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Reliability in Lean Systems

Robert S. Keyser
University of Tennessee - Knoxville

To the Graduate Council:

I am submitting herewith a dissertation written by Robert S. Keyser entitled "Reliability in Lean 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.

Rapinder Sawhney, Major Professor

We have read this dissertation and recommend its acceptance:

Xueping Li, Denise F. Jackson, Ramon V. Leon

Accepted for the Council:

Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

To the Graduate Council:

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RELIABILITY IN LEAN SYSTEMS

A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Robert Shegiharu Keyser
December 2008

DEDICATION

This dissertation is dedicated:

To

My father, Mr. Donald A. Keyser,
Who went to Heaven 14 years ago

My beloved mother, Mrs. Chieko (Tsujino) Keyser
Who is now in Heaven

and

To

My loving wife, Mamie A. Keyser

My precious daughter, Emily A. Keyser

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ABSTRACT

Implementation of Lean manufacturing systems often turn into expensive hit-or-miss propositions. Whereas many organizations that lack immediate success quickly abandon their 'Lean' plans in hopes that the next great marketing panacea will solve their efficiency woes, organizations that experience early success often have difficulty in *sustaining* their Lean efforts. To further exacerbate the dilemma, knowledge of the reliability of Lean systems is currently inadequate. This paper proposes a contemporary Lean paradigm – reliability in Lean systems – through the development of an innovative Lean System Reliability model (LSRM). Principally, LSRM models the reliability of Lean subsystems as a basis for determining the reliability of Lean systems as a whole. Lean subsystems, in turn, consist of reliability measures for Lean components. Once principal components analysis techniques are employed to determine critical subsystems, value stream mapping is used to illustrate the critical subsystem workflow sequence. Monte Carlo simulations are performed for the Lean system, its subsystems, and components and are then compared with historical data to determine the adequacy of the LSRM model. In addition, a regression model is developed to ascertain the contribution of LSRM towards predicting % on time delivery.

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1. Introduction

While much has been published with regard to both the implementation of Lean concepts and reliability measures, there has been a dearth of published research in the area integrating reliability with Lean systems. This is largely attributed to an organization's dedicated emphasis towards the successful application of one concept or the other, but not both simultaneously.

1.1 Integrating Reliability with Lean

Successful Lean systems that also prove reliable will likely result in *sustainable* Lean systems. Without knowledge of its reliability, however, a Lean system's benchmark for success is measured only by its components. For example, whereas decreases in order lead time and waste, along with increases in % on time delivery and machine uptime demonstrate success with Lean initiatives, neither provides information regarding the reliability of the system as a whole.

Research questions

The following research questions will be investigated with regard to the integration of reliability with Lean systems and will be rejoined in the conclusion.

1. What is the conceptual framework of a Lean System Reliability model (LSRM)?
2. What is the algorithm for developing a stochastic LSRM?
3. How are critical subsystems determined?
4. How does one determine the LSRM workflow sequence?
5. How is the reliability of LSRM determined?
6. How is the reliability of Lean critical subsystems determined?
7. How is the reliability of Lean components determined?
8. How is LSRM validated?
9. What is the contribution of LSRM to Lean systems?

1.2 Background

Reliability is the probability that an item will perform a required function under prescribed conditions for a stated period of time (Summers, 1997; Badcock, 1998). Therefore, reliability can be thought of in terms of its probability of survival, $R(t)$. The following equation illustrates the relationship between reliability and failure:

$$\text{The probability of survival, } R(t)\text{, + the probability of failure, } F(t)\text{, = } 1$$

In a Lean manufacturing system, the required function consists of satisfactory operations (i.e., survivals) such as machine uptime, on time delivery, and zero defects. The prescribed conditions include working with aged machinery involving dynamic, moving parts in a safe environment. The stated period of time varies but typically refers to the time during which satisfactory operation is desired such as the time required to setup and run a given order.

Modeling the reliability of a Lean system is an important issue because Lean systems are not necessarily reliable. Whereas Lean tools are effectively used to improve the efficiency, quality, and reliability of various aspects of the manufacturing system, the reliability of the Lean system as a whole, its subsystems, and components are important metrics because these terms represent a set of interrelated elements working together toward the attainment of on time delivery of high quality products at minimum cost.

Failures occur when an event adversely impacts the Lean system. Machine breakdowns, adjustments, parts replacement, product defects, lack of or inadequate inspection during a production run and environmental conditions such as power outages and safety issues are examples of failures. Failures in a manufacturing environment typically do not occur at a uniform rate, but rather follow a distribution known as a “bathtub curve” (Meeker and Escobar, 1998). The life of a product or system can be divided into three distinct regions: Infant Mortality period, which indicates a declining failure rate; Random Failures period, which indicates a constant failure rate; and a Wearout Failures period, which indicates increasing failure rates.

Products or systems that survive the Infant Mortality period have a high probability of surviving the conditions provided by the system and its prescribed environment. During the Random Failures period, failures may be residual defects surviving the Infant Mortality period or may occur randomly due to unpredictable system or environmental conditions or may wear out prematurely. Wearout failures are typically associated with excessive exposure to stress-related conditions such as pressure or thermal fatigue and cycle or use fatigue.

A system may be defined as an assemblage or combination of elements or parts forming a complex or unitary whole, such as an rail transportation system, or a coordinated body of methods or complex scheme, such as a manufacturing system.

1.2.1 Assumptions

The researcher shall consider the following assumptions with respect to using the appropriate method in analyzing data in this reliability study.

Use a nonparametric method if the data is:

- Distinctly non-normal and cannot be transformed
- From a sample that is too small to apply the central limit theorem and, therefore, cannot lead to normality of averages
- From a distribution not covered by parametric methods
- From an unknown distribution
- Nominal or ordinal

Use a parametric method when:

- The assumptions for the population probability distribution hold true
- The sample size is large enough to apply the central limit theorem leading to normality of averages
- The data is non-normal but can be transformed

Along with the application of a variety of mathematical and statistical techniques to address prominent, it is important to identify the probability distributions of Lean subsystems and components that satisfy certain assumptions from which the data follows as in the examples shown in Figure 1.

Assumptions for Principal Components Analysis (PCA) and multivariate regression techniques that are introduced in Chapter 3 include the absence of any outliers in the data, a lack of multicollinearity among the predictor variables, and the distribution of the response variables following a multivariate normal distribution. Should any of these assumptions be violated, a transformation of the data will be necessary in order to eliminate bias.

1.3 Elements of a System

A system may be defined as an assemblage or combination of elements or parts forming a complex or unitary whole, such as a rail transportation system; or a coordinated body of methods or complex scheme, such as a manufacturing system. Systems are comprised of components, attributes, and relationships. These are described as follows:

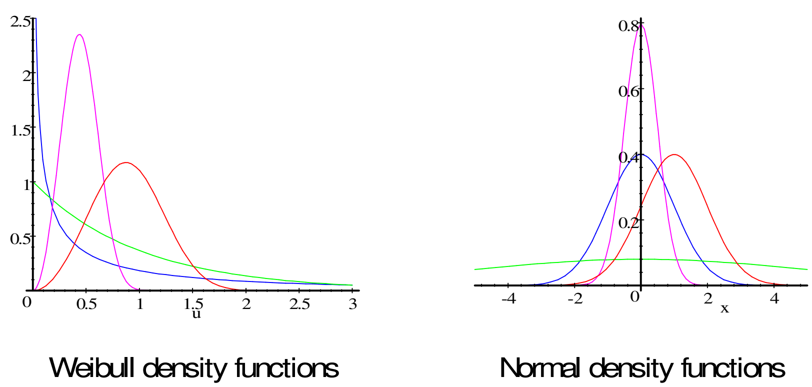


Fig. 1 Probability Distributions

1. *Components* are the operating parts of a system consisting of inputs, processes, and outputs. Each system component may assume a variety of values to describe a particular system state dictated by control action and one or more restrictions.

2. *Attributes* are the properties of discriminate features of the components of a system. These attributes characterize the parameters of a system.

3. *Relationships* concatenate components and attributes. Relationships that are functionally necessary to each other are designated as first-order relationships. An example is symbiosis, any interdependent or mutually beneficial relationship between two individual components. Second-order relationships, known as synergistic, are cooperative interactions that enhance system performance. Redundancy is characterized as a third-order relationship. Redundancy occurs when duplicate components are in place to ensure continued system performance in the event of primary component failure.

1.4 Methodology

This dissertation consists of the three phase development of a new reliability model for Lean systems, called Lean System Reliability model, or LSRM. This model is designed to measure the reliability of a Lean system with respect to its critical subsystems and components. Phase 1 consists of the model's conceptual framework. Phase 2 discusses the methodology necessary to design an LSRM. Phase 3 consists of methodology for validating the LSRM model. In addition, a regression model is developed to determine the contribution of LSRM to Lean systems.

1.5 Research Objective

The researcher's objective is to develop a mathematical model that measures the reliability of Lean systems (hence, LSRM) for manufacturing firms. The LSRM model is based on the manufacturer's Lean critical subsystems. LSRM is a pragmatic model for numerous reasons:

1) it provides a straightforward composite measure of the overall reliability of a Lean system

2) the model can be monitored over time for evaluation of improvement, sustainability, or deterioration

3) problem areas can be pinpointed with relative ease since each critical subsystem is monitored daily through data collection. Prompt corrective action allows the system to quickly regain full functioning capacity

By quantifying data obtained in the manufacturing process, LSRM can be used to effectively evaluate and assess the reliability performance of Lean systems.

1.6 Anticipated Conclusions

It is anticipated that the newly developed reliability model – LSRM, will serve as an informative and validated decision-making model of the reliability of a firm's Lean manufacturing system by comparing simulation results with historical data. Moreover, it is anticipated that LSRM will make a significant contribution towards predicting % on time delivery.

1.7 Organization of Chapters

The ensuing chapters are presented as follows: In Chapter 2, an extensive literature review of the Lean paradigm is conducted. Literature with regard to the integration of reliability with Lean manufacturing is also examined. Chapter 3 discusses the methodology for LSRM development, including its conceptual framework, its model development, and model validation techniques. Chapter 4 follows an application of LSRM and validation of the model through a case study. In Chapter 5, conclusions and areas of future research are discussed. Chapter 6 includes references cited in this paper.

2. Literature Review

The intent of the literature review is to discover models, methods, or software that integrate reliability with Lean systems. The following databases were searched resulting in over 150 articles that address some aspect of reliability and Lean systems.

Databases:

- Compendex
- Web of Science
- Academic Search Premier
- IEEE Xplore
- Material Business File
- National Technical Information Service
- Business Source Premier

Current software utilized in the literature include Root Cause Analysis (RCA) and Computer Maintenance Management System (CMMS) for reliability. Arena simulation software as well as Bootstrapping and Monte Carlo techniques are employed for simulation tests. Statistical software packages include SAS, JMP, Minitab, Excel, S-Plus, StatGraphics, and Splida.

Research with respect to the integration of reliability with Lean systems has revealed scant published works in this area. The essential focus of Lean manufacturing is the efficient use of scarce resources through the minimization of all forms of waste and non-value added activities in the organization. Current thinking comes from different perspectives whereby performance reliability, safety, and culture are believed to be important criteria for successful integration.

Roberts (1990) identifies High Reliability Organizations (HROs) as the subset of hazardous organizations that achieve a record of high safety over long periods of time. If an organization failures could result in catastrophic consequences on the order of tens of thousands of times, but these failures were prevented, then the organization is considered a 'high' reliability organization.

Hence, safety is the primary organizational objective for high reliability organizations. Such organizations hold the optimistic view that accidents can be prevented through good organizational design and management and that a 'high-reliability culture' breeds a value system that provides incentives for failure detection rather than punishment (Wieck, 1987). That is, the culture perpetuates the view that when employees see a problem, they 'own it' until it is solved or until others who can solve it take responsibility for it. This culture empowers people to stop and fix problems, ensuring quality results the first time (Liker, 2004).

Smart et al., (2003) poses the challenge of integrating design principles of both lean and high-reliability models where performance reliability and safety are critical, rather than merely substituting one for another. They further suggest incorporating design principles that focus on the achievement of medium- and long-term goals over short-term efficiency gains. High reliability organizations place an emphasis in organization design whereby 'failure is simply not an option'.

Resnick (2005) suggests going beyond traditional methods of reliability by widening an organization's scope of analysis to include all stages of the life cycle and additional interactions between system components. These interactions are evaluated to discern their effects on system reliability and to discover ways to identify sources of error or component failure.

Resnick also notes that reliability is affected at the management level by factors such as corporate culture, supervisory practices, and human resources. Citing the Columbia Space Shuttle failure in 2003, NASAs corporate culture was such that systems approval was given based on a previous history of success despite deviations in performance for this particular launch. This resulted in a failed mission caused by foam that struck the orbiter's wing. Supervisory policies that emphasize productivity measures over safety and quality may reduce systems reliability due to neglected maintenance issues and safety hazards. Moreover, inadequately trained employees can lead to product reliability issues.

A strict organizational structure, decentralized decision making, quality training, an experienced workforce, redundancy in the workplace, and simulation modeling are considered important requisites for becoming a highly reliable organization (LaPorte, 1991; Roberts, 1993). Bain (1999) suggests that lean and high-reliability should be viewed as 'complementary, not competing perspectives.'

2.1 Chronology of Lean

The transformation of production systems in the motor vehicle industry has been well chronicled (Hounshell, 1984); in particular, the success of the Toyota Production System (TPS) (Ohno, 1988; Fujimoto, 1999; Liker, 2004). TPS is a hybrid production system that merged Ford's mass production techniques with a small batch production system along with concepts derived from Toyota Motor Company founder Sakichi Toyoda's former loom business (Ohno, 1988; Monden, 1998; Fujimoto, 1999).

Toyoda Motor Company was founded in 1918 and, though struggling financially until 1930, made use of Ford and GM components to design Model AA automobiles (Cusumano, 1985). By 1930, the company changed its name to 'Toyota' to simplify its pronunciation.   By 1935, car production began and truck production began in 1936 under the leadership of Kiichiro Toyoda, Sakichi's son, in 1935. By 1937, the Toyota Motor Company was formally formed.

Although Eiji Toyoda, Kiichiro's cousin, is credited with first implementing mass production techniques at Toyota, Taiichi Ohno, a mechanical engineer, is credited with implementing a manufacturing system capable of economically producing a large variety of automobiles in small volumes (Ohno and Boden, 1988), which became the origin of the Just-in-Time philosophy

(Cusumano, 1985). Ohno's focus on waste elimination also led to the development of the Jidoka concept, which became an integral part of the Toyota Production System (TPS), and led to the establishment of the two pillars of TPS: autonomation and Just-in-Time (Ohno and Boden, 1988).

Shigeo Shingo, an industrial engineer, was hired as a consultant for Toyota in 1955. During his time with Toyota, Shingo developed the Single Minute Exchange of Dies (SMED) concept (Shingo, 1983; Dillon and Shingo, 1985; Shingo, 1996), which focused on changeover reduction methods and the concept of poka-yoke (Shingo, 1986; Shingo, 1988; Shingo and Dillon, 1992) – developing techniques for mistake-proofing production processes.

According to Ohno, the development of TPS began attracting attention during the first oil crisis in 1973 (Ohno and Kumagai, 1980). However, prior to the oil crisis, there was little interest from the outside world with regard to what Toyota was doing (Ohno, 1988).

The Toyota Production System (TPS) was established based on the philosophies of Jidoka and Just-in-Time (Womack, 1990). Jidoka has a number of meanings: 1) it means that a machine safely stops when normal processing is completed; 2) operators are empowered to stop the machine immediately upon the detection of defects in the process, thus preventing additional defective products from being produced; and 3) as a quality or equipment problem occurs, the machine detects the problem with the aid of sensors and immediately stops the machine. When a quality or equipment problem arises, it is communicated via a highly visible "andon" problem display board. As a result, only products that meet customer specifications are sent to the next process.

The emphasis with the Just-in-Time (JIT) concept is for every process to produce only what is needed, when it is needed, and in the quantity needed by the next process in a continuous flow. Spear and Bowen (1999) refer to TPS's use of powerful Lean concepts including just-in-time

(JIT) delivery of products; Kaizen (continuous improvement in all aspects of life); Kanban (emphasizing a "pull" production flow system); Jidoka, and Genba Kanri (consists of 3s, standard operations, skill control, and kaizen) as the 'DNA' of the TPS system. With Genba Kanri, if an operator follows standard operating procedures and maintains a correct level of skill to perform a given task in a controlled work environment, the potential for error, or failure, is minimized. When a failure does occur, systematic problem solving aids in the prevention of a repeat failure.

Other TPS Lean concepts include heijunka (the leveling of production volume); muda (the elimination of all forms of waste); the visual workplace (using andon lighted boards to provide shop floor visual feedback of production troubles and production performance); Single Minute Exchange of Dies, or SMED (reducing setup times to single digit minutes); and 5s (an emphasis on cleanliness and orderliness on the shop floor).

Although the Toyota Production System (TPS) placed less emphasis on employee satisfaction and the humanization of work, it works very well in attaining high levels of customer satisfaction – a direct result of strong efforts at quality improvement, operational efficiency, and manufacturing flexibility to meet the demands of highly competitive and diversified product markets (Ohno, 1988), (Womack et al., 1990), (Pil and Macduffie, 1999), and (Liker, 2004). Fucini and Fucini (1990) and (Babson, 1993) suggest that TPS achieves exceptional organizational performance at the expense of employee well-being. Whereas Toyota has made efforts to create group autonomy and worker identity with cellular manufacturing, its emphasis remains on controlling and reducing process variation and the use of standard operating procedures (SOPs) (Adler and Borys, 1996).

The term "Lean manufacturing" was first recognized in Womack's highly influential book, *The*

Machine That Changed The World, (Womack, 2003) cites Toyota's extraordinary success with using Lean manufacturing methods as a means of overcoming the mass production paradigm, given new customer requirements of smaller batch sizes coupled with demands for variety of product options. In *Lean Thinking* (Womack, 2003), Womack explains that Lean is a way of thinking – a whole-systems approach that creates a culture in which everyone in the organization continuously improves their processes and production. In *Becoming Lean – Inside Stories of U.S. Manufacturers*, (Liker, 1997) describes accounts by U.S. manufacturers on the principles and techniques needed in order to become Lean, the obstacles that might be encountered, and what it takes to overcome them. In *The Toyota Way*, (Liker, 2004) articulates the management principles of Toyota, whom he considers the world's greatest manufacturer.

In 1981, a study group called the 'Repetitive Manufacturing Group (RMG)' held a meeting at Kawasaki's Lincoln, Nebraska motorcycle plant. Out of participants' exposure to Kawasaki's implementation of JIT concepts came published works on JIT (Schonberger, 1982; Hall, 1983; Schonberger and Gilbert, 1983, and Schonberger, 1983).

2.2 Lean Sigma

Six Sigma utilizes quality management and statistical techniques for data collection, analysis, and interpretation Advanced statistical techniques such as design of experiments (DOE) provide the needed knowledge linking process parameters to performance measures that reflect the needs of the customer, known as critical to quality (CTQ)s, thus making optimization of key process parameters possible even for complex processes (Goh, 2002).

The emphasis of Six Sigma is the reduction of process variation and the key statistical measure to consider for processes that conform to a normal distribution is the standard deviation (Ha, 2005). In order to meet customer specification tolerances of nominal +/- specification limit, process variation must be both controlled and reduced. When the range of six standard deviations between the process mean and the specification limits is achieved, the process is said to operate within “Six Sigma,” which corresponds to a defective rate of 3.4 parts per million (ppm).

When the Six Sigma concept is applied to physical items such as product fill weight, for example, level of performance is often referred to as defective parts per million pieces. When applied to non-physical items, however, the level of performance is referred to in terms of defects per million opportunities, or dpmo. Therefore, at some sigma level, both manufacturing and administrative processes can be measured. The more consistent a manufacturing or administrative process, the smaller will be the value for the standard deviation, or sigma, and, consequently, process variation (Goh and Xie, 2004).

While Lean Sigma is a structured approach for continuous improvement, combining Lean concepts with Six Sigma, Nash et al. (2006) suggest synchronizing these concepts in an integrated manner. They propose that organizations that enter Six Sigma *after* working with Lean will derive the most benefits.

Although many philosophical similarities exist between Lean and Six Sigma such as a focus on the customer, use of a scientific approach, and teamwork, Pannell (2006) contrasts slight differences. For example, whereas Six Sigma achieves productivity improvements through reductions in process parameter variation, Lean focuses on process design and the elimination of wasted activities to improve productivity.

2.3 Lean Maintenance

Among the many problems associated with integrating reliability with Lean systems include operating with unreliable equipment, slow response time and lack of familiarity with the equipment by maintenance personnel, and poor communication between shifts (Hancock, 1998).

Maintenance can be classified into two main types: corrective and preventive (Li et al., 2006; Waeyenbergh and Pintelon, 2004). Whereas corrective maintenance refers to maintenance that occurs after a systems failure occurs, preventive maintenance is maintenance that is performed prior to the occurrence of a systems failure. Preventive maintenance is conducted to retain equipment in a specified condition by providing systematic inspections, detection, and prevention of incipient failure (Wang, 2002). This approach requires proactive maintenance personnel and uses a predictive, planned, and total maintenance scheme.

Reliability centered maintenance (RCM) is a process that focuses on optimizing maintenance effectiveness by determining the maintenance of physical assets in their present operating context (Smith, 2004). With this approach, the organization's maintenance department must be proactive in the prevention of equipment failures, plan and schedule periodic maintenance, have multi-skilled technicians with both mechanical and electrical backgrounds, and maintain a just-in-time philosophy regarding parts and materials ordering using a computerized maintenance system.

The practice of Total Productive Maintenance (TPM) is designed to make Lean processes and systems run smoothly and reliably by keeping three major categories of loss to a minimum or eliminating them (Butler, 2005). The three loss categories are: 1) machine availability, which is reduced through breakdowns and changeover losses; 2) performance losses, which include minor stops and losses through running at a reduced speed; and 3) quality losses, which include waste and start-up losses that involve production of scrap or rework. TPM requires machine operators and maintenance technicians to work together. Machine operators may be required to assume routine care and maintenance tasks so that maintenance technicians pursue more advanced maintenance tasks.

The use of a computerized maintenance management system (CMMS) and asset enterprise management (AEM) system assist Lean maintenance by monitoring and controlling parts inventory (Bagadia, 2008). In addition, this computerized system is capable of automating parts purchasing and refining performance metrics.

Finigan and Humphries (2006) suggest six Lean tools that fit naturally into a Lean maintenance program beginning with the use of clear and concise visual controls which display how maintenance activities measure up against identified key performance metrics and the use of andon lights or horns in the plant to alert the need for emergency repairs. The 5s concept is the practice of simplifying processes and workspaces by sorting, straightening, scrubbing, stabilizing, and sustaining on a daily basis. Additionally, the maintenance function can direct their focus on identifying and eliminating the seven sources of waste in their own department. These include waiting time by technicians for access to equipment, having suppliers deliver needed parts to point of use or other designated locations, and reducing spare parts inventory. Maintenance personnel can apply single-minute exchange of dies (SMED) principles to reduce product changeover times. Further, maintenance personnel can apply the “poka-yoke” mistake-proofing technique to eliminate repair errors and prevent accidents by using color coding, part location slots, and differing plugs for electrical connections.

Additionally, Lean concepts such as 5s and weekly Kaizen improvement events could be performed by maintenance employees. Lean maintenance involves the diagnosis of all machine failures using failure analysis techniques such as root cause failure analysis (RCFA), fault tree analysis (FTA), and cause-and-effect diagrams, to name a few. Hence, Lean maintenance plays a critical role in an organization’s reliability engineering discipline (Wang et al., 2006). Finigan (2006) suggests that a simultaneous focus on Lean maintenance and reliability improvement is an excellent strategy for optimizing asset performance.

Cost reductions result in maintaining reliable equipment for which a variety of methods are in use today. For example, if the state of the system is viewed as a function of system age, then using time-scaled criteria may assist in determining whether to repair or replace equipment (Lugtigheid et al., 2007). Another method in current practice is the use of a Markovian arrival process to decide whether to perform minimal or perfect equipment repair (Montoro-Cazorla, 2008), (Montoro-Cazorla, 2006), (Perez-Ocon, 2004).

By systematically surveying and analyzing each machine and control system to determine which basic stresses affect machinery over time and then outlining a scheme to protect each machine or control system from these stresses, Lean maintenance allows for maximum permanent reduction of scheduled downtime (Pal, 2006).

2.4 Lean Distribution

Lean distribution, a concept similar to Lean supply (Hines, 1994; MacDuffie and Helper, 1997) applies Lean principles to the distribution system, which follows downstream from the point of final manufacturing. Although it began to attract mainstream attention in the late 1980s (Davis, 1993; Lowson et al., 1999), much focus continues to depend on the manufacturing concern rather than the distribution system in the overall supply chain (Kiff, 1997, Holweg and Pil, 2004).

Lean distribution can best be described as an extension of the Lean "pull" concept, wherein customers "pull" products from the manufacturer rather than having products "pushed" on them by manufacturer's representatives. As Ohno (1988) points out, the application of this concept avoids "overproduction," one of the forms of waste in an organization. As customers pull products from the manufacturer, these products are then replenished in the quantities just pulled from the manufacturer.

Although Lean distribution can apply to all types of supply chains, there are exceptions that prohibit the notion of "one size fits all." For example, as one might imagine, build-to-order supply chain distributions, such as furniture and computers, will differ markedly from inventory-based supply chain distributions, such as automobiles, apparel, and books, where immediate variety to the customer is offered. Hence, the Lean concept of reducing production lead time in order to minimize stock on hand (Shingo, 1989; Monden, 1998) depends on various product and market-related variables.

The idea of minimizing stock on hand for inventory buildup items lends itself to the manufacturing paradigm known as Agile manufacturing, where quick response from highly skilled workers to demand volatility is the primary emphasis (Mason-Jones et al. 2000).

2.5 Recent Lean Developments

There has been considerable focus on error-proofing techniques to effectively design products and workflow to avoid making mistakes (Hoske, 2007). Dhafr et al., (2005) developed a methodology for quality improvement in manufacturing organizations that consists of a Fault tree model for the identification of various sources of quality defects on a finished product.

Rosenberg (2006) identifies two types of error-proofing techniques used in manufacturing: active and passive. Active error-proofing refers to the use of sensing devices to verify that a process step such as part installation, matching color schemes, labeling, and product delivery sequence are completed correctly, as well as tracking the overall process. Passive error-proofing refers to utilizes a mechanical means of ensuring that a part is present and in the correct orientation or position for further processing.

Manivannan's (2006) breakdown of mistake-proofing into three distinct categories – 1) physical, such as component installation; 2) operational, such as making modifications or installing devices that reinforce the correct procedure sequence; and 3) philosophical, which involves the identification of situations that cause defects and then providing a solution – is helpful in drawing attention to different categories of mistakes, thereby narrowing one's focus on corrective action procedures.

Safety issues are particularly important since injury rates are relatively high among the manufacturing sector (Brown, 1996). Existing evidence suggests a relatively high prevalence of shoulder pain among industrial workers who are subjected to extremes in reach during overhead work (Sood, et al., 2007). It is imperative that an organization create a safety culture, which is a set of values and policies shared by organizational members related to the reduction of exposure to occupational risks by employees (Fernandez-Muniz, 2007), thereby engaging employees' involvement with management's commitment to safety (Mearns et. al., 2003; Cox and Cheyne, 2000).

Yu et al., (1999) found that inappropriate design of standard operating procedures (SOPs) or standard assembly procedures (SAPs) were contributing factors to 'human error' in the workplace. This led to the development of the human error criticality analysis (HECA) method in order to identify the potentially critical problems caused by human error in the human operation system. For example, based on the SOP, a human error probability (HEP) is calculated for each human operation step, and its error effects to the entire system is then assessed, which shows the interrelationship between critical human tasks, critical human error modes, and human reliability information of the system.

Information technology (IT) can be viewed as a giant umbrella under which several categories such as information processing, radio-frequency identification (RFID), simulation modeling, automation, and robotics lay. In manufacturing, IT can be used to integrate systems in real time linking the organization with its supply chain, warehouse, and logistics functions (Wheatley, 2005) and generating automated warnings if disruptions in the supply chain occur (Bartels, 2005).

International Paper uses RFID technology to manage its inventory at its Texarkana, Texas paper mill and warehouse (Andel, 2003). RFID technology is used in warehouses when products are stored and retrieved and can also be mounted on forklifts to expedite information processing (Trebilcock, 2007; Albright, 2005). Dot Foods uses RFID to automate receipt and storage processes and for accurate inventory tracking of their 26,000 SKU's. A corollary to RFID, they use real-time locater system (RTLT) technology to track the location of assets in real-time, such as trailers in the yard, and to move them in and out of loading docks (Trebilcock, 2006).

Radio-frequency identification (RFID) technology offers substantial benefits to both manufacturers and their supply chain partners (Attaran, 2006). With RFID, smart tags can be applied to individual products or to pallets containing multiple units, and they can be read through most materials. Additionally, RFID technology is superior to traditional bar codes in that RFID readers can scan multiple items simultaneously versus the one at a time scanning technology of bar codes, and this information can be transmitted immediately to suppliers to improve just-in-time deliveries. Most importantly, RFID technology substantially improves the reliability of data tracking such as accurate inventory counts and their specific location in a warehouse.

Demand-driven supply networks (DDSN) focus on sustainable Lean supply chain improvements by making planning information and real-time scheduling visible via computerized information technology (Tinham, 2005).

Simulation models are used in manufacturing to expedite the assessment of potential outcomes without the necessity of costly setups and waste. Among other analyses, simulation is used to automate assembly lines (Croci, 2000), to understand kanban principles (where signaling systems are used to send product upstream when needed) and applications (Ren, 2006), to design cell formations (Wu, 2008), and to analyze value stream mapping (Lian, 2007; Abdulmalek, 2007), (Van Landeghem, 2006).

Automation is used to improve efficiencies and reduce labor costs (Pullin, 2006; Wallans, 2006) but is not restricted to the shop floor only. Rather, automation can also be used in the office environment to generate routine reports, to simplify administrative processes, and serve as a means for getting the entire organization working and thinking the same way (Holmes, 2007). Robotics are commonly used in assembly operations to minimize task completion times (Laslo, 2008), where custom grippers are designed to pick up parts or tools and perform routine tasks such as spray painting in the automotive industry (Chen, 2008), handling sliced fruit and vegetables (Davis, 2008), and operating an automated evaporation injection station in a chemistry laboratory (Manley, 2008).

Manufacturing has extended well beyond the local, regional, or even national level. During the past twenty five years, for various economic, technical, social, and political reasons, manufacturing, and their supply chain partners, has become globalized. Just as manufacturing has become globalized so, too, has the marketplace with the efficacy of communication and information technologies. Consequently, customer demand has become more unpredictable and dynamic leading to planning difficulties with regard to ordering raw materials with lead time constraints, scheduling orders to run, staffing, smaller lot sizes, more frequent setups, etc.

Currently, myriad books and articles in academic journals have been published aimed at demystifying the successful use of Lean principles around the world, in general; and at Toyota, in particular (Sugimori et al., 1977; Monden, 1998; Spear and Bowen, 1999; Swank, 2003; Womack and Jones, 2005; Morgan and Liker, 2006; Liker and Hoseus, 2007). Common to these contributions is a focus on shop floor techniques, inventory reduction, cellular manufacturing and group technology, production smoothing, service operations, and establishing a Lean culture.

3. Research Methodology

3.1 Reliability Relationships in Lean Systems

Lean does not necessarily imply that a system is reliable. As an organization practices Lean concepts in the workplace, reliability may go in any of three directions:

1) Reliability may increase, as Pratt and Whitney experienced by aligning value-creating activities with the concept of continuous flow (Womack and Jones, 2003)
2) Reliability may decrease, as may occur with the Lean concept of inventory reduction, where the cost of unscheduled equipment downtime in Lean manufacturing environments, without excessive inventory buffers, is five to thirty times what it is in other manufacturing environments because it results directly--and immediately--in lost opportunity, failed shipping schedules, and lost sales (Cooper, 2004).
3) Reliability may remain unchanged, as may occur with Lean concepts such as 5s (sort, stabilize, shine, standardize, and sustain), which is a teamwork-building series of activities for eliminating wastes that contribute to errors, defects, and injuries (Liker, 2004).

3.2 LSRM Development

A Lean systems reliability model (LSRM) is developed to measure the reliability of a stochastic Lean system. A stochastic system contains one or more random variables and allows for random variation in one or more of these variables over time based on fluctuations observed in historical data. This development of the model consists of three phases:

Phase 1: Conceptual framework
Phase 2: Development of LSRM
Phase 3: Model Validation

The overview algorithm for developing an LSRM is illustrated in Figure 2. The LSRM conceptual framework algorithm is illustrated in Figure 3.

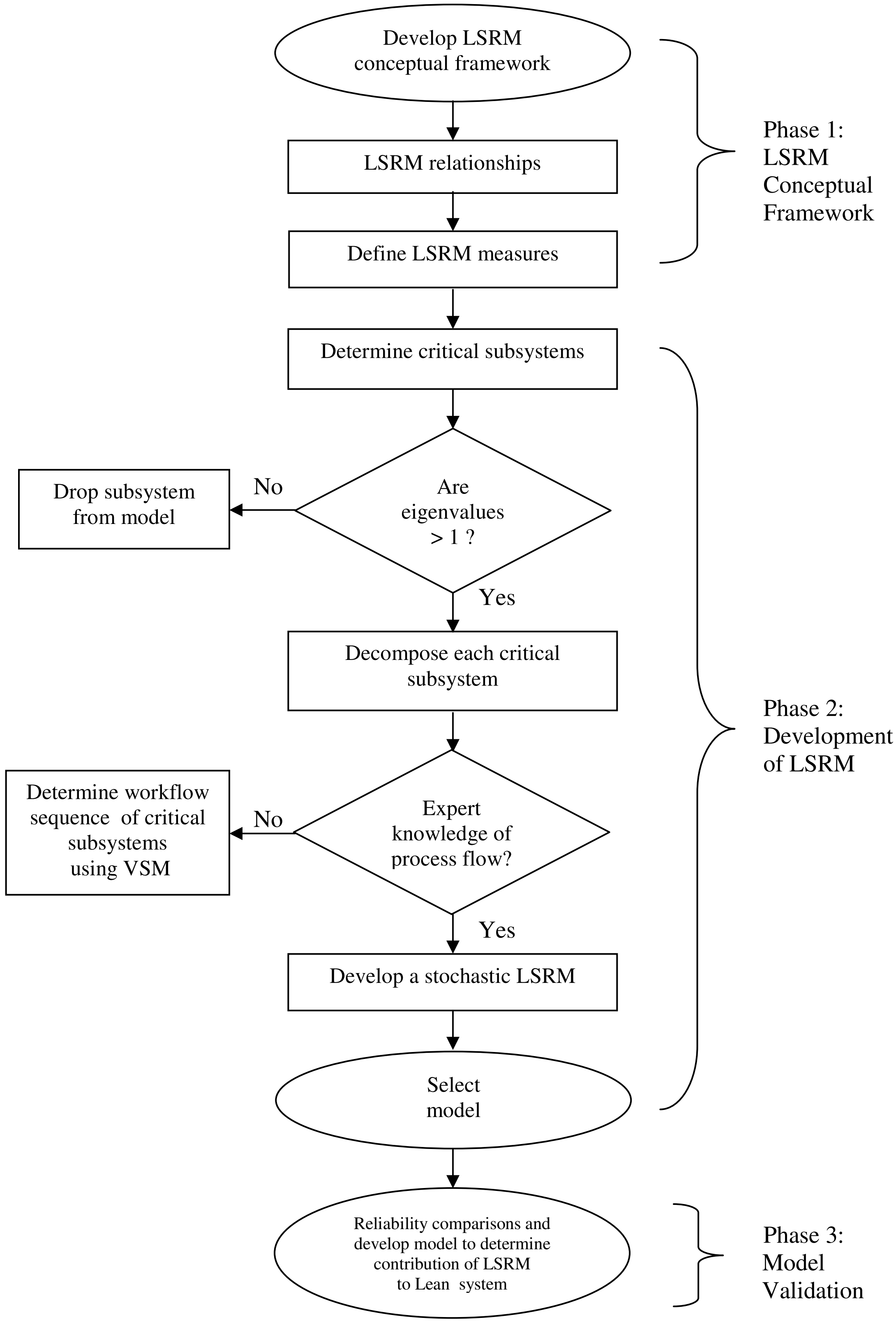


Fig. 2 Overview for Developing an LSRM

3.3 LSRM Conceptual Framework – Phase 1

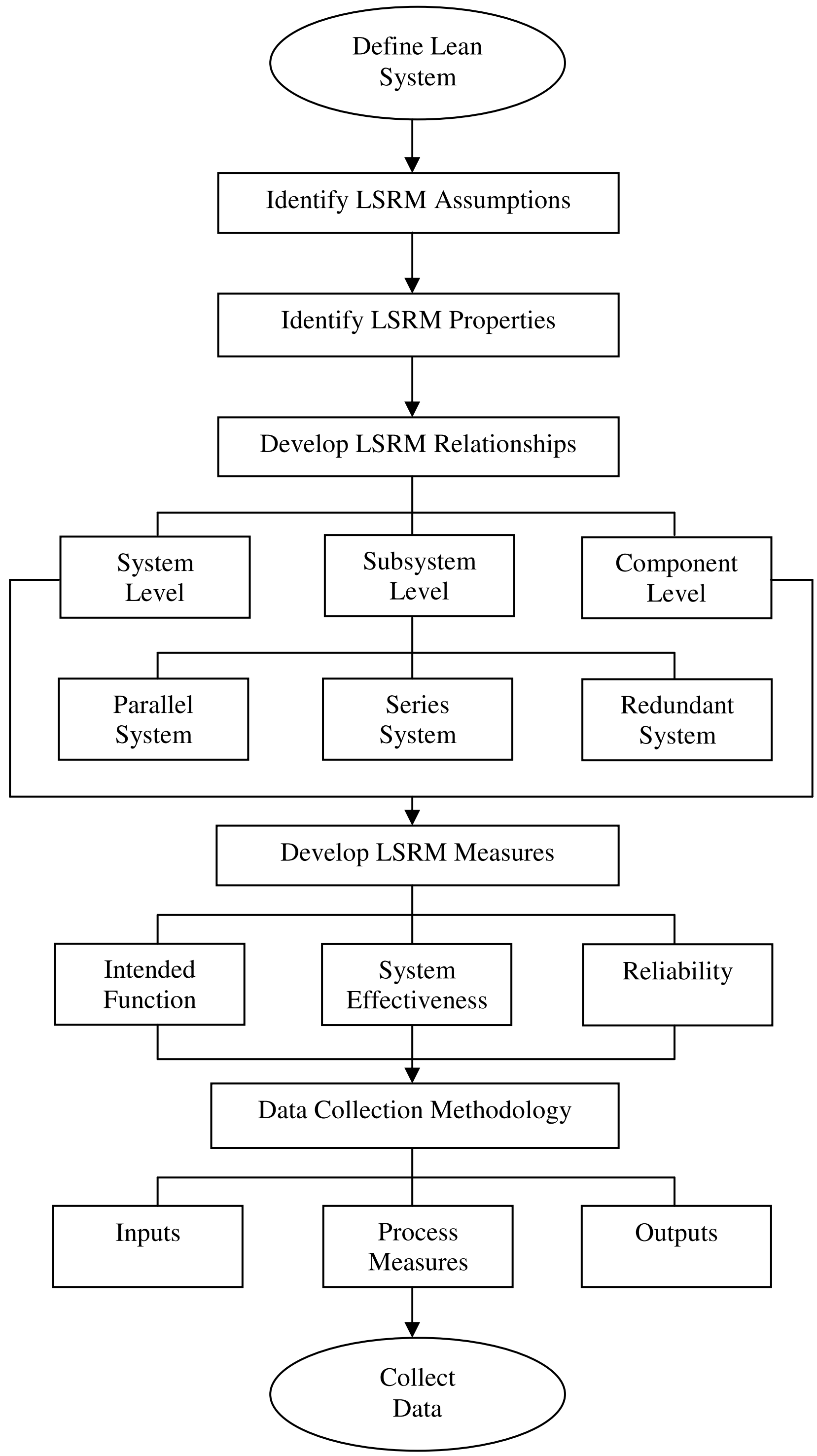


Fig. 3 LSRM Conceptual Framework

3.3.1 LSRM Assumptions

A Lean system is a set of interrelated components working together in a subtle balance toward a common objective of achieving targeted on time delivery of quality products in a manner that provides the manufacturer a competitive edge such as minimized cost. The objective of LSRM is to improve the reliability of the Lean system through the functional relationships between the interacting components of the system. A Lean system is dependent upon the components, attributes, and relationships required in order to accomplish its objective.

The set of Lean system components has the following properties:

1. The properties and behavior of each component of the set has an effect on the properties and behavior of the set as a whole.
2. The properties and behavior of each component of the set depends upon the properties and behavior of at least one other component in the set.
3. Each possible subset of components contains the two properties cited above; that is, the components cannot be divided into independent subsets.

The above properties ensure that the set of components constituting a Lean system always has some characteristic or pattern of behavior that cannot be exhibited by any of its subsets.

3.3.2 LSRM Overview

The definition of an LSRM is defined in terms of its intended function, system effectiveness, and Reliability as follows:

Intended Function: Minimum cost (given continuous pressure for reducing overall cost) for on time delivery of goods (given continuously reduced lead times) of quality products or services (given continuously increasing customer expectations).

System Effectiveness: The probability that the system can successfully meet an operational demand within a given time when operated under specified conditions is contingent upon factors such as system performance, operational readiness, and system cost.

System performance pertains to: 1) Technical capabilities, such as equipment, personnel, internal logistics, and sales forecasting; 2) Performance limitations, such as capacity, capabilities, and vulnerability to both competitors and the economy; 3) Special environmental issues impacting performance, such as pollution or emission controls; and 4) Special business conditions impacting performance, such as excessively high fuel and energy costs. Operational readiness refers to system reliability and maintainability. System cost refers to system design cost, system development cost, cost of production, and operational cost.

Reliability: The probability that the Lean system will perform satisfactorily for at least a given period of time under certain prescribed conditions significantly increases with properly maintained equipment, failure free operations, redundancy in the workplace, and maintaining a safe work environment.

3.3.3 LSRM Framework

3.3.3.1 System Level

Elements of the Lean system should be further decomposed. This conceptual framework for LSRM is represented by three hierarchical levels: the higher level is called the *system*; the middle level is called the *subsystem*; and the lower level is called the *component*. In our context, the entire manufacturing process is the system. Order Processing, Machinery, and Parts Availability at the Work Station are examples of subsystems. Suppliers and machinery are examples of subsystem components. Hence, the levels of system, subsystem, and component are relative terms, since the system at one level in the hierarchy is the component at another level.

An overview of the LSRM conceptual framework at the system level is illustrated in Figure 4.

3.3.3.2 Parallel, Series, and Redundant Systems

LSRM may be comprised of subsystems in a parallel system, subsystems in a series system, redundant subsystems, or any combination thereof.

In a parallel system, the Lean system will continue to function if at least one subsystem has not failed. Parallel systems offer the advantage of a paralleled subsystem taking over functioning of the failed subsystem. Hence, all subsystems must fail in order for the Lean system to shut down.

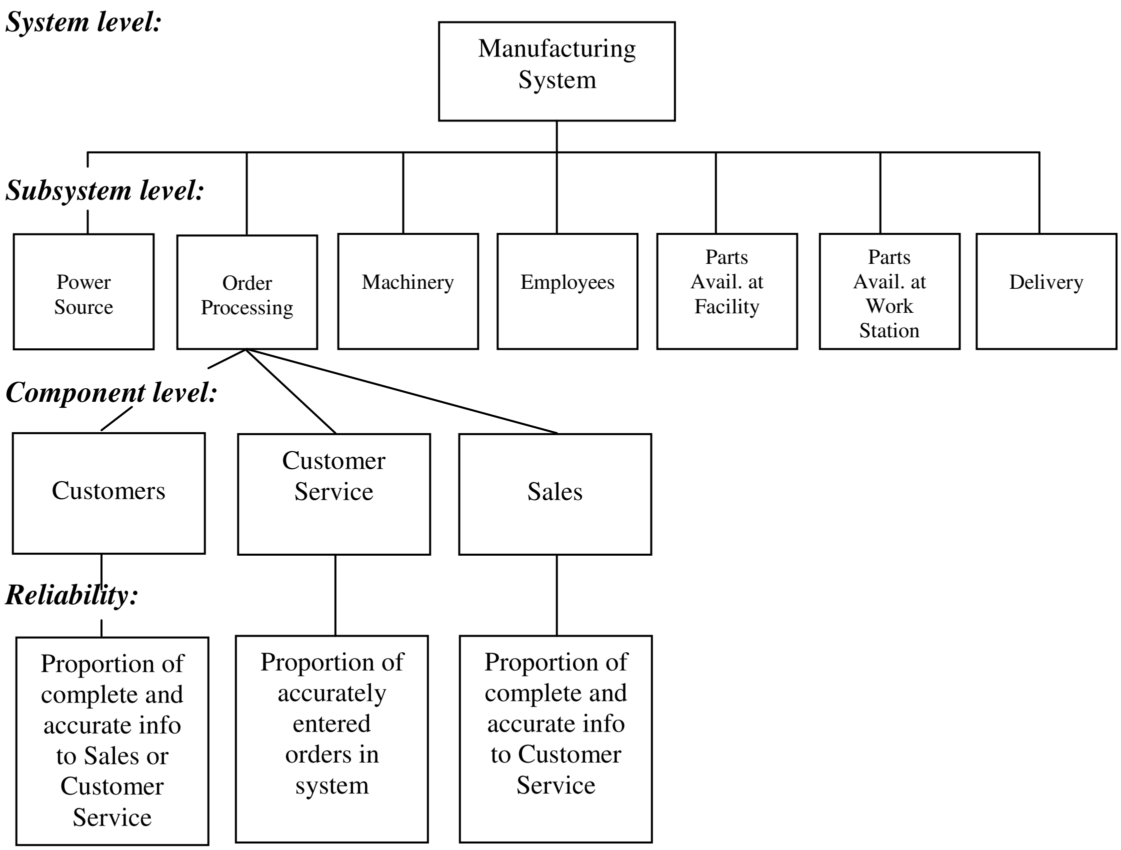


Fig. 4 Overview of LSRM Conceptual Framework

The formula for a parallel system is given by:

Parallel system:

$$R_p = 1 - [(1 - r_1)(1 - r_2)(1 - r_3) \cdots (1 - r_n)]$$

where

$R_p =$ reliability of a parallel system
$r_i =$ reliability of ith subsystem
$n =$ number of components in the system

Conversely, if one component fails in a series system, the entire Lean system fails, or shuts down. The formula for a series system is given by:

Series system:

$$R_s = r_1 \times r_2 \times r_3 \cdots \times r_n$$

where

$R_s =$ reliability of a series system
$r_i =$ reliability of ith subsystem
$n =$ number of components in the system

Redundant systems employ backup components to increase overall Lean system reliability. Backup components are only used if the primary component fails. The formula for a redundant system is given by:

Redundant (or backup) system:

$$R_b = r_1 + r_b(1 - r_1)$$

where

$R_b =$ reliability of redundant system
$r_1 =$ reliability of primary subsystem
$r_b =$ reliability of backup subsystem
$1 - r_1 =$ probability of having to use the backup subsystem

3.3.3.3 Calculating the Reliability of LSRM

An example for calculating the reliability of LSRM is given by:

$$R_s = r_{s(PS)} \times r_{p(OP)} \times r_{s(M)} \times r_{p(E)} \times r_{s(F)} \times r_{p(WS)} \times r_{p(D)}$$

where

$R_s =$ reliability of Lean system
$r_{s(PS)} =$ operational availability of series Power Source subsystem
$r_{p(OP)} =$ reliability of parallel Order Processing subsystem
$r_{s(M)} =$ operational availability of series Machinery subsystem
$r_{p(E)} =$ reliability of parallel Employee subsystem
$r_{s(F)} =$ reliability of series Parts Availability at Facility subsystem
$r_{p(WS)} =$ reliability of parallel Parts Availability at Work Station subsystem
$r_{p(D)} =$ reliability of parallel Delivery subsystem

3.3.3.4 Subsystem Level

The conceptual framework consists of subsystems. These subsystems are Power Source, Order Processing, Machinery, Employees, Parts Availability at the Facility, Parts Availability at the Work Station, and Delivery. Each of these subsystems will be discussed in terms of their respective intended function, system effectiveness, and reliability. The *intended function* of each subsystem component states the purpose of the subsystem with regard to the organization's purpose, *system effectiveness* refers to the probability that the Lean system can successfully meet an operational demand within a given time when operated under specified conditions. Finally, *reliability* is defined as the probability that the Lean system will perform satisfactorily for at least a given period of time when used under stated conditions. Following are examples of decomposed subsystems within a Lean system beginning with the decomposed Power Source subsystem in Figure 5.

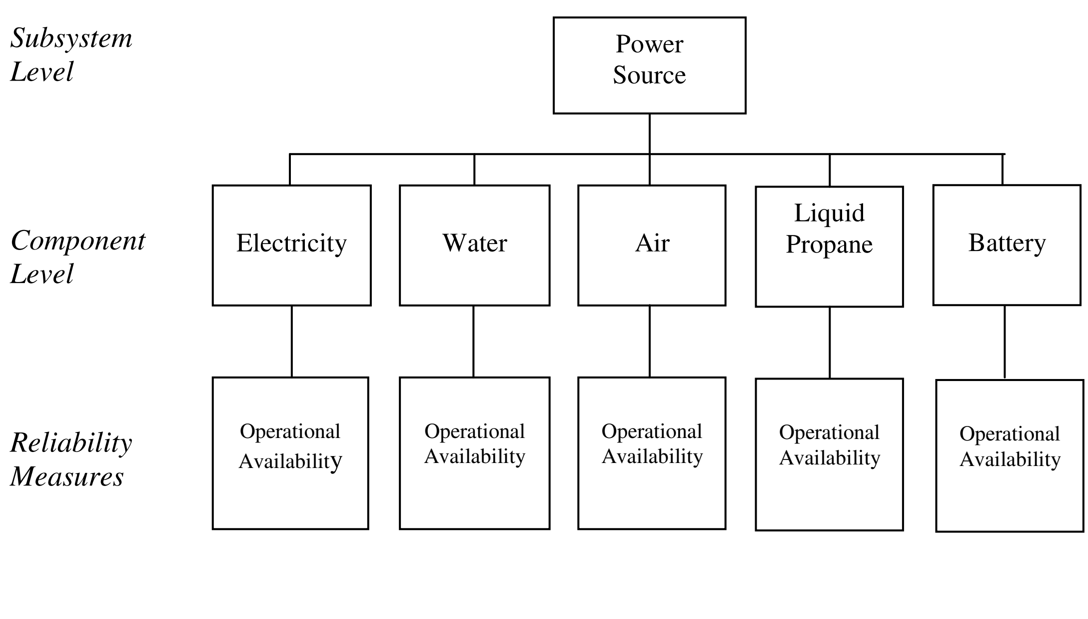


Fig. 5 Power Source Subsystem

Intended Function: Provide a constant supply of power when required to reduce the probability of a Lean systems failure due to disruptions in power.

System Effectiveness: The probability of successfully meeting operational demand depends on the availability of electricity, backup source, water, air, liquid propane, battery, etc.

Reliability Defined: Reliability for Power Source is defined as operational availability, or proportion of time that each source of power is available for use under specified conditions versus the total time required in a series system as follows:

$$R_{s(PS)} = [r_E + r_b(1 - r_E)] \times r_W \times r_A \times r_{LP} \times r_B$$

where

$R_{s\,(PS)}$ = operational availability of Power Source subsystem
r_E = operational availability of Electricity
r_b = operational availability of backup Electrical supply
r_W = operational availability of Water
r_A = operational availability of Air
r_{LP} = operational availability of Liquid Propane
r_B = operational availability of Battery

The decomposed Order Processing subsystem is shown in Figure 6.

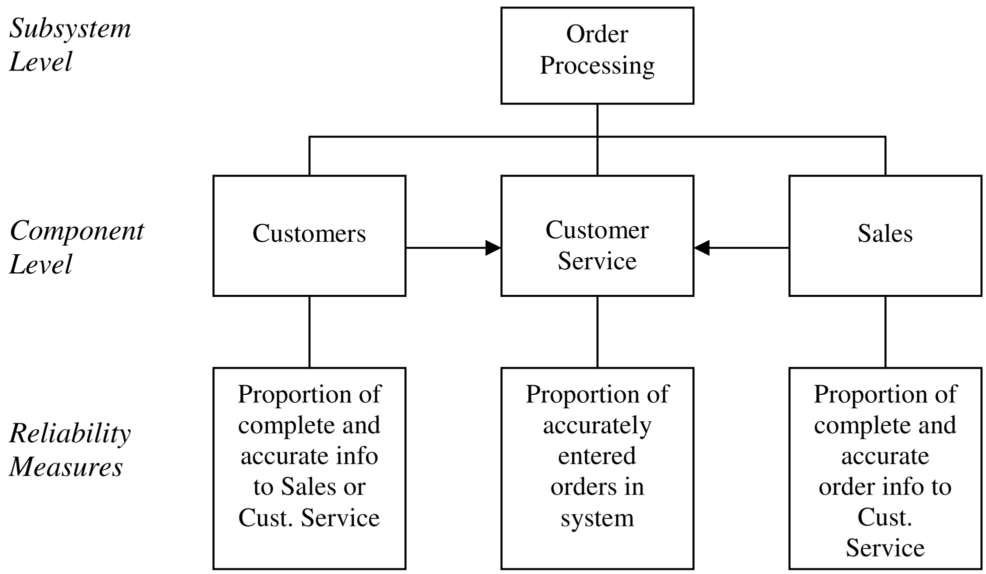


Fig. 6 Order Processing Subsystem

Intended Function: Receive and process accurate order information from customers, salespeople, and customer service into a computerized production scheduling system.

System Effectiveness: When work orders contain accurate information, system effectiveness is enhanced substantially because it entails all of the following when producing orders – the correct machine is available when needed, sufficient manpower is scheduled and available to produce the order, correct raw materials are available for materials processing, unitizing or packaging instructions are easily accessible to producers, and delivery information is immediately available for the Logistics department.

Reliability Defined: Reliability for Order Processing is defined as the proportion of orders that are completely and accurately entered into the production system over time in a parallel system as follows:

$$R_{p(OP)} = 1 - (1 - r_C)(1 - r_{CS})(1 - r_S)$$

where

$R_{p((OP)}$ = reliability of Order Processing subsystem
r_C = reliability of Customer-provided order information
r_{CS} = reliability of Customer Service-provided order information and order entries
r_S = reliability of Sales-provided order information

The decomposed Machinery subsystem is shown in Figure 7.

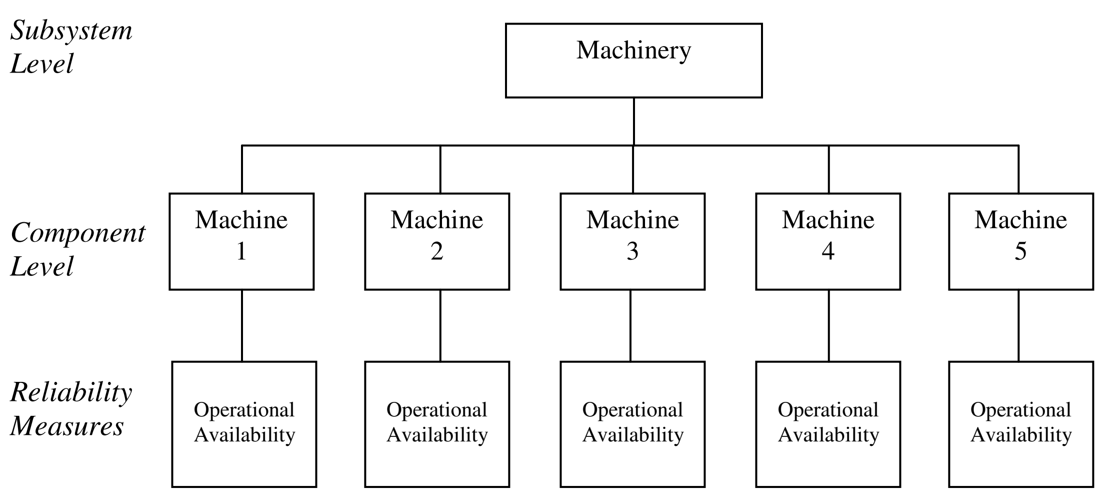


Fig. 7 Machinery Subsystem

Intended Function: Assure machinery availability when required by operational demand.

System Effectiveness: To successfully meet operational demand, system effectiveness depends on factors such as:

1) Properly maintained machinery with periodic preventive maintenance activities
2) Operating machinery under specified conditions
3) Following standard operating procedures.

Reliability Defined: Reliability for Machinery is defined as operational availability, or proportion of time each machine is available for use under specified conditions versus the total time required in a series system as follows:

$$R_{s(M)} = r_1 \times r_2 \times r_3 \times r_4 \times r_5$$

where

$R_{s(M)} =$ operational availability of Machinery subsystem
$r_1 =$ operational availability of Machine 1
$r_2 =$ operational availability of Machine 2
$r_3 =$ operational availability of Machine 3
$r_4 =$ operational availability of Machine 4
$r_5 =$ operational availability of Machine 5

The decomposed Employee subsystem is shown in Figure 8.

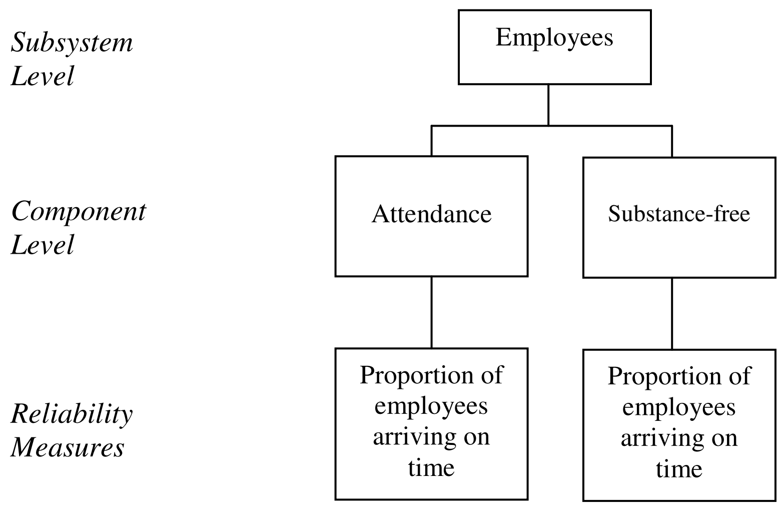


Fig. 8 Employees Subsystem

Intended Function: Stable, substance-free workforce with perfect attendance.

System Effectiveness: Successfully meeting operational demand is contingent upon factors such as:

1) Employees arriving on time for scheduled work
2) Employees who are "substance –free"
3) Employees following standard operating procedures

Reliability Defined: Reliability for Employees is defined as the proportion of substance-free employees arriving on time for scheduled work in a parallel systems as follows:

$$R_{p(E)} = r_A \times r_{SF}$$

where

$$R_{p(E)} = \text{ reliability of Employee subsystem}$$
$$r_A = \text{ reliability of employee attendance}$$
$$r_{SF} = \text{ reliability of ``substance-free'' employees}$$

The decomposed Parts Availability subsystem is shown in Figure 9.

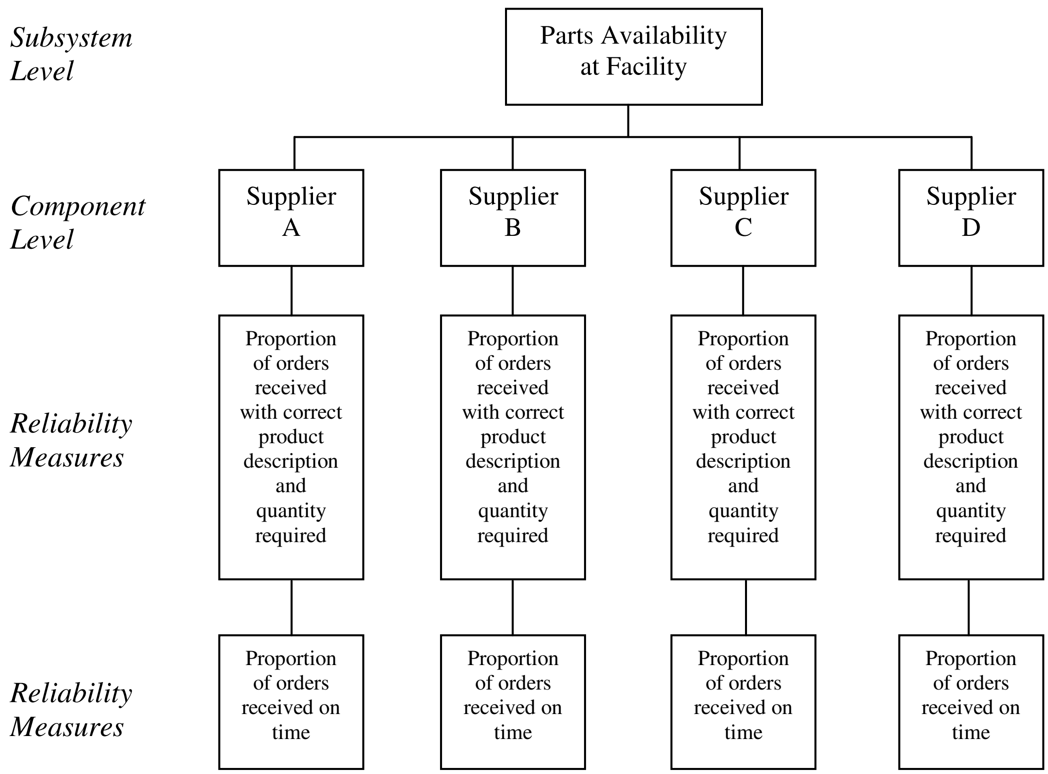


Fig. 9 Parts Availability at Facility Subsystem

Intended Function: Correct parts arriving on time at the facility.

System Effectiveness: Successfully meeting operational demand depends on factors such as:

1) Using parts that meet or exceed customer specifications
2) The transport of parts to eithera storage area or directly to the work station
3) Tracking system to easily locate parts.

Reliability Defined: Reliability for Parts Availability at Facility is defined as the proportion of orders received with correct product description and quantity and proportion of orders received on time in a series system as follows:

$$R_{s(F)} = r_A \times r_B \times r_C \times r_D$$

where

$R_{s(F)}$ = reliability of Parts Availability at Facility subsystem

r_A = reliability of supplier A

r_B = reliability of supplier B

r_C = reliability of supplier C

r_D = reliability of supplier D

The decomposed Parts Availability at Work Station is shown in Figure 10.

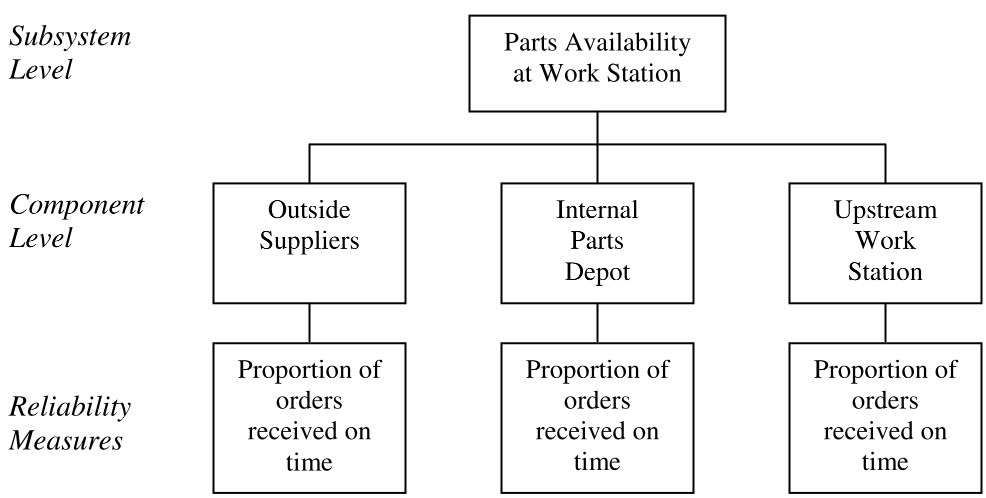


Fig. 10 Parts Availability at Work Station system

Intended Function: Correct parts arriving at the work station when required.

System Effectiveness: Successfully meeting operational demand depends on factors such as:

1) Using parts that meet or exceed customer specifications
2) The transport of parts directly to the work station
3) Tracking system to easily locate parts.

Reliability Defined: Reliability for Parts Availability at Work Station is defined as the proportion of orders received with correct product description and quantity and proportion of orders received on time is a series system as follows:

$$R_{p(WS)} = r_{OS} \times r_{IPD} \times r_{UWS}$$

where

$R_{p(WS)}$ = reliability of Parts Availability at Work Station subsystem
r_{OS} = reliability of Outside Suppliers
r_{IPD} = reliability of Internal Parts Depot
r_{UWS} = reliability of Upstream Work Stations

The decomposed Delivery subsystem is shown in Figure 11.

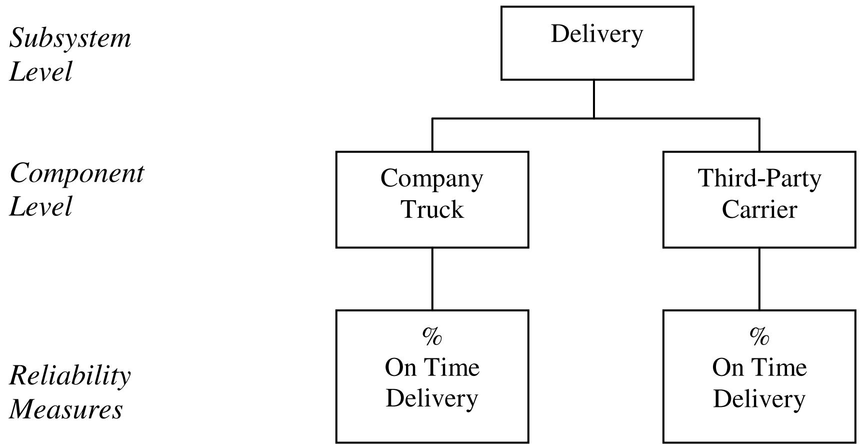


Fig. 11 Delivery Subsystem

Intended Function: Deliver orders on time at the proper destination at minimal cost.

System Effectiveness: The probability of successfully meeting operational demand from a Delivery standpoint is contingent on factors such as the production of customer orders with accurate information made with the correct parts, proper identification and loading of customer orders from the production line or from the warehouse, properly maintained delivery vehicles or reliable third-party freight carriers.

Reliability: Reliability for Delivery is defined as % on time delivery, whether by company-owned truck or via third-party carrier, under specified conditions over time in a parallel system as follows:

$$R_{p(D)} = 1 - (1 - r_{CT})(1 - r_{TPC})$$

where

$R_{p(D)} =$ reliability of parallel Delivery subsystem

$r_{CT} =$ reliability of Company Trucks

$r_{TPC} =$ reliability of Third-Party Carriers

3.3.3.5 Component Level

A description of subsystem components regarding their intended functions, system effectiveness, and reliability follows:

1. Power Source Components

Intended Function: Provide a constant supply of power when required to reduce the probability of a Lean systems failure due to a disruption in power.

System Effectiveness: The probability that the system can successfully meet an operational demand depends on a constant current of electrical, water, and air power when required.

Reliability Defined: Reliability for Power Source components is defined as operational availability, or proportion of time each source of power is available for use under specified conditions versus the total time required over time.

Components for Power Source are shown in Figure 12.

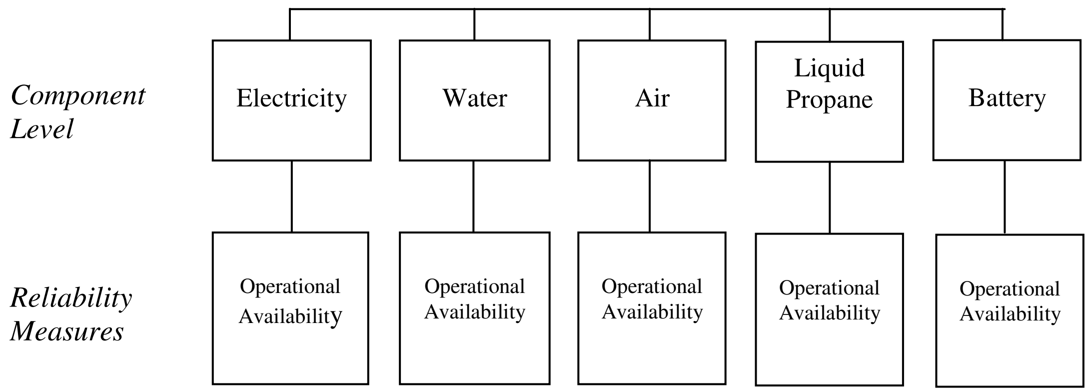


Fig. 12 Components of Power Source Subsystem

2. Order Processing Components

Intended Function: Provide customer service personnel complete and accurate order information for entry into the production scheduling system.

System Effectiveness: The ability of the system to meet an operational demand is contingent upon the acquisition of accurate order information and the provision of scheduled raw materials, available machinery, and manpower to produce the order.

Reliability Defined: Reliability for Order Processing components is defined as the proportion of orders that are completely and accurately communicated to customer service and entered into the production system over time.

Components for Order Processing are shown in Figure 13.

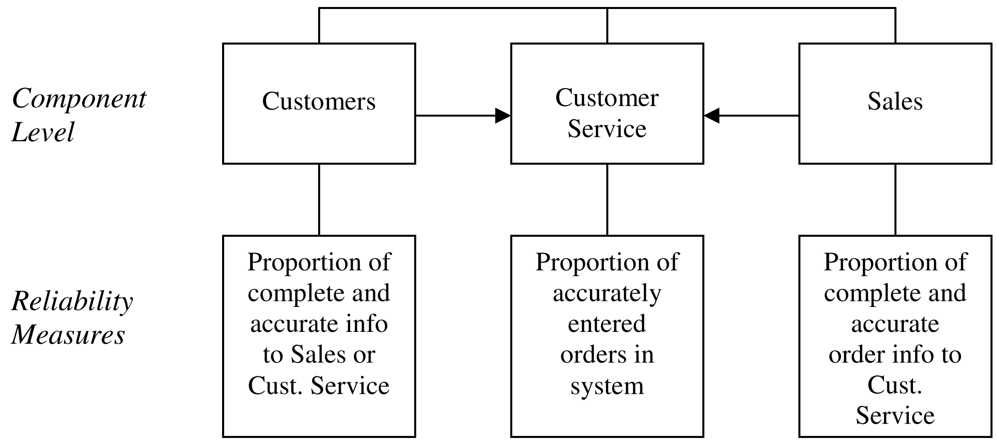


Fig. 13 Components of Order Processing Subsystem

3. Machinery Components

Intended Function: Machinery availability when required by operational demand.

System Effectiveness: To successfully meet operational demand, system effectiveness depends on factors such as: 1) Properly maintained machinery with periodic preventive maintenance activities; 2) Operating machinery under specified conditions; and 3) Following standard operating procedures.

Reliability Defined: Reliability for Machinery components is defined as operational availability, or proportion of time each machine is available for use under specified conditions versus the total time required.

Components for Machinery are shown in Figure 14.

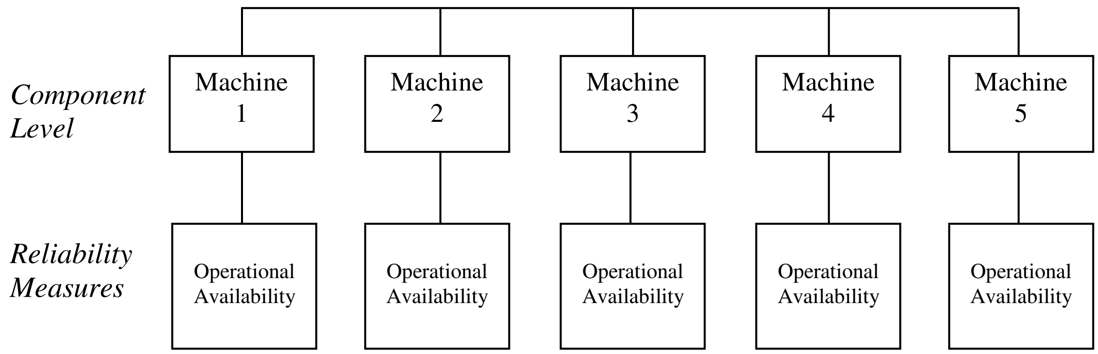


Fig. 14 Components of Machinery Subsystem

4. Employees Component

Intended Function: Stable workforce with perfect attendance.

System Effectiveness: Successfully meeting operational demand is contingent upon factors such as: 1) Employees arriving on time for scheduled work; 2) Employees who are free of distractions, including substance abuse; 3) Employees following standard operating procedures; and 4) Employees working together towards a common goal.

Reliability Defined: The reliability for Employees component is defined as the proportion of employees arriving on time for scheduled work.

Components for Employees are shown in Figure 15.

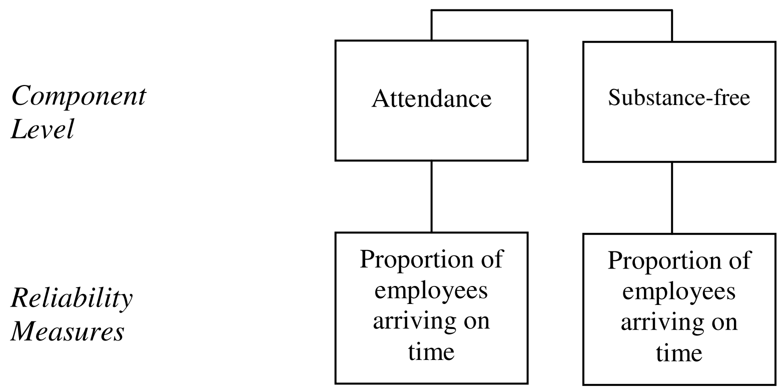


Fig. 15 Components of Employees Subsystem

5. Parts Availability at Facility Components

Intended Function: Correct parts arriving on time at the facility from each supplier.

System Effectiveness: Successfully meeting operational demand depends on factors such as:

1) Using parts that meet or exceed customer specifications
2) The transport of parts to either a storage area or directly to a work station
3) Tracking system to easily locate parts

Reliability Defined: Reliability for Parts Availability at Facility components is defined as the proportion of orders received on time with correct product description and quantity.

Components for Parts Availability at Facility are shown in Figure 16.

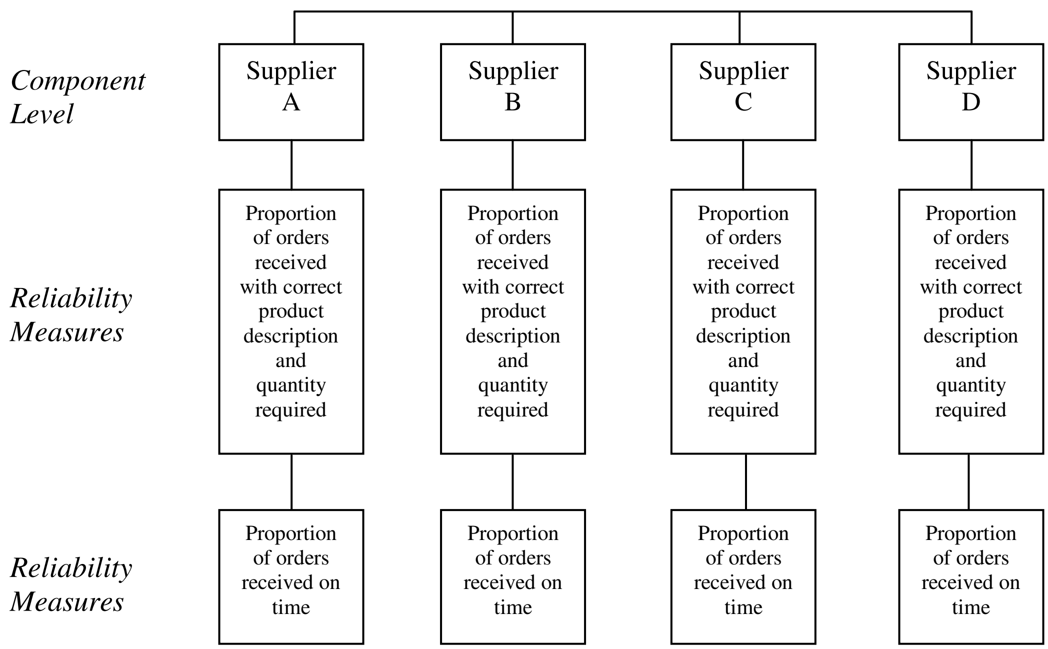


Fig. 16 Components of Parts Availability at Facility Subsystem

6. Parts Availability at Work Station Components

Intended Function: Correct parts arriving at the work station when required from each supplier.

System Effectiveness: Successfully meeting operational demand depends on factors such as:

1) Using parts that meet or exceed customer specifications
2) The transport of parts to either a storage area or directly to a work station
3) Tracking system to easily locate parts

Reliability Defined: Reliability for Parts Availability at Work Station components is defined as the proportion of orders received with correct product description and quantity and proportion of orders received that are defect-free.

Components for Parts Availability at Work Station are shown in Figure 17.

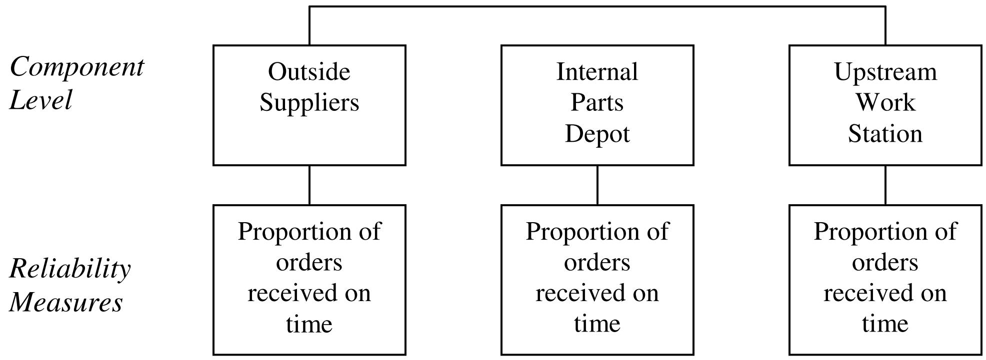


Fig. 17 Components of Parts Availability at Work Station Subsystem

7. Delivery Components

Intended Function: Deliver orders on time at the proper destination at minimal cost.

System Effectiveness: The probability of successfully meeting operational demand from a Delivery standpoint is contingent upon factors such as the production of customer orders with accurate information made with the correct parts, proper identification and loading of customer orders from the production line or from the warehouse, properly maintained delivery vehicles and reliable third-party freight carriers.

Reliability Defined: Reliability for Delivery components is defined as % on time delivery, whether by company-owned truck or via third-party carrier, under specified conditions over time.

Components for Delivery are shown in Figure 18.

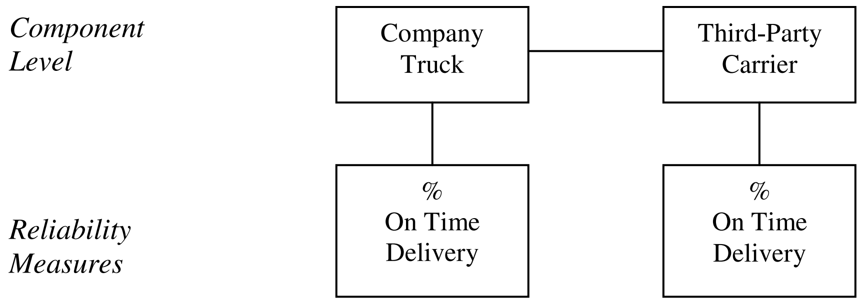


Fig. 18 Components of Delivery Subsystem

3.4 Data Collection Methodology

3.4.1 LSRM Operational Measures

An operational measurement scheme of inputs, process measures, and outputs is used to describe Lean subsystems.

1. Power Source

Input measures for the reliability of sources of power components including electricity, natural gas, liquid propane, air, and water consist of the amount of the time (measured in minutes) that each component is required during the workday.

Process measures include both the number of power failures and the length of time (using a timing device such as a stopwatch) of each failure.

Output measures consist of the percentage of workday time that each power source component is available for use versus the total time required for use.

2. Parts Availability at Facility

Input measures for the reliability of parts availability at the facility consist of the timeliness of arrival at the facility versus the requested time when parts or materials orders are placed.

Process measures include average wait time if parts or materials arrivals are delayed, correct quality levels (percentage of average deviation from the ideal for various critical parameters such as correct item description, size, color, etc.), and quantity levels (comparing the total quantity and unit counts of parts or materials arriving at the facility versus requested total quantity and unit counts when parts or materials orders are placed), and cycle time (minutes to complete an activity once started).

Output measures include output quality (percentage level of defects in finished parts or materials), and delivery accuracy (time of delivery of finished products versus required delivery time).

3. Parts Availability at Work Station

Input measures for the reliability of parts availability at the work station requires materials handling from station to station and consists of the timeliness of arrival at the work station versus the required time when parts or materials are needed and quality of incoming materials (number of errors).

Process measures include average wait time if parts or materials arrivals are delayed from upstream work stations, correct quality levels (percentage of average deviation from specifications for various critical parameters such as correct item description, size, color, etc.), quantity levels (comparing the total quantity and unit counts when parts or materials arriving at the work station versus the required total quantity and unit counts when parts or materials are needed), and rework levels (percentage of time rework activity occurs to correct errors), and cycle time (minutes to complete an activity once started).

Output measures include output quality (percentage level of defects in delivered parts or materials), delivery accuracy (time of delivery of finished products versus required delivery time), and employee satisfaction (downstream employee perception of department versus defined criteria).

4. Order Processing

Input measures for order processing involve three components in parallel – the customer, the salesperson, and the customer service representative and consists of the number of orders entered and the number of orders completed daily.

Process measures include number of handoffs (average number of people an order passes through before it is entered into the system) and average wait time (minutes that orders are held in queue until complete information is obtained from the customer or salesperson such as purchase order number, product identification, quantity, due date, special instructions, shipping destination, etc.).

Output measures include order accuracy (percentage of orders entered and invoiced with complete and accurate information) and employee satisfaction (downstream work station employee perception of department versus defined criteria).

5. Machinery

Input measures for the reliability of machinery consist of machine availability.

Process measures include order cycle time (minutes to complete an order once started at a machine center), average wait time (minutes waiting for people, parts, or materials), and downtime (percentage of time machines are unavailable for use).

Output measures consist of the proportion uptime each machine is available for use versus to total available machine time.

6. Employees

Input measures for the reliability of employees consist of the number of employees who are scheduled to work and the number of orders that are produced.

Process measures include setup failure levels (percentage of orders containing setup errors), problem diagnosis failure levels (percentage of orders containing run time problems that are mis-diagnosed by the machine operator), and inspection failure levels (percentage of orders that were produced products out-of-specification).

Output measures include employee attendance, that is, the proportion of employees who arrive at work on time, are tardy, or absent relative to the total number of employees scheduled to work and order accuracy (percentage of correctly produced orders versus the total number of orders run).

7. Delivery

Input measures for the reliability of deliveries include the percentage of completed orders that are ready for delivery from upstream work stations versus the number of orders that are scheduled for delivery each workday.

Process measures include average wait time (minutes waiting to load trucks at the manufacturer's facility or waiting to unload trucks at the customer's location), downtime (percentage of time delivery trucks are unavailable for use due to maintenance issues such as breakdowns or service work), and number of deliveries scheduled.

Output measures include on time delivery percentage and delivery accuracy; that is, the percentage of orders delivered to the correct destination, within the designated receiving hours, and via the correct mode of transport.

3.4.2 Data Collection

The primary purpose of data collection is to obtain accurate production information to support dynamic changes in the manufacturing process as a direct result of ongoing Lean initiatives. Reliability data for each Lean subsystem and subsystem components is collected in the following manner:

1. Power Source

Operational availability, which measures the proportion of time each power source is readily available for use relative to the total time required, is recorded each workday. A timing device such as a stopwatch is routinely used to measure the length of downtime (in minutes) due to power outages or power disruptions.

2. Order Processing

The reliability for Order Processing components is measured as the proportion of orders that are completely and accurately entered into the production scheduling system over time. This information is recorded daily by customer service personnel with regard to the communication of order information from salespeople and customers via telephone, fax, or email to customer service. Additionally, the proportion of orders with complete and accurate information entered by customer service personnel via computer into the production system is recorded daily.

3. Machinery

Operational availability, which measures the proportion of time each machine is readily available for use relative to the total time required, is recorded each workday. A timing device such as a stopwatch is routinely used to measure the length of downtime (in minutes) due to breakdowns, adjustments, replacement parts, or preventive maintenance.

4. Employees

The reliability of employees is measured as the proportion of employees arriving on time for scheduled work. An employee is considered “on time” when he or she clocks in prior to their scheduled start time and is ready for work when the shift begins. Vacation time and excused absences such as bereavement time or jury duty are omitted from data analysis as prior notice is provided. Unexcused absences, tardiness, and illness are considered failures in this subsystem and, therefore, impacts negatively with regard to the overall reliability of employees.

5. Parts Availability at Facility

The reliability of parts availability at facility is measured by the receiving clerk, who compares each parts arrival with a copy of the purchase requisition. The proportion of parts orders received when required with correct product description and quantity and that are defect-free during each workday is documented on a spreadsheet.

6. Parts Availability at Work Station

The reliability of parts availability at facility is measured by the shop floor supervisor, who compares each parts arrival with the internal parts requisition. Parts may arrive from outside suppliers, the internal parts depot, or from an upstream work station. The proportion of parts orders received when required with the correct product description and quantity and that are defect-free during each workday is documented on a spreadsheet.

7. Delivery

The reliability for Delivery is measured as % on time delivery, whether by company-owned truck or via third-party carrier. Hence, this metric is measured by the logistics manager as the daily proportion of orders that arrive at the proper destination per scheduled due date.

3.5 Development of LSRM – Phase 2

3.5.1 Methodology for Determining Critical Subsystems

When a data set consists of many variables, it is considered highly dimensional data, and redundancy may exist among the variables. In this context, redundancy implies that some of the variables are correlated with one another (Nagai et al., 2008). Because of this redundancy, it is possible to reduce the observed variables into a smaller set of critical subsystems that will explain most of the variation in the original set of observed variables.

The identification of critical subsystems for highly dimensional data involves the use of a procedure known as Principal Components Analysis (PCA), which is used to transform a set of correlated response variables into a smaller set of uncorrelated variables called principal components, or subsystems (Johnson, 1998); thus, reducing the dimensionality (i.e., the number of variables) in the data set. The mathematical technique used in PCA is called eigen analysis, which solves for the eigenvalues and eigenvectors of a square symmetrical matrix with sums of squares and cross products.

Critical subsystems are weighted linear combinations of input variables and are orthogonal (i.e., uncorrelated) to and independent of other components. The critical subsystems are generated so that the first subsystem accounts for the most variation, followed by the second subsystem, and so on. The flow chart in Figure 19 displays the algorithm used to determine critical subsystems.

PCA computes both eigenvalues and eigenvectors for a given data set. The number of eigenvalues is equal to the number of rows (or columns) in the matrix. Eigenvalues measure the strength (relative length) of an axis that is derived from a square symmetric matrix. The magnitude of the eigenvalues corresponds to the variance of the data along the eigenvector

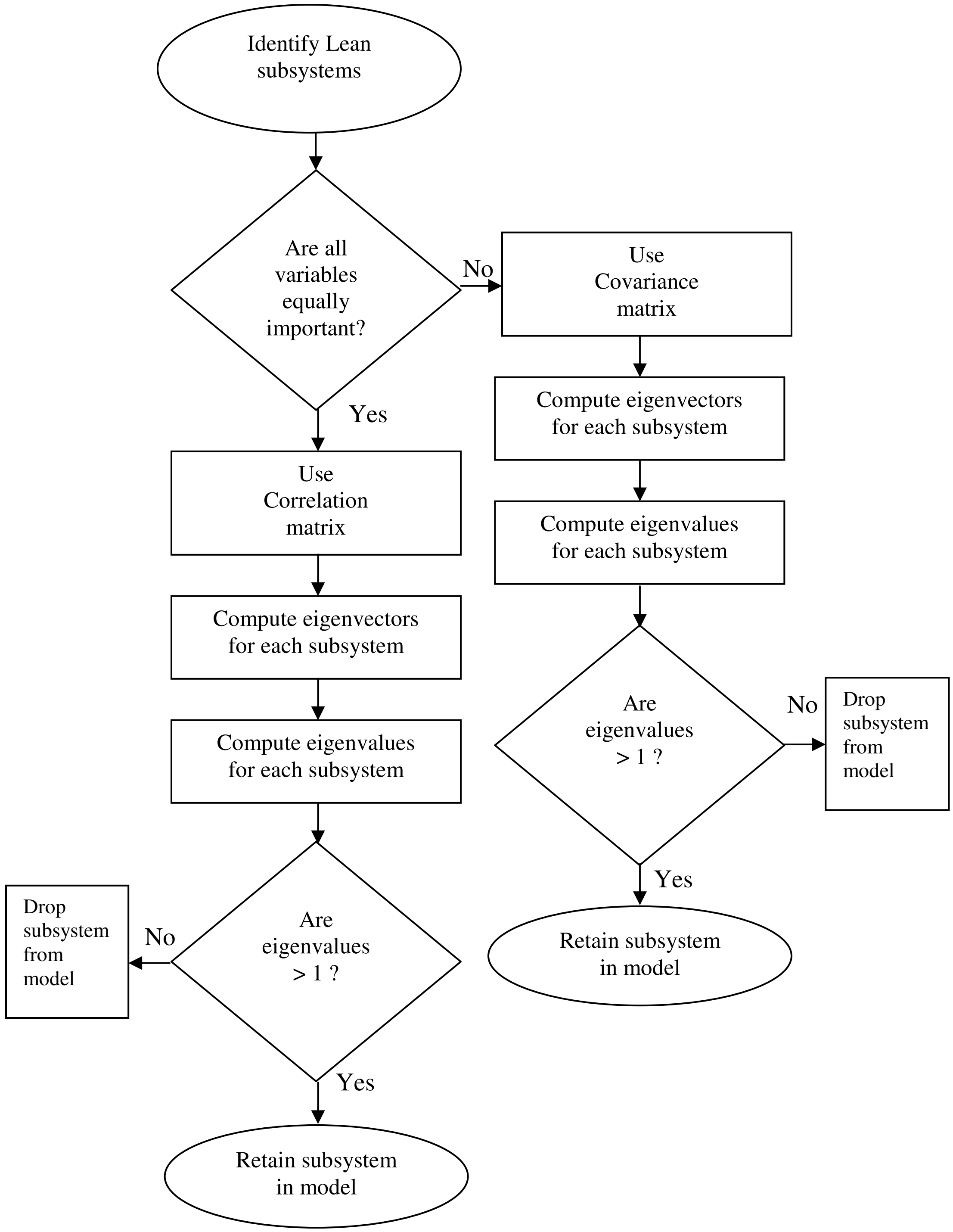


Fig. 19 Flow chart for Determining Critical Subsystems

directions. The sum of the eigenvalues is equal to the trace, which is the sum of the diagonal elements of the square matrix.

Each eigenvalue has a respective eigenvector. Whereas an eigenvalue provides us with the length of an axis, the eigenvector determines its orientation in space and is normally standardized; that is, eigenvectors convert data to normal scores with a mean of 0 and a standard deviation of 1 by thefollowing method:

$$\frac{x_i - \mu}{\sigma}$$, where μ and σ are the mean and standard deviation of x_i's

If all variables are considered equally important, then eigenvectors (shown in Table 1) and eigenvalues (shown in Table 2) are determined for all response variables using a correlation matrix (shown in Table 3), which standardizes the data. The principal subsystem values are derived from the eigenvector linear combination of the standardized variables.

A correlation matrix is a square symmetrical *N x N* matrix that describes correlation among the *N* variables (McClave and Benson, 1985). In this matrix, the (*ij*)th element, where

i = element in row *i*
j = element in column *j*

Table 1 Eigenvectors of Response Variables Using Correlation Matrix

Comp	Prin1	Prin2	Prin3	Prin4	Prin5
1	-0.42451	0.09821	0.89535	-0.05294	0.07549
2	0.52600	0.29886	0.29070	0.55934	-0.48645
3	-0.49820	0.12008	-0.22801	0.77532	0.29030
4	0.26811	0.76335	-0.01379	-0.16153	0.56491
5	0.47226	-0.55128	0.24833	0.23902	0.59520

Table 2 Eigenvalues of Response Variables Using Correlation Matrix

Number	Eigenvalue	Percent	Percent	Cum Percent
1	1.4096	28.191		28.191
2	1.1452	22.905		51.096
3	0.9091	18.181		69.277
4	0.8840	17.681		86.958
5	0.6521	13.042		100.000

Table 3 Correlation Matrix

Comp	1	2	3	4	5
1	1.0000	-0.0947	0.1040	-0.0504	-0.1244
2	-0.0947	1.0000	-0.0972	0.1973	0.1565
3	0.1040	-0.0972	1.0000	-0.0842	-0.1824
4	-0.0504	0.1973	-0.0842	1.0000	-0.1214
5	-0.1244	0.1565	-0.1824	-0.1214	1.0000

is equal to the correlation coefficient (also called the Pearson product moment coefficient of correlation), which is calculated as follows:

$$r = \frac{\sum_{i=1}^{n} x_i y_i - \frac{\left(\sum_{i=1}^{n} x_i\right)\left(\sum_{i=1}^{n} y_i\right)}{n}}{\sqrt{\left(\sum_{i=1}^{n} x_i^2 - \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n}\right)\left(\sum_{i=1}^{n} y_i^2 - \frac{\left(\sum_{i=1}^{n} y_i\right)^2}{n}\right)}}$$

where

$x_i =$ ith element of each predictor variable
$y_i =$ ith element of the response variable
$n =$ number of observations

The correlation coefficient, r, indicates the degree of linear relationship between two variables. The correlation coefficient always lies between -1 and +1. A value of r near or equal to zero implies little or no linear relationship between the two variables of interest. In contrast, the closer r is to -1 or +1, the stronger the linear relationship between the two variables of interest. Positive r values indicate that as one variable increases, the other variable increases. Negative r

values indicate that as one variable decreases, the other variable increases. The diagonal elements of a correlation matrix are always equal to 1, since they represent correlations of variables with themselves.

If all variables are not considered equally important, then eigenvectors (shown in Table 4) and eigenvalues (shown in Table 5) are computed using a covariance matrix (shown in Table 6), which computes the covariance between each of the columns of the data. Covariance is always measured between two dimensions.

The formula for covariance is given by:

$$\operatorname{cov}(X,Y) = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{n-1}$$

Table 4 Eigenvectors of Response Variables Using Covariance Matrix

Comp	Prin1	Prin2	Prin3	Prin4	Prin5
WS	-0.04878	-0.10792	-0.05099	0.77837	-0.61442
D	0.08337	0.54910	0.82309	0.11606	-0.02435
F	-0.07000	-0.13658	0.03699	0.59886	0.78514
M	-0.06878	0.81742	-0.55404	0.12530	0.06659
PS	0.99047	-0.00443	-0.10765	0.07959	0.03191

Table 5 Eigenvalues of Response Variables Using Covariance Matrix

Number	Eigenvalue	Percent	Percent	Cum Percent
1	0.0078	60.761		60.761
2	0.0021	16.127		76.888
3	0.0012	9.684		86.572
4	0.0009	7.152		93.725
5	0.0008	6.275		100.000

Table 6 Covariance Matrix

Comp	1	2	3	4	5
1	0.00091	-0.00011	0.00009	-0.00006	-0.00033
2	-0.00011	0.00153	-0.00011	0.00033	0.00054
3	0.00009	-0.00011	0.00090	-0.00011	-0.00048
4	-0.00006	0.00033	-0.00011	0.00182	-0.00045
5	-0.00033	0.00054	-0.00048	-0.00045	0.00767

However, calculating the covariance between one dimension and itself is reduced to the variance, whose formula is given by:

$$\mathrm{var}(X) = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(x_i - \bar{x})}{n-1} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}$$

Higher-dimensional data sets require a covariance measurement for each dimension. For an *n*-dimensional data set, one could compute $\frac{n!}{(n-2)!*2}$ different covariance values. For example, a covariance matrix for a 3-dimensional data set is given by:

$$C = \left\{ \begin{array}{ccc} cov\ (x,x) & cov\ (x,y) & cov\ (x,z) \\ cov\ (y,x) & cov\ (y,y) & cov\ (y,z) \\ cov\ (z,x) & cov\ (z,\ y) & cov\ (z,z) \end{array} \right\}$$

Using the Kaiser criterion (Havold, 2005), we would retain only subsystems with eigenvalues greater than 1 as shown in the example in Table 2, since these subsystems explain more of the variance than any single variable in the analysis. Eigenvalues close to zero measure nothing but random noise and may be ignored. In this hypothetical example, we would retain only two subsystems. We observe that the first principal subsystem accounts for 23.79% of the total variability, and the second principal subsystem accounts for 20.57% of the total variability. The first two principal subsystems together account for 44.36% of the total variability. Note that the eigenvalues sum to 5, the number of response variables in this analysis. With PCA, all response variables are measured in the same units.

Cattell (1966) offers a graphical criterion test known as a Scree plot to determine factor retention as shown in Figure 20. A Scree plot is constructed by plotting the value of each eigenvalue against the numbered eigenvalue in which it represents. This Scree plot suggests that the true dimensionality of the space in which the data lie is 2 within the 5-dimensional sample space. Therefore, the number of principal subsystems to use is also 2.

Under normal conditions, which means having relatively few factors and many cases, both subsystem retention criteria work quite well (Cattell and Sullivan, 1962; Cattell and Jaspers, 1967; Cattell, 1978; Zwick and Velicer, 1982; Heymann and Noble; 1989). In practice, one may examine several solutions with more or less factors, choosing the one that makes the best practical sense.

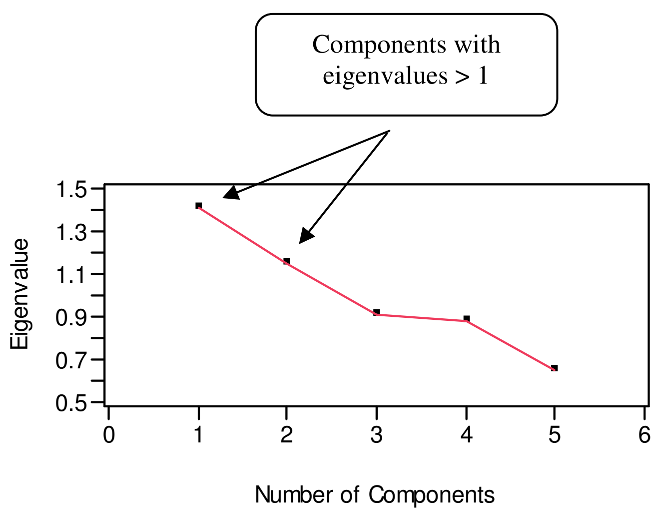


Fig. 20 Scree Plot

3.5.2 Characteristics of Critical Subsystems

The following is a brief explanation of the characteristics of critical subsystems:

1) The first subsystem obtained in the PCA accounts for the greatest amount of total variance in the observed variables. Total variance in the data set equals the sum of the variances of the observed variables. This implies that the first subsystem will be correlated with at least some of the observed variables. The eigenvectors associated with the largest eigenvalue has the same direction as the first critical subsystem.

2) The second subsystem obtained will have two significant characteristics. First, this subsystem will account for the greatest amount of total variance in the observed variables that was not accounted for by the first subsystem. This implies that the second subsystem will be correlated with at least some of the observed variables that did not exhibit strong correlations with the first subsystem. The eigenvector associated with the second largest eigenvalue determines the direction of the second critical subsystem.

   The second significant characteristic of the second subsystem is that it will be orthogonal, or uncorrelated, with the first subsystem. This implies that the correlation coefficient between the first and second subsystem will be zero.

The remaining subsystems are obtained in the same manner and with the same characteristics as in the second subsystem. That is, each successive subsystem will account for the greatest amount of total variance in the observed variables that were unaccounted for by all preceding subsystems; is orthogonal with all preceding components; and its eigenvalue determines the direction of the critical subsystem. Hence, each successive subsystem accounts for progressively smaller amounts of variation in the observed variables, is orthogonal with all preceding subsystems, and its direction is based on its respective eigenvalue.

3.6 Methodology for Determining Critical Workflow Sequence

Those with expert knowledge of a given Lean system are already familiar with the critical workflow sequence of its Lean subsystems. However, for those unfamiliar with the critical workflow sequence, a Value Stream Map (VSM) is a graphical depiction of the entire flow of activities and subsystems in a complex manufacturing system. Value streams consist of all the activities, both value added and non-value added, that are currently required to produce and deliver the product to the customer. A VSM is used to define value from the customer's perspective and to delineate which process steps create value and which are waste. The goal is to identify, demonstrate, and decrease sources of waste (Ohno, 1985) and create the most value while consuming the fewest resources (Womack, 1996). For example, a VSM for the current state of a hypothetical manufacturing firm is presented in Figure 21.

A natural presumption is that all employees arrive on time for scheduled work so that all required work activities can be performed (Employees subsystem). Moreover, it is naturally assumed that all power sources including electricity, water, and air are operationally available when needed (Power Source subsystem).

The workflow sequence begins with the customer in the form of orders placed. The customer may call the manufacturer directly to place an order via telephone, fax, or email, or may contact the manufacturer's rep to place an order. In this example, customer orders are placed weekly. Customer service personnel typically enter customer orders into a computerized scheduling system (i.e., Materials Requisition Purchasing (MRP) system or other scheduling system). Raw materials are then ordered from suppliers on a daily basis to produce customer orders (Order Processing subsystem). Parts and other raw materials arrive at the manufacturer's facility daily

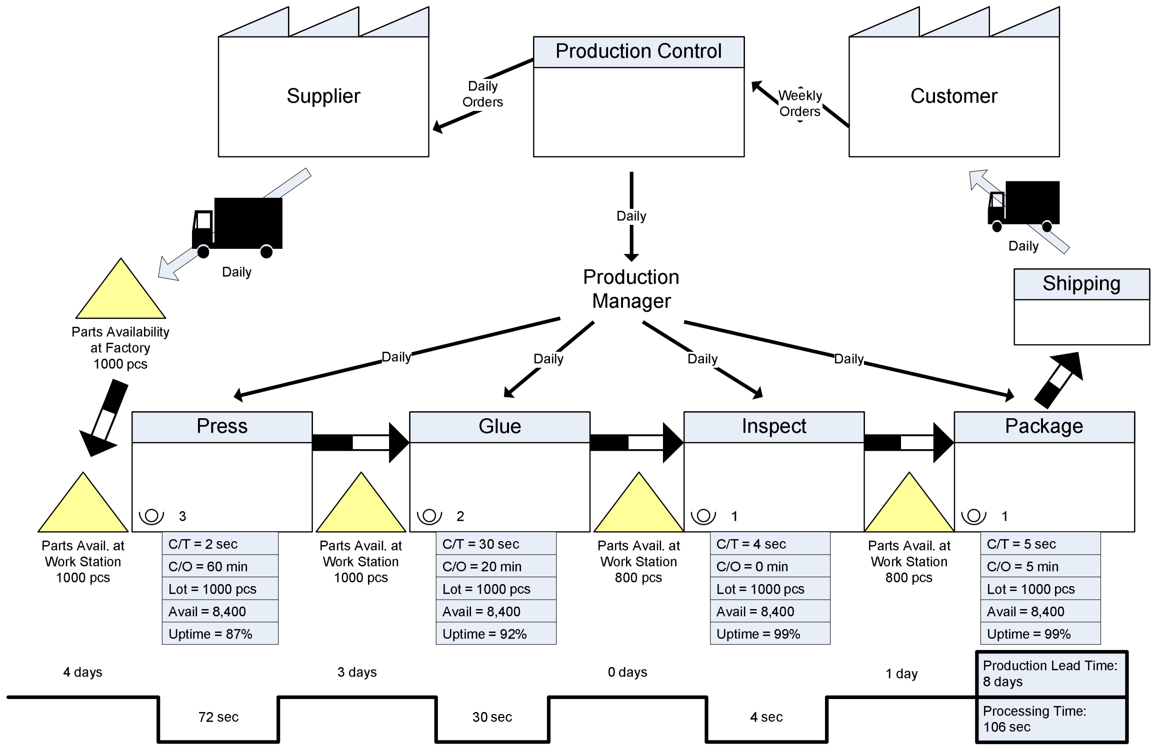


Fig. 21 Current State Value Stream Map

and are either stocked in inventory (i.e., at the internal parts depot or other designated storage location) until required for use, or transported directly to a machine center for processing. The receiving clerk compares parts arrivals with purchase requisitions for various attributes such as on time arrival, receipt of correct products, correct quantities, etc. (Parts Availability at Facility subsystem).

Parts or raw materials must arrive when required at the work station for conversion (Parts Availability at Work Station subsystem). These parts may arrive from outside suppliers, the internal parts depot, or from upstream work stations.

Next, available machinery to process orders (Machinery subsystem) are required. In this example, parts or raw materials are run through a series of value-added activities including processing through a press, then gluing, inspecting, and packaging operations. We observe in the current VSM that this aspect of the production process requires a total of 7 employees (3 employees for the press + 2 employees for gluing + 1 employee to inspect + 1 employee to package the products = 7 employees). We also observe that the manufacturer currently requires 8 days lead time to produce an order. During these 8 days, the total processing time requires only 106 seconds!

On time delivery to the customer (Delivery subsystem) is the final aspect of the Lean manufacturing system. A future VSM aids in prioritizing Lean activities that lead to the achievement of some future state.

3.7 Stochastic Nature of LSRM

Mathematical models can be classified as either probabilistic or deterministic. Because stochastic models involve collections of random variables indicated by parameters such as time and space, they are classified as probabilistic models. Stochastic models are based on random trials of random variables. Random variation is normally based on fluctuations observed in historical data.

A stochastic system integrates structural components with activity. An example is a Lean manufacturing system, combining a building, machinery, raw materials, production workers, management, and work order information. In a stochastic system, the inputs, processes, and outputs can only be described in statistical terms. Uncertainty often results in both the number of inputs as well as the distribution of these inputs over time. However, with sufficient data, these inputs can be described in terms of their probability distributions. Hence, a stochastic Lean system can be described in a probabilistic sense.

Stochastic modeling employs simulation techniques such as Monte Carlo simulation and variations of the Markov chain model, in which ranges of values for each variable are used for estimating probability distributions of potential outcomes. These probability distributions are derived from a large number of simulations, which reflect the random variation in the input variables. Then stochastic projections are made and the results are noted. The stochastic process is repeated thousands of times resulting in a probability distribution of outcomes from which additional information can be extracted, such as revealing both the most likely estimate as well as reasonable ranges of the outcome. If the probability distribution provides a good fit to the data, the properties of the data set may be approximated by the properties of the probability distribution. Volatility and variability (in the form of randomness) are built into the simulation in order to provide a more accurate representation of real life.

By comparison, deterministic models utilize point estimates to represent the value of each variable. Consequently, deterministic models always produce the same output for a given starting condition.

3.7.1 Monte Carlo Simulation

Simulation involves the development of mathematical models to imitate aspects of real life, or to make future predictions. Based on historical data, field expertise, or past experience, estimates can be drawn to project what actual future values will be.

Monte Carlo simulation is an iterative stochastic modeling technique, which involve inputs that are randomly generated from probability distributions to simulate the process of sampling from an actual population. Given a random seed number to start with, a number of mathematical operations can be performed on the random seed to generate pseudorandom numbers. The pseudorandom numbers are then analyzed with stringent statistical tests to ensure that the numbers are, indeed, random with respect to one another. For multiple trials, different random seeds are required to assure obtaining a different set of random numbers each time. A probability distribution for the inputs is chosen that most closely matches the process data set already obtained, which best represents the current state of knowledge.

The goal of Monte Carlo simulation is to determine how random variation and lack of sufficient knowledge affects model characteristics such as sensitivity, performance, and reliability. Monte Carlo simulation is conducted using the five-step process in Figure 22:

When the simulation is complete, a large number of results from the model are saved, each based on random input values from the chosen probability distribution. These results are used to describe the likelihood, or probability, of the resulting outcomes in the model.

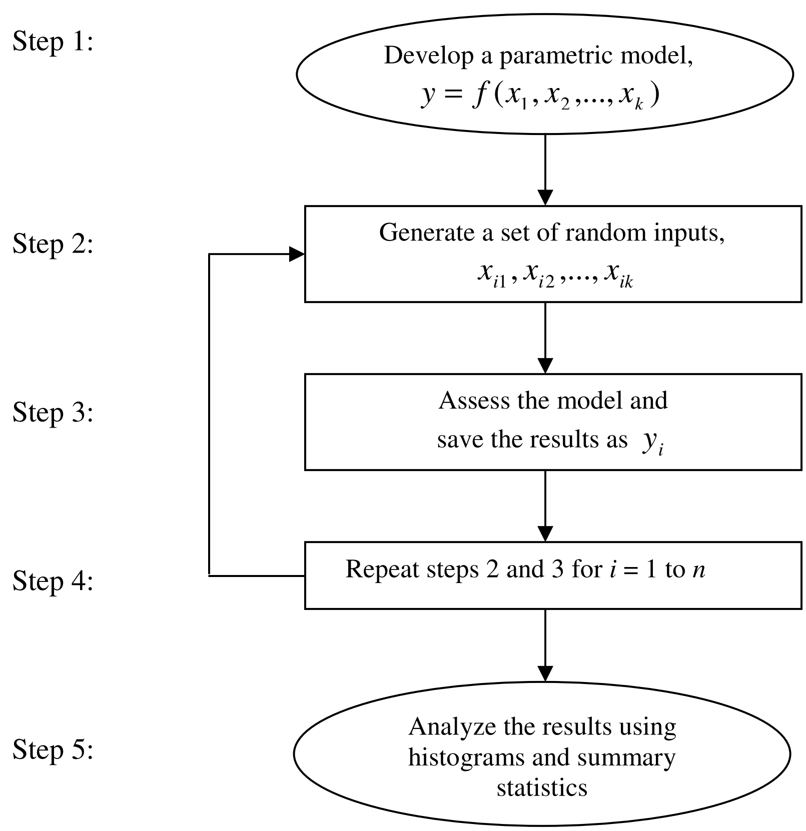


Fig. 22 Flow Chart of Monte Carlo Simulation

3.7.2 Methodology for Detecting Data Abnormalities

After the simulation is completed, outlier box plots, scatter plots, or histograms of the data will be constructed to detect abnormalities such as outliers or distinct patterns that may bias the results. Outliers are data points well outside the range of remaining values. Since Monte Carlo simulation entails the use of random data, abnormal patterns may consist of linearity, curvature, or clusters of data points. Abnormal patterns clearly lack the desired properties of "randomness." Once abnormalities are detected, they are excluded from further analyses in order to eschew the possibility of obtaining skewed results.

3.7.3 Methodology for Fitting Distributions of Subsystems and Components

Simulation data will be entered into a statistical software package such as SAS, SPSS, JMP, Minitab, Excel, etc., and various probability distributions will be fitted to the data. The probability distribution that provides the best "fit" to the data is selected as representative of the data and its associated assumptions will be adjudicated when analyzing the data. The properties of the data set can then be approximated by the properties of the distribution.

While it is possible to make inferences without prior assumptions of a particular parametric form for failure time data, it is appropriate to use a location-scale based parametric distribution form in order to fit the best model possible. A random response variable *Y* belongs to the location-scale family of distributions if its cdf can be expressed as

$$P(Y \leq y) = F(y;\mu,\sigma) = \Phi\left(\frac{y-\mu}{\sigma}\right)$$

Where Φ does not depend on unknown parameters.

3.7.3.1 Likelihood for Location-Scale Distributions

For a random failure variable $-\infty < T < \infty$, the likelihood for failure sample $t_1,....,t_n$ from a location-scale distribution with exact (i.e., not censored) and right-censored (i.e., observance for a given random variable ceases once a failure occurs) can be written as

$$L(\mu,\sigma) = \prod_{i=1}^{n} L_i(\mu,\sigma;data_i) = \prod_{i=1}^{n} [f(t_i;\mu,\sigma)]^{\delta_i}[1-F(t_i;\mu,\sigma)]^{1-\delta_i}$$

which can be expressed as

$$L(\mu,\sigma) = \prod_{i=1}^{n} \left\{ \frac{1}{\sigma t_i} \phi\left[\frac{\log(t_i)-\mu}{\sigma} \right] \right\}^{\delta_i} \times \left\{ 1-\Phi\left[\frac{\log(t_i)-\mu}{\sigma} \right] \right\}^{1-\delta_i},$$

where

$$\delta_i = \begin{cases} 1 & \text{if } t_i \text{ is an exact observation} \\ 0 & \text{if } t_i \text{ is a right-censored observation} \end{cases}$$

3.8 Model Validation – Phase 3

Recall that the levels of system, subsystem, and component are relative terms, since the system at one level in the hierarchy is the component at another level. If the range of mean reliability simulation results among Lean components, Lean subsystems, and the Lean system are accurate to within 3% of historical data results, then the LSRM model is considered a valid model because it is accurate at any level within the Lean system. Amodel validation flow chart is illustrated in Figure 23.

3.8.1 Monte Carlo Simulation of Components

To predict the reliability of Lean subsystem components, we employ Monte Carlo simulation based on historical data. Random data generated from historical observations will be used to

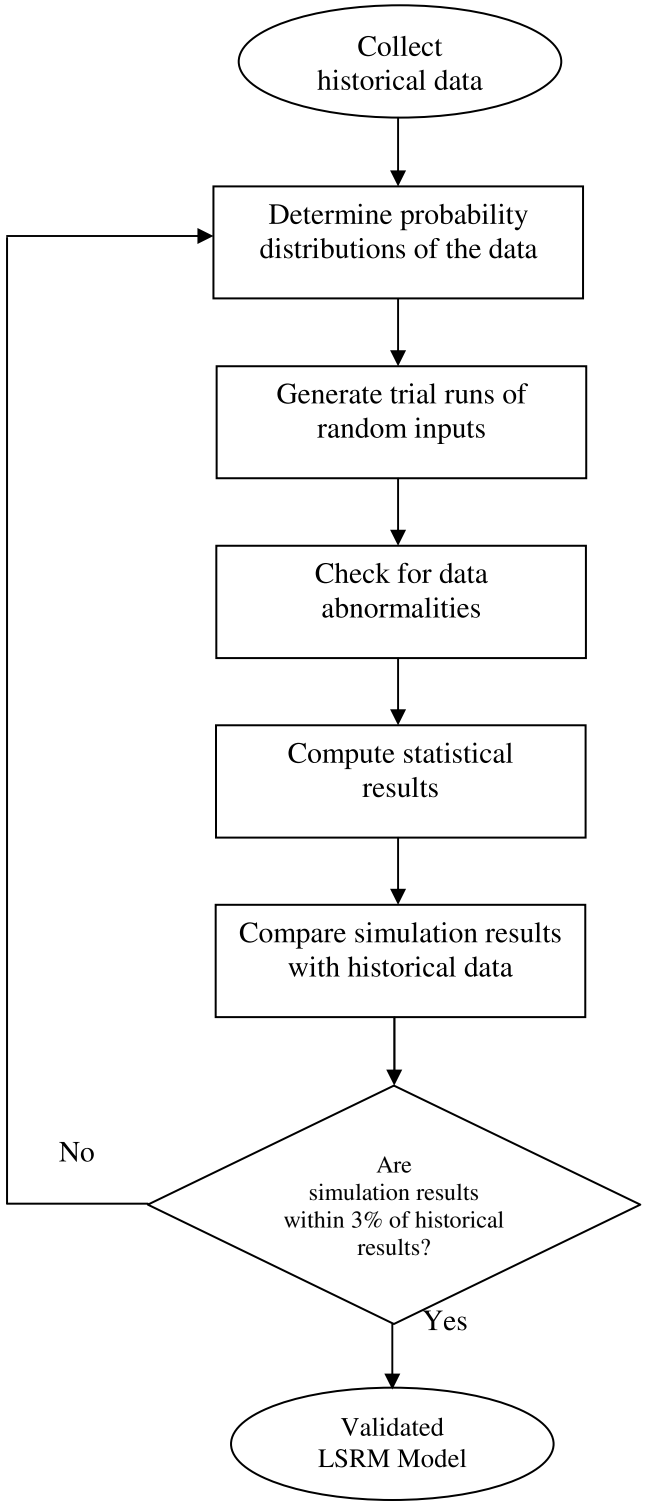


Fig. 23 Model Validation Flow Chart

simulate each subsystem component in the following manner. Histograms and summary statistics will be obtained from $n = 1000$ trial runs of 500 random samples for analysis. The probability distributions for the random samples in the simulation will resemble the probability distributions of the historical data. For each subsystem component, we will then be able to determine its mean and standard deviation as well as the range of reliability values. This information will be used later in comparison with the reliability of Lean subsystems.

3.8.2 Monte Carlo Simulation of Subsystems

Random data generated from historical observations will be used to simulate each critical subsystem in the following manner. Histograms and summary statistics will be obtained from $n = 1000$ trial runs of 500 random samples for analysis. The probability distributions for the random samples in the simulation will resemble the probability distributions of the historical data. For each subsystem, we will then be able to determine its mean and standard deviation as well as the range of reliability values. This information will be used later in comparison with both the reliability of its subsystem components and, more importantly, with the reliability of the Lean system.

3.8.3 Monte Carlo Simulation of Lean System

Random data generated from historical observations will be used to simulate the Lean system in the following manner. Histograms and summary statistics will be obtained from $n = 1000$ trial runs of 500 random samples for analysis. The probability distributions for the random samples in the simulation will resemble the probability distributions of the historical data. For the Lean system, we will then be able to determine its mean and standard deviation as well as the range of reliability values. This information will be used to estimate the true reliability of a stochastic Lean system.

3.8.4 Regression Model to Determine Contribution of LSRM

A substantial benefit of LSRM is the ability to measure its effect on % On Time Delivery. One could argue, in fact, that an efficient Lean system should have a statistically significant effect on predicting % On Time Delivery (% OTD). Therefore, a regression model is developed to analyze predictor variables against the response variable, % OTD, which is defined as the proportion of orders that are delivered on time in accordance with their scheduled due dates. An algorithm for regression analysis is presented in Figure 24.

3.8.4.1 Strategy for Regression Analysis

A. Conduct Preliminary Checks on Data Quality

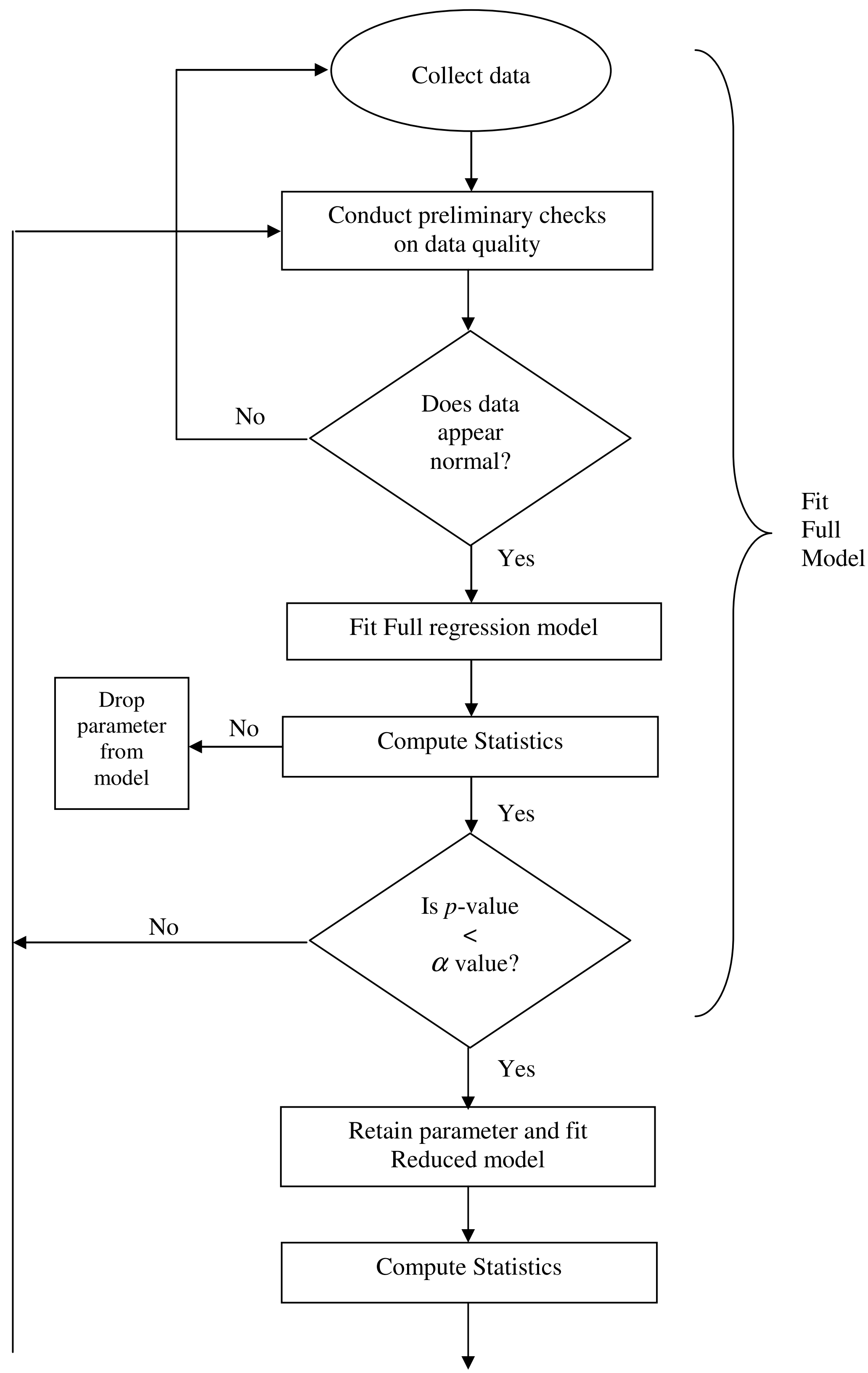
Beginning with a histogram to screen data for unusual behavior such as outliers and non-normality before fitting any model, we analyze a scatter plot matrix in order to detect unusual pattern behavior such as linearity or curvature among the data. A correlation matrix is then examined to determine whether a strong correlation exists among the predictor variables.

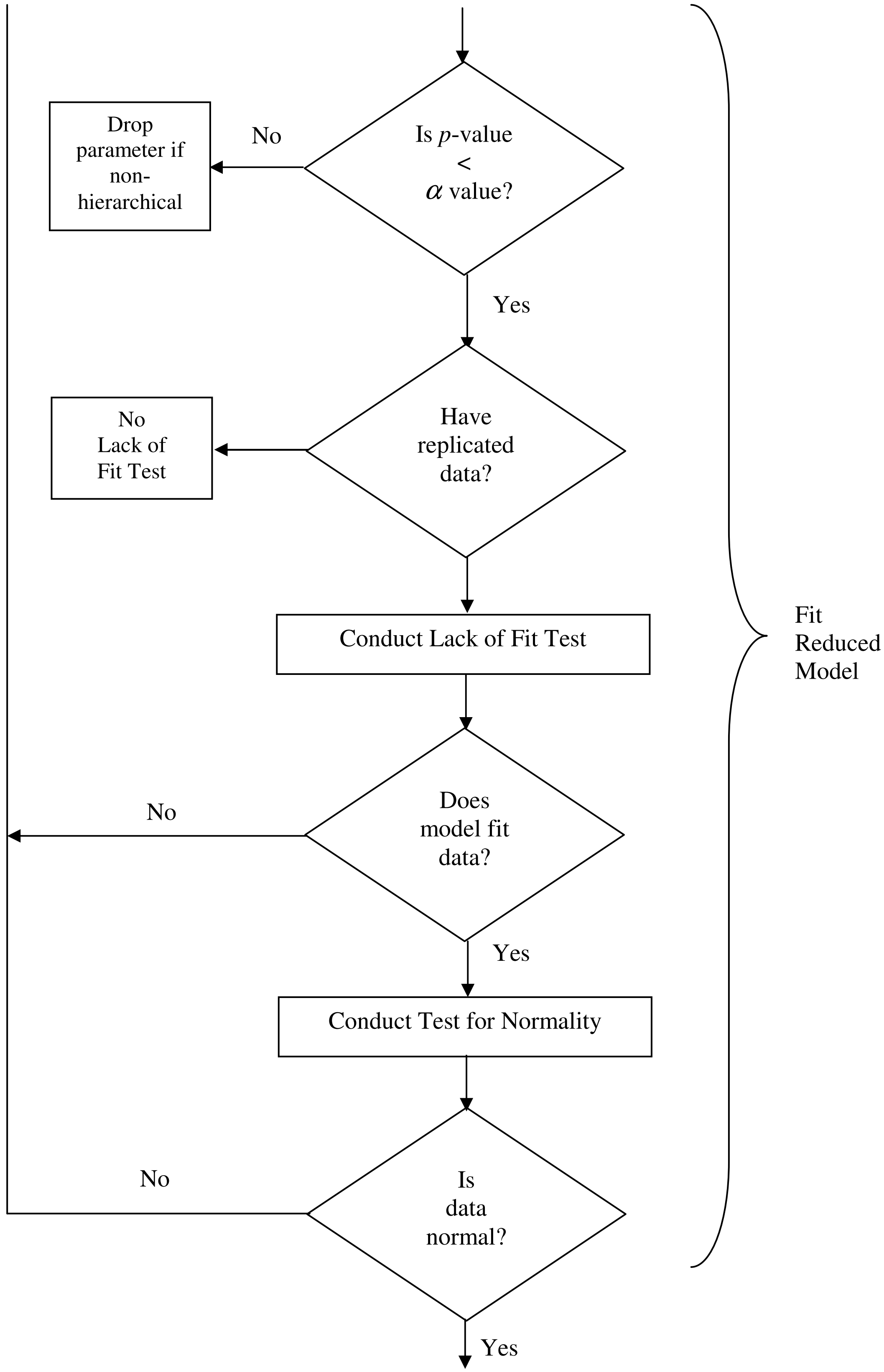
B. Develop a Full Model

Beginning with a general first-order model

$$y = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon$$

summary statistics including the mean, R^2, adjusted R^2, and root mean square error are obtained. The mean is simply the sample mean of the response variable. Computation of the coefficient of multiple determination, R^2, which measures the proportion of variation in % OTD explained by the model as a whole is given by


Collect data
Conduct preliminary checks on data quality
Does data appear normal?
No
Yes
Fit Full regression model
Compute Statistics
No
Drop parameter from model
Yes
Is p-value < α value?
No
Yes
Retain parameter and fit Reduced model
Compute Statistics
Fit Full Model


Is p-value < α value?
No
Drop parameter if non-hierarchical
Yes
Have replicated data?
No Lack of Fit Test
Conduct Lack of Fit Test
Does model fit data?
No
Yes
Conduct Test for Normality
Is data normal?
No
Yes
Fit Reduced Model

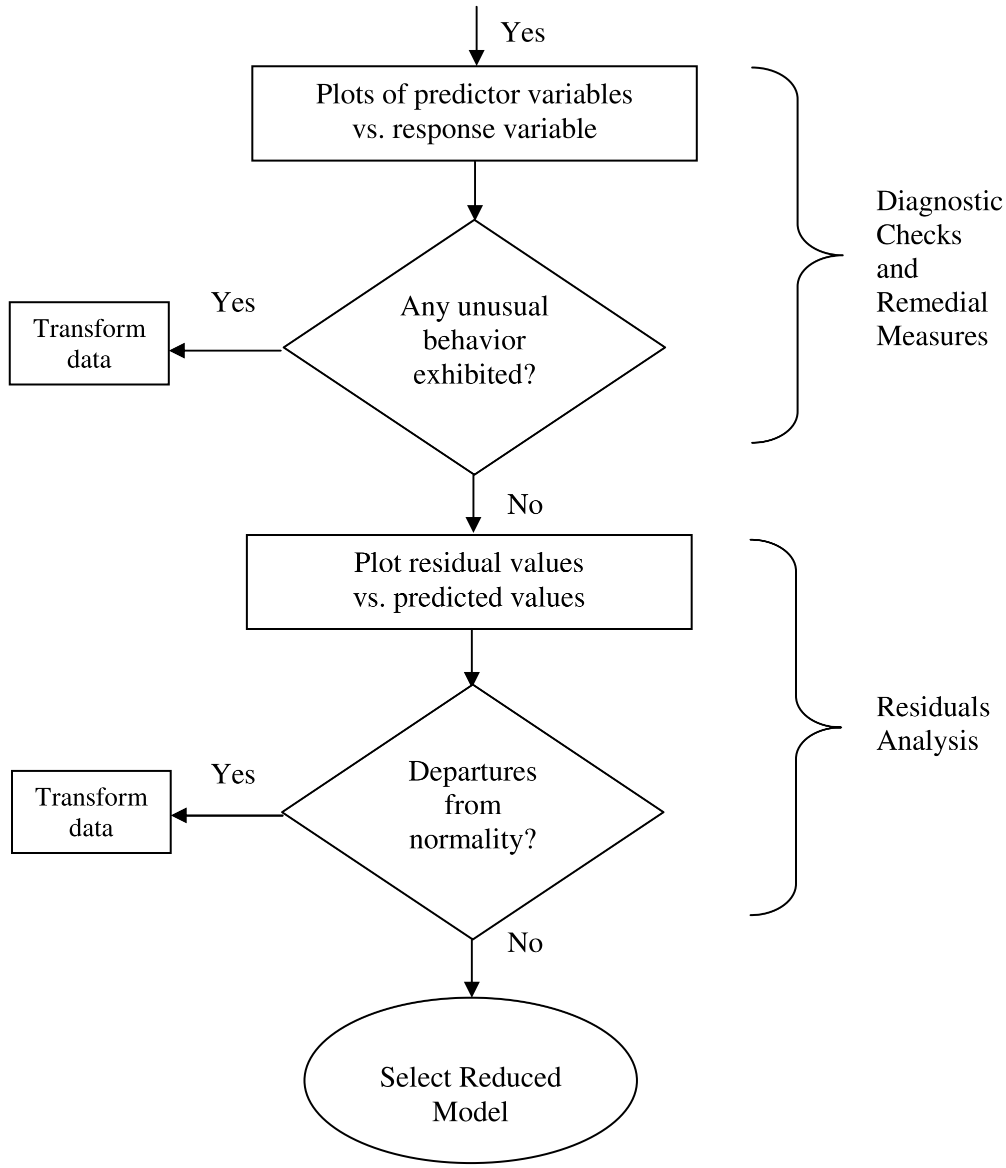


Fig. 24 Strategy for Regression Analysis

$$R^2 = \frac{SSR}{SST} = \frac{\sum(\hat{y}_i - \bar{y}_i)^2}{\sum(y_i - \bar{y}_i)^2}, \qquad 0 \le R^2 \le 1$$

The remaining error is attributed to random error. Since the sum of squared error terms for the model (SSR) and, therefore, R^2 increase as predictors are added to the model, we sometimes refer to the adjusted R_a^2, which adjusts R^2 by dividing each sum of squares by its associated degrees of freedom. Generally speaking, the degrees of freedom are equal to the number of independent scores that apply to an estimate minus the number of parameters estimated. Adjusted R_a^2 may increase or even decrease when another predictor variable is added to the model because any decrease in the sum of squared error terms for the data (*SSE),* may be more than offset by the loss of a degree of freedom in the denominator $n - p$, where *n* is the number of observations and *p* is the number of parameters estimated by the model. R_a^2 is calculated by

$$R_a^2 = 1 - \frac{\frac{SSE}{n-p}}{\frac{SST}{n-1}} = 1 - \left(\frac{n-1}{n-p}\right)\frac{SSE}{SST} = 1 - \frac{MSE}{MST}, \qquad 0 \le R_a^2 \le 1$$

where

$$SSE = \sum(y_i - \hat{y}_i)^2$$
$$SSR = \sum(\hat{y}_i - \bar{y}_i)^2$$
$$SST = \sum(y_i - \bar{y}_i)^2$$

and

$$MSE = \frac{SSE}{n-p}, \quad \text{where } p = \text{number of estimated parameters}$$

$$MST = \frac{SSR}{df}$$

The value for R_a^2 is significant since this value adjusts for the number of predictor terms in the model and, thus, provides a truer measure of goodness of fit than R^2 alone. That is, the R_a^2 value increases only if a new term improves the model more than would be expected by chance.

The standard error of the estimate, also known as root mean square error (RMSE), measures the average size of the prediction error in the model. In other words, RMSE measures the distance, on average, of a data point from the fitted line, measured along a vertical line. RMSE is calculated by

$$RMSE = \sqrt{MSE}$$

An Analysis of Variance (ANOVA) table, which captures the degrees of freedom, sum of squares, and mean square information, is also obtained. In the ANOVA table, an *F*-ratio is computed, which measures the ratio of the model mean square to the mean square for error. A large *F*-value indicates that the model is significant, meaning that we have obtained a good model to fit the data.

Next, parameter estimates for a full model are obtained. In addition, the standard error, *t*-ratio, and *p*-value for each estimate is displayed. The *t*-ratio is the ratio of the parameter estimate to its standard error. It is used to test for the hypothesis that the true estimate of each parameter is equal to zero; in other words, that the parameter has zero slope and, thus, is not a contributing variable in the model.

Another way to determine statistical significance of the model is to look at the *p*-value. The *p*-value is a measure of how much evidence we have against the null hypothesis, which typically represents a hypothesis of no change or no effect. The *p*-value measures consistency by computing the probability of observing sample results that are more extreme, assuming a true null hypothesis. The *p*-value is often compared to arbitrarily observed significance probabilities of 0.10 or 0.05. A small *p*-value is evidence against the null hypothesis while a large *p*-value means little or no evidence against the null hypothesis. We retain only those parameters whose *p*-value is less than the observed significance probability level. The significance of retained parameters can be verified in a Normal plot.

C. Fitting a Reduced Model

Whereas the Reduced model retains statistically significant parameters from the Full model, it may also include statistically non-significant parameters. For example, higher-order terms (i.e., interaction terms) *must* retain all lower-order terms that comprise the higher-order term. This results in a hierarchical Reduced model.

The Reduced model also includes analyses beyond the Full model. For example, if the Reduced model contains replicated data, we would conduct a Lack of Fit test to determine whether the model is a good fit to the data. In the Lack of Fit test, we test the null hypothesis that the model lacks fit versus the alternative hypothesis that the model is a good fit to the data.

Next, we conduct a test for normality as another criterion for the adequacy of the regression model. That is, we want to test the null hypothesis that the data in the Reduced model follows a normal distribution versus the alternative hypothesis that the data follows a non-normal distribution. With a large amount of data, one would expect the Central Limit

Theorem to apply, thereby hypothesizing that the data are normally distributed. The Shapiro-Wilk test for normality is used to test this hypothesis.

We will also check Predicted Sum of Squares (or PRESS), and PRESS root mean square error (RMSE) statistics to corroborate the results found by R^2 and R_a^2. The PRESS statistic is a measure of how well the use of the fitted values for a subset model can predict the observed responses, y_i. The PRESS statistic is computed as the sums of squares of the prediction residuals for those observations as follows.

$$PRESS_p = \sum_{i=1}^{n} (y_i - \hat{y}_{i(i)})^2$$

where

$PRESS_p =$ the sum of squared prediction errors over all n cases
$y_i =$ ith case of observed response
$\hat{y}_{i(i)} =$ fitted observed response, with first subscript (i) indicating a predicted value for the ith case and the second subscript (i) indicating that the ith case was omitted when the regression function was fitted

Minimizing $PRESS_p$ is desirable because when the prediction errors $y_i - \hat{y}_{i(i)}$ are small, so are the squared prediction errors and the sum of the squared prediction errors. The PRESS RMSE tests how well the reduced model would predict each of the data points if they were not included in the regression.

The analysis is concluded by estimating individual 95% confidence intervals on β_j, where β is the slope for $j = 0,1,...,k$ parameters. Confidence intervals for the transformed parameters are estimated by

$$b_j \pm t(1-\alpha/2; n-p)s\{b_j\}$$

D. Diagnostic Checks and Remedial Measures

Diagnostic checks play an important role in the development and evaluation of regression models. Box plots for each of the predictor variables and for the response variable can provide helpful, preliminary information about these variables. A scatterplot of the response variable against each predictor variable is helpful in determining the nature and strength of the bivariate relationship between the predictor variables and the response variable as well as in identifying gaps for the data points as well as outlying points. A scatterplot of each predictor variable against each of the other predictor variables is helpful in examining the bivariate relationships among the predictor variables and for finding gaps and detecting outliers.

A correlation matrix is helpful in confirming whether any linear associations exist among predictor variables and the response variable.

A plot of the residuals against the fitted values is helpful in assessing constancy of variance of the error terms, as well as providing information about outliers. In addition, residuals should be plotted against each of the predictor variables to provide further information about the adequacy of the regression function with respect to that predictor variable (i.e., whether a curvature effect is required for that variable).

Should the residuals exhibit unusual behavior, remedial measures such as a Box-Cox transformation may be necessary to remedy model deficiencies. Transformations on the response variable may be useful when the distributions of the error terms are quite skewed and the variance of the error terms is not constant. Transformations of some of the predictor variables may be helpful when the effects of these variables are curvilinear.

E. Residuals Analysis

Residuals analyses will be conducted by plotting a histogram of the residual values, plotting residuals vs. predicted values, and a normality plot of residuals to check for any departures from the normality assumption.

F. Conclusion

Comparing reliability results from a stochastic Lean system with respect to its components, subsystems, and the entire Lean manufacturing system serves to validate the model if all three reliability results are consistent.

Following diagnostic checks and remedial measures of the Reduced model, we formulate the regression model and assess the contribution of LSRM to the response variable, % on time delivery.

4. Case Study – Empty Box Company

4.1 Background

Empty Box Company (EBC) is a manufacturer of corrugated boxes in the Southeast. It operates as a sheet plant, which means that it converts sheet stock from its paper mill suppliers into finished boxes.

Orders are typically received by customer service personnel from customers or salespeople via telephone, fax, or email. In most cases, customers submit their orders on a weekly basis. These orders are then entered into a computerized scheduling system. A Master List, which is a daily production listing of all orders by customer due date, is generated and serves as a guideline for the continuous flow of orders through the factory.

Raw materials and parts, such as sheet stock and tooling (i.e., printing dies or cutting dies), are ordered on a daily basis. When raw materials arrive at the facility, they are either transported directly to a machine center for immediate processing or are temporarily stored in a staging area such as raw materials inventory or at the internal parts depot. Raw materials may go through several processing steps; hence, both upstream and downstream work stations are usually active. Work stations may require materials directly from outside suppliers, the internal parts depot, or from upstream work stations in order to perform required processing activities.

All orders are periodically inspected during and after each production run for quality attributes such as print quality, slot depth, gap dimensions, and bundle counts. Afterwards, the units of boxes are packaged, or palletized, for delivery. Orders are typically delivered in company-owned trucks. Occasionally, however, shipments are made via third-party carriers upon customer request.

Daily operating assumptions include:

1) Operational availability of all power sources
2) Perfect attendance of all employees who are scheduled to work
3) Operational availability of all machinery and equipment

Power sources include electricity, water, air, liquid propane, battery, and a backup generator for electricity. Perfect attendance means that employees clock in and are ready to work at their scheduled time.

The goals of the case study are to develop and validate an LSRM for Empty Box Company and then determine whether LSRM has a significant effect in predicting % on time delivery.

4.2 LSRM Conceptual Framework – Phase 1

An overview of EBCs Lean system are decomposed in Figure 25. The system level is represented by the entire manufacturing system. The subsystem level consists of subsystems such as Order Processing and Machinery. The component level for Order Processing, for example, consists of customers, customer service, and salespeople. Reliability measures for each component are also displayed.

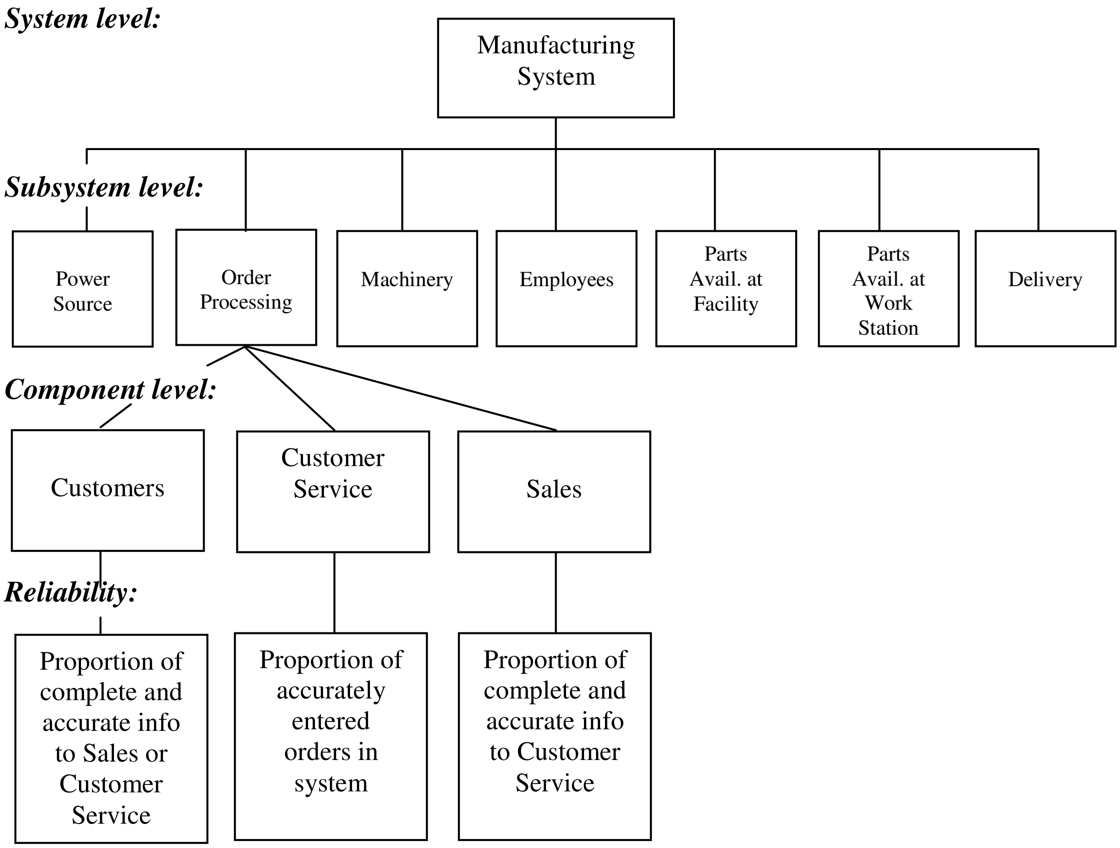


Fig. 25 Overview of LSRM at EBC

4.3 Development of LSRM – Phase 2

4.3.1 Determining EBCs Critical Subsystems

EBCs Lean subsystems were identified in Figure 23. All subsystem variables are considered equally important. Hence, eigenvectors and eigenvalues will be computed using a correlation matrix. Both the Kaiser criterion and Scree test will be used to determine critical subsystems with an eigenvalue threshold of 1. That is, only subsystems whose eigenvalue exceeds 1 are retained in the model as critical subsystems. Those subsystems whose eigenvalue do not exceed 1 are dropped from the model.

Eigenvectors for EBCs subsystem response variables are shown in Table 7. Eigenvalues are shown in Table 8.

Table 7 Eigenvectors of EBCs Response Variables

Comp	WS	F	D	M	PS	OP	E
WS	-0.29891	-0.01503	0.24652	0.47435	0.75566	0.22735	0.04397
F	0.52190	0.38195	0.24269	0.33275	-0.03611	-0.00203	-0.64094
D	-0.32303	-0.08851	0.42128	0.39286	-0.63389	0.38397	0.08219
M	0.00305	0.78224	0.12331	-0.32616	0.04589	0.38380	0.34221
PS	0.29031	-0.04619	-0.70174	0.36742	-0.05063	0.51510	0.13513
OP	0.32621	-0.46705	0.30628	-0.46028	0.14505	0.57230	-0.14567
E	0.58585	-0.11785	0.31842	0.23813	0.01228	-0.24640	0.65110

Table 8 Eigenvalues of EBCs Response Variables

Comp	Eigenvalue	Percent	Percent	Cum Percent
M	1.7867	25.524		25.524
WS	1.2042	17.203		42.728
D	1.0892	15.560		58.288
OP	1.0228	14.612		72.900
PS	0.8953	12.790		85.690
E	0.6145	8.778		94.468
F	0.3872	5.532		100.000

Using the Kaiser criterion, we would retain only subsystems whose eigenvalues are greater than 1, since these subsystems explain more of the variance than any single variable. In this example, we would retain four subsystems. Recall that the total variance in the data equals the sum of the variances of the observed subsystems. The first principal subsystem, Machinery, accounts for the greatest amount of total variance (25.52%) followed by the second principal subsystem, Parts Availability at Work Station (17.20%). The third principal subsystem, Delivery, accounts for 15.56% of the total variability and the fourth principal subsystem, Order Processing, accounts for 14.61% of the total variability. In sum, the first four principal subsystems account for 72.90% of the total variability in the data. Note that the eigenvalues sum to7, the number of response variables in this analysis.

Table 9 Correlation Matrix for EBC

Comp	WS	F	D	M	PS	OP	E
WS	1.0000	-0.0947	0.1040	-0.0504	-0.1244	-0.1312	-0.1247
F	-0.0947	1.0000	-0.0972	0.1973	0.1565	0.0444	0.4956
D	0.1040	-0.0972	1.0000	-0.0842	-0.1824	-0.1348	-0.1282
M	-0.0504	0.1973	-0.0842	1.0000	-0.1214	-0.1219	-0.1158
PS	-0.1244	0.1565	-0.1824	-0.1214	1.0000	-0.0449	0.1121
OP	-0.1312	0.0444	-0.1348	-0.1219	-0.0449	1.0000	0.2801
E	-0.1247	0.4956	-0.1282	-0.1158	0.1121	0.2801	1.0000

There appears to be a moderately positive correlation between Employee and Parts Availability at Facility $(r = 0.4956)$, but this has no substantive meaning. Otherwise, no correlations exist among the remaining subsystem variables.

A Scree plot to determine factor retention is displayed in Figure 26. This Scree plot suggests that the true dimensionality of the space in which the data lie is 4 within the 7-dimensional sample space. Therefore, the number of principal subsystems to use is also 4. The results of both the Kaiser criterion and the Scree plot concur.

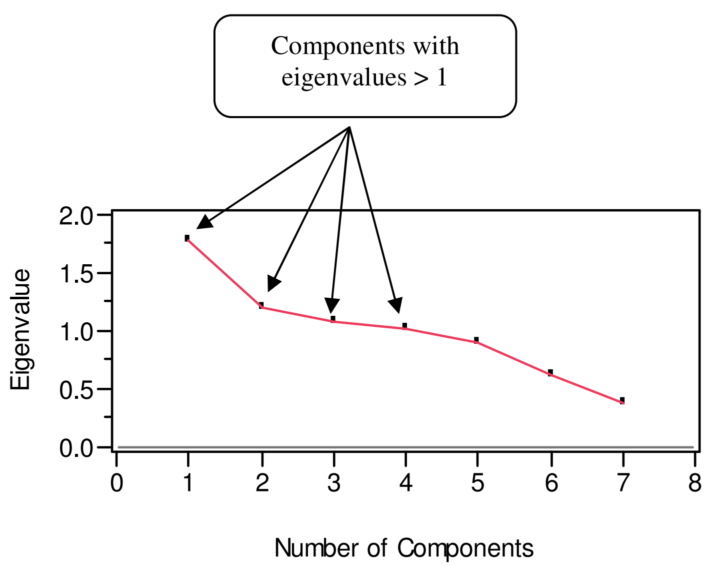


Fig. 26 Scree Plot for EBC

Therefore, based on its critical subsystems, the LSRM model is

$$R_s = r_M \times r_{WS} \times r_D \times r_{OP}$$

where

$R_s =$ reliability of the Lean system
$r_M =$ operational availability of Machinery subsystem
$r_{WS} =$ reliability of Parts Availability at Work Station subsystem
$r_D =$ reliability of Delivery subsystem
$r_{OP} =$ reliability of Order Processing

4.4 Determining EBCs Critical Workflow Sequence

A value stream map (VSM) for a manufacturer's current state was developed in Chapter 3. Recall that a value stream map is a graphical depiction of the entire flow of activities and subsystems in a complex manufacturing system. Value streams consist of all the activities, both value added and non-value added, that are currently required to produce and deliver the product to the customer. The goal of value stream maps is to identify, demonstrate, and decrease sources of waste and create the most value while consuming the fewest resources. An example of a future state value stream map is presented in Figure 27. By using group technology in the future state, the manufacturing processes of press, gluing, and inspecting are consolidated into a single work cell operation rather using than three separate work stations as inthe current state (VSM) shown in Figure 21. By doing so, the same volume of work is created with fewer employees. The benefits are substantial. They include a 62.5% reduction in lead time by reducing lead time from 8 days to 3 days. Processing time is reduced from 106 seconds to 50 seconds per piece, for a reduction in processing time of 53%. Additionally, by reducing related work activities that once required 7 employees down to 3 employees, the firm realizes a savings of 57% in labor costs.

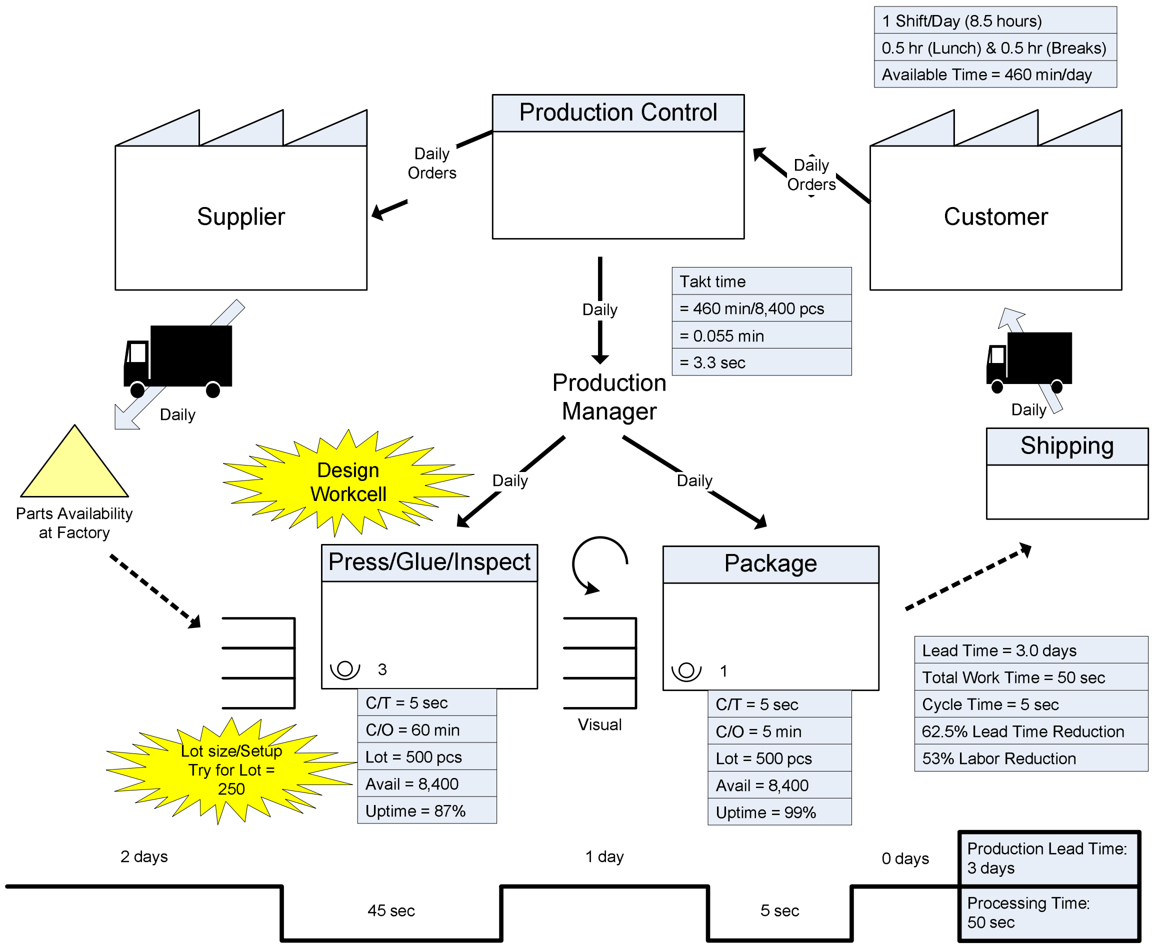


Fig. 27 EBCs Future State Value Stream Map

The workflow sequence in the future state begins with the customer in the form of orders placed. The customer may call the manufacturer directly to place an order via telephone, fax, or email, or may contact the manufacturer's rep to place an order on a daily basis. This aids both the customer and the manufacturer because both can realize economies of scale. For the customer, daily placement of orders enables a more level flow of incoming shipments into their facility during the week rather than large volumes of incoming shipments arriving on only certain days of the week. It also increases their cash flow, since their capital is not consumed in weekly batches of orders, some of which may not be processed until days after arrival. Now, the customer can receive their orders daily; that is, specifically when they require them. For the manufacturer, economies of scale are realized in scheduling and raw materials purchases. In scheduling, orders received may be scheduled to run in groups with common characteristics such as ink color, size, etc. For example, boxes requiring black ink would be grouped together before producing boxes requiring red ink in order to reduce press downtime when changing ink colors, which involves a setup procedure known as a "ink washup." Additionally, the manufacturer maintains better control over receipt of incoming raw materials when purchased with daily customer orders than with weekly customer orders.

EBC customer service personnel typically enter customer orders into a computerized scheduling system. Raw materials are then ordered from suppliers on a daily basis to produce customer orders (Order Processing subsystem). Parts and other raw materials arrive at the manufacturer's facility daily and are either stocked in inventory (i.e., at the internal parts depot or other designated storage location) until required for use, or transported directly to a machine center for processing. The receiving clerk compares parts arrivals with purchase requisitions for various attributes such as on time arrival, receipt of correct products, correct quantities, etc. Parts or raw materials must arrive when required at the work station for conversion (Parts Availability at Work Station subsystem). These parts may arrive from outside suppliers, the internal parts depot, or from upstream work stations.

Next, operationally available machinery to process orders (Machinery subsystem) are required. In this example, parts or raw materials are run through a series of value-added activities. As observed in the future state value stream map, group technology allows for consolidating multiple processes into work cells that run more productively and efficiently than individual work stations. At EBC, stock sheets are processed through a press, including gluing and inspecting, in the same work cell. Previously, this series of operations were performed at three separate work stations. Hence, lost time in the form of waiting time, materials handling time, searching for supervisory approval to run orders at each work station, etc. have been greatly reduced . Efficiencies gained will also allow for producing more orders with reduced lot sizes, thereby adding flexibility in the manufacturing system. Reduced lot sizes will accommodate a greater number and variety of orders in response to increasing customer demand.

Once the units of boxes are unitized, they are delivered to customers either on company-owned trucks or via third-party carriers. Daily deliveries to customers becomes the norm, rather than weekly deliveries, again benefitting both the customer and the manufacturer. Hence, based on EBCs critical subsystems, the workflow sequence is presented in Figure 28.

4.5 Model Validation – Phase 3

4.5.1 Monte Carlo Simulation of EBCs Lean Components

To predict the reliability of Lean subsystem components, we employ Monte Carlo simulation based on historical data. Random data generated from historical observations will be used to simulate each subsystem component in the following manner. Histograms and summary statistics will be obtained from n = 1000 trial runs of 500 random samples for analysis. The probability distributions for the random samples in the simulation will resemble the probability distributions of the historical data. For each subsystem component, we will then be able to determine its mean and standard deviation as well as the range of reliability values. This information will be used later in comparison with the reliability of Lean subsystems.

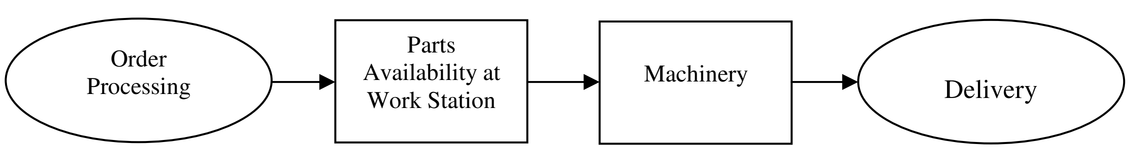


Fig. 28 EBCs Critical Workflow Sequence

4.5.1.1 Fitting Distributions to EBCs Lean Components

Order Processing Components

Fitted distributions for Customers, Customer Service, and Sales reliability data are shown in Figures 29 and 30. No outliers are observed in the outlier box plots or histograms for these three probability distribution. The mean, standard deviation, and range of reliability values for each component are shown in Table 10.

Order information provided by customers and salespeople to customer service personnel appears to be highly reliable, as is the entry of order information into the computerized scheduling system at EBC.

Table 10 Order Processing Component Statistics

Component	Mean	Standard deviation	Range of reliability values
Customers	0.9696	0.0182	(0.9375, 1.0)
Customer Service	0.9630	0.0211	(0.9277, 1.0)
Sales	0.9687	0.0179	(0.9375, 1.0)

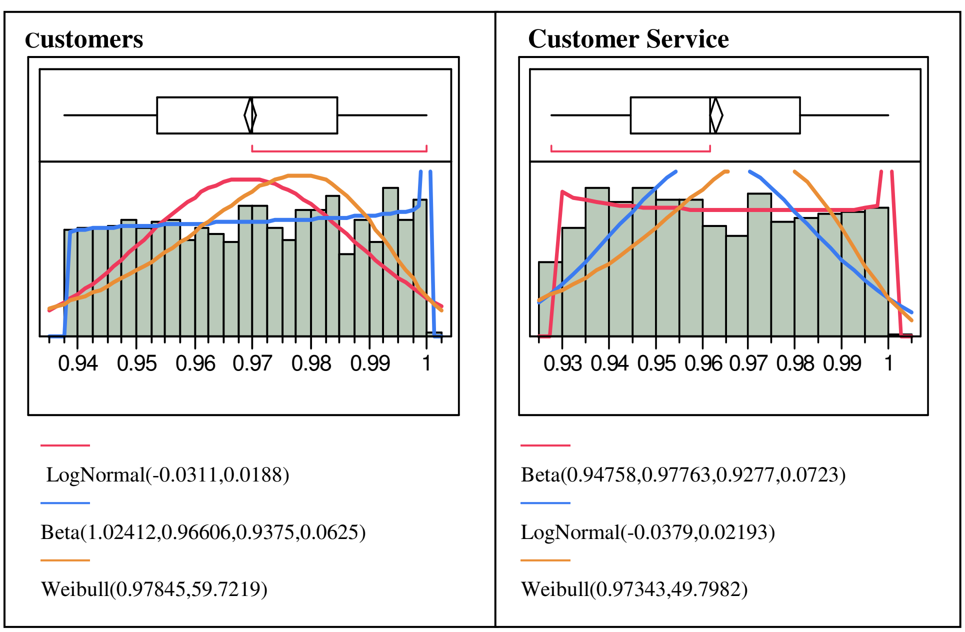


Fig. 29 Probability Distributions of Customers and Customer Service

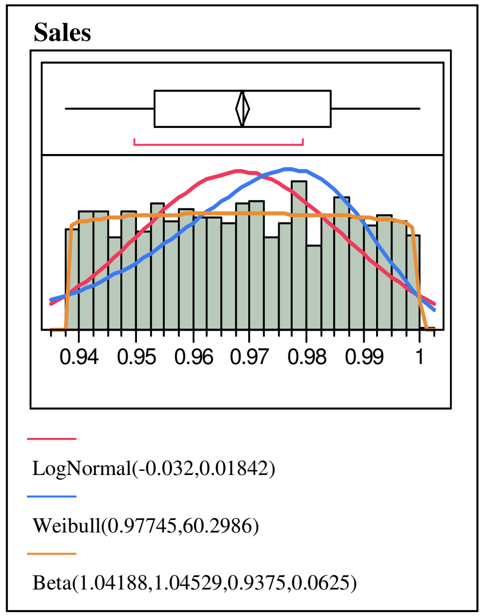


Fig. 30 Probability Distribution of Sales

Parts Availability at Work Station Components

Fitted distributions for Outside Suppliers, Internal Parts Depot, and Upstream Work Stations are shown in Figures 31 and 32. The data for the three components follow a Weibull probability distribution. The mean, standard deviation, and range of reliability values for each component are shown in Table 11.

Parts availability at the work station is highly reliable. The arrival of parts when required by downstream work stations from each of the three sources for parts and materials is very reliable.

Table 11 Parts Availability at Work Station Component Statistics

Component	Mean	Standard deviation	Range of reliability values
Outside Suppliers	0.9951	0.0196	(0.80, 1.0)
Internal Parts Depot	0.9954	0.0188	(0.81, 1.0)
Upstream Work Stations	0.9945	0.0214	(0.83, 1.0)

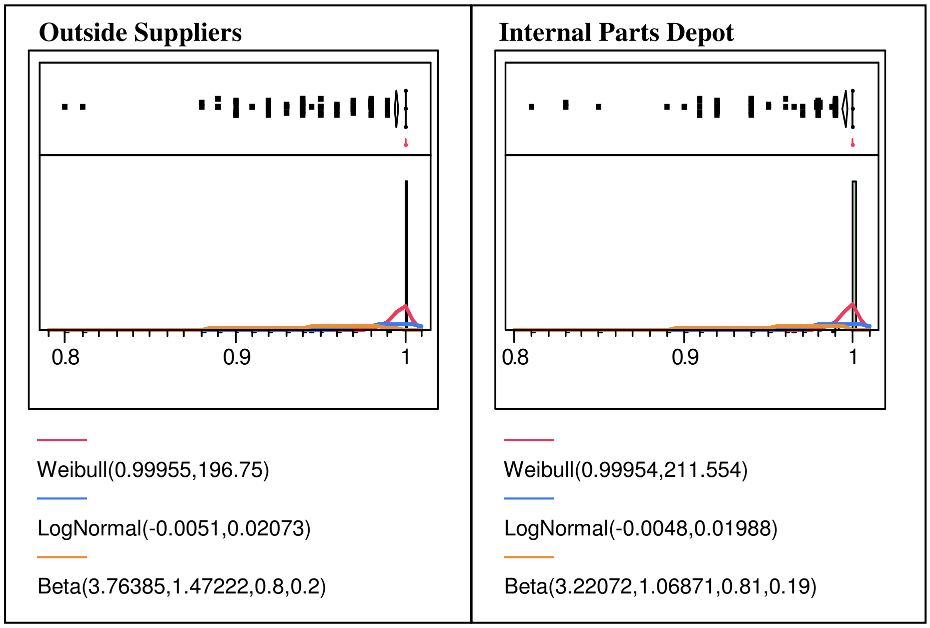


Fig. 31 Probability Distribution s of Outside Suppliers and Internal Parts Depot

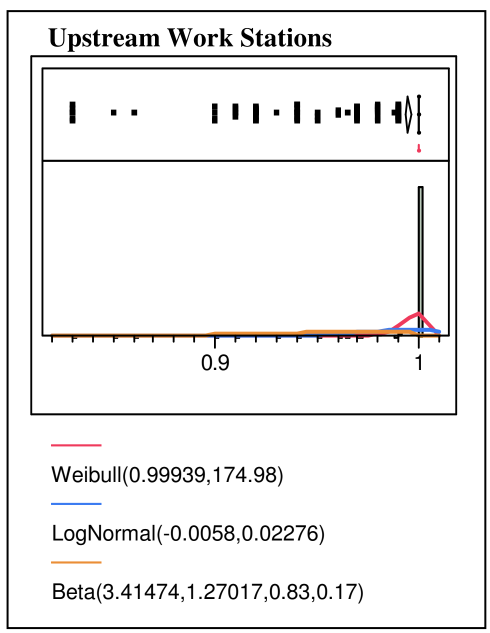


Fig. 32 Probability Distribution of Upstream Work Stations

Machinery Components

Fitted distributions for reliability data with regard to Machines 1 – 5 are shown in Figures 33 through 35. No outliers are observed in the outlier box plots or histograms for these five components. Additionally, it appears that the data for all five components follow the Weibull probability distribution. The mean, standard deviation, and range of reliability values for each component are shown in Table 12.

Utilizing a Lean maintenance program has enabled EBC to maintain high operationally available machinery.

Table 12 Machinery Component Statistics

Component	Mean	Standard deviation	Range of reliability values
Machine 1	0.9919	0.0196	(0.8, 1.0)
Machine 2	0.9957	0.0188	(0.8, 1.0)
Machine 3	0.9755	0.0482	(0.58, 1.0)
Machine 4	0.9969	0.0146	(0.80, 1.0)
Machine 5	0.9930	0.0236	(0.81, 1.0)

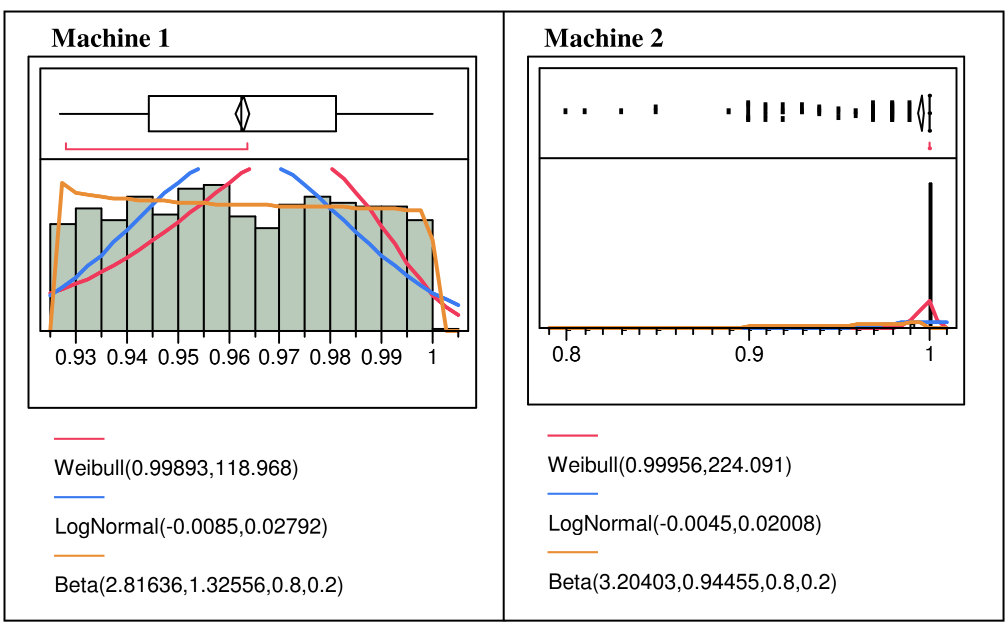


Fig. 33 Probability Distributions of Machine 1 and Machine 2

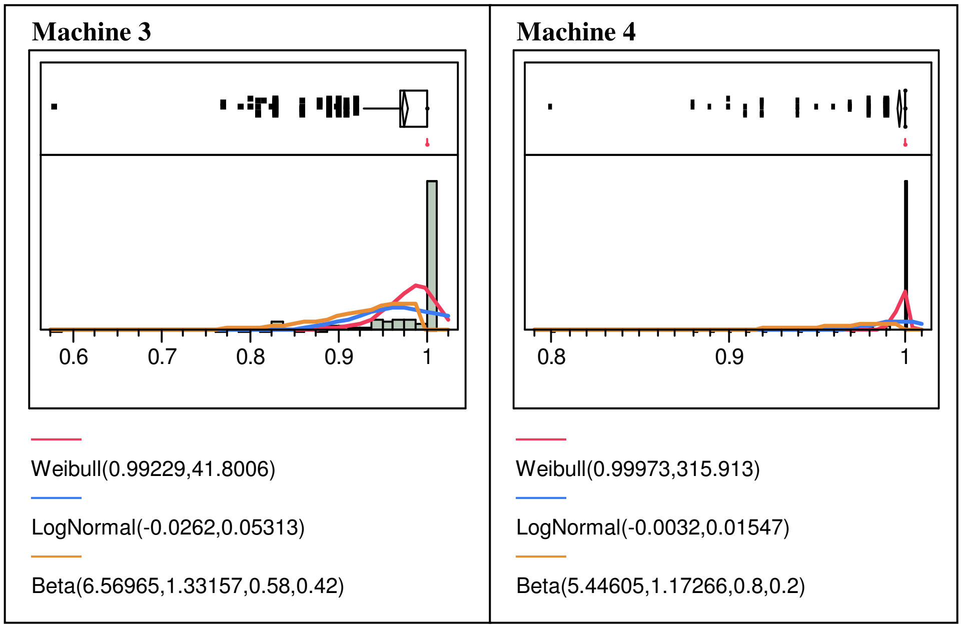


Fig. 34 Probability Distributions of Machine 3 and Machine 4

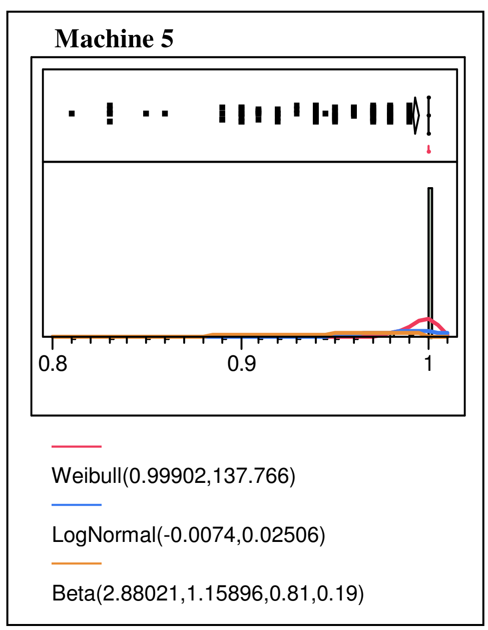


Fig. 35 Probability Distribution of Machine 5

Delivery Component

Fitted distributions for reliability data with regard to Deliveries are shown in Figure 36. One outliers is observed in the outlier box plots for company-owned trucks; however, no outliers are observed for third party carrier data. Additionally, it appears that the data for both components follow the Lognormal probability distribution. The mean, standard deviation, and range of reliability values for each component are shown in Table 13.

The most reliable components for EBCs Lean subsystems are the delivery components. Both company trucks and third-party carriers are highly reliable in delivering products of superior quality to customers on time.

Table 13 Delivery Component Statistics

Component	Mean	Standard deviation	Range of reliability values
Company Trucks	0.9984	0.0010	(0.9898, 1.0)
Third-Party Carriers	0.9983	0.0010	(0.9965, 1.0)

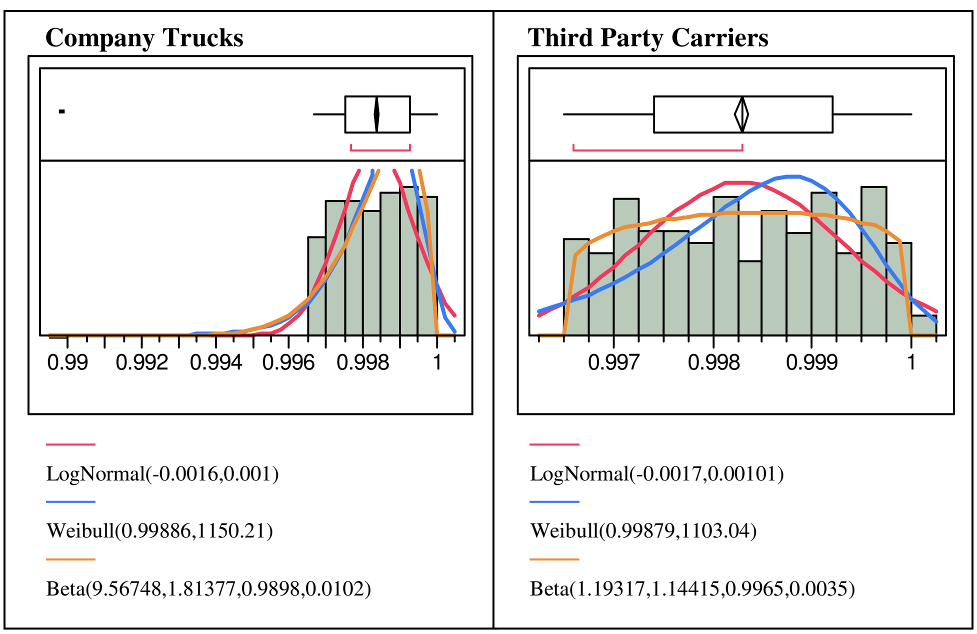


Fig. 36 Probability Distributions of Company Trucks and Third Party Carriers

4.5.2 Monte Carlo Simulation of EBCs Lean Subsystems

Random data generated from historical observations will be used to simulate each subsystem in the following manner. Histograms and summary statistics will be obtained from n = 1000 trial runs of 500 random samples for analysis. The probability distributions for the random samples in the simulation will resemble the probability distributions of the historical data. For each subsystem , we will then be able to determine its mean and standard deviation as well as the range of reliability values. This information will be used later in comparison with the reliability of subsystem components as well as the Lean system.

4.5.2.1 Fitting Distributions to Lean Subsystems

Order Processing Subsystem

A histogram of the Order Processing subsystem is shown in Figure 37. After n = 1000 trial runs, the distribution of reliability results clearly follows a Weibull distribution with $\mu = 0.99996$ and $\sigma = 0.0001$. Some outliers are observed in the simulated data. Additionally, a results summary and percentile distribution of simulation values is displayed in Table 14.

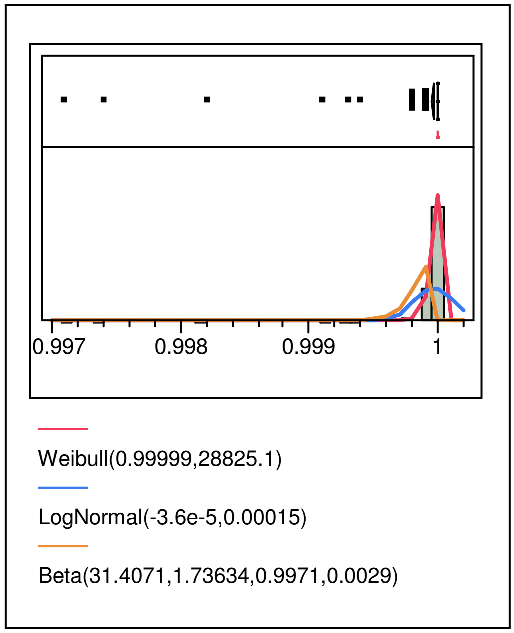


Fig. 37 Order Processing Simulation Histogram

Table 14 Simulation Results Summary for Order Processing

Mean	0.9999637
Std Dev	0.0001482
Std Err Mean	4.6855e-6
upper 95% Mean	0.9999729
lower 95% Mean	0.9999545
N	1000

100.0%	maximum	1.0000
99.5%		1.0000
97.5%		1.0000
90.0%		1.0000
75.0%	quartile	1.0000
50.0%	median	1.0000
25.0%	quartile	1.0000
10.0%		0.9999
2.5%		0.9998
0.5%		0.9993
0.0%	minimum	0.9971

A plot of n = 1000 trial runs for each subsystem in the Monte Carlo simulation is shown in Figure 38. The parallel system formula for computing reliability for Order Processing is

$$\begin{aligned} R_{OP} &= 1-(1-r_c)(1-r_{CS})(1-r_S) \\ &= 1-(1-.9696)(1-.9630)(1-.9687) \\ &= .99996 \end{aligned}$$

where

$R_{OP} =$ reliability of Order Processing subsystem
$r_C =$ reliability of Customer provided information
$r_{CS} =$ reliability of Customer Service
$r_S =$ reliability of Sales provided information

Random variation and statistical fluctuations are observed in the plot. However, no unusual patterns are detected.

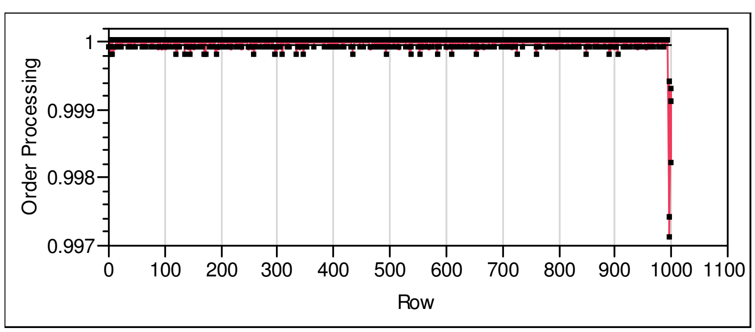


Fig. 38 Plot of *n* = 1000 Simulation Results for Order Processing

Parts Availability at Work Station Subsystem

A histogram of Parts Availability at Work Station is shown in Figure 39. After n = 1000 trial runs, the distribution of reliability results best follows a Weibull distribution with $\mu = 0.985$ and $\sigma = 0.0358$. Outliers are observed in the simulated data. A summary of results and a percentile distribution of simulation values is displayed in Table 15.

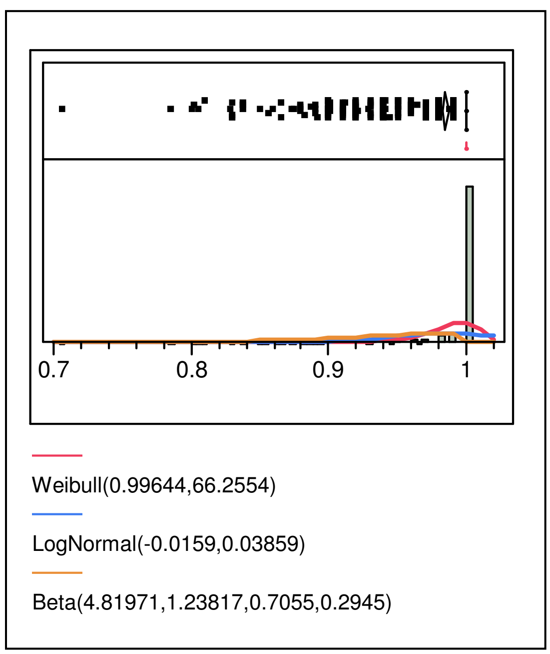


Fig. 39 Parts Availability at Work Station Simulation Histogram

Table 15 Simulation Results Summary for Parts Availability at Work Station

Mean	0.9849694
Std Dev	0.0357816
Std Err Mean	0.0011315
upper 95% Mean	0.9871898
lower 95% Mean	0.982749
N	1000

100.0%	maximum	1.0000
99.5%		1.0000
97.5%		1.0000
90.0%		1.0000
75.0%	quartile	1.0000
50.0%	median	1.0000
25.0%	quartile	1.0000
10.0%		0.9400
2.5%		0.8800
0.5%		0.8051
0.0%	minimum	0.7055

The plot of Parts Availability at Work Station is displayed in Figure 40. The series system formula for computing Parts Availability at Work Station is

$$
\begin{aligned}
R_{WS} &= r_{OS} \times r_{IPD} \times r_{UWS} \\
&= .9951 \times .9954 \times .9945 \\
&= .98497
\end{aligned}
$$

where

R_{WS} = reliability of Parts Availability at Work Station
r_{OS} = reliability of Outside Suppliers
r_{IPD} = reliability of Internal Parts Depot
r_{UWS} = reliability of Upstream Work Stations

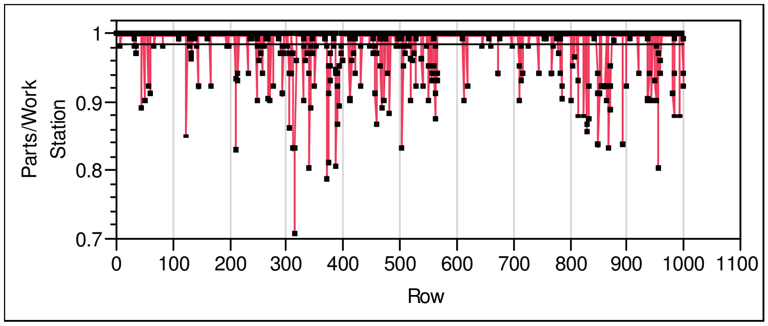


Fig. 40 Plot of *n* = 1000 Simulation Results for Parts Availability at Work Station

Random variation and statistical fluctuations are observed in the plot. No unusual patterns are detected.

Machinery Subsystem

A histogram of Machinery is shown in Figure 41. After n = 1000 trial runs, the reliability results for Machinery best follows a Weibull distribution with $\mu = 0.9537$ and $\sigma = 0.0622$. A summary of results and a percentile distribution of simulation values is displayed in Table 16.

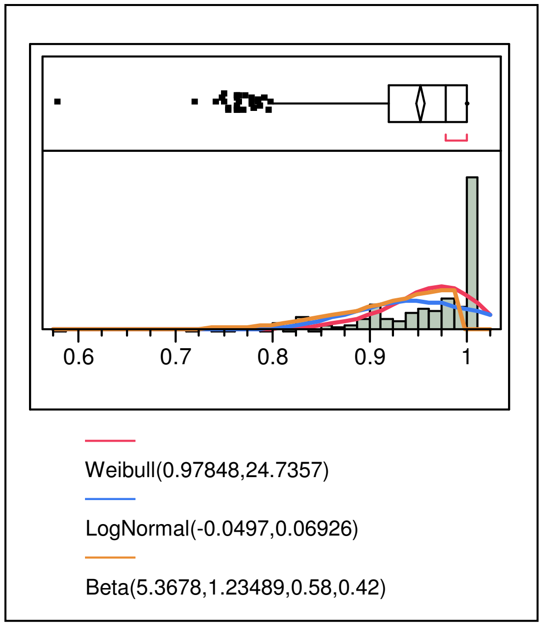


Fig. 41 Machinery Simulation Histogram

Table 16 Simulation Results Summary for Machinery

Mean	0.9536953
Std Dev	0.062244
Std Err Mean	0.0019683
upper 95% Mean	0.9575578
lower 95% Mean	0.9498328
N	1000

100.0%	maximum	1.0000
99.5%		1.0000
97.5%		1.0000
90.0%		1.0000
75.0%	quartile	1.0000
50.0%	median	0.9800
25.0%	quartile	0.9200
10.0%		0.8554
2.5%		0.7857
0.5%		0.7503
0.0%	minimum	0.5800

The time series plot of Machinery is shown in Figure 42. The series system formula for computing Machinery is

$$R_M = r_1 \times r_2 \times r_3 \times r_4 \times r_5$$

$$= .9919 \times .9957 \times .9755 \times .9969 \times .9930$$

$$= .9537$$

where

R_M = operational availability of Machinery subsystem

r_1 = operational availability of Machine 1

r_2 = operational availability of Machine 2

r_3 = operational availability of Machine 3

r_4 = operational availability of Machine 4

r_5 = operational availability of Machine 5

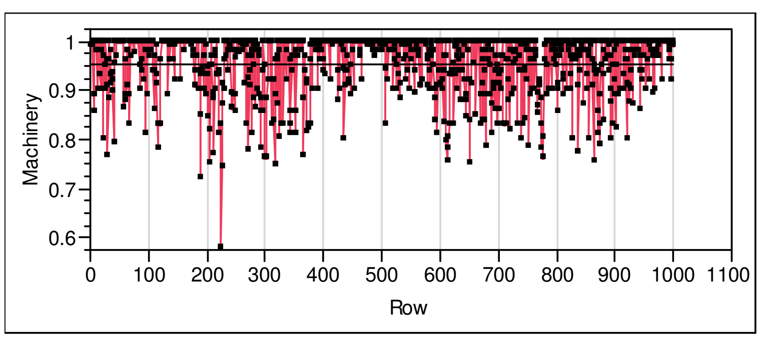


Fig. 42 Plot of *n* = 1000 Simulation Results for Machinery

Random variation and statistical fluctuations are observed in the plot. No unusual patterns are detected.

Delivery Subsystem

A histogram of Delivery is shown in Figure 43. After n = 1000 trial runs in the simulation, the distribution of reliability results clearly follows a Weibull distribution with $\mu = 1.0$ and $\sigma = 0$. A summary of results and a percentile distribution of simulation values is displayed in Table 17.

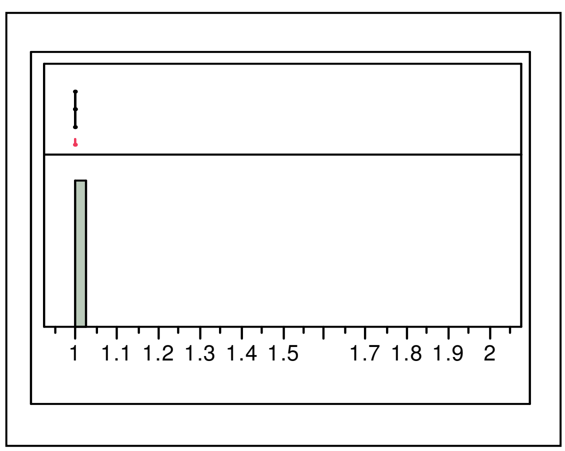


Fig. 43 Delivery Simulation Histogram

Table 17 Simulation Results Summary for Delivery

Mean	1
Std Dev	0
Std Err Mean	0
upper 95% Mean	1
lower 95% Mean	1
N	1000

100.0%	maximum	1.0000
99.5%		1.0000
97.5%		1.0000
90.0%		1.0000
75.0%	quartile	1.0000
50.0%	median	1.0000
25.0%	quartile	1.0000
10.0%		1.0000
2.5%		1.0000
0.5%		1.0000
0.0%	minimum	1.0000

The plot of Delivery is shown in Figure 44. The parallel system formula for computing Delivery is

$$R_D = 1-(1-r_{CT})(1-r_{TPC})$$

$$= 1-(1-.9984)(1-.9983)$$

$$= 1$$

where

$R_D =$ reliability of parallel Delivery subsystem
$r_{CT} =$ reliability of Company Trucks
$r_{TPC} =$ reliability of Third-Party Carriers

Random variation and statistical fluctuations are observed in the plot.

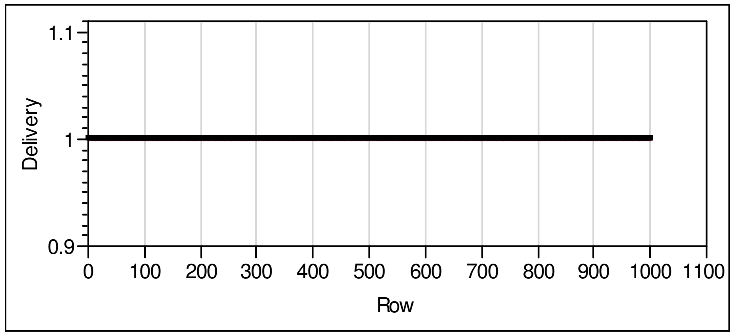


Fig. 44 Plot of *n* = 1000 Simulation Results for Delivery

4.5.3 Monte Carlo Simulation of EBCs Lean System

Random data generated from historical observations will be used to simulate the Lean system in the following manner. Histograms and summary statistics will be obtained from *n* = 1000 trial runs of 500 random samples for analysis. The probability distributions for the random samples in the simulation will resemble the probability distributions of the historical data. For the Lean system, we will then be able to determine its mean and standard deviation as well as the range of reliability values. This information will be used to estimate the true reliability of a stochastic Lean system.

4.5.3.1 Fitting Distributions to EBCs Lean System

Lean System

A histogram of the Lean system is shown in Figure 45. After *n* = 1000 trial runs in the simulation, the distribution of reliability results best follows a Weibull distribution with $\mu = 0.9394$ and $\sigma = 0.0709$. A summary of results and a percentile distribution of simulation values is displayed in Table 18.

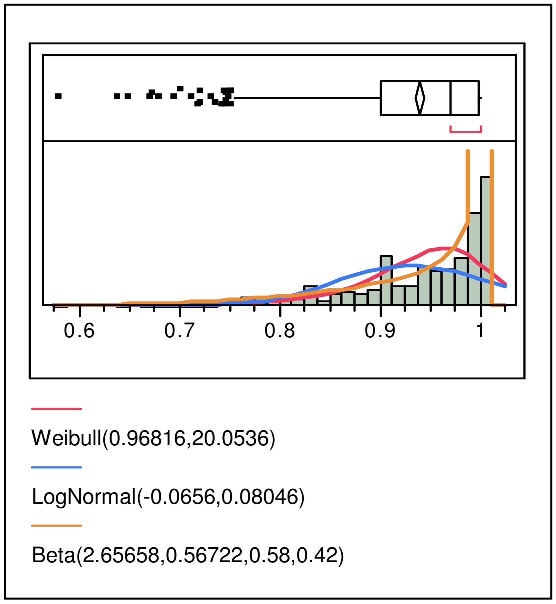


Fig. 45 Simulation Histogram of LSRM

The plot of LSRM is displayed in Figure 46. Random variation and statistical fluctuations are observed in the plot. No unusual patterns are detected.

Table 18 Simulation Results Summary for LSRM

Mean	0.9394008
Std Dev	0.0709138
Std Err Mean	0.0022425
upper 95% Mean	0.9438013
lower 95% Mean	0.9350003
N	1000

100.0%	maximum	1.0000
99.5%		1.0000
97.5%		1.0000
90.0%		1.0000
75.0%	quartile	0.9999
50.0%	median	0.9699
25.0%	quartile	0.9016
10.0%		0.8300
2.5%		0.7562
0.5%		0.6722
0.0%	minimum	0.5800

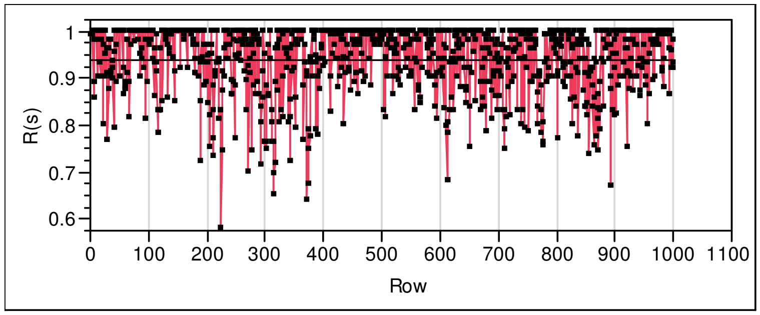


Fig. 46 Plot of *n* = 1000 Simulation Results for LSRM

4.6 EBCs Lean Subsystem Historical Data Results

Historical observations from EBCs manufacturing process were obtained. Probability distributions that provide the best 'fit' to the data are then determined via histograms. For each subsystem , we will then determine its mean and standard deviation as well as the range of reliability values. This information will be used later in comparison with the reliability of subsystem components as well as the Lean system.

4.6.1 Fitting Distributions to Lean Subsystems

Order Processing Subsystem

A histogram of the Order Processing subsystem is shown in Figure 47. Clearly, the distribution of historical values best fits a Weibull distribution. Additionally, a results summary and percentile distribution is displayed in Table 19.

The mean reliability is 0.9982 and the standard deviation is approximately 0.0080. A time series plot of n = 185 observations is shown in Figure 48.

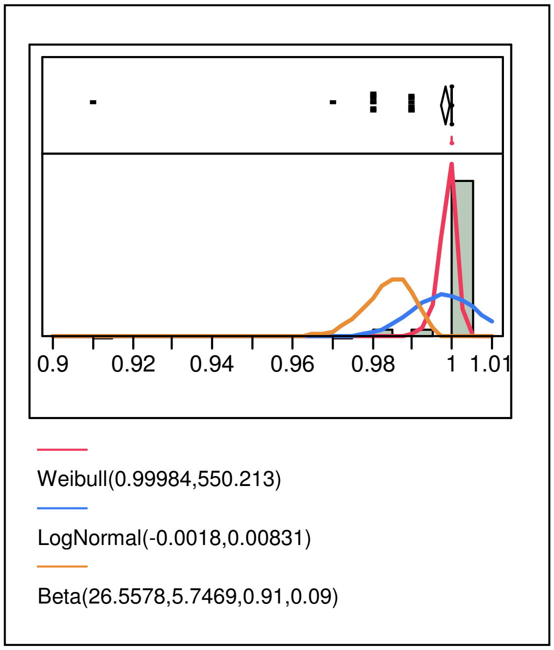


Fig. 47 Order Processing Histogram with Historical Data

Table 19 Historical Results Summary for Order Processing

Mean	0.9982162
Std Dev	0.0080458
Std Err Mean	0.0005915
upper 95% Mean	0.9993833
lower 95% Mean	0.9970491
N	185

100.0%	maximum	1.0000
99.5%		1.0000
97.5%		1.0000
90.0%		1.0000
75.0%	quartile	1.0000
50.0%	median	1.0000
25.0%	quartile	1.0000
10.0%		1.0000
2.5%		0.9800
0.5%		0.9100
0.0%	minimum	0.9100

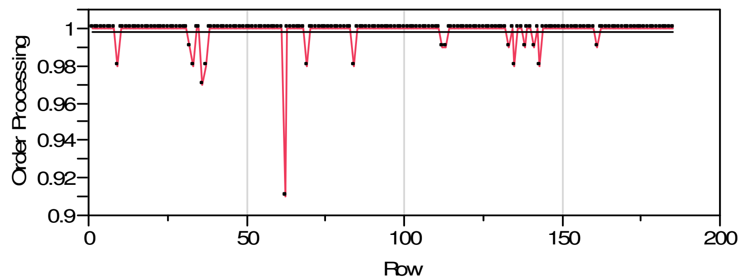


Fig. 48 Plot of Historical Data Results for Order Processing

Parts Availability at Work Station Subsystem

A histogram of the Parts Availability at Work Station subsystem is shown in Figure 49. Clearly, the distribution of historical values follows a Weibull distribution. Additionally, a results summary and percentile distribution is displayed in Table 20.

The mean reliability is 0.9994 and the standard deviation is approximately 0.0062. A time series plot of n = 185 observations is shown in Figure 50.

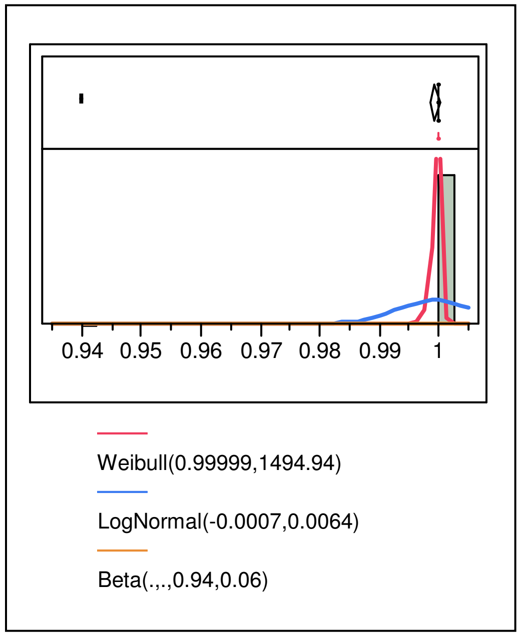


Fig. 49 Parts Availability at Work Station Histogram with Historical Data

Table 20 Historical Results Summary for Parts Availability at Work Station

Mean	0.9993514
Std Dev	0.0062215
Std Err Mean	0.0004574
upper 95% Mean	1.0002538
lower 95% Mean	0.9984489
N	185

100.0%	maximum	1.0000
99.5%		1.0000
97.5%		1.0000
90.0%		1.0000
75.0%	quartile	1.0000
50.0%	median	1.0000
25.0%	quartile	1.0000
10.0%		1.0000
2.5%		1.0000
0.5%		0.9400
0.0%	minimum	0.9400

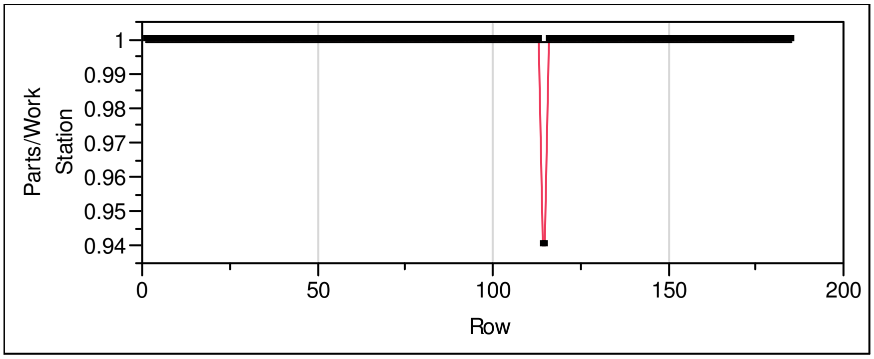


Fig. 50 Plot Historical Data Results for Parts Availability at Work Station

Machinery Subsystem

A histogram of the Machinery subsystem is shown in Figure 51. Clearly, the distribution of historical values follows a Weibull distribution. Additionally, a results summary and percentile distribution is displayed in Table 21.

The mean reliability is 0.9664 and the standard deviation is approximately 0.0623. A time series plot of n = 185 observations is shown in Figure 52.

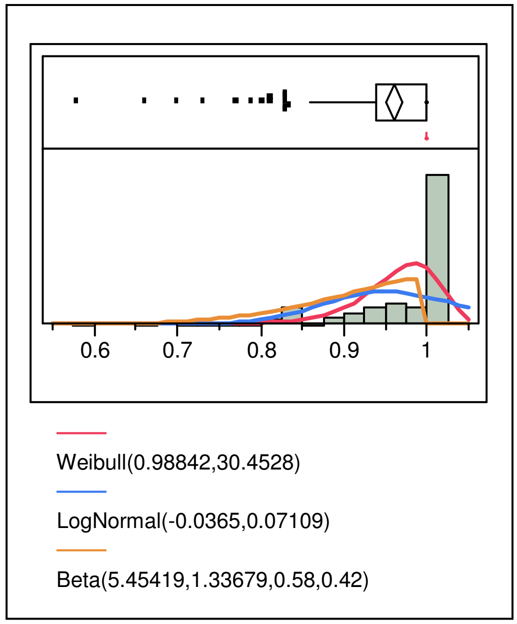


Fig. 51 Machinery Histogram with Historical Data

Table 21 Historical Results Summary for Machinery

Mean	0.9664324
Std Dev	0.0622777
Std Err Mean	0.0045787
upper 95% Mean	0.975466
lower 95% Mean	0.9573988
N	185

100.0%	maximum	1.0000
99.5%		1.0000
97.5%		1.0000
90.0%		1.0000
75.0%	quartile	1.0000
50.0%	median	1.0000
25.0%	quartile	0.9600
10.0%		0.8720
2.5%		0.8065
0.5%		0.5800
0.0%	minimum	0.5800

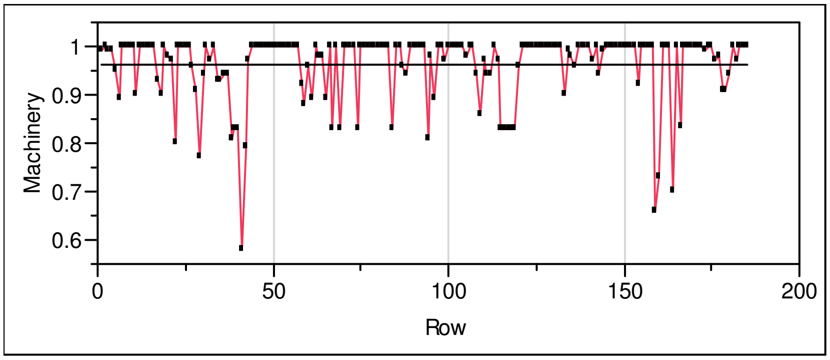


Fig. 52 Plot of Historical Data Results for Machinery

Delivery Subsystem

A histogram of the Delivery subsystem is shown in Figure 53. Clearly, the distribution of historical values follows a Weibull distribution. Additionally, a results summary and percentile distribution is displayed in Table 22.

The mean reliability is 0.9957 and the standard deviation is approximately 0.0266. A time series plot of n = 185 observations is shown in Figure 54.

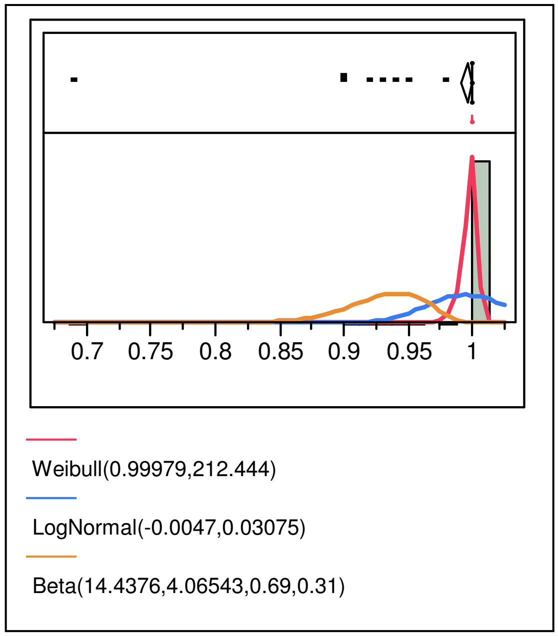


Fig. 53 Delivery Histogram with Historical Data

Table 22 Historical Results Summary for Delivery

Mean	0.9957297
Std Dev	0.0266342
Std Err Mean	0.0019582
upper 95% Mean	0.9995931
lower 95% Mean	0.9918663
N	185

100.0%	maximum	1.0000
99.5%		1.0000
97.5%		1.0000
90.0%		1.0000
75.0%	quartile	1.0000
50.0%	median	1.0000
25.0%	quartile	1.0000
10.0%		1.0000
2.5%		0.9265
0.5%		0.6900
0.0%	minimum	0.6900

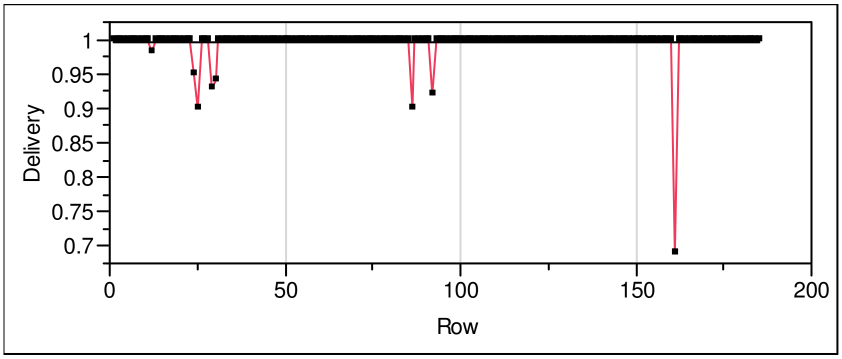


Fig. 54 Plot of Historical Data Results for Delivery

4.7 EBCs Lean System Historical Data Results

Historical observations from EBCs manufacturing process were obtained. The probability distribution that provide the best 'fit' to the data is then determined via a histogram. For the Lean system , we will then be able to determine its mean and standard deviation as well as the range of reliability values. This information will be used to estimate the true reliability of a stochastic Lean system.

4.7.1 Fitting Distributions to EBCs Lean System

Lean System

A histogram of the Lean system is shown in Figure 55. The distribution of historical values best fits a Weibull distribution. Additionally, a results summary and percentile distribution is displayed in Table 23.

The mean reliability is 0.960 and the standard deviation is approximately 0.0682. A time series plot of n = 185 observations is shown in Figure 56.

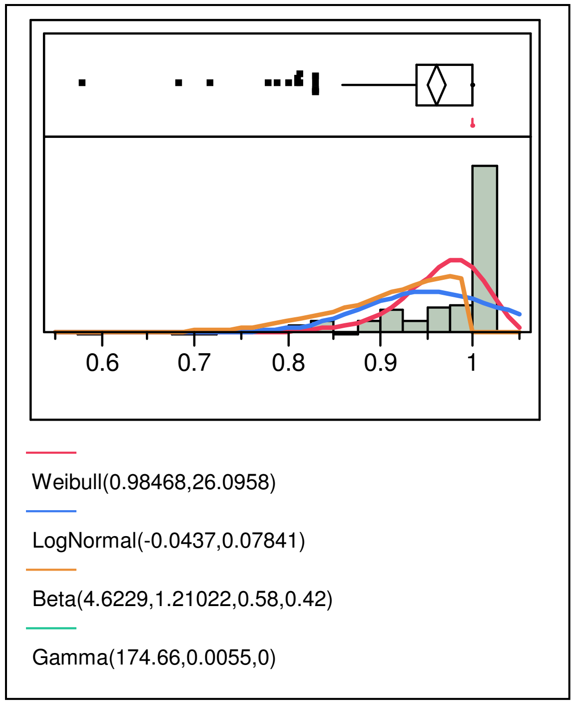


Fig. 55 Lean System Histogram with Historical Data

Table 23 Historical Results Summary for EBCs Lean System

Mean	0.9599914
Std Dev	0.0681906
Std Err Mean	0.0050135
upper 95% Mean	0.9698826
lower 95% Mean	0.9501001
N	185

100.0%	maximum	1.0000
99.5%		1.0000
97.5%		1.0000
90.0%		1.0000
75.0%	quartile	1.0000
50.0%	median	1.0000
25.0%	quartile	0.9400
10.0%		0.8480
2.5%		0.7866
0.5%		0.5800
0.0%	minimum	0.5800

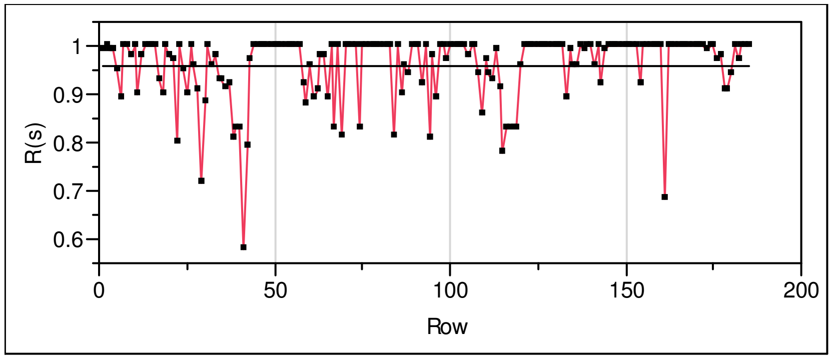


Fig. 56 Plot of Historical Data Results for EBCs Lean System

4.7.2 Select Regression Model

The reliability of the Lean system (LSRM) is a series system composed of subsystems given by

$$R_S = r_{OP} \times r_{WS} \times r_M \times r_D$$

$$= .9982 \times .9994 \times .9664 \times .9957$$

$$= .9599$$

where

R_S = reliability of the Lean system

r_{OP} = reliability of Order Processing

r_{WS} = reliability of Parts Availability at Work Station

r_M = operational availability of Machinery

r_D = reliability of Delivery

Since the reliability of the Lean system is computed as .9599, this means that, on average, the Lean system is functional and all subsystems are working in concert approximately 96% of the time.

4.8 Regression Model to Determine Contribution of LSRM

A substantial benefit of LSRM is the ability to measure its effect on % On Time Delivery. One could argue, in fact, that an efficient Lean system should have a statistically significant effect on predicting % On Time Delivery (% OTD). Therefore, a regression model is developed to analyze predictor variables against the response variable, % OTD, which is defined as the proportion of orders that are delivered on time in accordance with their scheduled due dates.

4.8.1 Developing the Regression Model

We shall develop a multivariate regression model to determine which predictor variables are significant contributors toward estimating response variable, % OTD. Predictor variables include R_s (reliability of the LSRM model), Operational Availability, and Cost of Quality. A brief explanation of each variable follows.

The response variable, % OTD, is defined as the proportion of orders that are delivered on time according to the scheduled due date versus the total number of orders due on the due date. Reliability of the Lean system, or R_s, is defined as the reliability of the Lean system based on four critical subsystems: Order Processing, Parts Availability at Work Station, Machinery, and Delivery. Operational Availability (OA) refers to proportion uptime , or the proportion of time that machinery is available for use relative to the total amount of work time. Cost of Quality (COQ) is defined as [1 – Total cost of quality as a percentage of sales revenues]. Total cost of quality includes cost of repairs, cost of quality complaints, and training. Cost of repairs refers to the total cost of investigating, troubleshooting, repairing, replacing, or adjusting equipment to make them functional again when a breakdown or the likelihood of a potential breakdown occurs. Cost of quality complaints refers to the total cost of investigating complaints (whether on site or at the customer's location) plus the cost of corrective action. This may involve rework, order replacement, or credit issued. Training costs refer to training for new hires or for cross-training. The diagram in Figure 57 provides an overview of the regression model.

4.8.2 Overview of % On Time Delivery Model

The functional relationships of the multiple regression model are represented by:

$$\%OTD = f\{R_s \times \text{OA} \times \text{COQ}\}$$

with

Response variable:

$$y = \%OTD = \text{\% On Time Delivery}$$

and

Predictor variables:

$$x_1 = COQ = 1 - \text{(Total cost of quality as a \% of Sales)}$$
$$x_2 = R_s = \text{Reliability of Lean System}$$
$$x_3 = OA = \text{Operation Availability}$$

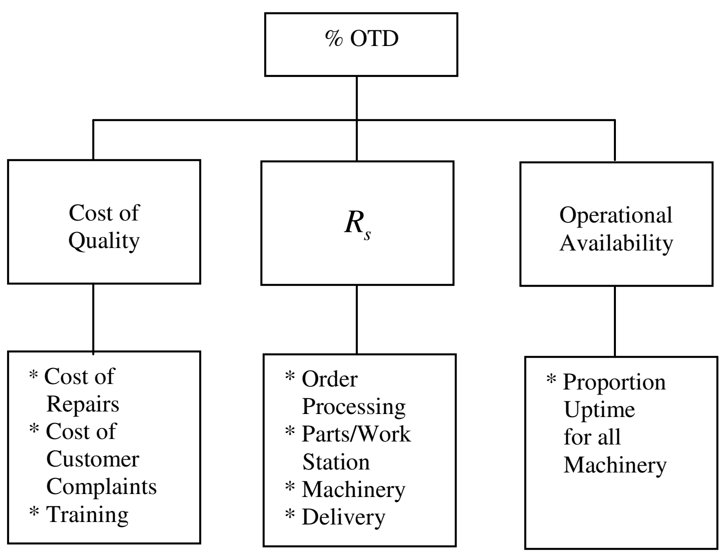


Fig. 57 Overview of % OTD Regression Model

4.8.3 Regression Analysis Procedure

A. Conduct Preliminary Checks on Data Quality

We begin by using histograms as shown in Figure 58 to screen data for unusual behavior such as outliers and non-normality before fitting any model. The histograms for all three predictor variables: R_s, Operational Availability, and Cost of Quality, indicate no unusual values and each variable appears to follow a Normal distribution.

Next, we analyze a scatter plot matrix in Figure 59 to determine whether relationships exist among the predictor variables and the response variable.

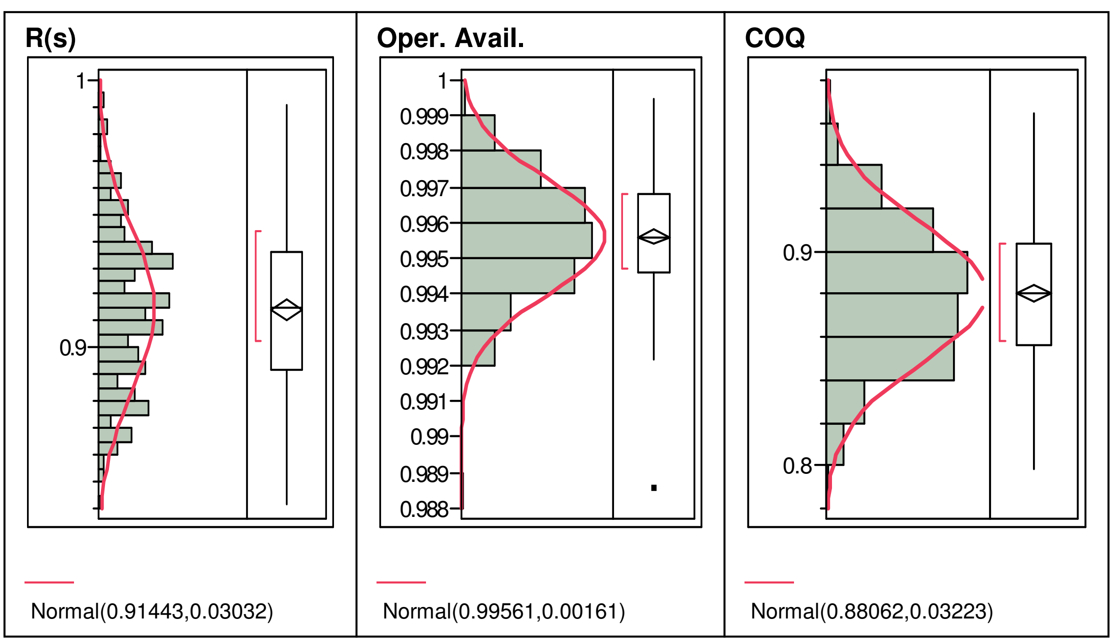


Fig. 58 Histograms of Predictor Variables

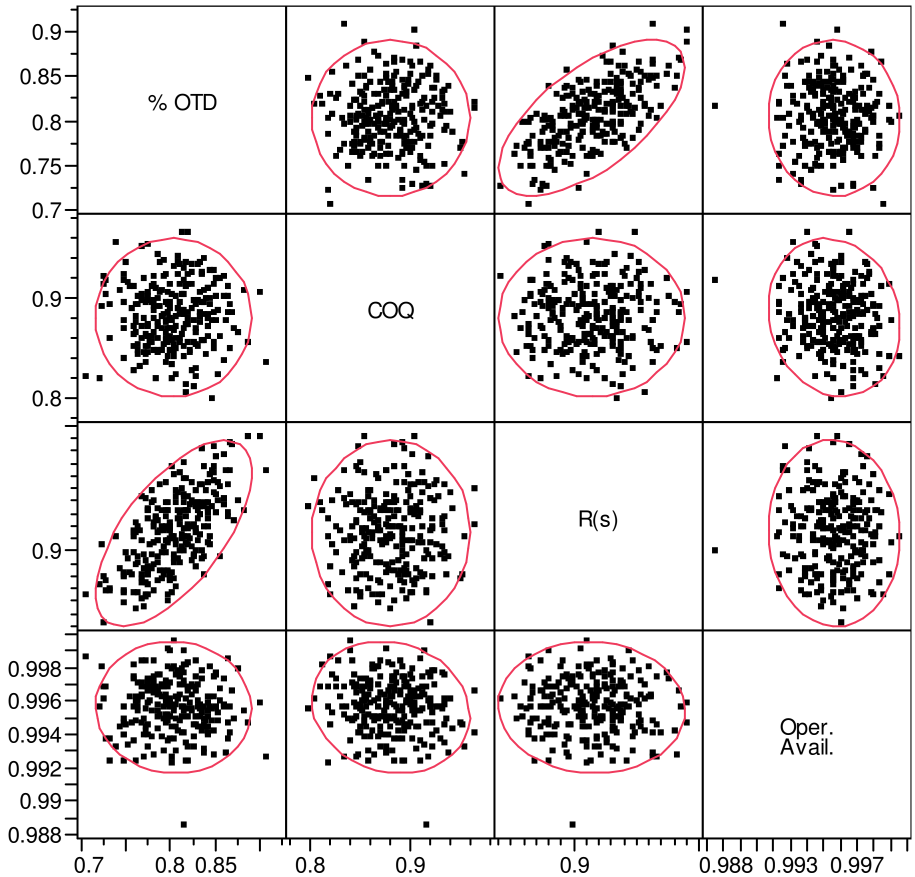


Fig. 59 Scatterplot Matrix for Full Model

In examining both the scatterplot matrix and the correlation matrix, there appears to be a strong positive correlation between % OTD and R_s. No correlations appear to exist among the other predictor variables.

A correlation matrix is displayed in Table 24 to determine the strength of relationships among the predictor variables and the response variable.

Table 24 Correlation Matrix for Full Model

	% OTD	COQ	R(s)	Oper. Avail.
% OTD	1.0000	0.0023	0.6447	-0.0291
COQ	0.0023	1.0000	0.0040	-0.1245
R(s)	0.6447	0.0040	1.0000	-0.0375
Oper. Avail.	-0.0291	-0.1245	-0.0375	1.0000

B. Develop a Full Model

We begin with a three-factor multiple regression model. That is, a regression model is developed to regress all main effects, all two-factor interactions, and all three-factor interaction terms against the response variable, Y_i.

$$y = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon$$

Where *y* is the response variable, % OTD, that we wish to predict; $\beta_0,\ \beta_1, \ldots, \beta_k$ are parameters with unknown values; $x_1,\ x_2, \ldots, x_k$ are information-contributing variables that are measured without error; and ε is the random error component. Since $\beta_0,\ \beta_1, \ldots, \beta_k$ and $x_1,\ x_2, \ldots, x_k$ are based on historical data and, therefore, are nonrandom, the quantity

$$y = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k$$

represents the deterministic portion of the model. Hence, *y* is composed of two components – one fixed and one random – and, consequently, *y* is a random variable.

$$\underbrace{y = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k}_{\text{Deterministic portion of model}} \quad + \quad \underbrace{\varepsilon}_{\text{Random error}}$$

C. Assumptions for Random Error ε

1. For any given set of values of $x_1,\ x_2,\ldots,x_k$, the random error ε has a normal probability distribution with mean equal to zero and variance equal to σ^2.
2. The random errors are independent.

D. Fitting the Full Model

Summary statistics for the Full model are shown in Table 25. We want to choose an estimated model

$$\begin{aligned}\hat{y} &= \hat{\beta}_o + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_k x_k + \varepsilon \\ &= .3783 + .0060x_1 + .7451x_2 + .9182x_1x_2 - .2626x_3 + 57.9674x_x x_3 \\ &\quad - 37.8798x_2x_3 - 461.5152x_1x_2x_3 + \varepsilon\end{aligned}$$

that minimizes

$$SSE = \sum (y_i - \hat{y}_i)^2 = 0.1823$$

Recall that σ^2 is the variance of the random error, ε. If $\sigma^2 = 0$, all the random errors will equal zero and the predicted values, $\hat{y}$, will be identical to the mean value, $E(y)$. Conversely, a large value of σ^2 implies large absolute values of ε and larger deviations between the predicted values, $\hat{y}$, and $E(y)$.

An ANOVA table is shown in Table 26.

Table 25 Summary of Fit for Full Model

Statistic	Result
RSquare	0.426559
RSquare Adj	0.412399
Root Mean Square Error	0.027447
Mean of Response	0.80318
Observations (or Sum Wgts)	250

Table 26 Analysis of Variance for Full Model

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	7	0.13561563	0.019374	25.7291
Error	242	0.18231393	0.000753	**Prob > F**
C. Total	249	0.31792956		<.0001

The mean is simply the sample mean of the response variable.

$$\bar{y} = 0.80318$$

This means that the overall reliability for % OTD, on average, given by this model is 80.318%.

The coefficient of multiple determination, R^2, which measures the proportion of variation in % OTD explained by the model as a whole is given by

$$R^2 = \frac{SSR}{SST} = \frac{\sum(\hat{y}_i - \bar{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} = \frac{.13561563}{.31792956} = .426559$$

The remaining error is attributed to random error. The adjusted R_a^2, which adjusts R^2 by dividing each sum of squares by its associated degrees of freedom is computed by

$$R_a^2 = 1 - \frac{\frac{SSE}{n-p}}{\frac{SST}{n-1}} = 1 - \left(\frac{n-1}{n-p}\right)\frac{SSE}{SST} = 1 - \left[\left(\frac{250-1}{250-7}\right)\left(\frac{.18231393}{.31792956}\right)\right] = .412399$$

The value for R_a^2 is significant since this value adjusts for the number of predictor terms in the model and, thus, provides a truer measure of goodness of fit than R^2 alone.

The standard error of the estimate, also known as root mean square error (RMSE), measures the distance, on average, of a data point from the fitted line, measured along a vertical line. RMSE is calculated by

$$RMSE = \sqrt{MSE} = \sqrt{.000753} = .027447$$

In the ANOVA table, an *F*-ratio is computed, which measures the ratio of the model mean square to the mean square for error. A large *F*-value indicates that the model is significant, meaning that we have obtained a good model to fit the data. The F-ratio is computed by

$$F = \frac{MSR}{MSE} = \frac{.019374}{.000753} = 25.7291$$

The *F*-value of 25.791 is relatively large, indicating that the model is a good fit to the data. We can assess the model's significance by it *p*-value. A *p*-value smaller than $\alpha = 0.05$ would corroborate our findings with regard to the *F*-value. In the Full model,

$$p - value < 0.0001$$

Parameter estimates for the full model are shown in Table 27. When we examine the *p*-value parameter estimates for statistical significance at $\alpha = 0.05$, only the parameter estimate, R_s, is significant with a *p*-value < 0.0001. This means that we are 95% confident that R_s has a statistically significant effect on predicting the response variable, % OTD. Note that the two-factor interaction term, COQ*Operational Availability, is significant at $\alpha = 0.10$. The significance of retained parameters can be verified in a Normal plot as shown in Figure 60, where the isolated R_s term is orthogonal to the Normal plot line.

Table 27 Parameter Estimates for Full Model

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.3782694	1.113097	0.34	0.7343
COQ	0.0060499	0.054854	0.11	0.9123
R(s)	0.745132	0.057942	12.86	<.0001
(COQ-0.88062)*(R(s)-0.91443)	0.9181537	1.902033	0.48	0.6297
Oper. Avail.	-0.262556	1.107718	-0.24	0.8128
(COQ-0.88062)*(Oper. Avail.-0.99561)	57.967385	33.60725	1.72	0.0858
(R(s)-0.91443)*(Oper. Avail.-0.99561)	-37.87975	38.79519	-0.98	0.3298
(COQ-0.88062)*(R(s)-0.91443)*(Oper. Avail.-0.99561)	-461.5152	1239.699	-0.37	0.7100

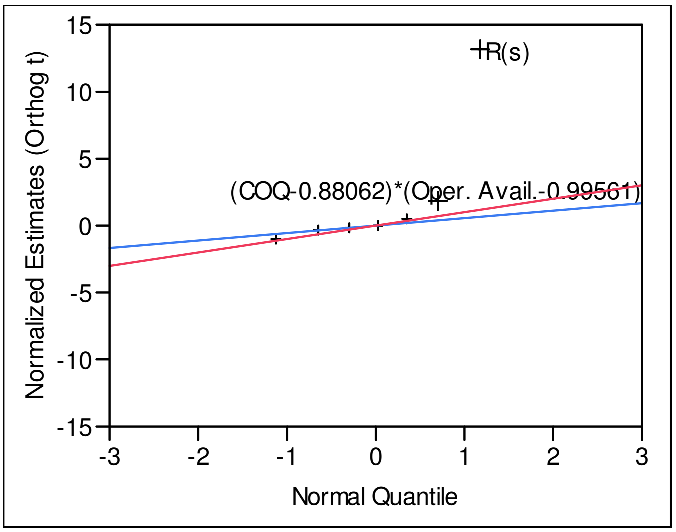


Fig. 60 Normal Plot of Full Model

E. Fitting the Reduced Model

The Reduced model retains statistically significant parameters from the Full model, but it may also include statistically non-significant parameters. For example, higher-order terms (i.e., interaction terms) *must* retain all lower-order terms that comprise the higher-order term. This results in a hierarchical Reduced model. However, since R_s is the only significant term in the Full model, we retain only this term and drop all other terms to fit a Reduced model.

Summary statistics for the Reduced model are shown in Table 28. An ANOVA table is shown in Table 29. Parameter estimates for the Reduced model are shown in Table 30. We want to choose an estimated model

$$\hat{y} = \hat{\beta}_o + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_k x_k + \varepsilon$$
$$= .1085 + .7597 x_2 + \varepsilon$$

that minimizes

$$SSE = \sum (y_i - \hat{y}_i)^2 = 0.1858$$

Table 28 Summary of Fit for Reduced Model

Statistic	Result
RSquare	0.415602
RSquare Adj	0.415602
Root Mean Square Error	0.027368
Mean of Response	0.80318
Observations (or Sum Wgts)	250

Table 29 Analysis of Variance for Reduced Model

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.13213228	0.132132	176.3686
Error	248	0.18579728	0.000749	**Prob > F**
C. Total	249	0.31792956		<.0001

Table 30 Parameter Estimates for Reduced Model

Term	Estimate	Std Error	t Ratio	Prob>|t|	Lower 95%	Upper 95%
Intercept	0.1084697	0.05234	2.07	0.0393	0.0053828	0.2115566
R(s)	0.7597235	0.057206	13.28	<.0001	0.6470511	0.8723959

The mean is simply the sample mean of the response variable.

$$\bar{y} = 0.80318$$

This means that the overall reliability for % OTD, on average, given by this model remains at 80.318%.

The coefficient of multiple determination, R^2, which measures the proportion of variation in % OTD explained by the model as a whole is given by

$$R^2 = \frac{SSR}{SST} = \frac{\sum(\hat{y}_i - \bar{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} = \frac{.13213228}{.31792956} = .415602$$

The remaining error is attributed to random error. The adjusted R_a^2, which adjusts for the single predictor term in the model by

$$R_a^2 = 1 - \frac{\frac{SSE}{n-p}}{\frac{SST}{n-1}} = 1 - \left(\frac{n-1}{n-p}\right)\frac{SSE}{SST} = 1 - \left[\left(\frac{250-1}{250-1}\right)\left(\frac{.18579728}{.31792956}\right)\right] = .415602$$

The value for R_a^2 is significant because, by retaining only one parameter estimate in the Reduced model, R_s it is equal to R^2.

The standard error of the estimate, also known as root mean square error (RMSE), measures the distance, on average, of a data point from the fitted line, measured along a vertical line. RMSE is calculated by

$$RMSE = \sqrt{MSE} = \sqrt{.000749} = .027368$$

The analysis includes estimating individual 95% confidence intervals on β_j, where β is the slope for $j = 0,1,...,k$ parameters. Confidence intervals for the transformed parameters are estimated by

$$b_j \pm t(1-\alpha/2; n-p)s\{b_j\}$$

From Table 30, we observe that the 95% confidence intervals on β_2 are (0.6471, 0.8724). This means that we are 95% confident that the true mean for the R_s parameter estimate lies between 0.6471 and 0.8724.

Lack of Fit test is conducted when the data contains replicated observations. The measured error for these replicates is called pure error. This is the portion of the sample error that is unaccounted for or predicted regardless of the form the model uses. The test for lack of fit for the Reduced model is shown in Table 31.

The Lack of Fit test tests the following hypothesis:

$$H_o : \text{Model lacks fit}$$
$$H_a : \text{Model does not lack fit}$$

Table 31 Test for Lack of Fit

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Lack Of Fit	219	0.17059181	0.000779	1.4856
Pure Error	29	0.01520546	0.000524	**Prob > F**
Total Error	248	0.18579728		0.1019
				Max RSq
				0.9522

Since the *p*-value > 0.10, we can *marginally* conclude that the model lacks fit to the data at $\alpha = 0.10$. The reduced model, however, with only one parameter estimate, R_s, as shown in Table 23, is statistically significant with a *p*-value < 0.0001.

Next, we conduct a test for normality as another criterion for the adequacy of the regression model. That is, we want to test the null hypothesis that the data in the Reduced model follows a normal distribution versus the alternative hypothesis that the data follows a non-normal distribution. The Shapiro-Wilk test for normality is used to test this hypothesis.

The Shapiro-Wilk test in Table 32 is a formal test to determine whether the reduced model is normally distributed. It tests the following hypothesis:

$$H_o : \text{Distribution is normal}$$
$$H_a : \text{Distribution is non-normal}$$

Since $W = 0.5148 > \alpha = 0.05$, we conclude that the data is normally distributed.

We will also check Predicted Sum of Squares (or PRESS), and PRESS root mean square error (RMSE) statistics to corroborate the results found by R^2 and R_a^2. The PRESS statistic is a measure of how well the use of the fitted values for a subset model can predict the observed responses, y_i. Minimizing $PRESS_p$ is desirable because when the prediction

Table 32 Shapiro-Wilk W Test

W		Prob<W
0.959933		0.5148

errors $y_i - \hat{y}_{i(i)}$ are small, so are the squared prediction errors and the sum of the squared prediction errors. The *PRESS* RMSE tests how well the reduced model would predict each of the data points if they were not included in the regression. The Press statistic of $PRESS_p = 0.18867$ shown in Table 33 indicates that the reduced model fits the data well in the sense of having small prediction errors.

The *PRESS* RMSE tests how well the reduced model would predict each of the data points if they were not included in the regression. *PRESS* RMSE = 0.02747 found in Table 33 indicates that the model is not overly sensitive to any single data point. In addition, this small $PRESS_p$ value also validates the small RMSE value found in Table 21.

A plot of actual % OTD vs. R_s is displayed in Figure 61 to determine fit. The plot confirms our earlier discovery that there exists a strong, positive, linear correlation between % OTD and R_s.

Table 33 Press Statistic

Press	Press RMSE
0.1886721011	0.02747159

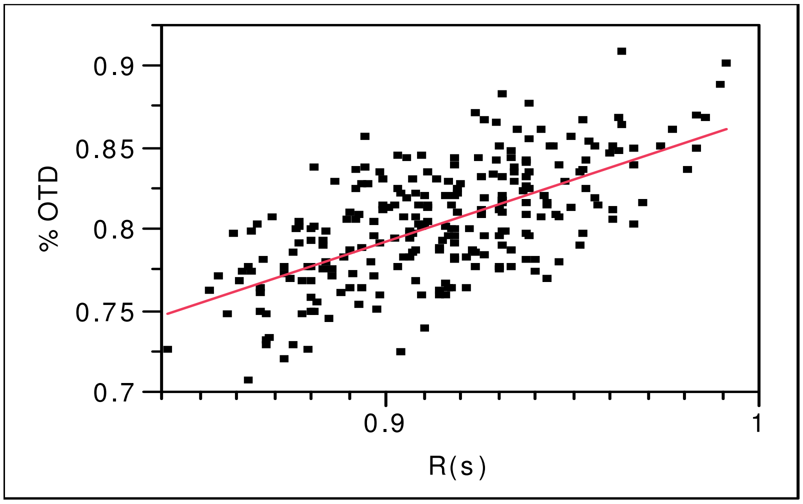


Fig. 61 Plot of % OTD vs. R_s

F. Diagnostic Checks and Remedial Measures:

A scatterplot matrix is helpful in determining the nature and strength of the bivariate relationship between the predictor variable, R_s, and the response variable, % OTD, as well as in identifying gaps for both the data points as well as outlying points as shown in Figure 62. The scatterplot matrix confirms a positive linear relationship between R_s and % OTD.

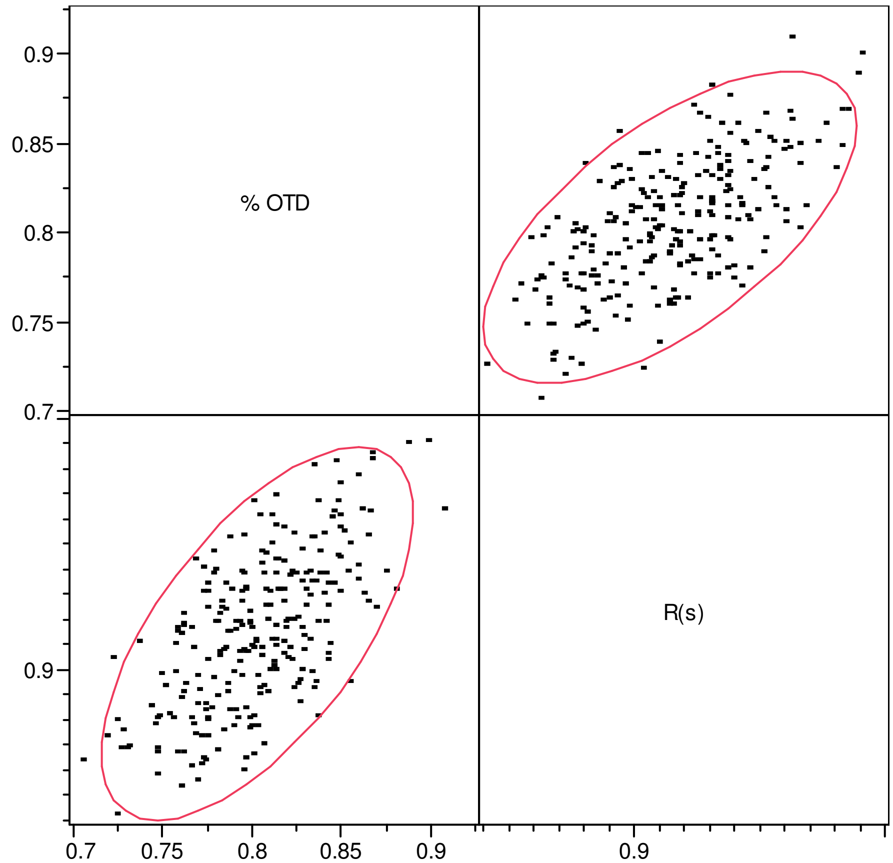


Figure 62 Scatterplot Matrix for Reduced Model

The correlation matrix found in Table 34 are helpful in confirming whether any linear associations exist among predictor variables and the response variable. Indeed, we observe a correlation coefficient of 0.6447 between R_s and % OTD, which indicates a fairly strong, positive linear relationship.

Table 34 Correlation Matrix for Reduced Model

	% OTD	**R(s)**
% OTD	1.0000	0.6447
R(s)	0.6447	1.0000

G. Residuals Analysis

Residuals analyses will be conducted by plotting a histogram of the residual values, plotting residuals vs. predicted values, plotting residuals vs. the predictors variable, and a normality plot of residuals to check for any departures from the normality assumption.

A histogram of residual values is found in Figure 63. The residuals appear to follow a normal distribution. Additionally, there is no indication of outliers in the residual values as observed in the outlier box plot above the histogram.

A plot of residuals vs. predicted values is shown in Figure 64. No abnormalities are detected in the scatter plot. Residuals appear to be random in nature.

A normality plot of residuals is shown in Figure 65. The residuals conform rather tightly to the normal quantile plot line. This is further evidence that the residuals are normally distributed.

After satisfying diagnostic checks and residuals analyses, our Reduced model is

$$\hat{y} = .1085 + .7597x_2 + \varepsilon$$

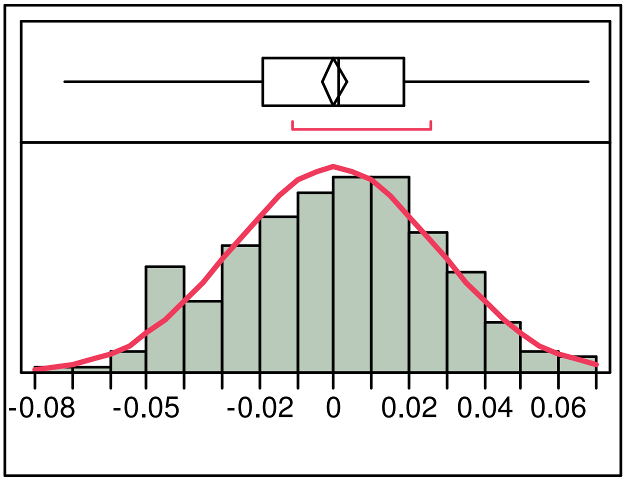


Fig. 63 Histogram of Residual % OTD

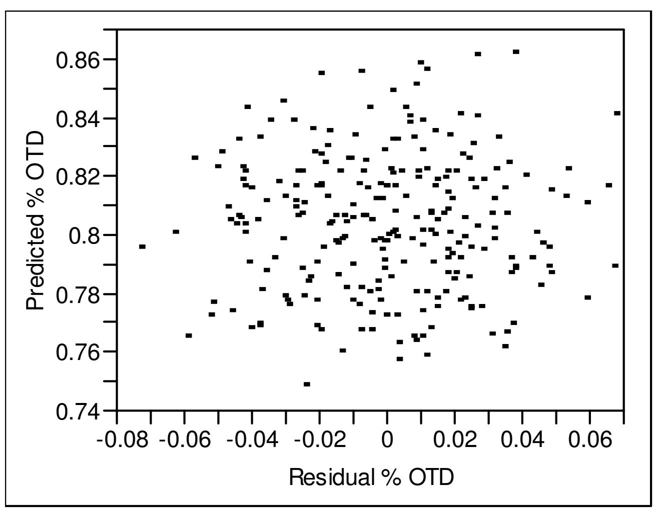


Fig. 64 Plot of Residuals vs. Predicted Values

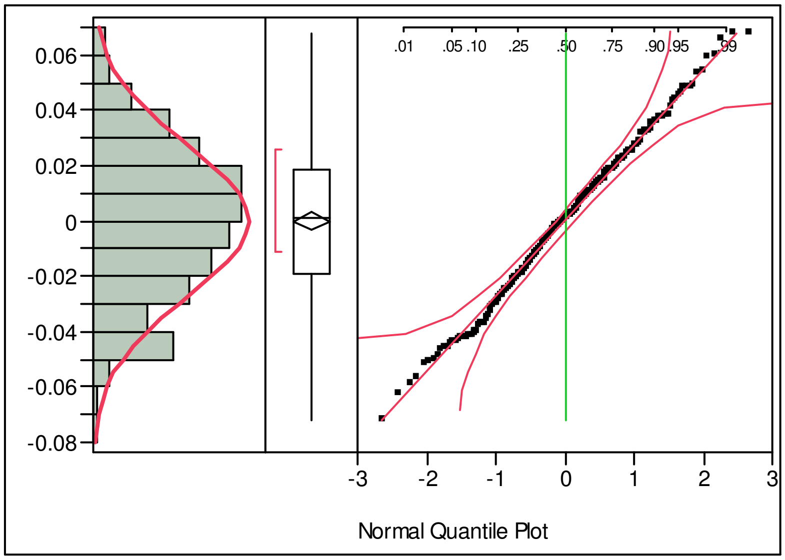


Fig. 65 Normality Plot of Residuals

5. Conclusions and Areas of Future Research

5.1 Conclusions

A reliable Lean system is essential in accomplishing its mission of minimizing cost for on time delivery of goods of quality products or services. A Lean systems reliability model (LSRM) was developed to measure the reliability of a stochastic Lean system. The LSRM model consists of three phases:

Phase 1 – Conceptual Framework
Phase 2 – Development of LSRM
Phase 3 – Model Validation.

In Phase 1, an infrastructure was developed for evaluating Lean systems. Operational measures for Lean systems, including inputs, processes, and outputs, were identified. Phase 2 consisted of using principal components analysis to identify Lean critical subsystems. A value stream map of the current state was used to represent a workflow sequence. Later, a value stream map of the future state was created to demonstrate how group technology enabled consolidation of a series of work activities into a single work cell, thereby improving both productivity and efficiency.

Research questions from Chapter 1with regard to the integration of reliability with Lean systems will now be revisited.

1. **What is the conceptual framework of a Lean System Reliability model (LSRM)?**

   The conceptual framework of LSRM consists of three hierarchical levels – System level, Subsystem level, and Component level – within the Lean system as shown in Figure 66. Reliability measures for each component are provided in the framework.

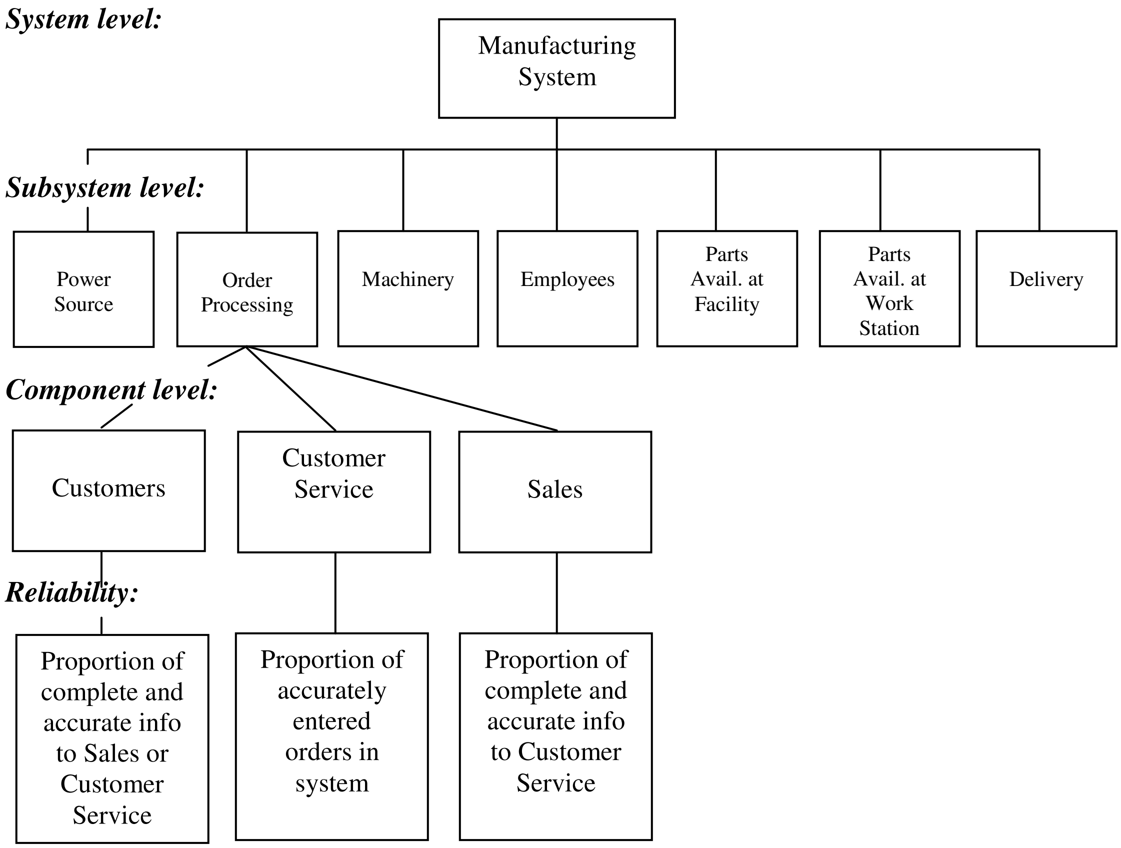


Fig. 66 Overview of LSRM Hierarchical Levels

2. What is the algorithm for developing a stochastic LSRM?

The algorithm for developing a stochastic LSRM is displayed in Figure 67 consisting of three phases:

Phase 1: Conceptual framework
Phase 2: Development of LSRM
Phase 3: Model Validation

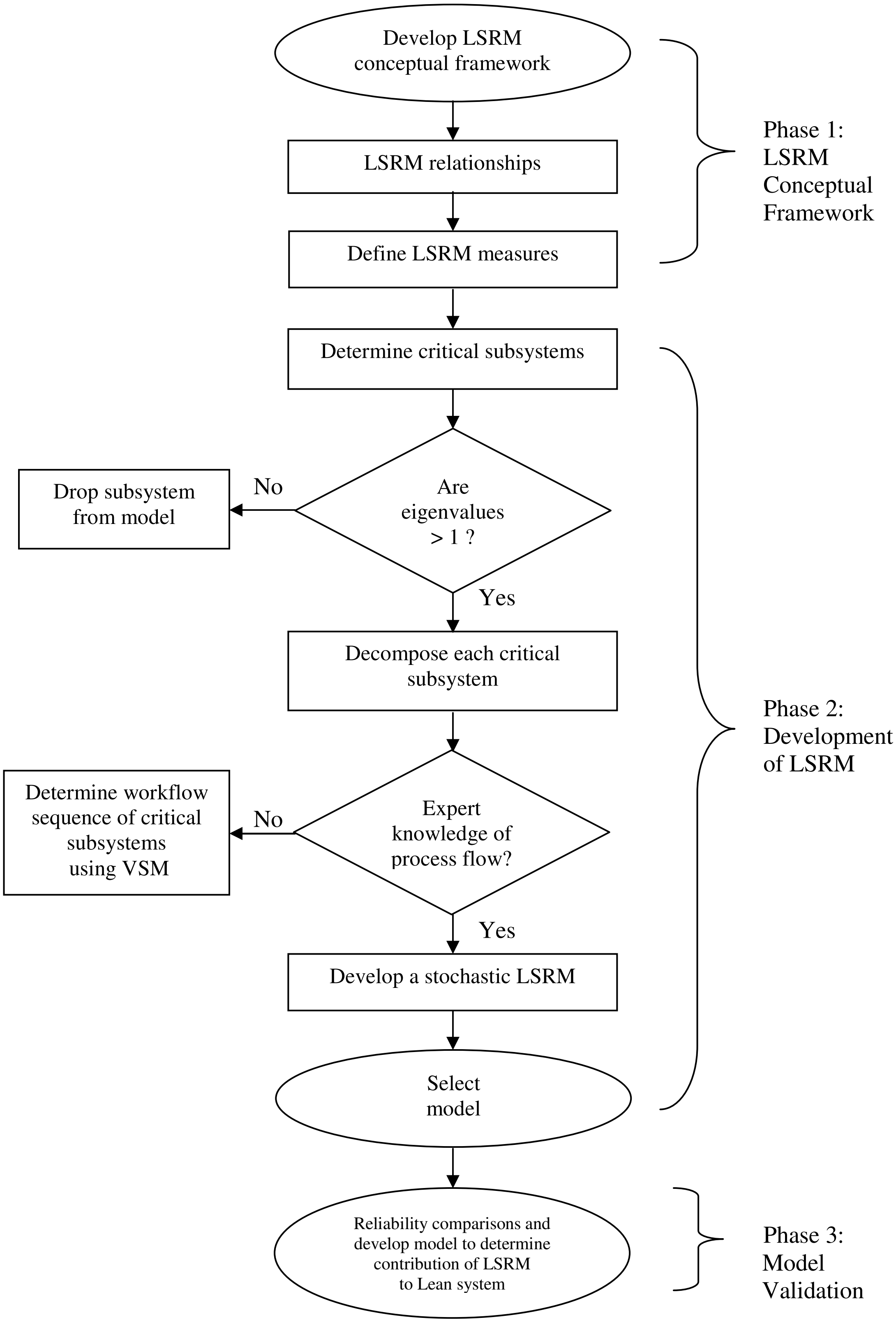


Fig. 67 Overview of LSRM Development

3. How are critical subsystems determined?

Critical subsystems are determined using a mathematical procedure known as Principal Components Analysis. Once a determination is made whether all subsystems are considered of equal importance, eigenvectors and eigenvalues are calculated for either a correlation matrix (if all subsystems are of equal importance) or a variance-covariance matrix (if all subsystems are not of equal importance). Whereas an eigenvalue provides us with the length of an axis, the eigenvector determines its orientation in space and is normally standardized A threshold value known as a Kaiser criterion is arbitrarily determined to assess the criticality of subsystems. In our example, only subsystems whose eigenvalues are > 1(Kaiser criterion) are retained in the model. A Scree plot is a graphical method for discriminating critical subsystems by employing a similar threshold criterion as the Kaiser criterion for retaining or dropping subsystems from the model.

4. How does one determine the LSRM workflow sequence?

A Value Stream Map (VSM) is a graphical depiction of the entire flow of activities and subsystems in a complex manufacturing system. A VSM is used to define value from the customer's perspective and to delineate which process steps create value and which are waste. A current state VSM is useful for identifying current value added and non-value added activities that are required to produce and deliver the product to the customer. A future state VSM provides a blueprint for improvements can be made to eliminate non-value added activities and remove waste for the manufacturing system. The goal is to identify, demonstrate, and decrease sources of waste and create the most value while consuming the fewest resources.

5. **How is the reliability of LSRM system determined?**

   The reliability of LSRM is determined by simulation techniques such as Monte Carlo simulation. Random samples are drawn from trial runs from probability distributions that represent historical data. The reliability of the Lean system is determined by its critical subsystems, represented in a series system reliability model.

6. **How is the reliability of Lean critical subsystems determined?**

   The reliability of LSRM is determined by simulation techniques such as Monte Carlo simulation. Random samples are drawn from trial runs from probability distributions that represent historical data. The reliability of Lean critical subsystems is determined by its subsystem components as represented by parallel, series, or redundant reliability system formulas within each subsystem.

7. **How is the reliability of LSRM components determined?**

   The reliability of LSRM is determined by simulation techniques such as Monte Carlo simulation. Random samples are drawn from trial runs from probability distributions that represent historical data. The reliability of components is determined by its reliability measures, or proportion success of key component characteristics.

8. **How is LSRM validated?**

   Recall that the levels of system, subsystem, and component are relative terms, since the system at one level in the hierarchy is the component at another level. If the range of mean reliability results among Lean components, Lean subsystems, and the Lean system are accurate to within 3%, then the LSRM model is considered a valid model due to its accurate at any level within the Lean system.

9. What is the contribution of LSRM to Lean systems?

LSRM can be shown through regression analysis to have a statistically significant effect on % on time delivery. This is important because the on time delivery of products or services at minimum cost is a fundamental tenet of Lean systems.

5.2 Case Study Conclusions

A stochastic reliability model for Lean systems was developed using Monte Carlo simulation leading to the scientific selection of a reliability model. The simulation was composed of three parts:

1. Performing a simulation of n = 1000 trial runs of 500 random samples for all Lean components based on historical observations.
2. Performing a simulation of n = 1000 trial runs of 500 random samples for all Lean critical subsystems based on historical observations.
3. Performing a simulation of n = 1000 trial runs of 500 random samples for the Lean system based on historical observations.

A comparison of simulation results for components, subsystems, and the Lean system is presented in Table 35. A comparison of historical data results are displayed in Table 36.

Table 35 Summary of Monte Carlo Simulation Results

	μ	σ	**Range of R(s) values**
Component Level			
Customers	.9696	.0182	.9375-1.0
Customer Service	.9630	.0211	.9277-1.0
Sales	.9687	.0179	.9375-1.0
Outside Suppliers	.9951	.0196	.80-1.0
Internal Parts Depot	.9954	.0188	.81-1.0
Upstream W. Stations	.9945	.0214	.83-1.0
Machine 1	.9919	.0196	.80-1.0
Machine 2	.9957	.0188	.80-1.0
Machine 3	.9755	.0482	.58-1.0
Machine 4	.9969	.0146	.80-1.0
Machine 5	.9930	.0236	.81-1.0
Company Trucks	.9984	.0010	.9898-1.0
Third Party Carriers	.9983	.0010	.9965-1.0
Subsystem Level			
Order Processing	.99996	.0001	.9971-.1.0
Parts/Work Station	.9851	.0358	.7055-1.0
Machinery	.9537	.0622	.58-1.0
Delivery	1.0	0	.9995-1.0
System Level			
Lean System	.9394	.0709	.58-1.0

The mean reliability results for the simulated data compare very favorably with the results from historical data. Subsystems for both sets of data follow a Weibull distribution. The mean reliability for the simulated stochastic Lean system is .9394, which is within 2.19% of the mean reliability of the stochastic Lean system using historical data. This satisfies the criterion of whether the simulated mean reliability is accurate to within 3% of the mean reliability based on historical data, as specified in the Model Validation Flow Chart shown in Figure 23. Therefore, we conclude that the LSRM model is a validated model. Moreover, the researcher's objective of developing a mathematical model that measures the reliability of Lean systems based on its critical subsystems has been achieved.

Table 36 Summary of Historical Data Results

	μ	σ	**Range of R(s) values**
Component Level			
Customers	.81	.0114	.785-1.0
Customer Service	.905	.016	.895-1.0
Sales	.896	.0135	.8788-1.0
Outside Suppliers	1.0	.015	.96-1.0
Internal Parts Depot	.9999	.0176	.945-1.0
Upstream W. Stations	.9995	.0128	.9615-1.00
Machine 1	1.0	.0162	.925-1.0
Machine 2	.9999	.0188	.9478-1.0
Machine 3	.9895	.0215	.93-1.0
Machine 4	.9831	.0266	.915-1.0
Machine 5	.9935	.0167	.9555-1.0
Company Trucks	.915	.0124	.8708-1.0
Third Party Carriers	.95	.0128	.9195-1.0
Subsystem Level			
Order Processing	.9982	.0080	.91-1.0
Parts/Work Station	.9994	.0062	.94-1.0
Machinery	.9664	.0623	.58-1.0
Delivery	.9957	.0266	.69-1.0
System Level			
Lean System	.960	.0682	.58-1.0

Reliability formulas presented in Chapter 3 will be repeated to provide a relative measure of mean reliability results when comparing the component level, subsystem level, and the system level of a Lean system based on historical data.

Component Level

$$\begin{aligned} R_{Components} &= [1-(1-r_C)(1-r_{CS})(1-r_S)]\times[r_{OS}\cdot r_{IPD}\cdot r_{UWS}] \\ &\quad \times[r_1\cdot r_2\cdot r_3\cdot r_4\cdot r_5]\times[1-(1-r_{CT})(1-r_{TPC})] \\ &= [1-(1-.81)(1-.905)(1-.896)]\times[1.0\cdot.9999\cdot.9995] \\ &\quad \times[1.0\cdot.9999\cdot.9895\cdot.9831\cdot.9935]\times[1-(1-.915)(1-.95)] \\ &= .9599 \end{aligned}$$

Subsystem Level

$$R_{Subsystems} = r_{OP} \times r_{WS} \times r_M \times r_D$$

$$= .9982 \times .9994 \times .9664 \times .9957$$

$$= .9599$$

System Level

$$R_{System} = .960$$

In Phase 3, a regression model was developed to determine the effect of three predictor variables and their interaction effects on the response variable, % on time delivery. The Reduced model confirms a strong positive relationship between a reliable Lean system, R_s, and % on time delivery. The reduced model is

$$\hat{y} = 0.1085 + 0.7597x_2 + \varepsilon$$

5.3 Areas of Future Research

Proposed future research includes a significant industrial validation study of reliability in Lean systems using the LSRM model with compatible statistical and simulation software based on the interrelationships among the Lean system as a whole, its subsystems, and its components. The beginning of the validation process is this paper and readers' response to it.

Another proposed area of future research involves the integration of human reliability with Lean systems. Exploration into the design of standard operating procedures (SOPs) and standard assembly procedures (SAPs) using human error criticality analysis (HECA) techniques may help to explain the phenomenon of how human error affects the reliability (and safety) of Lean systems.

Additionally, a thorough examination of organizational culture and its contribution to Lean initiatives may unveil a latent contributing factor towards the reliability of Lean systems.

List of References

Abdulmalek, Fawaz A. and Jayant Rajgopal (May 2007). Analyzing the benefits of lean manufacturing and value stream mapping via simulation: A process sector case study, *International Journal of Production Economics*, Vol. 107, No. 1, pp. 223-236.

Adler, P.S. Goldoftas, B., and Levine D. (1993). Ergonomics, employee involvement, and the Toyota Production System: A Case Study of Nummi's 1993 Model Introduction, *Industrial Labor Relations Review*, Vol. 50, pp. 416-437.

Adler, P.S. and Borys, B. (1996). Two types of bureaucracy: Enabling and coercive. *Administrative Science Quarterly*, Vo. 41, pp. 61-89.

Albright, Brian (May 2005). Forklift readers could give boost to RFID deployments, *Frontline Solutions*, Vol. 6, No. 5, pp. 23-25.

Alukal, George (Apr 2006). Building blocks, *Quality Progress*, pp. 87-88.

Andel, Tom (Apr 1, 2006). Healthy employees help to manage healthcare costs, *Official Board Markets*, Questex Media, Newton, MA.

Andel, Tom (Dec 2003). IP reads paper to the core, *Material Handling Management*, Vol. 58, No. 13, pp. 32-33.

Attaran, Mohsen (Sept 2006). RFID pays off, *Industrial Engineer*, pp. 46-50.

Babson, S. (1993). Lean and mean: The MIT model and lean production at Mazda, *Journal of Labor Studies*, Vol. 18, pp. 3-25.

Bagadia, Kris (May 2008). Asset reliability drives lean maintenance, *Plant Engineering*, Vol. 62, Issue 5, ppl 45-48.

Bain, W. A. (Sept 1999). Application of theory of action to safety management: Recasting the NAT/MRT debate, *Journal of Contingencies and Crisis Management*, p. 7.

Bartels, Nancy (Jun 2005). Start expecting the unexpected: Supply chain security means being ready for anything, *Manufacturing Business Technology*, Vol. 23, No. 6, pp. 52-54.

Bergren, Christian (1993). *Alternatives to lean production: Work Organization in the Swedish auto industry*, Ithaca, NY: ILR Press.

Bloswick, Donald S. (1984). *System Safety Analysis*, NIOSH P.O. #939341.

Box, G.E.P, and D.R. Cox (1964). An analysis of transformations, *Journal of the Royal Statistical Society*, B, Vol. 26, pp. 211-234.

Brown, Karen A. (Jun 1996). Workplace safety: A call for research, *Journal of Operations Management*, Vol. 14, Issue 2, pp. 157-171.

Bruce, M., Daly, L., and Towers, N. (2004). Lean or agile: A solution for supply chain management in the textiles and clothing industry? *International Journal of Operations and Production Management*, Vol. 24, No. 2, pp. 151-170.

Burnham, K.P. and D.R. Anderson (1998). *Model Selection and Inference*, New York: Springer-Verlag.

Butler, Richard (May 2005). Cut your losses, *Professional Engineering*, Vol. 18, No. 9, pp. 32-33.

Campbell, Kevin (Aug 2006). The endless journey, *Plant Engineering*, pp. 51-56.

Cattell, R. B., and Sullivan, W. (1962). The scientific nature of factors: A demonstration by cups of coffee, *Behavioral Science*, Vol. 7, pp. 184-193.

Cattell, R.B. (1966). The scree test for the number of factors, *Multivariate Behavioral Research*, Vol. 1, pp. 245-276.

Cattell, R.B., and Jaspers, J. (1967). A general plasmode (No. 30-10-5-2) for factor analytic exercises and research, *Multivariate Behavioral Research Monographs*, Vol. 67, No. 3, pp. 1-211.

Cattell, R.B. (1978). *The scientific use of factor analyses*, New York: Plenum.

Chalmers, Raymond E. (Aug/Sept 1995). Cells spell success, *Forming and Fabricating*.

Chase, Robert B., F.Robert Jacobs and Nicholas J. Aquilano (2004). *Operations management for competitive advantage*, Boston: McGraw-Hill/Irwin.

Chen, Heping and Ning Xi (Jan 2008). Automated tool trajectory planning of industrial robots for painting composite surfaces, *International Journal of Advanced Manufacturing Technology*, Vol. 35, No. 7-8, pp. 680-696.

Chen, Yong and Jionghua Jin (2005). Quality-reliability chain modeling for system-reliability analysis of complex manufacturing processes, *IEEE Transactions on Reliability*, Vol. 54, Issue 3, pp. 475-488.

Condra, L.W. (1993). *Reliability improvement with design of experiments*, New York: Marcel Dekker .

Conway, Bill (Jan 22-26, 1990). *Proceedings from "Waste Elimination" seminar*, Bill Conway & Associates, Union Camp Corporation, Tarpon Springs, FL.

Cooper, Howard (2004). Lean maintenance maximizes cost savings, *Manufacturing Engineering*, Vol. 133, No. 6.

Copley, Frank Barkley (1923). *Frederick W. Taylor: Father of scientific management*, New York: Harper & Brothers.

Cox, S. and A.J.T. Cheyne (2000). Assessing safety culture in offshore environments, *Safety Science*, Vol. 34, pp. 111-129.

Croci, F. M. Perona, and A. Pozzetti (Mar 2000). Work-force management in automated assembly systems, *International Journal of Production Economics*, Vol. 64, Issues 1-3, pp. 243-255.

Cusumano, M.A. (1985). *The Japanese automobile industry: Technology and management at Nissan and Toyota* (Harvard East Asian Monographs, No. 122), Harvard University Press, Boston.

Davis, T. (1993). Effective supply chain management, *Sloan Management Review*, Vol. 34, pp. 35-46.

Davis, S., J.O. Gray, and Darwin G. Caldwell (Apr 2008). An end effector based on the bernoulli principle for handling sliced fruit and vegetables, *Robotics and Computer-Integrated Manufacturing*, Vol. 24, No. 2, pp. 249-257.

De Toni, A., and Tonchia, S. (1998). Manufacturing flexibility: A literature review, *International Journal of Production Research*, Vol. 36, No. 6, pp. 1587-1617.

Department of Defense (1980). *MIL-STD-1629A: Military standard: Procedures for performing a failure mode, effects and criticality analysis*, Washington, DC, 24 November 1980,

Department of Defense (1984). *MIL-STD-882B: System safety program requirements*, Washington, DC, 30 March 1984.

Dhafr, N., Ahmad, M, Burgess, B., Canagassababady, S. (2006). Improvement of quality performance in manufacturing organizations by minimization of production defects, *Robotics and Computer-Integrated Manufacturing*, Vol. 22, pp. 536-542.

Dillon, Andrew P. and Shigeo Shingo (1985). *A revolution in manufacturing: The SMED system*, New York: Productivity Press.

Dolan, Thomas G. (Nov 2005). Lean manufacturing – An idea whose time is coming to forest products?" *Industrial Reporting, Inc.*, Ashland, VA.

Drozda, Thomas J., Stranahan, Judy D., and Gloria Farr (1988). *Flexible manufacturing systems*, Dearborn, MI: Society of Manufacturers.

Fernandez-Muniz, Beatriz, Jose Manuel Montes-Peon, and Camilo Jose Vazques-Ordas (2007). Safety culture: Analysis of the causal relationships between its key dimensions, *Journal of Safety Research*, Vol. 38, Issue 6, pp. 627-641.

Finigan, Tim and Jim Humphries (Oct 2006). Maintenance gets lean. *Industrial Engineer*, Vol. 38, Issue 10, pp. 26-31.

Flinchbaugh, Jamie (2006). Lead yourself to lean, *Assembly*, p. 152.

Franceschini, Samuela, and Christina W. Tsai (2008). Incorporating reliability into the definition of the margin of safety in total maximum daily load calculations, *Journal of Water Resources Planning and Management*, Vol. 134, No. 1, pp. 34-44.

Freedenberg, Paul (Mar 2004). The condition of American manufacturing cannot be ignored, *American Machinist*, Vol. 148, Issue 3, p. 22.

Fucini, J.J. and Fucini, A. (1990). *Working for the Japanese*, New York: Free Press.

Fujimoto, T. (1999). *The evolution of a manufacturing system at Toyota*. Oxford University Press, Oxford.

Gaither, N. and G. Frazier (2002). *Operations management*, Cincinnati, OH: South Western.

Gharajedaghi, Jamshid (2006). *Systems thinking: Managing chaos and complexity: A platform for designing business architecture*, Second edition, Burlington, MA: Butterworth-Heinemann, pp. 17-18.

Goe, T.N. (1994). New approach to quality in a near-zero defect environment, *Total Quality Management*, Vo. 5, No. 3, pp. 3-10.

Goe, T.N. (2002). The role of statistical design of experiments in six sigma: Perspectives of a practitioner, *Quality Engineering*, Vol. 14, No. 4, pp. 659-71.

Goldman, S.L. and Nagel, R.N. (1991). *21st century manufacturing enterprise strategy: An industry-led view*, Iacocca Institute, Lehigh University, Bethlehem, PA.

Greenwood, N.R. (1988). *Implementing flexible manufacturing systems*, New York: Palgrave Macmillan.

Gumbel, E.J. (1958). *Statistics of extremes*, New York: Columbia University Press.

Gunasekaran, A. (2001). *Agile manufacturing: The 21st century competitive strategy*, Kidlington, Oxford: Elsevier Science Ltd.

Ha, SiewMun (Nov 2005). Above the curve: Six Sigma learning begins at home, *Industrial Engineer*, pp. 36-41.

Hall, R.W. (1983). *Zero inventories*, New York: McGraw-Hill.

Hancock, Walton M. and Matthew J. Zayko (Jun 1998). Lean production: Implementation problems, *IIE Solutions*, Vol. 3, No. 6., pp. 38-42.

Havold, Jon Ivar (2005). Safety culture in a Norwegian shipping company, *Journal of Safety Research*, Vol. 36, No. 5, pp. 441-458.

Hayes, R.H. and Wheelwright, S.C. (1984). *Restoring our competitive edge: Competing through manufacturing*, New York: Wiley.

Heizer J. and B. Render (2001). *Operations management*, Upper Saddle River, NJ: Prentice-Hall.

Herron, C. and P.M. Braiden (2007). Defining the foundation of lean manufacturing in the context of its origins (Japan), *International Journal of Agile Manufacturing*, Vol. 10, Issue 2, pp. 89-101.

Heymann, H., and A.C. Noble (1989). Comparison of canonical variate and principal component analyses of wine descriptive analysis data, *Journal of Food Science*, Vol. 54, Issue 5, pp. 1355-1358.

Hines, P. (1994). *Creating world class suppliers: Unlocking mutual competitive advantage*, London: Pitman Publishing Ltd.

Holland, John (1984). *Flexible manufacturing systems*, Dearborn, MI: Society of Manufacturers.

Holmes, F. Brian (Sept 7, 2007). Is your office as lean as your production line?, *Manufacturing Engineering*, Vol. 139, No. 3.

Holweg, M. and Pil, F.K. (2004). *The second century: Reconnecting customer and value chain through build-to-order*, Cambridge, MA: MIT Press.

Hopp, Wallace J. and Mark L. Spearman (Spring 2004). To pull or not to pull: What is the question?, *Manufacturing & Service Operations Management*, Vol. 6, No. 2, p. 133-148.

Hoske, Mark T. (Dec 2007). How to control quality: Err not, *Control Engineering*, Vol. 54, Issue 12, p. 33.

Hounshell, David A. (1984). From the American system to mass production, 1800-1932: The development of manufacturing technology in the united states, Baltimore, MD: *Johns Hopkins University Press*, pp. 217-230.

Huang, B., Sun, Y., and Sun, Y.M. (2008). Scheduling of flexible manufacturing systems based on petri net and hybrid heuristic search, *International Journal of Production Research*, Vol. 46, Issue 16, pp. 4553-4565.

Jobse, D. (Jun 2007). Managing calorie intake, *tce*, No. 792, pp. 50-51.

Johnson, Dallas E. (1998). *Applied multivariate methods for data analysts*, Pacific Grove, CA: Brooks/Cole Publishing Co., pp. 93-146.

Jusko, Jill (Dec 2005). On the up and up, *Industry Week*, Vol. 254, No. 212, pp. 34-37.

Katz, Jonathan (Dec 2007). Lean takes the driver's seat at Lear. *Industry Week*, p. 14.

Kessler, Fred (Mar 2006). Nine fatal mistakes in lean, *Assembly*, Vol. 49, No. 3, pp. 44-51.

Kidd, Paul T. (1994). *Agile manufacturing: Forging new frontiers*, Reading, MA: Addison-Wesley.

Kiff, J.S. (1997). The lean dealership – a vision for the future: “From hunting to farming”, *Marketing Intelligence Planner*, Vol. 18, pp. 112-126.

Korem, Yoram (1983). *Computer control of manufacturing systems*, New York: McGraw-Hill.

Kotte, Baskar (Nov 4, 2007). Why lean hasn’t worked, *Official Board Markets*, Questex Media, Newton, MA.

Krafcik, J.F. (Fall 1988). Triumph of the lean production system. *Sloan Management Review*, Vol. 30, No. 1, pp. 41-52.

LaPorte, T., and Consolini, P.M. (1991). Working in practice but not in theory: Theoretical challenge of high reliability, *Journal of Public Administration Research and Theory*, Vol. 1, pp. 19-47.

Larkin, John (Jan 2006). GM’s cup of woes, *Automotive Industries*, Vol. 186, Issue 1, p. 2.

Laslo, Zohar, Baruch, Keren, and Hagai Ilani (Jun 16, 2008). Minimizing task completion time with the execution set method, *European Journal of Operational Research*, Vol. 187, No. 3, pp. 1513-1519.

Leitao, Paulo and Francisco Restivo (2008). A holonic approach to dynamic manufacturing scheduling, *Robotics and Computer-Integrated Manufacturing*, Vol. 24, Issue 5, pp. 625-634.

Leventon, William (Sept 2004). Manufacturer’s get lean to trim waste. *Medical Device & Diagnostic Industry*, pp. 64-70.

Levinson, William A. (2002). *Henry Ford’s lean vision: Enduring principles from the first Ford motor plant*, London: Taylor & Francis Group.

Li, J.R., Khoo, L.P., and Tor, S.B. (2006). Generation of possible multiple components disassembly sequence for maintenance using a disassembly constraint graph. *International Journal of Production Economics*, Vol. 102, pp. 51-65.

Lian, Yang-Hua. and Hendrik Van Landeghem (Jul 2007). Analysing the effects of lean manufacturing using a value stream mapping-based simulation generator, *International Journal of Production Research*, Vol. 45, No. 13, pp. 3037-3058.

Liker, Jeffrey K. (1998). *Becoming Lean – Stories of U.S. manufacturers*, Portland, OR: Productivity, Inc.

Liker, Jeffery K. (2004). *The Toyota way: 14 management principles from the world’s greatest manufacturer*, McGraw Hill, New York.

Liker, Jeffrey K. and Michael Hoseus (2007). *Toyota culture: The heart and soul of the Toyota way*, New York: McGraw-Hill.

Linebaugh, Kate (2008). Honda's flexible plants provide edge, *The Wall Street Journal – Eastern Edition*, 23 Sept 2008, Vol. 252, Issue 71, pp. B1.

Lowson, B., King, R., and Hunter, A. (1999). *Quick response*, Chichester: Wiley.

Lugtigheid, Diederik, Dragan Banjevic, and Andrew K.S. Jardine (2008). System repairs: When to perform and what to do?, *Reliability Engineering and System Safety*, Vol. 93, pp. 604-615.

MacDuffie, J.P. and S. Helper (1997). Creating lean suppliers: Diffusing lean production through the supply chain, *California Management Review*, Vol. 39, pp. 118-151.

Magretta, J., and N. Stone. (2002). *What management is: How it works and why it's everyone's business*, New York: Free Press, p. 129.

Manivannan, Subramaniam (Nov 2006). Error-proofing enhances quality, *Manufacturing Engineering*, Vol. 137, Issue 5, p. 99.

Manley, John D., Thomas J. Smith, John Holden, Rob Edwards, and Gary Liptrot (Feb 2008). Modular approaches to automation system design using industrial robots, *Journal of the Association for Laboratory Automation*, Vol. 13, No. 1, pp. 13-23.

Mason-Jones, Rachel, Naylor, Ben, and Denis R. Towill, (2000). Lean, agile, or leagile? Matching your supply to the marketplace, *International Journal of Production Research*, Vol. 38, No. 17, pp. 4061-1070.

McClave, James T. and P. George Benson (1985). *Statistics for business and economics, Third Edition*, San Francisco: Dellen Publishing Company.

McGivern, Michael H. and Alex Stiber (1998). Lean manufacturing techniques, *DDI White Paper,* p. 1.

McLachlin, R. (1997). Management initiatives and just-in-time manufacturing, *Journal of Operations Management*, Vol. 15, No. 4, pp. 271-292.

Mearns, Kathryn, Sean M. Whitaker, and Rhona Flin (2003). Safety climate, safety management practice and safety performance in offshore environments, *Safety Science*, Vol. 41, pp.641-680.

Meeker, Willam O. and Luis A. Escobar (1998). *Statistical methods for reliability data*, New York: John Wiley & Sons.

Melnyk, Steven A., Douglas M. Stewart, and Morgan Swink (2004). Metrics and performance measurement in operations management: Dealing with the metrics maze, *Journal of Operations Management*, Vol. 22, No. 3, pp. 209-217.

Monden, Yasushiro (1998). *Toyota production system: An integrated approach to Just-in-time*, Third edition, Boca Raton, FL: Chapman & Hall.

Montoro-Cazorla, Delia, and Rafael Perez-Ocon (Apr 2008). A maintenance model with failures and inspection following Markovian arrival processes and two repair modes, *European Journal of Operational Research*, Vol. 186, Issue 2, pp. 694-707.

Montoro-Cazorla, Delia, and Rafael Perez-Ocon (2006). A deteriorating two-system with two repair modes and sojourn times phase-type distributed, *Reliability Engineering and SystemSafety*, Vol. 91, pp. 1-9.

Morgan, James M. and Jeffrey K. Liker (2006). *The Toyota product development system: Integrating people, process and technology*, New York: Productivity Press.

Nagai, Kiyoshi, and Zhengyong Liu (2008). Introducing kinematical redundancy into parallel mechanism with force redundancy, *IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM, Proceedings of the 2008 IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM 2008*, pp. 534-539.

Nash, Mark, Poling, Sheila R., and Ward, Sophronia (2006). *Using lean for faster six sigma results: A synchronized approach*, New York: Productivity Press.

Naylor, J.B., Naim, M.M., and Berry, D. (1999). Leagility: Integrating the lean and agile manufacturing paradigm in the total supply chain, *Engineering Costs and Production Economics*, Vol. 62, pp. 107-118.

Nelson, Daniel (1980). *Frederick W. Taylor and the rise of scientific management*, Madison, WI: University of Wisconsin Press.

Norcliffe, Glen (1997). Popeism and Fordism: Examining the roots of mass production, *Regional Studies*, Vol. 31.3, pp. 267-280.

O'Brien, Katherine (May 2008). Fast, fancy, & flexible, *American Printer*, Vol. 125, Issue 5, pp. 20-26.

Ohno, T., and T. Kumagai (1980). *Toyota production system*, International Conference on Industrial Systems Engineering in Developing Countries, Bangkok, November 1980.

Ohno, Taiichi and Norman Boden (1988). *Toyota production system: Beyond large-scale production*, 8th translation, New York: Productivity Press.

Olhager, J. (2003). Strategic positioning of the order penetration point, *International Journal of Production Economics*, Vol. 85, pp. 319-329.

Pal, B.K. (2006). Lean maintenance – Concept, procedure and usefulness, *Journal of Mines, Metals and Fuels*, Vol. 52, No. 11, pp. 318-321.

Pannell, Allen (Mar 2006). Happy together, *Industrial Engineer*, pp. 46-49.

Perez-Ocon, Rafael, and Delia Montoro-Cazorla (Jun 2004). Transient analysis of a repairable system, using phase-type distributions and geometric processes, *IEEE Transactions on Reliability*, Vol. 53, No. 2, pp. 1185-192.

Phillips, Edward J. (2002). *The pros and cons of lean manufacturing for the small to medium size fabricationsShop*", The Sims Consulting Group, Inc., p. 2.

Pietrykowski, Bruce (1999). Beyond the Fordist/Post-Fordist dichotomy: Working through the second industrial divide, *Review of Social Economy*, Vol. 57, No. 2, pp. 177-198.

Pil, F.K. and MacDuffie, J.P. (1999). Transferring competitive advantage across borders. A study of Japanese transplants in North America, *Journal of World Business*, Vol. 34, pp. 372-391.

Piore, M.J. and Sabel, C.F. (1984). *The second industrial divide: Possibilities for prosperity*, New York: Basic Books.

Pretty, Jules (Oct 2004). We are what we eat, *New Scientist*, Vol. 184, No. 2468, pp. 44-47.

Productivity Press (2005). *Lean culture: Collected practices and cases*, New York: Productivity Press, pp. 17-21.

Pullen, John (Nov 22, 2006). Automation saves jobs, *Professional Engineering*, Vol. 19, No. 21, p. 39.

Pyzdek, Thomas (2003). *Quality engineering handbook*, 2nd Edition, New York: Marcel Dekker.

Ren, Yifeng, Shaojun Wang, and Doug Koch (May 20-24, 2006). Design of a hands-on kanban simulation kit, *2006 IIE Annual Conference and Exhibition*.

Resnick, Mark (Aug 2005). Ultra-reliability, *Industrial Engineer*, pp. 44-49.

Riesch-Opperman, H., et al. (2007). Uncertainty analysis of reliability predictions for brittle fracture, *Engineering Fracture Mechanics*, Vol. 74, pp. 2933-2942.

Robataille, Denise (2007). Invaluable contributions: Putting industrial engineers back into quality management systems, *Industrial Engineer*, pp. 32-35.

Roberts, Karlene (1990). Managing high reliability organizations, *California Management Review*, Vol. 32, Issue 4, pp. 101-114.

Roberts, Karlene (1993). *New challenges to understanding organizations*, New York: Macmillan.

Rosenberg, Tom (July 2006). Assembling products correctly, *Manufacturing Engineering*, Vol. 137, No. 1, pp. 131-140.

Saaty, Thomas L. (1994). *Fundamentals of Decision Making with the Analytic Hierarchy Process*, Pittsburgh, PA: RWS Publications.

Sanchez, L.M. and Nagi, R. (2001). A review of agile manufacturing systems, *International Journal of Production Research*, Vol. 39, pp. 3561-3600.

Sawhney, Rupy and Ike C. Ehie (2006). A management model for planning change based on the integration of lean and six sigma, *Handbook of Industrial and Systems Engineering*, Philadelphia, PA: Taylor & Francis, p. 34-2.

Schonberger, Richard J. (1982). The transfer of Japanese manufacturing management approaches to U.S. industry, *Academy of Management Review*, Vol. 7, No. 3, pp. 479-488.

Schonberger, R. and J.P. Gilbert (1983). Just-in-time purchasing: A challenge for US industry, *California Management Review*, Vol. 26, Issue 1, pp. 54-68.

Schonberger, R.J. (1983). Work improvement programmes: Quality control circles compared with traditional western approaches, *International Journal of Operations and Production Management*, Vol. 3, No. 2, pp. 18-33.

Schonberger, Richard J. (1996). *World class manufacturing*, New York: Free Press.

Shah, Rachma and Peter T. Ward (2003). Lean manufacturing: Context, practice bundles, and performance, *Journal of Operations Management*, Vol. 21, No. 2, pp. 129-150.

Sharma, Rajiv Kumar, Dinesh Kumar, and Pradeep Kumar (2007*). FM – a pragmatic tool to model, analyse and predict complex behavior of industrial systems, Engineering Computations*, Vol. 24, No. 4, pp. 319-346.

Sharma, Rajiv Kumar, Dinesh Kumar, and Pradeep Kumar (2008). Predicting uncertain behavior of industrial system using FM – A practical case, *Applied Soft Computing*, Vol. 8, pp. 96-109.

Shingo, Shigeo (1983). *A revolution in manufacturing: The SMED system*, Stamford, CA: Productivity Press.

Shingo, Shigeo (1986). *Zero quality control: Source inspection and the poka-yoke system*, Portland, OR: Productivity Press.

Shingo, Shigeo (1989). *A study of the Toyota production system*, New York: Productivity Press.

Shingo, Shigeo and Andrew P. Dillon (1992). *The Shingo production management system*, New York: Productivity Press.

Shingo, Shigeo (1996). *Quick changeovers for operators: The SMED system*, New York: Productivity Press.

Smart, P. K., D. Tranfield, P. Deasley, R. Levene, A. Rowe, and J. Corley (2003). Integrating 'Lean' and 'High Reliability' thinking, *Proceedings of the Institution Mechanical Engineers*, Vol. 217, No. 5, pp. 733-739.

Smith, Ricky (Oct 2004). What is lean maintenance? *Maintenance Technology*.

Sood, D., Nussbaum, M., and Hager, K. (2007). Fatigue during prolonged intermittent overhead Work: reliability of measures and effects of working height, *Ergonomics*, Vol. 50, No. 4, pp. 497-513.

Spear, Steven J. and H. Kent Bowen (Sept-Oct 1999). Decoding the DNA of the Toyota production system, *Harvard Business Review*, Vol. 77, No. 5, pp. 96-106.

Suarez, F.F., Cusumano, M.A. and Fine, C.H. (Fall 1995). An empirical study of flexibility in manufacturing, *Sloan Management Review*, pp. 25-32.

Sugimori, Y., Kusunoki, K., Cho, F. and Uchikawa, S. (1977). Toyota production system and Kanban system materialization of just-in-time and respect-for-human system, *International Journal for Production Research*, Vol. 15, pp. 553-564.

Summers, Donna C. S. (1997). *Quality*, Upper Saddle River, NJ: Prentice-Hall.

Swank, C.K. (2003). The lean service machine, *Harvard Business Review*, Vol. 81, pp. 123-129.

Sward, Keith (1948). *The legend of Henry Ford*, First edition, New York: Rinehart & Company.

Taylor, Frederick W. (1911). *The principles of scientific management*, New York: W.W. Norton & Company, Reprinted in 1967.

Teresko, John (Feb 2005). It came from Japan! *Industry Week*, Vol. 254, No. 2., pp. 49-50.

Thompson, D. and P. Mintz (Dec 15, 1999). Lean manufacturing, *[http://www.citec.org/lean_manufacturing.html], Business Journal.*

Tinham, Brian (2005). How to make your supply chain lean, *Manufacturing Computer Solutions*, Vol. 11, No. 3, pp. 4-7.

Trebilcock, Bob (Jun 1, 2007). RFID out of the box, *Modern Materials Handling*, Reed Business Information, New York, pp. 47, 49-52.

Trebilcock, Bob (Jul 1, 2006). RTLS: Find a needle in a haystack, *Modern Materials Handling*, Reed Business Information, New York, pp. 42-46.

Trebilcock, Bob (Oct 1, 2006). Balancing customer service and productivity, *Modern Materials Handling*, Reed Business Information, New York, pp. 39-45.

Tseng, H.-E., Chen, M.-H., Chang, C.-C., and Wang, W.-P. (2008). Hybrid evolutionary multi-objective algorithms for integrating assembly sequence planning and assembly line balancing, *International Journal of Production Research*, Vol. 46, Issue 21, pp. 5951-5977.

Van den Bossche, Filip A.M., Geert Wets, and Tom Brijs (2007). Analysis of road risk by age and gender category, *Transportation Research Board*, Vol. 2019, pp. 7-14.

Van Ledeghem, Hendrik and Yang-Hua Lian (May 20-24, 2006). Engineering the lean transition using value stream map simulation, *2006 IIE Annual Conference and Exhibition*.

Waeyenbergh, G., Pintelon, L. (2002). A framework for maintenance concept development, *International Journal of Production Economics*, Vol. 77, pp. 299-313.

Wallams, Brad (Oct/Nov 2006). Workflow automation, *Canadian Printer*, Vol. 114, No. 7, pp. 30-32.

Wang, H. (2002). A survey of maintenance policies of deteriorating systems, *European Journal of Operations Research*, Vol. 139, pp. 469-489.

Wang, L., Chu, J., and Wu, J. (2006). Selection of optimum maintenance strategies based on a fuzzy analytic hierarchy process, *International Journal of Production Economics,* Vol. 107, pp. 151-163.

Waters, Mike and Jon Bevan (Aug/Sept 2005). Journey to lean. *IEE Engineering Management*, pp. 10-13.

Weick, K. E. (Winter 1987). Organizational culture as a source of high reliability, *California Management Review*, p. 2.

Wheatley, Malcolm (Jun 2005). Think lean for the long term, *Manufacturing Business Technology*, Vol. 23, No. 6, pp. 36-38.

Wiendahl, H.P. and Scholtissek, P. (1994). Management and control of complexity in manufacturing, *CIRP Annual – Manufacturing Technology*, Vol. 43, pp. 533-540.

Womack, James P. and Daniel T. Jones and D. Roos (1990). *The machine that changed the world: The story of lean production*, New York: HarperCollins Publishers.

Womack, James P. and Daniel T. Jones (2003). *Lean thinking: Banish waste and create wealth in your corporation*, New York: Free Press.

Womack, James P. and Daniel T. Jones (2005). Lean consumption, *Harvard Business Review*, Vol. 83, pp. 58-68.

Wu, Tai-Hsi, Chin-Chih Chang, and Shu-Hsing Chung (Apr 2008). A simulated annealing algorithm for manufacturing cell formation problems, *Expert Systems with Applications*, Vol. 34, Issue 3, pp. 1609-1617.

Young, Clifford and Alice Green (1986). *Flexible manufacturing systems*, New York: Amacom Books.

Yu, Fan-Jang, Hwang, Sheue-Ling, and Huang, Yu-Hao (1999). Task analysis for industrial work process from aspects of human reliability and system safety, *Risk Analysis*, Vol. 19, No. 3, pp. 401-415.

Zieger, Robert H. and Gilbert J. Gall (2002). *American workers, American unions*, Third edition, Baltimore, MD: Johns Hopkins University Press.

Zwick, William R. and Wayne F. Velicer (1982). Factors influencing four rules for determining the number of components to retain, *Multivariate Behavioral Research*, Vol. 17, Issue 2, pp. 253-269.

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