	0.418	1.248	1.983
7	0.026	0.026	0.026	0.026	0.026	0.026	0.169	0.420	1.265	2.000
8	0.022	0.022	0.022	0.022	0.022	0.022	0.171	0.414	1.233	2.007
9	0.020	0.020	0.020	0.020	0.020	0.020	0.168	0.417	1.246	1.995
10	0.018	0.018	0.018	0.018	0.018	0.018	0.160	0.413	1.243	1.986
11	0.016	0.016	0.016	0.016	0.016	0.016	0.167	0.415	1.277	1.975
12	0.014	0.014	0.014	0.014	0.014	0.014	0.162	0.413	1.270	2.006
13	0.013	0.013	0.013	0.013	0.013	0.013	0.166	0.412	1.252	1.995

4.4.2 Statistical Model to Identify Significant High Variation Elements

The next step in the prioritization algorithm is to develop statistical models of the efficiency metrics and the variables shown in Table 4.13 for identifying the significant HVs affecting $\eta_{CT}(j)$ and $\eta_{INV}(j)$.

Cycle Time Efficiency

Stepwise regression was used to achieve a statistical fit from the pool of top ten elements for $\eta_{CT}(j)$. The corresponding significant HVs are:

$$x1 = r_a \text{ @Unpacking}$$

$$x3 = r_a \text{ @Scratch \& Date}$$

$$x6 = r_a \text{ @Final Weld}$$

ECT Regression Analysis

```
1. Adding x3, FStat = 1275.4862, pValue = 1.047594e-29
2. Adding x6, FStat = 14.1285, pValue = 0.000623433
3. Adding x1, FStat = 109.0132, pValue = 3.819593e-12

mdl_ECTj =
Linear regression model:
    y ~ 1 + x1 + x3 + x6

Estimated Coefficients:
                   Estimate       SE         tStat       pValue
                   --------    ---------    -------    ----------

    Intercept     1.0084     0.0010568      954.2    7.2467e-77
    x1             -1370.5        131.26    -10.441    3.8196e-12
    x3              -650.2        91.642    -7.0949    3.3883e-08
    x6              2018.6        156.32     12.913    1.1513e-14

Number of observations: 38, Error degrees of freedom: 34
Root Mean Squared Error: 0.0021
R-squared: 0.995,  Adjusted R-Squared 0.995
F-statistic vs. constant model: 2.43e+03, p-value = 1.05e-39
```

The stepwise regression model for Cycle Time Efficiency is interpreted as follows:

- The p-value of the overall model is 1.05e-39, which signifies that the stepwise regression model is statistically significant.
- The overall R-squared of the model is 0.995, which means that the model can explain 99.5% of the variation in $\eta_{CT}(j)$.
- There are three significant independent variables in the analysis.

There is a high degree of collinearity in the stepwise regression model, as would be expected from the nature of production system in the case study, i.e., a cellular manufacturing system. Each station of the Pro01 manufacturing cell is directly related to the previous station, as there is a direct movement of material. It is untenable to determine the individual significant variables' effects on system efficiencies due to collinearity in the model; however, the effect of the bundle of significant variables on efficiency measures can be considered (Dormann et al., 2013).

Inventory Efficiency

The stepwise regression model also achieves statistical fit from the pool of top ten elements for $\eta_{INV}(j)$. The corresponding significant HVs are:

$$x1 = r_a \text{ @Unpacking}$$

$$x7 = t_o \text{ @Assembly}$$

$$x8 = t_o \text{ @Packaging}$$

$$x9 = t_o \text{ @Stem Weld}$$

$$x10 = t_o \text{ @Final Weld}$$

Einv Regression Analysis

```
1. Adding x10, FStat = 158.0684, pValue = 9.8405e-15
2. Adding x9, FStat = 51.9501, pValue = 2.06544e-08
3. Adding x7, FStat = 9.3758, pValue = 0.0042777
4. Adding x8, FStat = 7.7171, pValue = 0.0089527
5. Adding x1, FStat = 9.9399, pValue = 0.0035032

mdl_Einvj =
Linear regression model:
    y ~ 1 + x1 + x7 + x8 + x9 + x10
```

```
Estimated Coefficients:
                   Estimate        SE         tStat       pValue
                   _________    _________    _______    __________

    Intercept        0.63078     0.023878     26.417    2.6648e-23
    x1             -0.052011     0.016497    -3.1528     0.0035032
    x7              0.096641     0.025529     3.7855    0.00063719
    x8               0.08106     0.022046     3.6768    0.00085999
    x9              0.092579    0.0089092     10.391    8.7884e-12
    x10             -0.15704    0.0072897    -21.543    1.2965e-20

Number of observations: 38, Error degrees of freedom: 32
Root Mean Squared Error: 0.000743
R-squared: 0.964,  Adjusted R-Squared 0.958
F-statistic vs. constant model: 170, p-value = 4.44e-22
```

The stepwise regression model for Inventory Efficiency is interpreted as follows:

- The p-value of the overall model is 4.44e-22, which signifies that the stepwise regression model is statistically significant.
- The overall R-squared value of the model is 0.964, which means that the model can explain 96.4% of the variation in $\eta_{CT}(j)$.
- There are five significant independent variables in the analysis affecting $\eta_{INV}(j)$.

In the prioritization algorithm, if a statistically significant model cannot be fit using the top ten *cv*s, the pool of independent variables is increased to fifteen by adding the KOMs with the next five highest *cv*s. This procedure is repeated until a statistical model with reasonable fit is achieved. This iterative process is not required for the Pro01 manufacturing cell, as identification of statistical models based on the top ten HVs was possible for both Cycle Time Efficiency and Inventory Efficiency.

4.4.3 Forecasting Effect of Significant HVs on System Performance

It is recommended that curve-fitting techniques based on polynomial or rational functions be used to extrapolate significant HVs identified using stepwise regression. In this study, extrapolations of all significant disruptive variables were performed using MATLAB's Curve-Fitting Toolbox. The result of curve-fitting is a mathematical expression fitting the trend of a variable. In BVPM, these mathematical expressions are used to forecast the trends of significant HVs. For the case study, data points containing these projections were substituted into the stepwise regression equations identified for $\eta_{CT}(j)$ and $\eta_{INV}(j)$. Table 4.14 shows the resulting forecast trends in $\eta_{CT}(j)$ and $\eta_{INV}(j)$ following the bundle of HVs.

- $\eta_{CT}(j)$ for the Pro01 manufacturing cell for days 43 to 54 is stable at 99%, which is the same as in the baseline model (Figure 4.5). Therefore, the bundle of HVs does not have an effect on the efficiency of cycle time.
- $\eta_{INV}(j))$ for the Pro01 manufacturing cell for days 43 to 54 decreases from 48% to 46% if no changes are made to improve the operating conditions. Thus, the company has 12 days to implement the suggestions of the prioritization algorithm before a decrease in Inventory Efficiency.

Table 4.14: Predictions for $\eta_{CT}(j)$ and $\eta_{INV}(j)$

Days	η_{CT}	η_{INV}
43	0.997	0.482
44	0.998	0.482
45	0.998	0.482
46	0.999	0.482
47	1.000	0.482
48	1.000	0.482
49	1.000	0.482
50	1.000	0.482
51	0.999	0.482
52	0.997	0.482
53	0.995	0.462
54	0.991	0.462

The forecast effect of the five HVs is the degradation of the Inventory Efficiency of Pro01. The HVs listed below are significant regarding their effect on the trend of Inventory Efficiency for Pro01. Therefore, the Bundle of High Variation Elements (BHVs) affecting the performance of the Pro01 manufacturing cell are presented in Equation 4.13. Improving performance of the change points identified by BHVs will result in improvement of performance of the Pro01 manufacturing cell.

$$
\begin{aligned}
x1 &= r_a \text{ @Unpacking} \\
x7 &= t_o \text{ @Assembly} \\
x8 &= t_o \text{ @Packaging} \\
x9 &= t_o \text{ @Stem Weld} \\
x10 &= t_o \text{ @Final Weld}
\end{aligned} \tag{4.13}
$$

4.5 BVPM Validation using Theory of Constraints

The BVPM algorithm prioritizes High Variation Elements (HVs) to identify a Bundle of High Variation Elements (BHVs) having significant impact on the performance of a manufacturing system. The effectiveness of BVPM to improve system performance is compared to Theory of Constraints (TOC). TOC is applied to the baseline model to identify process improvement projects and compared to the BHVs determined in the previous section.

The goal of TOC is to improve system performance through the identification of constraints in the production system. Such constraints (bottleneck) can change based on the TOC criteria. For example, the bottleneck station of a production system is the station with the highest utilization and/or longest processing time if processing time is the TOC criteria. As the bottleneck station has the lowest Rate of Production, it controls the pace of production of the entire manufacturing line. Theoretically, if the pace of production of the bottleneck process is improved, the performance (Throughput) of the whole system will be enhanced. The two criteria utilized by TOC to identify constraints in the Pro01 manufacturing cell are Rate of Arrival of raw material and Processing Time at stations.

The constraint in a production system is any process that causes a degradation in the performance of a system. In the Pro01 manufacturing cell, it was observed that there was no standard operating procedure governing the pickup and unpacking of kits from the initial raw material inventory at the first station. The operator performed kit pickups at a frequency ($r_a@Unpacking$) of one every 10 minutes. This results in the longest wait time for raw material in the Pro01 manufacturing cell. Therefore, it is determined to be the primary constraint of the system.

Table 4.15: Progressive changes implemented in baseline model of Pro01 manufacturing cell based on TOC

		$r_a@Unpacking$ in minutes	$t_o@Final\ Weld$ in minutes	$t_o@Stem\ Weld$ in minutes	No. of Operators
Baseline	**Mean**	10	2	1.25	2
	Standard Deviation	0.2	0.3	0.17	0
Ext1	**Mean**	8			
	Standard Deviation	0.1			
Ext2	**Mean**	3			
	Standard Deviation	0.1			
Ext3	**Mean**	2			3
	Standard Deviation	0.1			0
Ext4	**Mean**	2	1.1		3
	Standard Deviation	0.1	0.05		0
Ext5	**Mean**	1.6	1.1	1	3
	Standard Deviation	0.05	0.05	0.05	0

$r_a@Unpacking$ is progressively reduced in the baseline simulation to increase Throughput of Pro01 manufacturing cell and identify the secondary constraint. Table 4.15 presents the progressive changes implemented in the simulation to achieve improvement in Throughput of the Pro01 manufacturing cell. $r_a@Unpacking$ is reduced from 10 minutes to 8 minutes in model Ext1 leading to an increase in Throughput to 176.47 units/day. In the second model, Ext2, the $r_a@Unpacking$ is further reduced to 3 minutes resulting in an improvement in Throughput to 461.58 units/day of production. Analysis of the simulation revealed the utilization of operators to be 95% in the Ext2 model. Therefore, further increase in Throughput can be achieved by alleviating the personnel constraint and employing 3 operators at Pro01 manufacturing cell instead of 2.

In model Ext3, $r_a@Unpacking$ is reduced to 2 minutes and the number of operators is increased to 3 resulting in an improvement in Throughput to 600 units/day. Simulation of Model Ext3 indicated a change in the constraint of Pro01 manufacturing cell from $r_a@Unpacking$ to $t_o@Final\ Weld$. Model Ext4 expands on Ext3 by reducing $t_o@Final\ Weld$ to 1.1 minutes resulting in a Throughput of 667.67 units/day. Analysis of simulation of Ext4 leads to the identification of $t_o@Stem\ Weld$ as the tertiary constraint of the system. Ext5 adds to changes implemented by Ext4 by reducing $t_o@Stem\ Weld$ to 1 minute resulting in a Throughput of 857.12 units/day. Figure 4.9 presents the improvement in Throughput of Pro01 manufacturing cell caused by the progressive alleviation of constraints in the system. The Ext5 model including changes to $r_a@Unpacking$, $t_o@Final\ Weld$, and $t_o@Stem\ Weld$ results in the highest Average Throughput of 857.14 units/day. This leads to completion of 6000 units of production in 7 days. By comparison, the baseline model requires 42 days to complete the same production volume.

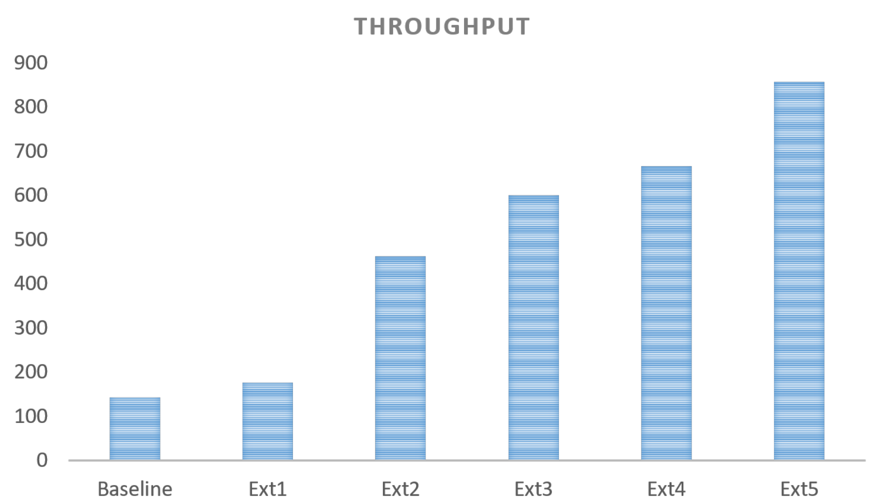

Figure 4.9: Average Throughput (units/day) to produce 6000 units of product at Pro01 manufacturing cell for TOC implementation

4.5.1 Comparison of TOC and BVPM models

In Section 4.4, the BVPM methodology was applied to Pro01 manufacturing cell to prioritize and identify a Bundle of High Variation Elements (BHVs). Equation 4.14 presents the BHVs selected by BVPM.

$$
\begin{aligned}
&x1 = r_a \text{ @Unpacking} \\
&x7 = t_o \text{ @Assembly} \\
&x8 = t_o \text{ @Packaging} \\
&x9 = t_o \text{ @Stem Weld} \\
&x10 = t_o \text{ @Final Weld}
\end{aligned} \tag{4.14}
$$

Ext5 leads to the highest Throughput among the TOC models, therefore, chosen to be compared with BVPM. The three constraints identified by TOC methodology ($r_a@Unpacking$, $t_o@Final\ Weld$, and $t_o@Stem\ Weld$) are also included in the BHVs identified by BVPM. The impact of projects selected by Ext5 and BHVs on the performance of Pro01 manufacturing cell can be compared by applying the same magnitude of changes for the common parameters. The improvements identified by BHVs not included in Ext5 do result in a minor increase the changes to be implemented in the Pro01 manufacturing cell as presented in Table 4.16. $t_o@Packaging$ is reduced to 0.33 while the Standard Deviation of $t_o@Assembly$ is reduced to 0.01. Appendix C presents the tables for parameters and calculation for η_{CT} and η_{INV} for Ext5 model. Appendix D presents the tables for parameters and calculations of η_{CT} and η_{INV} for BVPM model.

Table 4.16: Improvement projects suggested by Ext5 and BVPM models

		Baseline		**Ext5**		**BVPM**	
		Mean	**Standard Deviation**	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
$r_a@Unpacking$	**minutes**	10	0.2	3	0.1	3	0.1
$t_o@Stem\ Weld$	**minutes**	1.25	0.17	1.00	0.05	1.00	0.05
$t_o@Assembly$	**minutes**	0.17	0.05			0.17	0.01
$t_o@Final\ Weld$	**minutes**	2.00	0.30	1.10	0.05	1.10	0.05
$t_o@Packaging$	**minutes**	0.42	0.07			0.33	0.05
No. of Operators		2	0	3	0	3	0

Average Throughput of the Pro01 manufacturing cell for production of 6000 units is presented in Figure 4.10. The baseline model achieves an Average Throughput of 142.85

units/day and completes production in 42 days. Both Ext5 and BVPM model produce parts at a rate of 857.14 units/day resulting in the completion of production in 7 days.

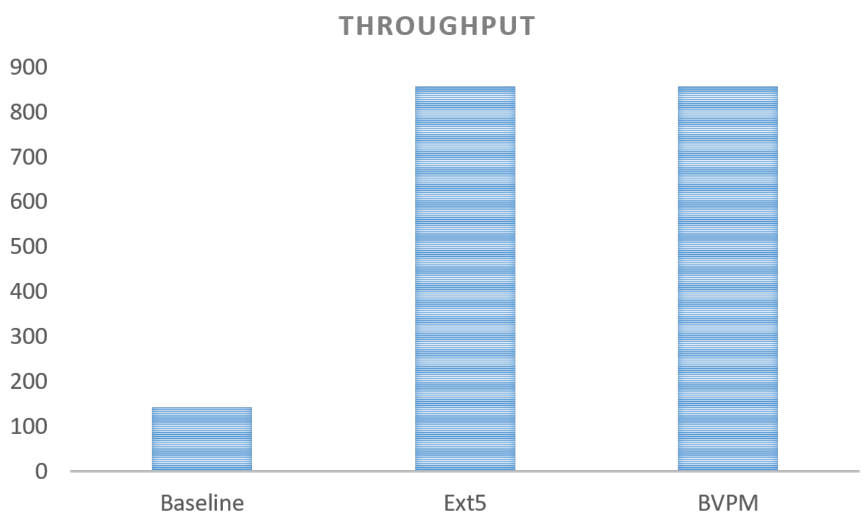

Figure 4.10: Average Throughput (units/day) to produce 6000 units of product at Pro01 manufacturing cell

Figure 4.11 charts the **Cycle Time Efficiency** of Pro01 manufacturing cell. Both Ext5 and BVPM models complete production before reaching the high η_{CT} attained by the baseline model. 96.3% on day 7 is the highest η_{CT} for both Ext5 and BVPM models.

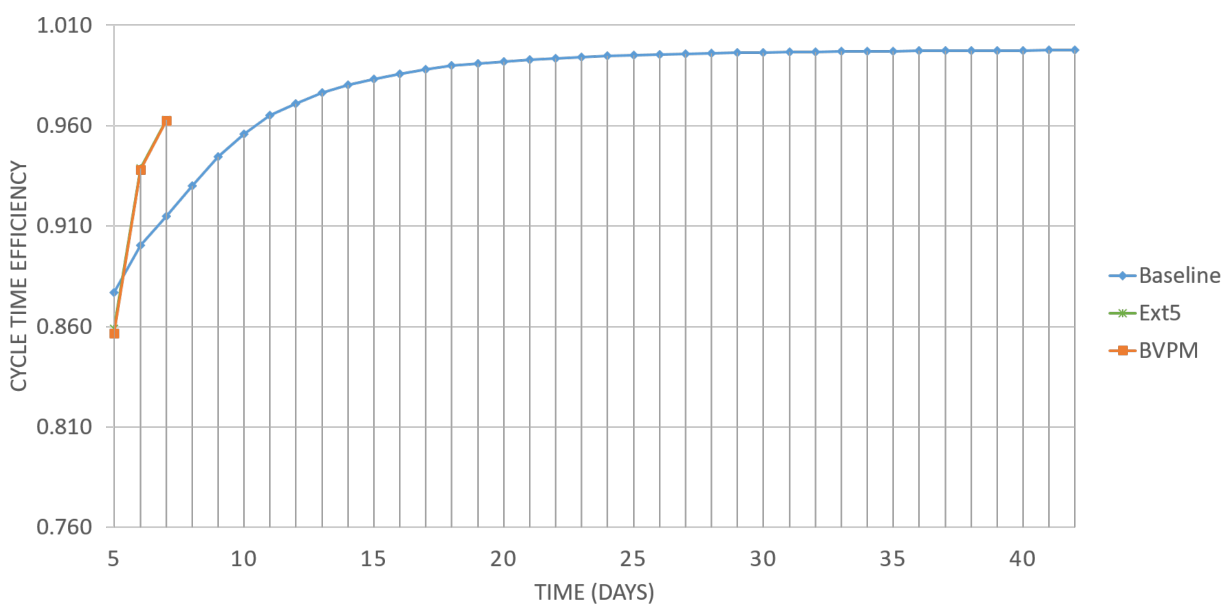

Figure 4.11: Cycle Time Efficiency (η_{CT}) of Pro01 Manufacturing Cell during production of 6000 units of product

Inventory Efficiency of Pro01 manufacturing cell is charted in Figure 4.12. The baseline model achieves the lowest efficiency among the Three models with an average η_{INV} of 48.2% over 42 days of production. By contrast, both Ext5 and BVPM model result in higher η_{INV} during 7 days of production. Ext5 achieves the highest η_{INV} at an average of 69.2%, followed by BVPM at 67.9%.

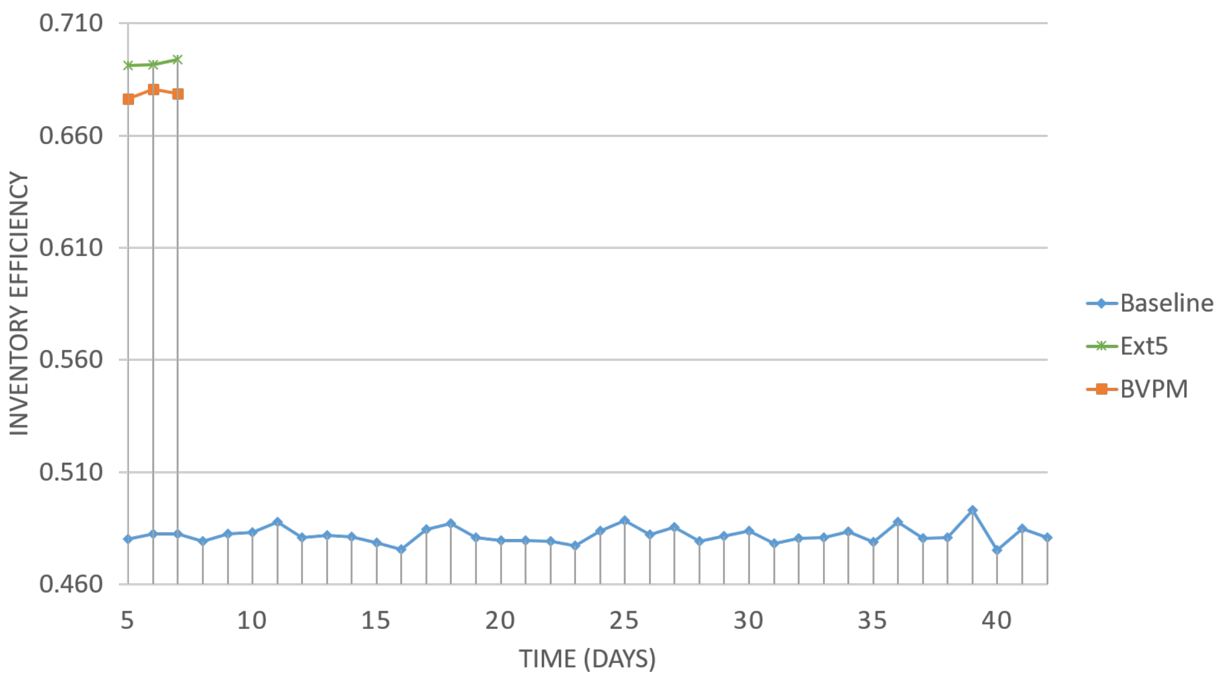

Figure 4.12: Inventory Efficiency (η_{INV}) of Pro01 Manufacturing Cell during production of 6000 units of product

Improvement projects suggested by the Ext5 and BVPM models coincide in the Rate of Arrival at the Unpacking station, the Processing Time at the Stem Weld station, and the Processing Time at the Final Weld station. The BVPM model identifies two more improvement projects compared to TOC resulting in a marginal increase in changes implemented in the production system. The improvement projects identified by BVPM model are obtained by monitoring variation and performance of entire production system. BVPM includes a statistical analysis to identify root causes for the degradation of performance in a manufacturing system and a forecast to estimate time before occurrence of degradation, leading to a robust decision-making process.

Among the three models, the baseline model achieves the lowest Average Throughput and Inventory Efficiency over the 6,000-unit production run. Regarding Average Throughput and Cycle Time Efficiency, the performance of the system is identical under both the BVPM and TOC models. There is a 1.3 percent difference in the Inventory Efficiency metric of TOC model and BVPM model. Therefore, implementation of changes suggested by either BVPM or TOC models would lead to comparable improvement in performance of the baseline Pro01 manufacturing cell. Changes proposed by BVPM and TOC models would require monetary investment by the company including refurbishment of welding machines, installation of fixtures and addition of personnel to improve system performance.

BVPM is applicable to work in conjunction with Lean and Six Sigma methodologies. Lean manufacturing strives to improve the flow of product through a production system and reduce waste. Similarly, reduction of variation due to waste is the goal of Six Sigma methodology. The inclusion of variation in data collection and decision-making process allows BVPM to select improvement projects based on the reducing impact of waste in movement, process, equipment, and inventory on system performance.

Chapter 5

Conclusions & Future Work

This dissertation presents a Bundled Variation-based Project Prioritization Model (BVPM) to identify and prioritize High Variation Elements (HVs) in a manufacturing system. The proposed model identifies Bundle of High Variation Elements (BHVs) as suggestions for continuous improvement projects that have a significant impact on the performance of the system. This chapter will review the conclusions of the study and suggest possible future work.

5.1 Variation as a basis for performance improvement

Variation has an adverse impact on the performance of a manufacturing system as evidenced by literature. Lean and Six Sigma methodologies are applied to manufacturing systems to identify performance improvement projects. Lean efforts aim to stabilize a system by reducing variation through 5s, mistake proofing, and others. However, there does not exist a system that utilizes variation as the basis for performance measurement and improvement. BVPM utilizes variation to record station level changes and their effect on performance of the manufacturing system. It allows variation to be the key driver for identifying improvement projects.

5.2 Contributions of the research

Performance Measurement

The present research developed quantitative metrics in two areas to measure the effect of variation on performance of a discrete manufacturing system:

- Cycle Time Efficiency, to monitor utilization of time available to manufacture the product, and;
- Inventory Efficiency, to monitor utilization of inventory in the system;

Variation in a station is classified under Inbound, Process or Quality variability. The Inbound segment encompasses the arrival of raw material at the station and related parameters. The Process segment includes parameters pertaining to processing, setup times, and equipment. The Quality segment encompassed the yield of the stations.

The parameters for data collection are identified based on the station segments defined above and are designed to measure the current state of a manufacturing system. Alternative methods, such as simulation modeling were utilized to fill in unavailable Operational Metric (OM) data. Data smoothing techniques are used to modify data to comply with the time series format as required by BVPM. Cycle Time Efficiency and Inventory Efficiency metrics are computed from formatted OMs. Performance measurement in BVPM is designed to be independent of scale of a manufacturing system. It can monitor efficiency metrics for individual production line, manufacturing facility and supply chains of a company.

Prioritization Algorithm

The variation based prioritization algorithm utilizes OM and efficiency data to identify HVs in the system and estimate their effect on the overall system. A subset of OMs, known as the Key Operational Metrics (KOMs), are utilized to identify possible HVs. Specifically, the Coefficient of Variation is applied to standardize and rank the most varying KOMs for all stations in the production line. Based on the identified HVs, stepwise regression analysis and curve-fitting techniques are used to determine the bundle of significant HVs and predict their effect on the performance of the overall production system. Time before

BHVs result in degradation of system performance is calculated to aid in the decision-making and implementation processes. Implementing changes to the production system based on Bundle of High Variation Elements (BHVs) will reduce the impact of variability and improve the performance of the assessed manufacturing system.

When BVPM is implemented in a production system, decision makers are provided with periodic analyses of the current state of the system, including lists of HVs and their effects on the production system. BVPM is a closed-loop system in which each iteration identifies a bundle of high variation elements, implementation of which results in a new state of system performance and a new set of BHVs. Through this process, the occurrence of high variability is identified, and the productivity of the manufacturing line improves continuously. BVPM provides decision-makers with a small number of relevant improvement projects regardless of size of the manufacturing system or supply chain.

Case Study

A pilot study was conducted at a discrete manufacturing facility to validate the BVPM. The production flow of the plant follows a cell manufacturing concept comprising six operations: Unpacking, Stem Weld, Assembly, Final Weld, Scratch & Date, and Packaging. The process is managed by two operators, who strive to increase production volume. The prioritization algorithm is utilized to identify the BHVs of the Pro01 manufacturing cell.

The effectiveness of BHVs in improving system performance is compared to projects selected by Theory of Constraints (TOC). TOC is utilized to select performance improvement projects for the baseline of Pro01 manufacturing cell. The three constraints identified by TOC are discovered to be included in the BHVs identified by BVPM. The system performance resulting from implementation of BVPM is comparable to TOC model. BVPM aids the decision-making process by providing a robust methodology to analyze and forecast the impact of improvement projects on system performance.

5.3 Future Work

Personnel Efficiency

Equipment, Material and Personnel are three components of a manufacturing system required to transform raw material into finished product. Similar to Cycle Time and Inventory Efficiencies, the formulation for Personnel Efficiency was developed. It was not validated in present case study due to minimal personnel requirements in the manufacturing cell.

The term "Personnel" generally refers to operators of machines, maintenance staff, material handlers, production support and management. This study considers personnel in direct contact with production, for instance, machine operators, maintenance personnel and material handlers. Personnel Efficiency (Equation 5.1) is the ratio of the Ideal Available Time to the Actual Available Time for manufacturing personnel assigned to product line j. The Ideal Available Time is measured based on the operating schedule of the production system with allowable personnel breaks during a shift. The Actual Available Time has two components: the Ideal Available Time and the Idle Time of personnel.

$$\eta_{PER}(j) = \sum_{k=1}^{w} \left(\sum_{i=1}^{n} \left(\frac{T_A(k)}{T_A(k) + T_I(k)} \right) \right) \tag{5.1}$$

where, k = Operator number

w = Number of personnel available for product j

i = Station location of product j

n = Number of stations in production line

$T_A(k)$ = Ideal Available Time of operator k

$T_I(k)$ = Idle Time of operator k

Three factors affecting the ability of operators to work at a station are setups, equipment breakdowns, and repairs. The Availability of a station (Equation 3.11) includes the time lost due to equipment breakdowns and repairs. Adding operator Idle Time, $T_I(k)$, reduces the efficiency of personnel utilization of production line j.

$$T_I(k) = \sum_{i=1}^{n} (t_s(i) + t_o(i) \cdot (1 - A(i))) \tag{5.2}$$

$$\begin{aligned} \text{where, } t_s(i) &= \text{Setup Time} \\ t_o(i) &= \text{Raw Process Time at station } i \\ A(i) &= \text{Availability of station } i \end{aligned}$$

The Hierarchy of Metrics for $\eta_{PER}(j)$ is shown in Figure 5.1.

$$\eta_{PER}(j) = \sum_{k=1}^{w} \left(\sum_{i=1}^{n} \left(\frac{T_A(k)}{T_A(k) + T_I(k)} \right) \right)$$

$$T_I(k) = \sum_{i=1}^{n} (t_s(i) + t_o(i) \cdot (1 - A(i)))$$

$$A(i) = \frac{t_f(i)}{t_r(i) + t_f(i)}$$

Figure 5.1: Hierarchy of Metrics for Personnel Efficiency

5.3.1 Other Future Work

The BVPM developed in this dissertation can be further expanded in the following directions:

- **Developing methodologies to include cost estimates in prediction:** In this study, cost was not utilized as a component of measurement and prediction as it is a lagging indicator of performance. Financial information of system components such as machinery, personnel, and product price can be utilized to provide decision-makers with in-depth analyses of High Variation Elements (HVs) in a system and their estimated impacts based on cost. This would enhance the decision-making process by identifying the best possible methodology to reduce the impact of disruptions.
- **Developing threshold-based systems for identifying HVs:** BVPM uses Coefficient of Variation to identify HVs in a manufacturing system. An alternative methodology is the use of Operational Metric thresholds to identify HVs in the production system. As an example, thresholds of upper and lower limits to the rate

of arrivals of raw material at a machine can trigger an HV when the rate of arrivals breaches these values.

- **Developing weighted measurements of system productivity:** In its present form, BVPM considers all machines and processes in a production system as having an equal effect on the performance of the overall system. Based on their importance to the overall system, weights can be assigned to the individual processes in a manufacturing system or to individual companies in a supply chain to increase or decrease their respective impact on efficiencies of the overall system.
- **Developing a benchmarking tool to identify best practices:** BVPM was developed with standardization of data collection in mind. The utilization of a standard set of Operational Metrics (OMs) and quantitative efficiency metrics ensures that the performance of companies in the same sector can be compared to determine best practices and help companies achieve higher productivity.

In summary, performance measurement and management systems are complex entities essential to the management of a company's resources and achievement of its productivity goals. The work presented in this dissertation presents methodologies that can be used to aid companies in improving their productivity. Some future work has been identified with the goal of improving the system presented in this thesis as well as the overall field of performance management.

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Appendix

Appendix A

Nomenclature

Symbol	**Definition**
j	Product manufactured in system
i	location of product (station) j
cv	Coefficient of Variation
$\eta_{CT}(j)$	Cycle Time Efficiency of product j
$\eta_{INV}(j)$	Inventory Efficiency of product j
$r_b(j)$	Rate of Bottleneck Station of product j
$T_o(j)$	Raw Cycle Time of product j
$OCT(j)$	Overall Cycle Time of product j
$OI(j)$	Overall Work-in-Process (WIP) in production line j
$CT_q(i)$	Wait Time in Queue at station i
$WIBT(i)$	Wait-in-Batch time at station i
$t_e(i)$	Effective Processing Time at station i (including setups and downtimes)
$c_e(i)$	cv of Effective Processing Time
$RI(i)$	Instantaneous Raw Material Inventory at station i
$WIP_q(i)$	WIP in queue at station i
$A(i)$	Availability of station i
$t_o(i)$	Raw Process Time (no downtimes, setups, etc)
$c_o(i)$ or $\sigma_o(i)$	cv of Raw Processing Time
$r_a(i)$	Rate of Arrival of material at station i
$c_a(i)$	cv of Rate of Arrival of material at station i

Symbol	**Definition**
$t_r(i)$	Mean Time to Repair for station i
$c_r(i)$	cv of Mean Time to Repair $t_r(i)$
$t_f(i)$	Mean Time to Failure for station i
$t_s(i)$	Setup Time at station i
$c_s(i)$ or $\sigma_s(i)$	cv of Setup Time
$m_(i)$	Number of parallel machines assigned to station i
$C_m(i)$	Instantaneous Capacity of station
Y	Yield of station i
$b_p(i)$	Batch Size of product j at station i

Appendix B

Case Study: Baseline Pro01 Model

Table B.1: Instantaneous Raw Material Inventory $RI(i)$

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.498	0.498	0.498	0.500	0.500	0.498
6	0.500	0.500	0.500	0.500	0.500	0.500
7	0.500	0.500	0.500	0.498	0.502	0.500
8	0.500	0.500	0.500	0.502	0.498	0.500
9	0.500	0.500	0.500	0.500	0.500	0.500
10	0.500	0.500	0.500	0.500	0.500	0.500
11	0.500	0.500	0.500	0.498	0.502	0.500
12	0.500	0.500	0.500	0.500	0.498	0.500
13	0.500	0.500	0.500	0.500	0.502	0.500
14	0.500	0.500	0.500	0.500	0.498	0.502
15	0.500	0.500	0.500	0.500	0.502	0.498
16	0.500	0.500	0.500	0.502	0.498	0.500
17	0.500	0.500	0.500	0.500	0.500	0.500
18	0.500	0.502	0.500	0.498	0.500	0.500
19	0.500	0.500	0.500	0.500	0.500	0.500
20	0.500	0.498	0.500	0.500	0.500	0.500
21	0.500	0.500	0.500	0.500	0.500	0.500
22	0.502	0.500	0.500	0.500	0.500	0.500
23	0.498	0.502	0.500	0.500	0.500	0.500
24	0.500	0.500	0.500	0.500	0.500	0.500
25	0.500	0.498	0.500	0.502	0.500	0.500
26	0.500	0.500	0.500	0.498	0.502	0.500
27	0.500	0.500	0.500	0.500	0.498	0.500
28	0.500	0.500	0.500	0.500	0.500	0.502
29	0.500	0.500	0.500	0.500	0.502	0.498
30	0.500	0.500	0.500	0.500	0.500	0.500
31	0.500	0.500	0.500	0.500	0.500	0.500
32	0.500	0.500	0.500	0.500	0.500	0.500
33	0.500	0.500	0.500	0.500	0.500	0.500
34	0.500	0.500	0.500	0.500	0.500	0.500
35	0.500	0.500	0.500	0.502	0.498	0.500
36	0.500	0.500	0.500	0.498	0.502	0.500
37	0.500	0.500	0.500	0.500	0.498	0.500
38	0.500	0.500	0.500	0.500	0.500	0.500
39	0.500	0.500	0.500	0.502	0.500	0.500
40	0.500	0.500	0.500	0.500	0.500	0.500
41	0.500	0.500	0.500	0.498	0.502	0.500
42	0.497	0.497	0.497	0.497	0.495	0.500

Table B.2: Calculating Coefficient of Variation of Effective Processing Time $c_e(i)$

(a) Ideal Processing time $t_o(i)$ in minutes

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.995	1.261	0.174	2.011	0.953	0.423
6	1.005	1.248	0.161	1.983	0.939	0.418
7	1.002	1.265	0.169	2.000	0.945	0.420
8	0.999	1.233	0.171	2.007	0.953	0.414
9	0.999	1.246	0.168	1.995	0.955	0.417
10	1.003	1.243	0.160	1.986	0.954	0.413
11	0.999	1.277	0.167	1.975	0.948	0.415
12	0.997	1.270	0.162	2.006	0.941	0.413
13	1.000	1.252	0.166	1.995	0.945	0.412
14	1.000	1.255	0.160	1.999	0.944	0.413
15	1.002	1.260	0.167	2.030	0.961	0.410
16	1.002	1.233	0.166	2.024	0.944	0.406
17	0.999	1.259	0.164	1.985	0.952	0.412
18	0.999	1.265	0.165	1.976	0.940	0.429
19	0.994	1.245	0.169	1.998	0.943	0.415
20	1.004	1.259	0.160	2.020	0.954	0.415
21	1.001	1.260	0.160	2.023	0.955	0.421
22	0.997	1.243	0.162	2.006	0.954	0.409
23	1.003	1.260	0.163	2.030	0.942	0.414
24	0.996	1.268	0.173	1.999	0.950	0.414
25	1.000	1.256	0.166	1.969	0.960	0.419
26	1.000	1.241	0.166	1.987	0.948	0.409
27	0.999	1.276	0.166	1.988	0.951	0.409
28	0.998	1.252	0.162	2.010	0.945	0.412
29	1.001	1.250	0.167	1.994	0.942	0.409
30	0.999	1.255	0.175	1.992	0.942	0.420
31	1.004	1.248	0.161	2.020	0.948	0.414
32	0.999	1.231	0.167	1.986	0.937	0.405
33	1.003	1.245	0.162	2.003	0.946	0.420
34	1.001	1.246	0.166	1.990	0.954	0.417
35	0.997	1.271	0.157	2.011	0.938	0.405
36	1.001	1.269	0.161	1.975	0.956	0.420
37	1.004	1.240	0.170	2.015	0.958	0.425
38	0.998	1.237	0.153	1.988	0.939	0.422
39	1.004	1.288	0.166	1.954	0.960	0.409
40	0.996	1.217	0.174	2.028	0.948	0.420
41	1.003	1.266	0.170	1.997	0.956	0.417
42	1.002	1.240	0.167	2.001	0.958	0.406

(b) Coefficient of Variation of Effective Processing Time $c_e(i)$

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	3.998	0.107	0.127	2.219	0.113	0.114
6	1.999	0.108	0.150	2.806	0.121	0.123
7	1.333	0.110	0.174	2.918	0.130	0.132
8	0.999	0.111	0.199	2.839	0.138	0.142
9	0.800	0.112	0.225	2.680	0.146	0.151
10	0.666	0.113	0.253	2.495	0.153	0.161
11	0.571	0.115	0.281	2.311	0.161	0.170
12	0.500	0.116	0.311	2.137	0.169	0.179
13	0.444	0.116	0.342	1.973	0.177	0.189
14	0.400	0.117	0.375	1.821	0.185	0.198
15	0.363	0.118	0.409	1.683	0.193	0.208
16	0.333	0.118	0.445	1.556	0.200	0.217
17	0.308	0.118	0.483	1.437	0.207	0.226
18	0.286	0.119	0.522	1.328	0.215	0.235
19	0.267	0.119	0.563	1.229	0.222	0.243
20	0.250	0.119	0.607	1.137	0.228	0.251
21	0.235	0.119	0.653	1.051	0.234	0.259
22	0.222	0.119	0.702	0.972	0.240	0.267
23	0.210	0.119	0.753	0.898	0.245	0.274
24	0.200	0.119	0.806	0.831	0.250	0.281
25	0.190	0.119	0.862	0.767	0.254	0.287
26	0.182	0.118	0.922	0.707	0.258	0.292
27	0.174	0.118	0.984	0.651	0.261	0.297
28	0.167	0.117	1.050	0.599	0.264	0.301
29	0.160	0.117	1.119	0.550	0.265	0.304
30	0.154	0.116	1.189	0.504	0.266	0.306
31	0.148	0.115	1.264	0.460	0.264	0.306
32	0.143	0.115	1.342	0.419	0.262	0.305
33	0.138	0.114	1.421	0.380	0.258	0.302
34	0.133	0.113	1.498	0.343	0.253	0.295
35	0.129	0.112	1.568	0.308	0.245	0.288
36	0.125	0.111	1.626	0.274	0.236	0.276
37	0.121	0.110	1.667	0.243	0.222	0.260
38	0.118	0.109	1.679	0.212	0.207	0.242
39	0.114	0.108	1.592	0.183	0.190	0.217
40	0.111	0.107	1.420	0.156	0.166	0.187
41	0.108	0.106	0.976	0.130	0.138	0.151
42	0.105	0.105	0.106	0.105	0.105	0.105

Table B.3: Effective Processing Time $t_e(i)$ in minutes

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.995	1.263	0.174	2.011	0.954	0.423
6	1.005	1.250	0.161	1.983	0.939	0.418
7	1.002	1.267	0.169	2.001	0.945	0.420
8	0.999	1.235	0.172	2.007	0.953	0.414
9	0.999	1.248	0.169	1.995	0.955	0.417
10	1.003	1.245	0.160	1.986	0.954	0.413
11	1.000	1.279	0.167	1.975	0.948	0.416
12	0.997	1.272	0.162	2.007	0.941	0.413
13	1.000	1.255	0.166	1.995	0.945	0.412
14	1.000	1.257	0.160	1.999	0.944	0.413
15	1.002	1.262	0.167	2.031	0.962	0.410
16	1.003	1.235	0.166	2.024	0.945	0.407
17	0.999	1.261	0.164	1.985	0.952	0.413
18	1.000	1.267	0.165	1.976	0.940	0.429
19	0.994	1.247	0.170	1.999	0.943	0.416
20	1.004	1.261	0.161	2.020	0.955	0.415
21	1.001	1.262	0.160	2.024	0.955	0.421
22	0.998	1.245	0.162	2.007	0.954	0.409
23	1.003	1.263	0.164	2.031	0.942	0.414
24	0.997	1.271	0.174	1.999	0.951	0.414
25	1.000	1.258	0.166	1.969	0.960	0.419
26	1.000	1.243	0.166	1.988	0.948	0.409
27	0.999	1.278	0.166	1.988	0.951	0.410
28	0.998	1.254	0.162	2.011	0.945	0.412
29	1.001	1.252	0.167	1.994	0.942	0.410
30	0.999	1.257	0.176	1.992	0.942	0.421
31	1.004	1.250	0.161	2.020	0.949	0.415
32	0.999	1.233	0.167	1.986	0.937	0.405
33	1.003	1.247	0.162	2.003	0.946	0.420
34	1.002	1.248	0.166	1.990	0.955	0.418
35	0.997	1.273	0.157	2.012	0.938	0.405
36	1.001	1.271	0.162	1.975	0.956	0.420
37	1.004	1.243	0.170	2.015	0.958	0.425
38	0.998	1.239	0.153	1.989	0.939	0.423
39	1.004	1.290	0.167	1.954	0.960	0.409
40	0.996	1.219	0.175	2.028	0.948	0.420
41	1.003	1.268	0.170	1.997	0.956	0.417
42	1.003	1.243	0.167	2.001	0.958	0.406

Table B.4: Effective Rate of Production $r_e(i)$ in units/min

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	1.005	0.792	5.737	0.497	1.049	2.365
6	0.995	0.800	6.199	0.504	1.065	2.390
7	0.998	0.789	5.921	0.500	1.058	2.379
8	1.001	0.810	5.825	0.498	1.050	2.414
9	1.001	0.801	5.932	0.501	1.047	2.395
10	0.997	0.803	6.241	0.503	1.048	2.422
11	1.000	0.782	5.977	0.506	1.055	2.406
12	1.003	0.786	6.156	0.498	1.062	2.421
13	1.000	0.797	6.015	0.501	1.058	2.428
14	1.000	0.795	6.242	0.500	1.060	2.418
15	0.998	0.792	5.987	0.492	1.040	2.437
16	0.997	0.810	6.019	0.494	1.059	2.459
17	1.001	0.793	6.080	0.504	1.050	2.423
18	1.000	0.789	6.049	0.506	1.064	2.332
19	1.006	0.802	5.898	0.500	1.060	2.406
20	0.996	0.793	6.226	0.495	1.048	2.411
21	0.999	0.792	6.231	0.494	1.047	2.376
22	1.002	0.803	6.181	0.498	1.048	2.445
23	0.997	0.792	6.106	0.492	1.061	2.416
24	1.003	0.787	5.760	0.500	1.052	2.415
25	1.000	0.795	6.029	0.508	1.041	2.387
26	1.000	0.804	6.008	0.503	1.055	2.445
27	1.001	0.782	6.020	0.503	1.051	2.441
28	1.002	0.797	6.169	0.497	1.059	2.427
29	0.999	0.799	5.986	0.501	1.062	2.442
30	1.001	0.796	5.694	0.502	1.061	2.377
31	0.996	0.800	6.199	0.495	1.054	2.412
32	1.001	0.811	5.982	0.504	1.067	2.468
33	0.997	0.802	6.172	0.499	1.057	2.379
34	0.998	0.801	6.029	0.503	1.048	2.394
35	1.003	0.785	6.356	0.497	1.066	2.467
36	0.999	0.787	6.191	0.506	1.046	2.380
37	0.996	0.805	5.890	0.496	1.044	2.352
38	1.002	0.807	6.537	0.503	1.065	2.366
39	0.996	0.775	5.998	0.512	1.042	2.444
40	1.004	0.820	5.723	0.493	1.055	2.380
41	0.997	0.789	5.884	0.501	1.046	2.396
42	0.997	0.805	5.975	0.500	1.044	2.463

Table B.5: Calculating Instantaneous Utilization $u(i)$

(a) Rate of Arrivals of Inventory $r_a(i)$ in units/min

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.036	0.036	0.036	0.036	0.036	0.036
6	0.030	0.030	0.030	0.030	0.030	0.030
7	0.026	0.026	0.026	0.026	0.026	0.026
8	0.022	0.022	0.022	0.022	0.022	0.022
9	0.020	0.020	0.020	0.020	0.020	0.020
10	0.018	0.018	0.018	0.018	0.018	0.018
11	0.016	0.016	0.016	0.016	0.016	0.016
12	0.014	0.014	0.014	0.014	0.014	0.014
13	0.013	0.013	0.013	0.013	0.013	0.013
14	0.012	0.012	0.012	0.012	0.012	0.012
15	0.011	0.011	0.011	0.011	0.011	0.011
16	0.011	0.011	0.011	0.011	0.011	0.011
17	0.010	0.010	0.010	0.010	0.010	0.010
18	0.010	0.010	0.010	0.010	0.010	0.010
19	0.009	0.009	0.009	0.009	0.009	0.009
20	0.009	0.009	0.009	0.009	0.009	0.009
21	0.008	0.008	0.008	0.008	0.008	0.008
22	0.008	0.008	0.008	0.008	0.008	0.008
23	0.007	0.007	0.007	0.007	0.007	0.007
24	0.007	0.007	0.007	0.007	0.007	0.007
25	0.007	0.007	0.007	0.007	0.007	0.007
26	0.007	0.007	0.007	0.007	0.007	0.007
27	0.006	0.006	0.006	0.006	0.006	0.006
28	0.006	0.006	0.006	0.006	0.006	0.006
29	0.006	0.006	0.006	0.006	0.006	0.006
30	0.006	0.006	0.006	0.006	0.006	0.006
31	0.005	0.005	0.005	0.005	0.005	0.005
32	0.005	0.005	0.005	0.005	0.005	0.005
33	0.005	0.005	0.005	0.005	0.005	0.005
34	0.005	0.005	0.005	0.005	0.005	0.005
35	0.005	0.005	0.005	0.005	0.005	0.005
36	0.005	0.005	0.005	0.005	0.005	0.005
37	0.005	0.005	0.005	0.005	0.005	0.005
38	0.004	0.004	0.004	0.004	0.004	0.004
39	0.004	0.004	0.004	0.004	0.004	0.004
40	0.004	0.004	0.004	0.004	0.004	0.004
41	0.004	0.004	0.004	0.004	0.004	0.004
42	0.004	0.004	0.004	0.004	0.004	0.004

(b) Instantaneous Utilization of Station $u(i)$

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.034	0.044	0.006	0.070	0.033	0.015
6	0.029	0.036	0.005	0.057	0.027	0.012
7	0.024	0.031	0.004	0.049	0.023	0.010
8	0.021	0.026	0.004	0.042	0.020	0.009
9	0.019	0.023	0.003	0.037	0.018	0.008
10	0.017	0.021	0.003	0.033	0.016	0.007
11	0.015	0.019	0.003	0.030	0.014	0.006
12	0.014	0.018	0.002	0.028	0.013	0.006
13	0.013	0.016	0.002	0.025	0.012	0.005
14	0.012	0.015	0.002	0.023	0.011	0.005
15	0.011	0.014	0.002	0.022	0.010	0.004
16	0.010	0.013	0.002	0.021	0.010	0.004
17	0.010	0.012	0.002	0.019	0.009	0.004
18	0.009	0.011	0.001	0.018	0.008	0.004
19	0.009	0.011	0.001	0.017	0.008	0.004
20	0.008	0.010	0.001	0.016	0.008	0.003
21	0.008	0.010	0.001	0.016	0.007	0.003
22	0.007	0.009	0.001	0.015	0.007	0.003
23	0.007	0.009	0.001	0.014	0.007	0.003
24	0.007	0.009	0.001	0.013	0.006	0.003
25	0.006	0.008	0.001	0.013	0.006	0.003
26	0.006	0.008	0.001	0.012	0.006	0.003
27	0.006	0.008	0.001	0.012	0.006	0.002
28	0.006	0.007	0.001	0.012	0.005	0.002
29	0.006	0.007	0.001	0.011	0.005	0.002
30	0.005	0.007	0.001	0.011	0.005	0.002
31	0.005	0.006	0.001	0.010	0.005	0.002
32	0.005	0.006	0.001	0.010	0.005	0.002
33	0.005	0.006	0.001	0.010	0.005	0.002
34	0.005	0.006	0.001	0.009	0.005	0.002
35	0.005	0.006	0.001	0.009	0.004	0.002
36	0.004	0.006	0.001	0.009	0.004	0.002
37	0.004	0.005	0.001	0.009	0.004	0.002
38	0.004	0.005	0.001	0.008	0.004	0.002
39	0.004	0.005	0.001	0.008	0.004	0.002
40	0.004	0.005	0.001	0.008	0.004	0.002
41	0.004	0.005	0.001	0.008	0.004	0.002
42	0.004	0.005	0.001	0.008	0.004	0.002

Table B.6: Wait Time in Queue $CT_q(i)$ in minutes

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.355	0.021	0.0004	0.423	0.012	0.0023
6	0.090	0.017	0.0003	0.515	0.009	0.0018
7	0.040	0.014	0.0003	0.472	0.008	0.0016
8	0.022	0.012	0.0002	0.389	0.007	0.0013
9	0.014	0.011	0.0002	0.303	0.006	0.0012
10	0.010	0.009	0.0002	0.236	0.006	0.0010
11	0.008	0.009	0.0002	0.183	0.005	0.0010
12	0.006	0.008	0.0001	0.150	0.005	0.0009
13	0.005	0.007	0.0001	0.119	0.004	0.0008
14	0.004	0.007	0.0001	0.096	0.004	0.0007
15	0.004	0.006	0.0001	0.081	0.004	0.0007
16	0.003	0.006	0.0001	0.067	0.003	0.0006
17	0.003	0.006	0.0001	0.053	0.003	0.0006
18	0.003	0.005	0.0001	0.044	0.003	0.0006
19	0.003	0.005	0.0001	0.039	0.003	0.0006
20	0.002	0.005	0.0001	0.034	0.003	0.0005
21	0.002	0.004	0.0001	0.029	0.003	0.0005
22	0.002	0.004	0.0001	0.025	0.003	0.0005
23	0.002	0.004	0.0001	0.022	0.002	0.0005
24	0.002	0.004	0.0001	0.019	0.002	0.0005
25	0.002	0.004	0.0001	0.016	0.002	0.0004
26	0.002	0.003	0.0001	0.015	0.002	0.0004
27	0.002	0.004	0.0001	0.013	0.002	0.0004
28	0.002	0.003	0.0001	0.013	0.002	0.0004
29	0.002	0.003	0.0002	0.011	0.002	0.0004
30	0.002	0.003	0.0002	0.010	0.002	0.0004
31	0.002	0.003	0.0002	0.010	0.002	0.0004
32	0.002	0.003	0.0002	0.009	0.002	0.0003
33	0.002	0.003	0.0002	0.008	0.002	0.0003
34	0.002	0.003	0.0002	0.008	0.002	0.0003
35	0.001	0.003	0.0002	0.007	0.002	0.0003
36	0.001	0.003	0.0002	0.007	0.002	0.0003
37	0.001	0.002	0.0002	0.007	0.002	0.0003
38	0.001	0.002	0.0002	0.006	0.001	0.0003
39	0.001	0.002	0.0002	0.006	0.001	0.0003
40	0.001	0.002	0.0002	0.006	0.001	0.0003
41	0.001	0.002	0.0001	0.006	0.001	0.0002
42	0.001	0.002	0.0000	0.006	0.001	0.0002

Table B.7: Cycle Time Efficiency ($\eta_{CT}(j)$) of Pro01 Manufacturing Cell

Days	$\eta_{CT}(j)$
5	0.877
6	0.900
7	0.915
8	0.930
9	0.944
10	0.956
11	0.965
12	0.971
13	0.976
14	0.980
15	0.983
16	0.986
17	0.988
18	0.990
19	0.991
20	0.992
21	0.993
22	0.993
23	0.994
24	0.995
25	0.995
26	0.995
27	0.996
28	0.996
29	0.996
30	0.996
31	0.997
32	0.997
33	0.997
34	0.997
35	0.997
36	0.997
37	0.997
38	0.997
39	0.997
40	0.997
41	0.998
42	0.998

Table B.8: Instantaneous Capacity $C_m(i)$ of station

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	1.000	0.998	0.998	0.998	0.998	0.998
6	1.000	0.999	0.999	0.999	0.999	0.999
7	1.000	0.999	0.999	0.999	0.999	0.999
8	1.000	0.999	0.999	0.999	0.999	0.999
9	1.000	0.999	0.999	0.999	0.999	0.999
10	1.000	0.999	0.999	0.999	0.999	0.999
11	1.000	0.999	0.999	0.999	0.999	0.999
12	1.000	0.999	0.999	0.999	0.999	0.999
13	1.000	0.999	0.999	0.999	0.999	0.999
14	1.000	0.999	0.999	0.999	0.999	0.999
15	1.000	1.000	1.000	1.000	1.000	1.000
16	1.000	1.000	1.000	1.000	1.000	1.000
17	1.000	1.000	1.000	1.000	1.000	1.000
18	1.000	1.000	1.000	1.000	1.000	1.000
19	1.000	1.000	1.000	1.000	1.000	1.000
20	1.000	1.000	1.000	1.000	1.000	1.000
21	1.000	1.000	1.000	1.000	1.000	1.000
22	1.000	1.000	1.000	1.000	1.000	1.000
23	1.000	1.000	1.000	1.000	1.000	1.000
24	1.000	1.000	1.000	1.000	1.000	1.000
25	1.000	1.000	1.000	1.000	1.000	1.000
26	1.000	1.000	1.000	1.000	1.000	1.000
27	1.000	1.000	1.000	1.000	1.000	1.000
28	1.000	1.000	1.000	1.000	1.000	1.000
29	1.000	1.000	1.000	1.000	1.000	1.000
30	1.000	1.000	1.000	1.000	1.000	1.000
31	1.000	1.000	1.000	1.000	1.000	1.000
32	1.000	1.000	1.000	1.000	1.000	1.000
33	1.000	1.000	1.000	1.000	1.000	1.000
34	1.000	1.000	1.000	1.000	1.000	1.000
35	1.000	1.000	1.000	1.000	1.000	1.000
36	1.000	1.000	1.000	1.000	1.000	1.000
37	1.000	1.000	1.000	1.000	1.000	1.000
38	1.000	1.000	1.000	1.000	1.000	1.000
39	1.000	1.000	1.000	1.000	1.000	1.000
40	1.000	1.000	1.000	1.000	1.000	1.000
41	1.000	1.000	1.000	1.000	1.000	1.000
42	1.000	1.000	1.000	1.000	1.000	1.000

Table B.9: Inventory Efficiency ($\eta_{INV}(j)$) of Pro01 Manufacturing Cell

Days	$\eta_{INV}(j)$
5	0.480
6	0.482
7	0.483
8	0.479
9	0.483
10	0.483
11	0.488
12	0.481
13	0.482
14	0.481
15	0.479
16	0.476
17	0.485
18	0.487
19	0.481
20	0.480
21	0.479
22	0.479
23	0.477
24	0.484
25	0.488
26	0.482
27	0.485
28	0.479
29	0.482
30	0.484
31	0.478
32	0.480
33	0.481
34	0.484
35	0.479
36	0.488
37	0.481
38	0.481
39	0.493
40	0.475
41	0.485
42	0.481

Table B.10: Top 10 most varying elements of baseline model of Pro01 manufacturing cell

Days	r_a **@UP**	r_a **@SW**	r_a **@S&D**	r_a **@P**	r_a **@AS**	r_a **@FW**	t_o **@AS**	RI **@P**	t_o **@SW**	t_o **@FW**
5	0.036	0.036	0.036	0.036	0.036	0.036	0.174	0.423	1.261	2.011
6	0.030	0.030	0.030	0.030	0.030	0.030	0.161	0.418	1.248	1.983
7	0.026	0.026	0.026	0.026	0.026	0.026	0.169	0.420	1.265	2.000
8	0.022	0.022	0.022	0.022	0.022	0.022	0.171	0.414	1.233	2.007
9	0.020	0.020	0.020	0.020	0.020	0.020	0.168	0.417	1.246	1.995
10	0.018	0.018	0.018	0.018	0.018	0.018	0.160	0.413	1.243	1.986
11	0.016	0.016	0.016	0.016	0.016	0.016	0.167	0.415	1.277	1.975
12	0.014	0.014	0.014	0.014	0.014	0.014	0.162	0.413	1.270	2.006
13	0.013	0.013	0.013	0.013	0.013	0.013	0.166	0.412	1.252	1.995
14	0.012	0.012	0.012	0.012	0.012	0.012	0.160	0.413	1.255	1.999
15	0.011	0.011	0.011	0.011	0.011	0.011	0.167	0.410	1.260	2.030
16	0.011	0.011	0.011	0.011	0.011	0.011	0.166	0.406	1.233	2.024
17	0.010	0.010	0.010	0.010	0.010	0.010	0.164	0.412	1.259	1.985
18	0.010	0.010	0.010	0.010	0.010	0.010	0.165	0.429	1.265	1.976
19	0.009	0.009	0.009	0.009	0.009	0.009	0.169	0.415	1.245	1.998
20	0.009	0.009	0.009	0.009	0.009	0.009	0.160	0.415	1.259	2.020
21	0.008	0.008	0.008	0.008	0.008	0.008	0.160	0.421	1.260	2.023
22	0.008	0.008	0.008	0.008	0.008	0.008	0.162	0.409	1.243	2.006
23	0.007	0.007	0.007	0.007	0.007	0.007	0.163	0.414	1.260	2.030
24	0.007	0.007	0.007	0.007	0.007	0.007	0.173	0.414	1.268	1.999
25	0.007	0.007	0.007	0.007	0.007	0.007	0.166	0.419	1.256	1.969
26	0.007	0.007	0.007	0.007	0.007	0.007	0.166	0.409	1.241	1.987
27	0.006	0.006	0.006	0.006	0.006	0.006	0.166	0.409	1.276	1.988
28	0.006	0.006	0.006	0.006	0.006	0.006	0.162	0.412	1.252	2.010
29	0.006	0.006	0.006	0.006	0.006	0.006	0.167	0.409	1.250	1.994
30	0.006	0.006	0.006	0.006	0.006	0.006	0.175	0.420	1.255	1.992
31	0.005	0.005	0.005	0.005	0.005	0.005	0.161	0.414	1.248	2.020
32	0.005	0.005	0.005	0.005	0.005	0.005	0.167	0.405	1.231	1.986
33	0.005	0.005	0.005	0.005	0.005	0.005	0.162	0.420	1.245	2.003
34	0.005	0.005	0.005	0.005	0.005	0.005	0.166	0.417	1.246	1.990
35	0.005	0.005	0.005	0.005	0.005	0.005	0.157	0.405	1.271	2.011
36	0.005	0.005	0.005	0.005	0.005	0.005	0.161	0.420	1.269	1.975
37	0.005	0.005	0.005	0.005	0.005	0.005	0.170	0.425	1.240	2.015
38	0.004	0.004	0.004	0.004	0.004	0.004	0.153	0.422	1.237	1.988
39	0.004	0.004	0.004	0.004	0.004	0.004	0.166	0.409	1.288	1.954
40	0.004	0.004	0.004	0.004	0.004	0.004	0.174	0.420	1.217	2.028
41	0.004	0.004	0.004	0.004	0.004	0.004	0.170	0.417	1.266	1.997
42	0.004	0.004	0.004	0.004	0.004	0.004	0.167	0.406	1.240	2.001

Appendix C

Case Study: Validation (TOC)

Table C.1: Instantaneous Raw Material Inventory $RI(i)$ in units

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.614	0.964	0.4997	1.189	0.989	0.5936
6	0.644	1.058	0.5025	1.232	1.016	0.6207
7	0.708	1.092	0.5025	1.301	1.076	0.6207

Table C.2: Ideal Processing time $t_o(i)$ in minutes

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	1.000	1.000	0.1674	1.114	0.945	0.4137
6	0.999	0.999	0.1655	1.118	0.948	0.4156
7	1.000	1.000	0.1692	1.117	0.951	0.4154

Table C.3: Coefficient of Variation of Effective Processing Time $c_e(i)$

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	1.000	1.000	0.1674	1.114	0.945	0.4137
6	0.999	0.999	0.1655	1.118	0.948	0.4156
7	1.000	1.000	0.1692	1.117	0.951	0.4154

Table C.4: Effective Processing Time $t_e(i)$ in minutes

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	1.001	1.003	0.1677	1.115	0.945	0.4140
6	1.000	1.002	0.1657	1.118	0.948	0.4159
7	1.000	1.003	0.1694	1.118	0.951	0.4157

Table C.5: Effective Rate of Production $r_e(i)$ in units/min

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.999	0.997	5.9647	0.897	1.058	2.4156
6	1.000	0.998	6.0348	0.894	1.055	2.4045
7	1.000	0.997	5.9024	0.895	1.051	2.4057

Table C.6: Rate of Arrivals of Inventory $r_a(i)$ in units/min

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.036	0.036	0.0364	0.036	0.036	0.0364
6	0.030	0.030	0.0304	0.030	0.030	0.0304
7	0.026	0.026	0.0263	0.026	0.026	0.0263

Table C.7: Instantaneous Utilization $u(i)$

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.035	0.035	0.0058	0.039	0.033	0.0143
6	0.029	0.029	0.0048	0.032	0.027	0.0120
7	0.025	0.025	0.0042	0.028	0.024	0.0104

Table C.8: Wait Time in Queue $CT_q(i)$ in minutes

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.359	0.057	0.0027	0.278	0.051	0.0117
6	0.089	0.047	0.0045	0.105	0.043	0.0112
7	0.040	0.040	0.0011	0.051	0.037	0.0069

Table C.9: Cycle Time Efficiency ($\eta_{CT}(j)$) of Pro01 Manufacturing Cell

Days	$\eta_{CT}(j)$
5	0.859
6	0.939
7	0.963

Table C.10: Instantaneous Capacity $C_m(i)$

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	1.000	1.000	0.9994	0.999	0.999	0.9987
6	1.000	1.000	0.9995	0.999	0.999	0.9989
7	1.000	1.000	0.9995	0.999	0.999	0.9990

Table C.11: Inventory Efficiency ($\eta_{INV}(j)$) of Pro01 Manufacturing Cell

Days	$\eta_{INV}(j)$
5	0.691
6	0.692
7	0.694

Appendix D

Case Study: Validation (BVPM)

Table D.1: Instantaneous Raw Material Inventory $RI(i)$ in units

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.592	0.962	0.5010	1.167	0.910	0.5776
6	0.593	0.949	0.5025	1.122	0.917	0.5712
7	0.607	0.950	0.4992	1.144	0.978	0.5712

Table D.2: Ideal Processing time $t_o(i)$ in minutes

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.999	1.000	0.1668	1.120	0.949	0.3278
6	1.001	1.000	0.1660	1.115	0.949	0.3289
7	1.002	0.999	0.1670	1.121	0.947	0.3300

Table D.3: Coefficient of Variation of Effective Processing Time $c_e(i)$

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	3.998	1.326	2.0173	3.341	1.346	1.6936
6	1.999	1.326	3.1482	2.063	1.348	2.0245
7	1.333	1.326	1.3294	1.333	1.333	1.3311

Table D.4: Effective Processing Time $t_e(i)$ in minutes

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.999	1.003	0.1670	1.120	0.949	0.3281
6	1.001	1.003	0.1663	1.115	0.949	0.3292
7	1.003	1.002	0.1673	1.122	0.947	0.3303

Table D.5: Effective Rate of Production $r_e(i)$ in units/min

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	1.001	0.997	5.9869	0.893	1.054	3.0482
6	0.999	0.997	6.0144	0.897	1.053	3.0376
7	0.997	0.998	5.9787	0.892	1.056	3.0280

Table D.6: Rate of Arrivals of Inventory $r_a(i)$ in units/min

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.036	0.036	0.0364	0.036	0.036	0.0364
6	0.030	0.030	0.0304	0.030	0.030	0.0304
7	0.026	0.026	0.0263	0.026	0.026	0.0263

Table D.7: Instantaneous Utilization $u(i)$

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.035	0.035	0.0058	0.039	0.033	0.0113
6	0.029	0.029	0.0048	0.032	0.027	0.0095
7	0.025	0.025	0.0042	0.028	0.024	0.0083

Table D.8: Wait Time in Queue $CT_q(i)$ in minutes

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	0.358	0.057	0.0026	0.283	0.051	0.0080
6	0.090	0.047	0.0045	0.104	0.043	0.0086
7	0.041	0.040	0.0011	0.051	0.036	0.0043

Table D.9: Cycle Time Efficiency ($\eta_{CT}(j)$) of Pro01 Manufacturing Cell

Days	$\eta_{CT}(j)$
5	0.857
6	0.938
7	0.963

Table D.10: Instantaneous Capacity $C_m(i)$

Days	Unpacking	Stem Weld	Assembly	Final Weld	Scratch and Date	Packaging
5	1.000	1.000	0.9994	0.999	0.999	0.9987
6	1.000	1.000	0.9995	0.999	0.999	0.9990
7	1.000	1.000	0.9996	0.999	0.999	0.9991

Table D.11: Inventory Efficiency ($\eta_{INV}(j)$) of Pro01 Manufacturing Cell

Days	$\eta_{INV}(j)$
5	0.676
6	0.681
7	0.679

Vita

Bharadwaj Venkatesan was born in Chennai, India on August 11, 1984, to Varalakshmi Pokuru & Venkatesan Viswanathan. He completed high school in 1999. He enrolled in Mechanical Engineering Bachelor's Degree program of Vidya Jyothi Institute of Technology (Affiliate of JNTU, Hyderabad) in 2001 and graduated in May 2005. He came to Knoxville, TN in Fall 2005 to pursue graduate studies. He graduated with a Master's degree from Mechanical Engineering Department at University of Tennessee, Knoxville. Bharadwaj started his Ph.D in Industrial Engineering at University of Tennessee, Knoxville in Jan 2009 focusing on development of performance measurement and management tools for manufacturing systems. As a graduate research assistant working for Dr. Rupy Sawhney, he worked on projects in Lean & Six Sigma Implementation, Metric Analysis, and Simulation Modeling. He completed his Ph.D in Spring 2017.