MEASUREMENT OF RESILIENCE IN JOB SHOP SYATEM

A Dissertation by

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ABSTRACT

Resilience in relation to the maintenance and management of job shop systems has not yet received significant consideration or adequate study. Yet resilience is increasing in usage within engineering fields, although its application varies from one system to another. The matrices for resilience depend on the structure of the system and the failure factors. Machine stability is significant to the industry because of the need to build quality and to minimize production loss resulting from machine breakdown. A disruptive event on the machine leads to full loss of production in the job shop. In order to mitigate the impact of machine break down, it is essential to pinpoint a new resilience definition, measurements, and a new model design and evaluate the resilience using analysis tools. In a job shop, machines are considered most important, and they are always the most susceptible to disruptions during different kinds of operations. A disruptive event in a machine causes errors in the machine workload, operations dynamic, and the job shop system. This dissertation proposes a new definition for resilience in a job shop and analysis frameworks. The report includes the resilience curve, modeling, estimations, quantification, and measurement techniques.

TABLE OF CONTENTS

Chapter Page

1. INTRODUCTION 1

1.1. Introduction: 1
1.2. Research Background and Motivation: 4
1.3. Resilience Curve: 6
1.4. Machine resilience: 8
1.5. A System of interest: 10
1.6. Resilience Metrics: 11
1.7. Resilience Scale: 12
1.8. Dissertation Scope: 13

2. LITERATURE REVIEW 14

2.1. Introduction: 14
2.2. Manufacturing resilience: 16
2.3. Resilience in Engineering: 17
2.4. Related field: 17
2.5. Dynamic scheduling: 20
2.6. Resilience metrics: 20
2.7. Conclusion: 23

3. MEASURING STATIC AND DYNMAIC RESILIENCE FOR MACHINE BREAKDOWN 24

3.1. Introduction: 24
3.1.1 Machine Resilience: 26
3.2. Literature review: 26
3.2.1. Resilience Definition in Manufacturing: 26
3.2.2. Resilience Metrics: 29
3.3. Manufacturing Resilience formulation: 38
3.4. Machine resilience as a function of time: 41

TABLE OF CONTENTS (continued)

Chapter Page

3.5. Numerical Example:.....44
3.5.1. Modeling the System: 45
3.6. Conclusion:.....54

4. JOB SHOP RESILIENCE BASED ON RELIABILITY AND RESTORATION 56

4.1. Introduction:.....56
4.2. Literature review: 57
4.2.1. Resilience Metrics Based on Reliability and Restoration:.....60
4.2.2. Scale:.....66
4.3. Resilience Metric and Definition in job shop: 67
4.4. A General Framework of Modeling Job Shop Resilience: 70
4.4.1. Reliability Block Diagram:.....70
4.4.1. Framework:.....73
4.5. Numerical example: 74
4.5.1. Case 1:.....74
4.5.2. Case 2:.....78
4.6. Conclusion:.....79

5. RESILIENCE OF MACHINES WITH PRODUCTIVITY CHANGING 80

5.1. Introduction:.....80
5.2. Resilience Quantification Metrics:.....84
5.3. Numerical Example:.....87
5.3.1. Case 1:.....87
5.3.1. Case 2:.....90
5.4. Conclusion:.....92

6. CONCLUSION AND FUTURE WORK 94

6.1. Conclusion:.....94

TABLE OF CONTENTS (continued)

Chapter Page

6.2. Future Work: 95

REFERENCES 95

LIST OF FIGURES

Figure Page

1.1. Job shop system 2

1.2. General resilience curve (Yodo & Wang, 2016) 6

1.3. Resilience as function of time. (Henry & Ramirez-Marquez 2012).....7

1.4. Seismic resilience (Bruneau et al, 2003).....8

1.5. Machine resilience 9

1.6. Performance improved after repairing 10

1.7. Performance loss after repairing 10

1.8. Machine resilient behavior.....11

3.1. Predicted performance loss (Bruneau et al., 2003; Zobel & Khansa, 2014) 31

3.2. Performance loss before and after disaster (C. S. Renschler et al., 2010).....32

3.3. Robustness and rapidity performance measures (Chang & Shinozuka, 2004).....37

3.4. System performance B (t) and A (t).....41

3.5. Machine performance 42

3.6. Machine performance when disruption occurred 43

3.7. Idle Time.....43

3.8. Disruption Time.....44

3.9. Arena Model for Manufacturing Job Shop 47

3.10. Job Segment.....48

3.11. Dialog box of the create a jobs 48

3.12. Dialog box of the assign module 49

3.13. Dialog box of the Process module 49

LIST OF FIGURES (continued)

Figure Page

3.14. Dialog spreadsheet of Failure module 50

3.15. Job Departure Segment 50

3.16. Dialog box of Run Setup.....51

3.17. Gantt Charts for Job shop 51

4.1. Robustness performance measures (Chang & Shinozuka, 2004) 63

4.2. Resilience as function of time. (Henry & Ramirez-Marquez 2012).....64

4.3. Notations for Eq. 4.7 (Ayyub, 2015) 65

4.4. Reliability block diagram with n components in series 71

4.4. Reliability block diagram with n parallel components 71

4.5. Job shop problem for a series-parallel system 74

4.6. Reliability and efficiency for machines 75

4.7. Resilience for every component.....76

4.8. Series system resilience 76

4.9. Series job shop 78

4.10. Reliability and efficiency.....78

4.11. Resilience measurement for Series system 79

5.1. Relation between machine health and production (Yang, Djurdjanovic, & Ni, 2007).....82

5.2. Throughput decrease on machine health.....83

5.3. Throughput increase machine health 84

5.4. System performance with decreasing in productivity level.....86

5.5. System performance productivity level 86

LIST OF FIGURES (continued)

Figure Page

5.6. Gantt Charts for Job shop 89

5.7. Machine 2 disruption 89

5.8. Gantt Charts After disruption in M2.....90

5.9. Gantt Charts second scenario.....91

5.10. Gantt Charts after decreasing in throughput 92

LIST OF TABLES

Table Page

3.1. Machines processing times 45

3.2. The process time based on SPT 52

3.3. Results of resilience 52

3.4. The process time of two different scenario 53

3.5. Results for expected resilience 54

4.1. Machines sequence 77

4.2. Resilience based on job sequence 77

5.1. Machines processing times 87

5.2. Performance of machines 89

5.3. Resilience under a disruption of M2 90

5.4. Performance of machines with throuput changing 91

5.5. Resilience with decreasing in throughput 92

CHAPTER 1: INTRODUCTION

1.1 Introduction:

Resilience is regularly used as a controls aspect for a variety of fields from natural research to material science. The concept is generally used to indicate both quality and adaptability (Bruneau et al., 2003). Resilience is the ability of the system to both resist disruption and recover from disruption back to its normal state. Resilience could be a widely attractive field of study because it de-emphasizes the old reliance on human estimation and considers the whole system in its configurations (Huber, van Wijgerden, de Witt, & Dekker, 2009). Many people wrongfully assume that the framework is fundamentally protected from human estimation errors. However, there will always be human error and external factors to guard against, which will require more protection methodology and tight monitoring.

Resilience is also newly considered as having correlation to safety; it is not about reducing negatives, errors or violations, but about identifying and enhancing the positive capacities of people and organizations that allow safe adaptation under pressure (Dekker, Hollnagel, Woods, & Cook, 2008). The system safety is not expressed as the only concept of protection against accidents; there are systems in place to also control the causes and analyze the performance.

Resilience is highly context dependent on its operational environment and the disruptive event. Systems are often inherently resilient to various disruptions. For instance, O'Hare International Airport (ORD) is sensibly very much prepared to deal with snowstorms, but 3 inches of snow in the southern United States caused Atlanta-Hartsfield International Airport (ATL) to close up the operation in early 2014 (Uday & Marais, 2015). Understanding the size of disruption will help the organization to prevent failure and promote preparedness for an event to keep operation performance at an even efficiency level.

In a job shop, the product or job goes through a process sequence which utilizes multiple machines. The product processing cannot be conducted if raw material, auxiliary devices such as jigs and fixtures or machines are not available. The cumulative waiting times due to lack of resources or raw material can be a major contributor to the production lead time.

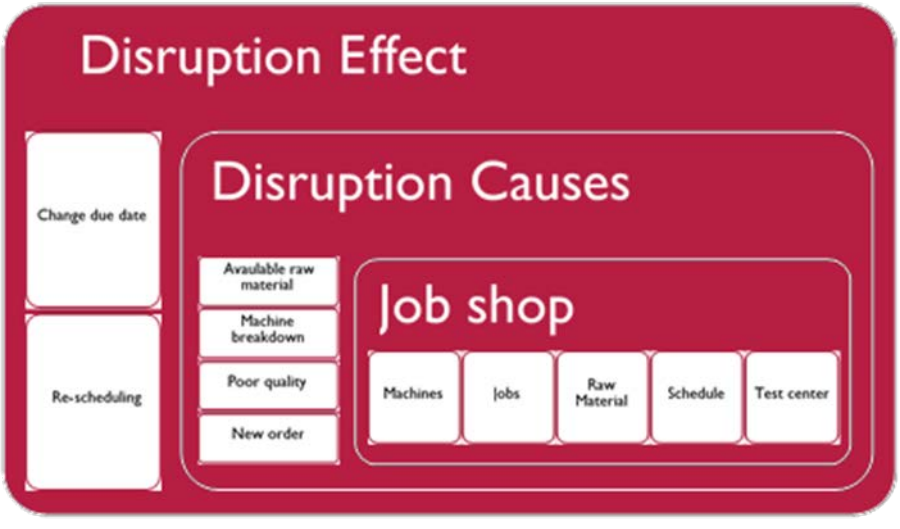


Figure 1.1. Job shop system

Figure 1.1 is a schematic of the disruptions in a job shop. The production in job shop can be managed by determining the customer due dates, material planning, and production scheduling. Each order has a routing sequence and types of material. These factors are interdependent and it cannot be performed independent of each other. When disruption occurs, the issues in job shop management are aggravated by several factors including:

- Re-scheduling
- Poor quality
- Changes in due date
- New order

The impact of these factors can affect bottlenecks, lead times, utilization, delivery time, and machine throughput. Some job shops have fixed due dates for customer orders irrespective of the disruption. Therefore, job shops managers often have to make quick decisions when disruptions occur based on their experience and heuristics that have been developed over the years. These decisions lead to moving jobs from one work center to another and changes the due dates of the jobs and its priorities based on the progress attained by each job. Resilience estimations help to determine the impact of disruptions on the job shop and defines its ability in dealing with disruptions. Researchers in manufacturing have contended and in some cases exhibited that assembling procedure can significantly affect an systems' ability to achieve prevalent work (Ahmad and Schroeder, 2003).

Today many companies are making transitions toward achieving resilience in manufacturing operations. These are aimed at the provision of higher organizational process-optimization needs. In the field of manufacturing industries, there are many driving forces linked to resilience as it relates to plant performance. Understanding theses forces and production capabilities is imperative in order to have the critical responsiveness in the system. The factors that is aggravated after the disruption drives the decisions of planners at manufacturing to transition toward resilience.

Two of the four factors responsible for disruption, which are discussed previously are related to time: re-scheduling, and change in due date. This leads to the idea of transforming from the originally approved design to a design which supports greater production to achieve profitable growth. Companies make important operational decisions based on production efficiency, and must actualize and maintain quality control goals in manufacturing in order to achieve long term profitability. This means ensuring that the manufacturing machine keeps the right pace with the demand to produce the required quantities o fproducts.

Production quality has become a significant factor and it is now focusing more on avoiding adverse events, in addition to maintaining superior quality. For this reason, the visibility of the granular quality data in the plant is critical to achieving responsiveness in the drop in quality. For example, if a machine is seriously impaired and damaged, the technology's throughput capacity gets rather lower, making a machine less capable of carrying out its original functions, which leads to its degradation and reduction of performance. With a slow degradation process, a machine can still be active, yet at the definitely lower level of performance. In this case, maintenance operation is necessary.

1.2 Research Background and Motivation:

Resilience is new to manufacturing frameworks, and it has not generally been considered in structural plans. The research on manufacturing framework resilience hasn't pulled in much consideration until recent years when there are more frequent and significant disruption events taking place in the industry. The majority of researchers have concentrated on an assortment of troublesome outer occasions to the frameworks, extending from natural disasters. Most of these research focus on network systems where emergency instruments are created to reduce the effect of network disruptions (Jin & Gu, 2016).

The concept of resilience is often found because of disruption to the system. In job shop, disruption can happen to the product, machine, scheduling, or quality. Disruption in a machine is the main factor that cause defective product outputs, re- scheduling, and quality issue.

Schedule repair alters an existing schedule to account for changes related to unexpected events/disruptions. Generally, schedule repairs are manually adjusted based on the experience of the scheduler. However, the scheduler's ability to see the long-term ripple

effect of his changes is limited, and his decisions can frequently cause unintended and even irreversible complications.

In quality management, there are two concepts of quality. One characterizes it as the level of conformance to plan. The second, considers the design quality itself. Quality characterizes as the degree to which a system or process meets determined necessities or meets customers' desires. (Aas et al., 1992). Quality of an item is a measure of completeness. Poor quality leads to additional processing time requirements. Such extra time spent at a resource, defers the arranged work to be discharged to the resource (Xiong, Xing, & Chen, 2013). The quality of the manufactured product depends on the machine state and the quality control policy, which in turn helps to minimize the number of defective units.

Job shop planning issues are among the most serious combinatorial issues in industry. As of recently, scheduling problems were the focus under the assumption that the majority of the issue parameters are known in advance. Such an assumption is flawed since it does not recognize the reality that unanticipated events occur in real manufacturing systems (Al-Hinai & ElMekkawy, 2011).

Machine stability is significant to the industry because of the need to build products with high quality and to minimize production loss resulting from machine breakdowns. A disruptive event on the machine leads to loss of production in the job shop or will cause at least partial loss if the shop contain more than one machine (Yang, Djurdjanovic, & Ni, 2007). In order to mitigate the impact of machine break down, it is essential to pinpoint a new resilience definition, measurements, and a new model design and evaluate the resilience using analysis tools.

The objective of this dissertation is to quantify and analyze metrics of resilience in a job shop and design a tool to promote general application of job shop resilience. Also, the

dissertation will examine data from the analysis to form the basis for developing effective resilience design strategies. In addition, quality and scheduling of job shop will be examined after machine disruption to reduce the magnitude of disruption.

1.3 Resilience Curve:

Most system resilience designs describe the system performance as having four transition states. Figure 1.2 illustrates transition in the system performance when the disruptive event occur as described by Yodo and Wang (2016). The system performance and resilience action depends on a numbers of factors based on the system structure and reliability. A resilience system can take possession of capacity and recover the system from disruptions that occur to the system performance

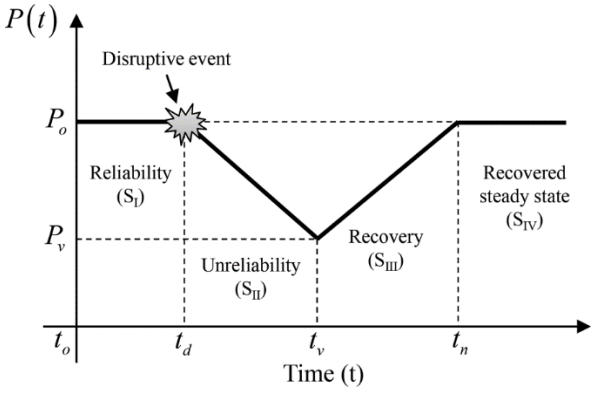


Figure 1.2. General resilience curve (Yodo & Wang, 2016)

The initial state P_o in Figure 1.2 represents the performance of the system in normal situation. Following the disruption, the system moves to the next stage: the unreliability state. In this case, the system performance level reduces from P_o to P_v at time t_d, which represents the time when the system was losing performance because of the disruption.

The third stage is at time t_v where the performance is improving in the recovery state, and that is defined as the behavior of resilience. In this state, the action is taken after the system performance reduces to the lowest degree to go back to the normal state at time t_n.

The recovered steady state is the last stage where the system is fully restored, and the system performance matches the reliability state at level P_o. The resilience action could be different from one system to another. However, the stages will remain the same. The only difference will be on the disruptive event and the resilience action.

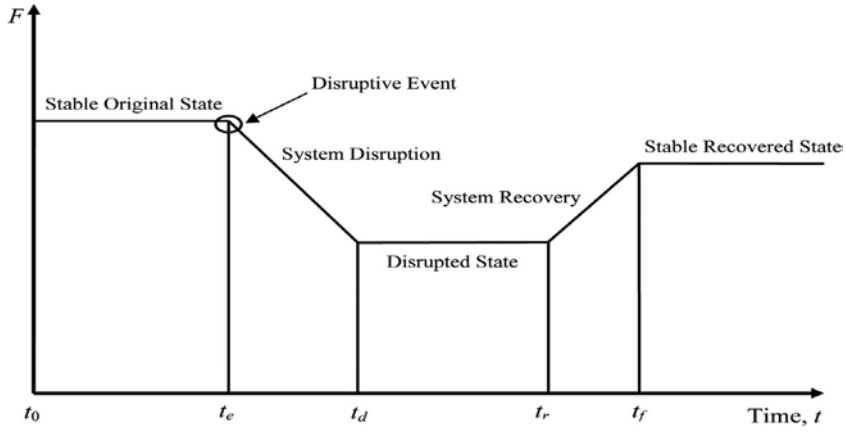


Figure 1.3. Resilience as function of time. (Henry & Ramirez-Marquez 2012)

In a different scenario proposed by Henry and Ramirez-Marquez (2012) (Figure 1.3), three transitions have been defined to represent system resiliency. The transition states are original state, disrupted state, and recovered state as represented in Figure 1.3. Original state provides the baseline performance of the service when the transportation network is stable in the absence of disruptive event. A disrupted state refers to the state when the ability of system considerably reduces due to negative impact of disruptive event. Finally, recovered state is related to understanding the ability as related to “the speed at which an entity or system recovers from a sever shocks to achieve a desirable state.

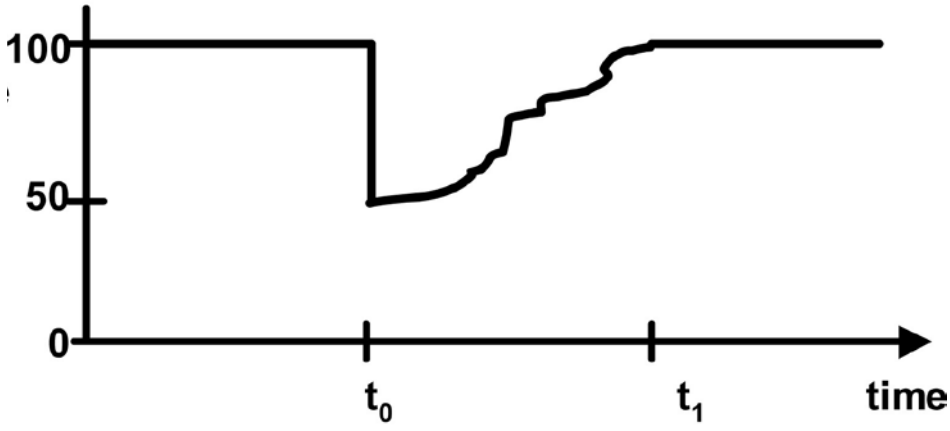


Figure 1.4. Seismic resilience (Bruneau et al, 2003)

Figure 1.4 expressed by Bruneau et al in 2003 for earthquake resilience, shows a curve representing a different scenario where the damage occurs at t_0 to the infrastructure such that the quality immediately reduces from 100% to 50% and the restoration begins after the fail or disruption until it reaches t_1, at which time it is fully repaired.

The above approaches have been used to define and to develop resilience in the fields of complex system, networking, and seismic fields respectively. These definitions are not sufficient to define and express the concept of machine resilience because the behavior of a manufacturing system during disruptions are often different in nature.

1.4 Machine resilience:

The resilience curves for machines in a job shop can be categorized as static and dynamic resilience. Static resilience is defined and determined by solely studying the impact of the machine disruption on its resilience and its ability to meet performance requirements. The impact of one machine failure on other machines and the manufacturing system are ignored while defining static resilience. Dynamic resilience of a machine is calculated by taking into consideration the impact of failures of other machines which in turn influences the performance of the machine under study.

A typical static resilience curve for a machine is shown in Figure 1.5. In a job shop, when a disruptive event such as a breakdown affects a machine, the performance typically degrades to a non-working machine and hence the productivity of the machine is zero. Thus until the machine is repaired, the productivity of the machine is zero. On the other hand, typical resilience studies and curves for non-machine type systems show a trend of declining performance until it reaches the point where recovery is initiated as shown in Figure 1.2 to Figure 1.4. Another factor that makes machine resilience different is that the recovery levels can be different from the original condition before the disruption. The machine may be recovered to a productivity level that is the same, higher, or lower depending on the type of repair and recovery conducted.

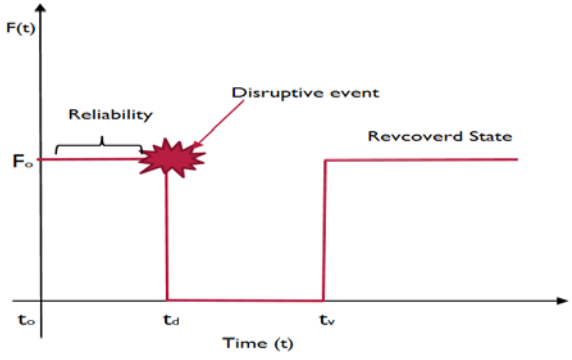


Figure 1.5. Machine resilience

Figure 1.5 shows the case of a machine disruption. The disruption occurs at time t_d and the productivity of the machine will be zero from t_d to t_v . At time t_d, the repair activity is initiated. The repair is completed at time t_v. The time to repair $t_d - t_v$ will vary from one machine to another. After repair, the machine will return to its original productivity F_o.

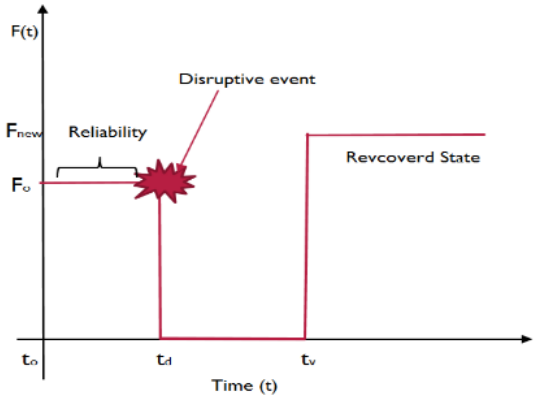


Figure 1.6. Performance improved after repairing

When a disruptive event occurs, it is possible that the machine may undergo extensive repairs and as a result, the productivity may be increased to a level F_n beyond the original condition F_o as shown in Figure 1.6.

It is also possible that after repair, the machine may have less productivity than before. Thus, the productivity of the machine F_n will be less than the productivity of the machine prior to disruption as shown in Figure 1.7. Thus, the efficiency of the machine may decrease, and the ability of the machine to complete the jobs may depend on the time of disruption. For example, if the disruption occurred towards the end of the period under study, the impact of the disruption and the decreased productivity may be less compared to a disruption that occurs earlier in the time-period under study.

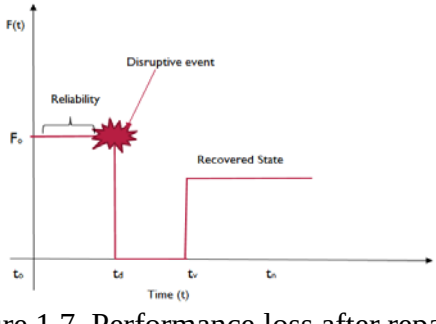


Figure 1.7. Performance loss after repairing

1.5 A System of interest:

In the field of ecology, resilience is defined as the speed at which the subject returns to its equilibrium state after disruption (DeAngelis, 1980). In engineering, the speed to go back to the original state is regularly connected with how quickly an engineered framework can adjust to deviation after a disruption, or how quickly an engineered structure can reestablished stability from its upset states (Yodo & Wang, 2016). Based on these definition and others that have been expressed previously, the definition of resilience can shift from one field to another. In a job shop, the definition for machine resilience is the ability of the machine to returning to original production capacity and completing the work required for the time period. Based on the following definition the recovery action starts at t_v. Also, the resilience of machine will be defined as a function of time.

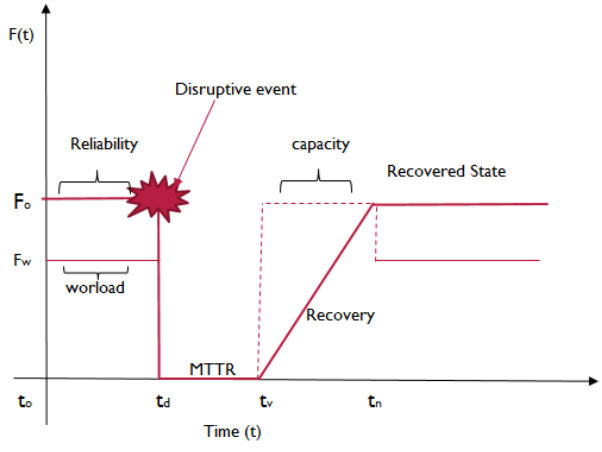


Figure 1.8. Machine resilient behavior

Figure 1.8 shows how the machine needs time to return to original states after the repairing time. The time for the machine to reach the stable state at t_n will depend on the amount of productivity lost between t_d and t_v and the new product assigned to the machine between t_v and t_n. The utilization of the machine will be 100% at t_v until the machine covers all jobs from t_d to t_n, then the machine will resume the normal workload

1.6 Resilience Metrics:

For a job shop, resilience can be measured as the ratio of the areas that are below the curve representing system performance after a failure *A(t)* over the system's baseline response *B(t)* from time t_0 to the length of the period of time *T**(Ouyang, Dueñas-Osorio, & Min, 2012; Shafieezadeh & Burden, 2014; Yodo & Wang, 2016a). Mathematically, this can be shown as follows:

$$\Psi = \frac{\int_{t_o}^{T^*} A(t)\, dt}{\int_{t_o}^{T^*} B(t)\, dt} \tag{1.1}$$

This formula indicates the ability of the system to rebound, and if the recovery is equal to the loss that happened during the disruption, then the system is fully recovered and 100% resilient. However, Equation 1.1 needs to be more defined so we can have a reliable quantitative formula.

In order to have resilience formulation for machines in a job shop, we need to compute the time under a disruptive event and the capacity of the machines at time t.

1.7 Resilience Scale:

Even though resilience has been measured in various perspectives for diverse goals as mentioned in the previous section, it is still important to find a consensus on a scale of the designed system's resilience and the ways it can be calculated. Additionally, the scale of the resilience metrics ranges between 0 and 1 (Cimellaro, Reinhorn, & Bruneau, 2010; Henry & Ramirez-Marquez, 2012; Yodo & Wang, 2016). Other work that has risen out of MCEER proposes a resilience index in the scale of 0 and 1 for every foundation system and afterward offers a method to aggregate all the lists for a general resilience measure (Renschler et al.,

2010). However, not all of these researchers measure resilience as a ratio because the resilience depends on the structure of the system. Still, the different metrics can be used to evaluate the overall resilience for a design. In addition, the proposed metric measures for a resilience rate from 0 to 1 will give a decent vision to decision makers to comprehend the capacity of their framework against disruptive occasions.

1.8 Dissertation Scope:

Since there is not significant literature in the application of resilience to manufacturing systems, and in particular job shops, and there is no general accepted definition of resilience in this field, this dissertation proposes defining and analyzing the resilience in a job shop and designing a tool to promote general application in job shop resilience. In particular, there is a pressing need to develop methods to model and manage resilience for job shop machines and measure the static and dynamic ability of the system to recover the system after a shock. Also, this dissertation will examine the configuration of systems by using reliability block diagram to analyze the probability of system failure.

In this dissertation, we will use quantitative approach in a manufacturing system to evaluate the performance of the machine when disruption occurs. Also, the resilience curve is used to illustrate the resilient behavior and to describe the overall variation for the machine. For resilience quantification, metrics is defined based on resilience curve, restoration and reliability by using reliability block diagram.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction:

Resilience refers to the ability of any process, system or organization's to effectively respond to, survive, and recover from any disturbances and disruptions. However, resilience comes at a cost that is often quite expensive; therefore, it is more preferable to maintain and improve the performance of the system rather than solely investing in building resilience (Bruneau et al., 2003). Doing so would result in a system that is partially resilient to certain types of disruptions. It is not uncommon to see that the idea of resilience has become an important part of the educational curriculum and a plethora of disciplines from both engineering and non-engineering backgrounds are based on this concept (Bruneau et al., 2003). Strength and flexibility, when combined, results in resilience. This phenomenon can be best explained by a system, which can not only absorb the shock or disruption but also holds power to recover from the disrupted state to its normal state (Omer, Nilchiani, & Mostashari, 2009).

Change happens in our world at a quick pace. Therefore, engineering systems ought to be adaptive and should have built-in abilities to cope up with such variations. This is termed as engineering resilience (Yodo & Wang, 2016). Resilience Engineering has its roots in human error and when researched upon, emerged as a nascent field of study (Youn, Hu, & Wang, 2011). It refers to safety but in a more innovative sense. Unlike the methods of risk management which hinges upon calculating the probability of failure, resilience engineering provides companies with the methods and processes that are robust at the same time flexible enough to monitor and revisit the risk management strategies (Dekker, Hollnagel, Woods, & Cook, 2008). As mentioned before, the concept of resilience engineering is being utilized in copious engineering fields. This idea helps industries to prepare for disruptions such as system failures before their

actual occurrence by providing guidance to the maintenance group members and suppliers of system (Pant, Barker, Ramirez-Marquez, & Rocco, 2014). It has been recommended by specialists in supply chain that to minimize the risks of disruptions, the vulnerabilities of the company must be thoroughly understood. The cause of outages can be either internal or external which can eventually lead to loss of revenue. Introduction of resilience is a useful intervention for the supply chain as it provides a framework to the organizations to tackle the change (Soni & Jain, 2011). In has been experienced that as the complexity of the system increases, the frequency of disturbances and disruptions also increase (Soni & Jain, 2011). There is no question that resilience plays an important role in guarding against any disruptive events and also enhances the industrial unit's safety (Dinh, Pasman, Gao, & Mannan, 2012). In the context of the significance of resilience strategic planning to reap better results, it is crucial to account for all the dimensions of this concept (Soni & Jain, 2011).

Resilience is also characterized by the capability of the system to mitigate the impact of these disruptions and quickly recover (Blackhurst, Dunn, & Craighead, 2011). This capability can only be achieved from flexibility and redundancy embedded within the system. For instance, built-in redundancy and flexibility of the system enable it to resume the given function from the components failures or faults with the use of task rescheduling and workload reallocation (Gupta & Goyal, 1989). These kinds of capabilities are pivotal in the field of engineering system operation, design and life management to handle the disruptive and the adverse events. Engineering resilience is also an important concept, which is based on fusing the resilience ability into the engineering capabilities. It also implies the method and ability of an engineering system to sense and then respond to adverse changes.

2.2 Manufacturing resilience:

The idea of resilience in the manufacturing systems is a relatively new one. Even as of now, resilience engineering has not been adopted to a large extent at the two major fields of the manufacturing systems – multi-stage manufacturing systems and discrete manufacturing systems (Jin & Gu, 2016). The functioning of these systems may be hampered by a myriad of disruptive events such as sudden failure or degradation of the components. Encountering such type of events can eventually result in loss of components at least partially over a period of time (Hu, Li, & Holloway, 2013). For example, in 1996, with an 18-day of labour strike at General Motors brake supplier plant, approximately 26 assembly plants remained idle, which caused a loss of $900 million. A similar situation occurred when fire broke out at the Philips plant in New Mexico that resulted in $40 million worth of damage in terms of reduction of sales for the high-tech chips and a direct damage of around $39 million (Hu et al., 2013).

Production plant modernization has recently grown important in industry, particularly with automation, speed, miniaturization and robotics making use of advanced computer application with high availability, maintainability and reliability. Resilience is also a very popular term used in the modern business organizations of today. Some research considers resilience to be an ability to manage personal misfortune and personal stress (Coutu, 2002). However, others consider it to be a complete strategic ability for a corporation to adjust their operations based on the requirements of the turbulent age (Hendricks & Singhal, 2003; Horne III, 1997).

2.3 Resilience in Engineering:

From the definition of U.S. Department of Defense, resilience is reported to be a system that is able to exhibit specific resilience properties (Goerger, Madni, & Eslinger, 2014). For instance, resilience is the ability to resist, absorb, and recover from the major failure or any such issue. From various research and analysis, engineering resilience is reported as an alternative or a complement to the major traditional view of system safety. The concept of resilience has developed in importance so that it is now an independent study area called "Engineering Resilience". Until now, the concept of resilience has been implemented effectively within the engineering domain, and included in a wide range of disciplines such as transportation, power systems, multi-tier supply chain, production systems, spacecraft swarms, health care systems and general infrastructure systems (Yodo & Wang, 2016).

In spite of all the developments that have taken place in resilience engineering research, there is still confusion about how resilience engineering can be improved, designed and quantified in engineered systems. The concept of resilience is also largely dependent on the working of system architecture and operating conditions, the type of disruptive events that might take place, and the magnitude of damage (Hollnagel, Woods, & Leveson, 2007). There are different systems subjected to different disruptions, thus causing different levels of damage. The major catch is to find out the best approach in order to understand the resiliency that needs to be implemented. Resilience is mostly the combination of recoverability and survivability in the system to achieve the needed outcomes (Balchanos, 2012).

2.4 Related field:

Historically, resilience has not been considered as a useful, quantifiable and accurate design objective. A majority of the studies conducted are pertinent to supply chain interruptions (Hu et al., 2013). In global level, it has provided valuable insights to a plethora of serious problems as a result of disruptions in the supply chain network at a global level and also suggest mitigation measures to cope with such grave situations (Blackhurst*, Craighead, Elkins, & Handfield, 2005). The management of supply chain should be able to respond to threats of terrorism, and must attempt to reduce the system's vulnerability (Sheffi, 2001; Sheffi & Rice Jr, 2005; Sheffi, Rice Jr, Fleck, & Caniato, 2003). It is evident that building redundancy as well as flexibility can help in strengthening resilience, although doing so would significantly increase the cost (Sheffi & Rice Jr, 2005). According to the previous literature, which provides a detailed study on risks within the supply chain networks, a Bayesian belief network has been proposed to gauge the effects of the risk and model the chances of risk in the system (Badurdeen et al., 2010). Also, scheduling as part of supply chain has been discussed in case of unforeseen circumstances within the manufacturing systems. Several approaches are explains including the predictive-reactive approach for scheduling (Aytug, Lawley, McKay, Mohan, & Uzsoy, 2005). Furthermore, the option of deferment in the supply chain has been analyzed with an explanation for how manufacturing firms can substantially minimize their risk via diversification of it orders between multiple suppliers, and also by deferring the orders until all the pertinent issues have been resolved (Babich, 2006). Research has also been conducted to model the production via framework in a continuous time domain that is inclusive of all the material flows such as inputs and outputs (Chopra, Reinhardt, & Mohan, 2007). Such research suggests

reformulation of standard linear programs, critical path methods and planning of manufacturing resource (Hackman & Leachman, 1989). Moving on, mathematical models are being developed that can provide an analysis of the strategies of placing orders with two distinct suppliers out of which one is being subject to a disruptive event (Tomlin, 2006). In such a case, it has been proposed to devise strategies such as contingent rerouting and inventory mitigation. Nakano and Tatano also reveal that in case of natural calamities, a two-sector model can be used to analyze the economic growth of the supply chain. This study found that as the capital and the production of all the intermediate goods falls downs, so does the production taking place in the final goods sector (Nakano & Tatano, 2008). For the representation of the production node in the supply chain networks and to subsequently optimize the inventory levels, a hybrid inventory production model has been proposed. Another model explaining the manufacturer-retailer dynamic is formulated to define various inventory policies in accordance with varying objectives in supply chains, and to maintain safety stocks to cope with unanticipated events (Giglio, Minciardi, Sacone, & Siri, 2008). Furthermore, it has been revealed that a decision-making process is quite important in tactical planning in case of disruptive events under uncertainty for the environment (Gharbi, Mercé, Fontan, & Moalla, 2010).

Literature reviews show that a disruption in the supply network is more than often defined as the one that is an unanticipated happening able to hamper the normal flow of materials and goods in the supply network (Hendricks & Singhal, 2003; Kleindorfer & Saad, 2005). Though it provides a general description, this definition does not state how severe the disruption is and what is the extent of its impacts (Y. Kim, Chen, & Linderman, 2015).

Inability to provide such a specification can make risk management a difficult task (Y. Kim et al., 2015).

2.5 Dynamic scheduling:

Scheduling as well as process planning holds paramount importance within the manufacturing systems, mainly because they have a direct impact on other activities going on in the manufacturing firm. If properly managed, scheduling and process planning can fully optimize the organization's performance. In the classical scheduling research, only the static environments are being considered. However, in real environments a plethora of dynamic events may take place at the same time, including machine breakdown, uncertainty in processing time and irregularity in the job arrivals. In conjunction, classical scheduling presumes that there is no flexibility within the process planning and takes into account a uniquely distinct plan for every job. However, more modern manufacturing systems have great flexibility in their process planning (Shen, Hao, Yoon, & Norrie, 2006).

Therefore, to fulfil the requirements of the next generation of manufacturing systems, scheduling that takes into account immense flexibility in the process planning is a must. These flexible features of the manufacturing systems have motivated the researchers to design an appropriate process planning and scheduling system in line with these requirements (Kim, Park, & Ko, 2003). Scheduling performance can be improved significantly using machine selection rules such as rules for assembling job shop scheduling or rules pertinent to rescheduling the current schedule in case a task gets delayed more than a specific time and the sequence-dependent time set ups (Vinod & Sridharan, 2008).

2.6 Resilience metrics:

According to the Attoh-Okine et al. (2009), urban infrastructure can be assigned a resilience index by virtue of a framework of belief function. Li and Lence (2007) were of the opinion that a formula could be used for the resilience index, which can be described as the proportion of possibility of failure to the possibility of the recovery of the system.

Omer et al. defined as well as measured the resilience of the telecommunication cable system using network topology. They provided a definition that the base resilience is the ratio between the network's value delivery after a disruptive event and the value delivery prior to a disruptive event. Value delivery refers to the actual quantity of information that needs to be carried through the network (Omer et al., 2009). Reed and his team members provided a method for the evaluation of the engineering resilience to the natural hazards for the subsystems of network infrastructure using the example of power breakdowns and restorations during the time of the Katrina hurricane (Reed, Kapur, & Christie, 2009). Such a quality function has been derived from the field of earthquake engineering, and can provide a description of the structural performance in the aftermath of the earthquake events (Reed et al., 2009).

Disaster resilience is another term that has been described by Tierney and Bruneau as the capabilities of the social systems to mitigate and offset hazards, minimize the impacts of hazards at the time of their occurrence, recover from the adverse impacts of disaster, and at the same time provide rehabilitation to better prepare for the forthcoming disasters in the future. The graph of infrastructure's quality versus time can be used to define the resilience triangle. In this graph the quality of the infrastructure plummets abruptly in the aftermath of the disaster, which is then followed by recovery. Measures to build and increase resilience are actually targeted at decreasing the size of the resilience triangle. The smaller the size of the triangle, the less impact

there would be on the quality of the infrastructure, and it would take less time to recover from a disaster (Tierney & Bruneau, 2007).

Todini provides an example of urban water distribution network design comprising interconnected loops. The problem arising in this system is pictured as a vector optimizing issues for which resilience and cost are considered as the objective functions. This results in provision of optimal solutions in Pareto sets, taking into account the trade-off relationship between resilience and cost. The water that is in surplus can then be utilized to build resilience of the system to tackle with any sudden failures within the system. The design approach is such that it starts with the resilience index value as the target and then moves ahead to identify the diameter of the pipes for every node-node connection (Todini, 2000).

Najjar and Gaudiot provided two types of measures to gauge the network fault tolerance for any multicomputer system. The first one is the network resilience and the second one is relative network resilience. Traditionally network fault is defined as the degree or the level of the network, which usually excludes the measure of the number of nodes and the possibility of disconnection. In this context, Network Resilience NR(p) refers to the maximum number of failures taking place at nodes which can still be sustained without compromising the connectedness of the network with a probability (1 - p). On the other hand relative network resilience RNR(p) refers to the network resilience divided by the number of nodes N. Mathematically it means NR(p)/N (Najjar & Gaudiot, 1990).

Rosenkrantz et al. provides the definition for resilience within service-oriented networks. According to these researchers, edge resilience is expressed as the self-sufficiency of the sub network despite the failure of the largest value k or fewer edges. Node resilience is also

described in a similar way. These metrics can be quite imperative in the assessment of the fault tolerance of any network (Rosenkrantz, Goel, Ravi, & Gangolly, 2009).

Whitson and Ramirez-Marquez suggested an approach to measure the static resiliency of any network using Monte-Carlo simulation such that service can be provided even if there are external failures. This metric accounts for the resiliency by virtue of probability distribution curve and illustrates this resiliency on the two-terminal networks (Whitson & Ramirez-Marquez, 2009).

2.7 Conclusion:

Just like many other fields and domains, the field of manufacturing has been the target of many uncertainties and disruptions. For this reason, the control system and the need for effective scheduling has become crucial in modern manufacturing systems. Disruptions are common on the shop floor, and usually if disruptions within the domain are unavoidable then their effect on the performance of the system can be minimized. However, in order to alleviate all kinds of errors, reactive scheduling is needed and repair tools are also essential.

CHAPTER 3: MEASURING STATIC AND DYNAMIC RESILIENCE FOR MACHINE BREAKDOWN

3.1 Introduction:

Upheavals and disruptions are inherent in engineering fields, particularly in manufacturing. As such, modern manufacturing systems require efficient scheduling and control systems to help minimize the effects of the disruption. Research into engineering upheavals often center their work on analysis of the underlying environment, which is inherently in flux, developing unpredictable events and interruptions at any point.

Machine breakdowns are one of the most challenging issues in production scheduling (Said, Mouelhi, & Ghedira, 2015). To show and evaluate framework resiliency, physical states identified with a framework that was influenced by disruptive events should be characterized. A disruptive event on the machine leads to full loss of production in the job shop or will cause at least partial loss if the shop contain more than one machine (Yang, Djurdjanovic, & Ni, 2007). In order to mitigate the impact of machine break down, it is essential to pinpoint a new resilience definition, measurements, and evaluate the resilience using analysis tools.

The shop planning issue can be described as follows: an assembling framework involving M machines with each job complying with a predetermined arrangement of operations that must be performed in a specified sequence on the machine. The choice as to which job is to be loaded on a machine when the machine is idle, is typically made with the assistance of a dispatching scheduling rule. Many dispatching rules have been proposed and contemplated in the last four decades by many researchers (Blackstone, Phillips, & Hogg, 1982; Haupt, 1989). For instance, a study by Rajendran and Holthaus was based on the comparison of performances of certain

dispatching rules applied in job shops and flow shops, and the assessment of dynamic flow shops as opposed to the evaluation of the absent operations and job shops (Rajendran & Holthaus, 1999). The researchers offered three dispatching rules, and the empirical evidence proved the effectiveness of the proposed rules in terms of several performance measures based on tardiness and flow time. Afterwards, Holthaus conducted a comparative analysis of several dispatching rules related to dynamic job shop. Machine breakdown and the impact of different breakdown levels on dispatching rules' performance were among major focuses of this study (Holthaus, 1999). Hence, the pronounced impact of the mean time of restoration and the breakdown level on dispatching rules was among the key findings of the research. Furthermore, Sabuncuoglu and Bayiz analyzed the impact of some system configurations on the effectiveness of both online and offline scheduling in the context of chaotic and fixed environments. The robustness of dispatching rules in the context of system uncertainty and the less pronounced decrease in online methods' performance in dynamic environments as opposed to that of offline ones are major conclusions of the study(Sabuncuoglu & Bayız, 2000). Dynamic scheduling techniques do not resort to selection rules and rarely consider alternate production routes, though Subramaniam et al. emphasized the role of route flexibility. The application of machine selection rules provided their approach with considerable scheduling performance. In turn, Thiagarajan and Rajendran pointed out the necessity of certain dispatching rules aimed at assembling job shop scheduling. Besides, the when-to-schedule policy offered by Suwa and Sandoh deserves special attention since this policy is focused on a determined threshold. Thus, this policy implies that the existing scheduling needs to be altered once the excess of communicative task delay occurs at each planning dimension (Suwa & Sandoh, 2007).

3.1.1 Machine Resilience:

Most of the studies in manufacturing field have focused on production capacity and flexibility in planning (Gu et al., 2015; Singh, 2013). Resilience is an important operational function of manufacturing that can help to improve productivity by determining the capability of machines during the breakdown event. There are limited studies that focus on defining the concept of resilience of a manufacturing system. With the limited research in resilience in manufacturing systems, there are various definitions of resilience. The next section will focus on investigating these studies to exhibit the different definitions of resilience that are used in manufacturing.

3.2 Literature review:

3.2.1 Resilience Definition in Manufacturing:

Xi and Jin (2015) considered resilience in manufacturing and identified three resilience measures: production loss, throughput settling time, and total underproduction. They defined resilience as the capability of the manufacturing system to mitigate the effect of the disruption by increasing the speed of the other machines in the system when the disruption occurs. The metrics of these three types of resilience measure the system performance for the production loss total underproduction time. PL^P is a measure that provides the production loss caused by the disruption under different policies (Equation 3.1), where PR (k) denotes the production rate under three different policy where the first one is to increase the speed of the machines, the second is to reconfigure the system, and the last one is without control action during the disruption. T_D is the duration of the disruption, and T is the duration of the reconfiguration. However, practitioners in the field of manufacturing will state that machine speed cannot be

increased to speed up production. Reconfiguration does not make sense when there is only one product in the manufacturing system, since excess machines are not available typically.

$$PL^P = \frac{T_D}{T} PR^s - \sum PR(K) + (PR^s - PR^p) \tag{3.1}$$

Xi and Jin (2015) assumed that there are multiple machines of the same type in the system. They also assumed that the production rate or speed of machines could be changed to compensate for the production loss. In addition, their measurement of resilience is an amount of production lost by using Bernoulli reliability model, and their goal was to design manufacturing system for resilience, and study how the resilience measures are affected by the system configurations. Again, the concept of speeding up other machines when there is a machine failure is not practical.

Hu and Li (2013) considered the optimization of manufacturing systems when planned disruptive events with prior warnings are available in the system. Such events could include plant shutdowns. In their research, they investigated real-time resilient control for manufacturing systems. They used the concept of look-ahead time windows and the possibility of disruptions within these time windows to determine the control strategy that minimizes the lost production as the primary objective and the reduction of cost as the second objective. After solving the optimization problem of the Decreasing Storage Cost and Decreasing Capacity (DSCDC) network, more complex serial networks was transformed into DSCDC networks. Normalization is investigated to change the operation, and other variables to be connected with the demand as a unit. Then, the system is divided into a number of sections, and the nodes in each section have a fixed ratio of operation. The research was limited to serial manufacturing systems, which

assumed that there was only one product coming into a manufacturing unit and one product coming out of the manufacturing unit.

Zhang and Van Luttervelt (2011) attempted to develop a framework for production system resilience using various concepts of failures. They proposed principles for design and management of a resilient manufacturing system by discussing a new behavioral property of manufacturing system resilience. They defined resilience as a failure of two types: 1) the user's demand is not satisfied, and 2) required resource is not available. Their definition of resilience was the capability to recover from failures. However, there is no quantifiable technique proposed for the measurement of resilience, but there were several examples discussed to illustrate the use of the guidelines that were proposed in design and management for enhancing resilience. In one of these examples, the machine has two servomotors, four moving components, and one foundation structure. The machine system has software to respond in real-time. If one servomotor is partially broken, the system still has one constant velocity motor and one servomotor, which is called as hybrid actuation system. The hybrid actuation system can still implement the desired function of the machine by reprogramming the software of the machine. The resilience gained in this way by following Guideline III, where the authors proposed five guidelines that useful for design of the resilient manufacturing, and Guideline III is the learning and training component works with the types of redundancy to deal with unexpected disruption caused by external mishaps.

3.2.1.1 Summary:

Based on the papers reviewed, it is apparent that the machine performance and disruption are not studied using a quantitative approach in a manufacturing system. Furthermore, there is no illustration to describe the overall variation of machine disruption over time. Measurement

and analysis of manufacturing system resilience are significant to manufacturing. In order to know the disruption effect in manufacturing, resilience must be defined and quantified in the field of manufacturing. There are many different definitions of resilience currently in use in other fields. These definitions lead to different metrics and approaches. There is no prescribed and quantitative method to deal with resilience in the field of manufacturing. Although quantitative approaches available in the field of resilience are limited, it is non-existent in manufacturing field. Thus, in the field of manufacturing system resilience, a standard definition has to be developed. Some of the research in dealing with resilience in the presence of disruptions have used the strategy of speeding the production. This is not a practical approach, since speeding up production is typically not possible and may affect quality and other parameters of the product.

3.2.2 Resilience Metrics:

Resilience quantification plays a major role to define resilience of any given systems and further using the resilience concept in the process of engineer design. Although these disciplines have been explored, to date, the quantification metrics of the available engineering fields still exhibit few standardizations. Agreement on the quantifiable measures remain a challenge. A number of aspects and approaches, which include uncertainties, should be taken into consideration when it comes to quantified resilience. On manufacturing system, quantification metrics are highly dependent, and is classified as deterministic-probabilistic as well as static-dynamic. Here, the available metrics are under the derivation approaches where some metrics could occupy a single category. Resilience quantification metrics has a range of strengths and weaknesses, which depend on the study's purpose as well as application of interest. A number of

resilience metrics based on resilience curve, pre- and post-disruption performances, and restoration and reliability are detailed below.

3.2.2.1 Resilience Metrics based on Resilience Curve:

Because the resilience curve is usually applied in illustrating the resilient behavior of the system, which undergoes a disruptive event, a lot of researchers have applied the properties from measuring the resilience curve quantitatively. As shown in Figure 3.1, the resilience curve is identified as the shaded area. This area is known as IA (impacted area) that defines the loss of performance, which is approximated as the integral method. The magnitude qualifies R-loss, which is the expected degradation in performances quality other than the recovery time. Mathematically expressed in the following equation:

$$\Psi\text{-loss}=\int_{td}^{tn}[Po(to)-p(t)]dt \qquad (3.2)$$

Where $P_o(t_o)$ is the first performance functions prior to a disruptive event at t_d (time), and performance quality P(t) of a system varying with time. The shaded area in Figure 3.1 is also referred to in literature as the resilience triangle (Ayyub, 2015; Rose, 2007). When there is an assumption of the recovery profile in Figure 3.1, a triangle formulation could be integrated to quantify resilience.

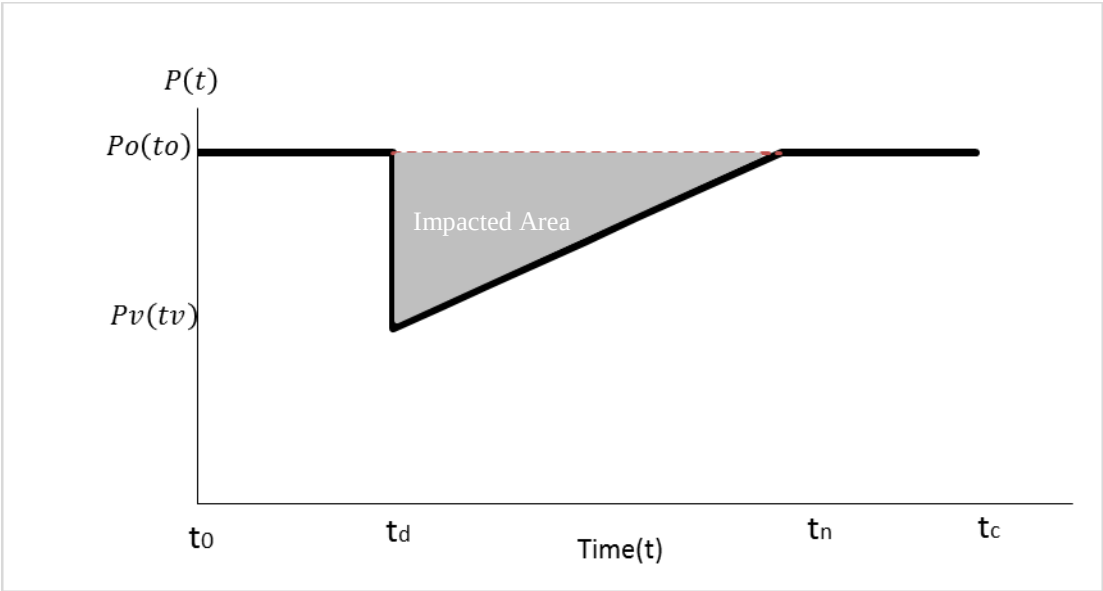


Figure 3.1. Predicted performance loss (Bruneau et al., 2003; Zobel & Khansa, 2014)

The performances of the system does not necessarily demonstrate an extreme or a steep drop in the disruptive event aftermath as shown in Figure 3.1. During the time-period between t_d and t_n, there will be a gradual performance degradation, which is experienced by the disruptive system as shown in Figure 3.2. Accordingly, most of the drops in gradual performances exhibit or show a nonlinear behavior. In the case, for the nonlinear unreliability as well as recovery of profiles, this type of resilience can be explained and emphasized as the system's functionality capability, which follows an implication or hazard over the control period indicated as ($T=t_n-t_d$). As shown in Equation 3.3 (C. S. Renschler et al., 2010):

$$\Psi = \int_{t_d}^{t_n} \frac{A(t)}{\mathrm{T}} dt \qquad (3.3)$$

Mathematically, Ψ is quantified as the normalized shaded region under the response of the system (which describe the functionality of the general system) following a disruptive events shown as the A(t) in Figure 3.2.

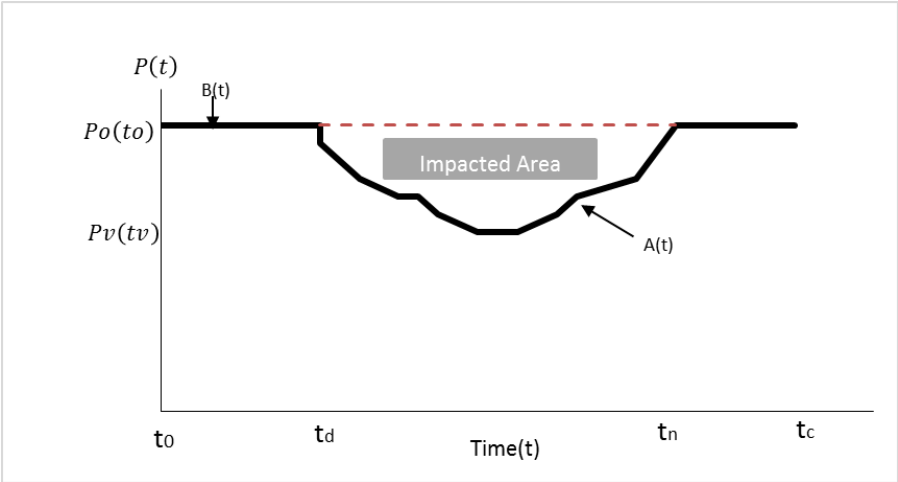


Figure 3.2. Performance loss before and after disaster (C. S. Renschler et al., 2010)

3.2.2.2 Resilience Metrics based on Pre-disruption and Post-disruption Performances:

Engineering resilience is always associated with the system's performance loss when undergoing disruptive events. In this case, among the approaches in quantifying resilience is the performance changes measurement whereby resilience metrics may be represented to be a system performance ratio prior to (pre-) and after the disruption. Based on system performances, expressing resilience is highly application-specific given that various applications have different performances functions in general. Additionally, there are numerous cases where unique applications can be identified and described by a series of performance functions. For instance, the performance function, in a networked system, could be characterized in a number of ways such as the system travel time (STT), the flow/delivery network value, and the demand, which can be satisfied, among others. Here, where V (the flow/delivery value) was used as system

performance in networked-system applications, the following or corresponding metrics is demonstrated in the equation below (Omer, Mostashari, & Nilchiani, 2013):

$$\Psi = \frac{V_{\text{initial}} - V_{\text{loss}}}{V_{\text{initial}}} \tag{3.4}$$

Where $V_{initial}$ refers to the amount of data or information, which needs to be carried via network, and the V_{loss} is the loss of information because of the disruptions results. In the same application of the networked-system, resilience index is defined as the differences between the SO (optimal travel time) and the critical STT (system travel time) (Bhavathrathan & Patil, 2015). The proposition of the resilience index has been normalized relative to the system travel time as:

$$\Psi = \frac{SST - \text{SO}}{\text{SST}} \tag{3.5}$$

Considering all the nodes within the networked-system, the resilience metrics accompanying the expected demand fraction E(D) is also demonstrated in Eq. (3.6) (Dixit, Seshadrinath, & Tiwari, 2016; Miller-Hooks, Zhang, & Faturechi, 2012). In this case, $D_{w,pre}$ is the initial demand of pre-distribution for the O-D (origin-destination) pair w as well as $D_{w,post}$, which is a post-disruption maximum demand satisfying 0-D pair w.

$$\Psi = \text{E}\left[\frac{\sum_{w \in W} D_{w,post}}{\sum_{w \in W} D_{w,pre}}\right] \tag{3.6}$$

Adding to the pre-disruption and post-disruption ratio, is a resilience formula that was introduced on the basis of the post-disruption reliability of all suppliers within the networked-system application (D. Wang & Ip, 2009). And it has been mathematically formulated as follows:

$$\Psi_i = \frac{p_j q_k \min\{di, sj, ck\}}{d_i} \tag{3.7}$$

As previously discussed, Ψ_i is resilience of the systems demand for node i, which possess the ability for survival as well as recovery from potential damage because of the disruptive mishaps or events. p_j is the reliability for supply node j, and q_k represent the supply link k.

3.2.2.3 Resilience Based on Reliability and Restoration:

Resilience is defined as the systems' ability to detect and withstand mishaps or events as well as recover from the implications of these disruptive events (Cimellaro et al., 2008). There is a derivation of the mathematical formula which has been derived and formulated to quantitatively measure and determine the systems resilience with two important attributes as restoration and reliability, in which system reliability quantifies the effort of systems in maintaining its performance and capacity above safety limits during a specific time period under certain conditions. In this case, restoration measures the systems resilience as well as the ability to restore capacity and performance to detect, predict, and mitigate/recover from effects of disruptive events. Mathematically, this can be expressed as follows:

$$\Psi = \text{Reliability}(R) + \text{Restoration}\ (p) \qquad (3.8)$$

The restoration capacity (p) can be considered as the reliability recovery degree. The restoration and reliability can be derived as a series of conditional probabilities.

The system's reliability generally describes the ability of the system to function for a certain period without failing. It is often measure and determined by using probability functions. For the reliability analysis of the system, failure is often determined based on the system performances of interest (p). Generally (p) is a representation of a function of a system with random variables as input within random spaces. (p) is less than 0. 0 indicates system failure.

This random input space is broken down into two primary domains namely the safe domain and the failure domain, and is identified by the state function P = 0 (Li & Lence, 2007; Z. Wang & Wang, 2014). The random input variables probability falls into the safe region identified as reliability. Accordingly, the probability of these variables falling into the failure region is identified as the probability of failure. Resilience can be represented as the probable system failure recovery, along with the probability of recovery and reliability of the system. Given system failures at time (t_1) as well as the recovery of failures after some time (t_2) in which resilience was formulated at two points t_1 and t_2 as (Li & Lence, 2007):

$$\Psi(\mathrm{t1}, \mathrm{t2}) = \mathrm{pr}[\mathrm{P}(\mathrm{t2}) \geq 0, \mathrm{P}(\mathrm{t1}) < 0] \tag{3.9}$$

In which Ψ (t_1, t_2) is the conditional probability based on the system failures at t1 and recovery period at t_2. Considering P_{FS} (state transition probabilities) between the reliable and failure states, as well as the failure probability (P_F), resilience can be further quantification as(Attoh-Okine et al., 2009; Li & Lence, 2007):

$$\Psi = \frac{P_{FS}(t1, t2)}{P_F(t1)} \tag{3.10}$$

There is also the expression of reliability on the basis of damage loss in available resilience quantifications metrics (Equation 3.11). The quantification of resilience is shown as Pr(A/i) that refers to the conditional probability that the system seeks to meet performance standards (A) of predefined systems after i, which is the disruptive event (Attoh-Okine, Cooper, & Mensah, 2009). Attoh-Okine et al. introduced performance standards such as robustness (r*) and rapidity (t*). Accordingly, robustness is defined as the maximum loss that is acceptable. This can be regarded as the systems' ability to guarantee reliability or endure failure. Additionally,

rapidity is defined and identified as the minimum level of acceptability of disruption time or maximum time to fully recover. Following the presence of disruptive events, the r_o (initial loss) and the t_n (time to full recovery) should not surpass the performance standards as demonstrated in Figure 3.3. Here, r_o>r* and t_n<t*. Given this resilience quantification metrics, resilience objectives shown as Pr(A/i) ought to satisfy the reliability objective of r* prepared and put forward as :

$$\Psi = \Pr(\mathrm{A/i}) = \Pr(r_o < \mathrm{r}^* \text{ and } t_n < \mathrm{t}^*) \tag{3.11}$$

$$\Psi = \Pr(\mathrm{A/i}) \geq R^*$$

Equation 3.11 offers resilience metrics by understanding and taking into consideration individual disruptive events. In the presence of various disruptive events, for example, different failure events, conditional resilience metrics were proposed (Han, Marais, & DeLaurentis, 2012), which employs the system performance percentage maintained in alignment with these disruptive events. Therefore, although these disciplines have been explored to date. The quantification metrics still exhibit few standardizations.

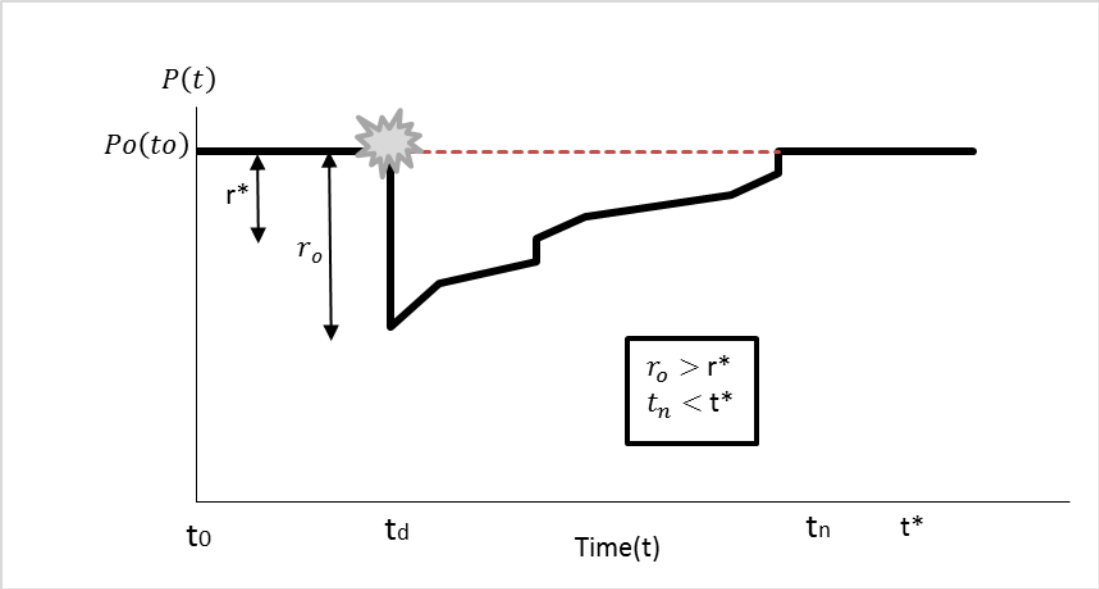


Figure 3.3. Robustness and rapidity performance measures (Chang & Shinozuka, 2004)

This paper focuses on the concept of resilience and performance of the machine when disruption occurs. The resilience of machines is measured as a function of time. The objectives of this paper is to present a new method describing the resilience property in manufacturing in the presence of machine disruption, and measure the resilience of machines. The resilience of any given machine at time t, when the machine is repaired, is the ratio of the areas that are below the curve representing the machine performance before and after disruption. When the machine completes all jobs that have to be completed during the disruption period, then the machine is fully recovered. To address these issues in details, this section investigates thoroughly about the concept of resilience due to machine disruptions in the job shop.

3.3 Manufacturing Resilience formulation:

Intermediate buffers, inspection stations, and machines are basic elements of modern manufacturing systems. The interconnectivity of these elements is a prerequisite for a successful performance of the required operations. Any failure occurring in the machines' functioning affects the productivity of the entire system. Hence, acquiring better knowledge of failures/disruptive events and assessing them adequately are of paramount importance in the context of ensuring the economic growth of manufacturing companies. A system's ability to endure significant disruptive episodes is generally referred to as resilience. To be more precise, this capability is essential for addressing the effects of failures in the most effective way, thus facilitating a fast recovery.

The purpose of this paper is to examine a situation in which a failure occurs unexpectedly and incapacitates the machine for a duration within the period of study. There is no significant literature in the application of resilience to manufacturing systems, and in particular job shops. There is no generally accepted definition of resilience in this field. Hence, it is essential to develop a new definition for resilience as applied to the field of manufacturing. Along with that, the measurement of resilience and the evaluation of resilience using analysis tools when a disruptive event occurs on the machine that leads to loss of production in the job shop has to performed. Thus, it can be either planned or unforeseen (Walker et al., 2004). As soon as the mitigation of a disruption's consequences occurs, the machines' condition is restored. The decrease in throughput and the increase in work-in-process are among the most common measures that are vulnerable to the disruption. Resilience can be measured as the ratio of the areas that are below the curve representing system performance after a failure $A(t)$ over the

system's baseline response *B(t)* from current time t_c to the end of time period (*T**) (Ouyang, Dueñas-Osorio, & Min, 2012; Shafieezadeh & Burden, 2014; Yodo & Wang, 2016a). Mathematically, this can be shown as follows:

$$\boldsymbol{\Psi}_{t_c} = \frac{\int_{t_c}^{T^*} \boldsymbol{A(t)\, dt}}{\int_{t_c}^{T^*} \boldsymbol{B(t)\, dt}} \tag{3.12}$$

B(t) is characteristic of the performance of the system in the absence of disruptions from time t_c to time *T**. In turn, *A(t)* is characteristic of the system response in case a failure occurs from time $t_c$time *T**.

In job shop, the system's baseline response can be defined as the proportion of the areas of workload time for the machine during the time-period. So, B (t) can be formulated as follows:

$$\int_{t_c}^{T^*} B(t)\, dt = \int_{t_c}^{T^*} P(t)\, dt \; - \int_{t_c}^{T^*} I(t)\, dt \tag{3.13}$$

P(t) represents the productivity level of the machine in the absence of disruptions, and I(t) is the idle time for the machine without disruption, and both are from time t_c to time *T**

Areas that are below the curve representing system performance after a failure can be formulated as the following equation:

$$\int_{t_c}^{T^*} A(t)\, dt = \int_{t_c}^{T^*} P(t)\, dt \; - \int_{t_c}^{T^*} I(t)\, dt - n \int_{t_c}^{T^*} D(t)\, dt \tag{3.14}$$

Where *n* is the number of failures that can happen in a single time-period, because in some cases the disruption can happen more than once in a single time-period for the machine. D(t) represent the average time that the machine spends in a disruptive event.

A resilience scale makes it possible to measure the amount of resilience, which the system has acquired or lost. A survey of the literature shows that a resilience scale between 0 and 1 is preferable for resilience metrics. In the percentage value, the resilience metrics can range between 0% and 100%. Measuring resilience through the prism of various system performances of interest with the use of the 0-1 scale has the potential to avoid unnecessary complications occurring due to different resilience metrics.

Since resilience is a system feature, the convenience of a relative scale focusing on performance differences that are evident before and after a failure is out of the question. Furthermore, a probabilistic resilience metric that involves the 0 to 1 probability value is applicable when a resilience analysis implies uncertainties. The use of a resilience scale makes it possible to interpret resilience through a recovery from the consequences of a disruptive event based on the resilience value. Besides, one can also interpret it by applying a probabilistic concept that defines the manner in which the system's recovery would occur. For instance, a system with a 0.9 resilience value is one that is 90% resilient to any potential failure. More specifically, it can survive a disruptive event and return to its pre-failure condition within a certain period with a probability of 90%.

A successful resilience, if analyzed from the perspective of a resilience scale, is the one indicating the system's ability to detect alterations in its condition, and recover from the failure's effects. The system's incapability to adjust to changes, which follow the incident, is defined as a resilience failure (Rahimi & Madni, 2014). Moreover, the availability of a wide range of potential disruptive events is indicative of an engineered system possessing different levels of resilience that occur in response to different challenges. Hence, the magnitude of incidents defines varying levels of the system's resilience since different types of disruption require

different responses. While a system can respond to one challenge adequately, it may fail to do it appropriately if another one takes place.

3.4 Machine resilience as a function of time:

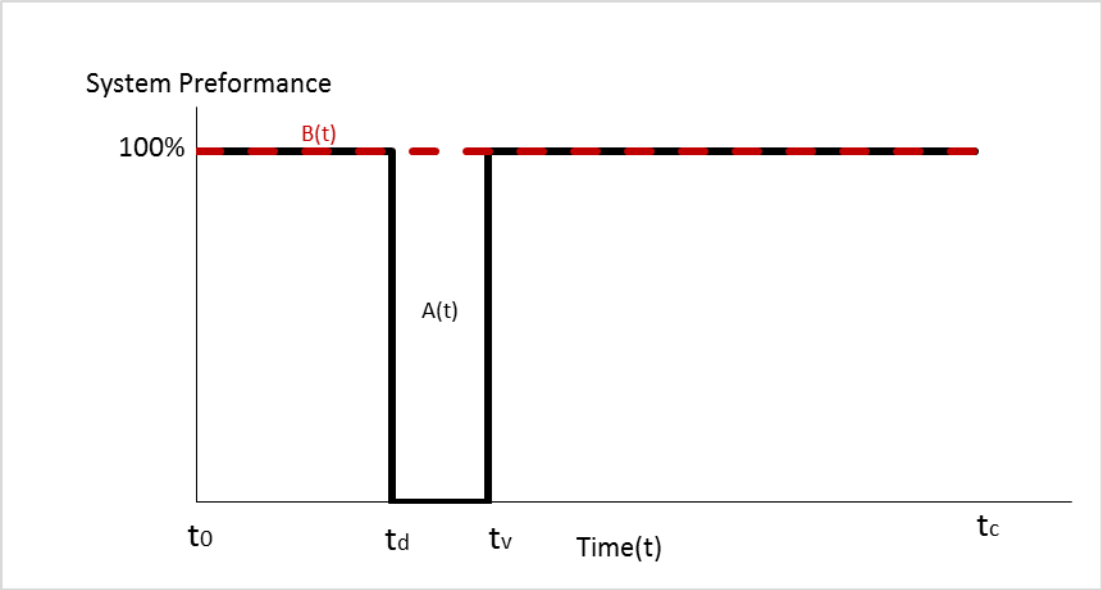


Figure 3.4. System performance B (t) and A (t)

The resilience concept is connected with systems performance within the interest period. Figure 3.4 shows curves of machine performance with the disruption effects A(t), and without the disruption effects B(t). The general overview, shows time-dependent system performance as well as illustrates the essence of time during the systems response. It is expected that, when disruption occurs, there is degradation of performance. This performance with respect to the disruption time occurrences can be divided into stages that are mutually exclusive namely the pre-disruption ($t_o<t_d$), during the disruption ($t_d<t<t_v$) and, lastly, post-disruption ($t>t_v$) periods. In the first stage, the system functions under the normal conditions whereby the systems' capacity as well as demand are not impacted by the disruption. This time or period starts at the

time of reference, t0, and terminates at the occurrence t_d disruption time. During the disruption period, which is the time when the machine is hit by the disruption, t_d, until the termination of disruption, the system does not operate as a result of the disruption. The system operates, in the pre-disruption stage, under normal scenarios or conditions. Following the disruption, in a short time, undergo restoration and recovery.

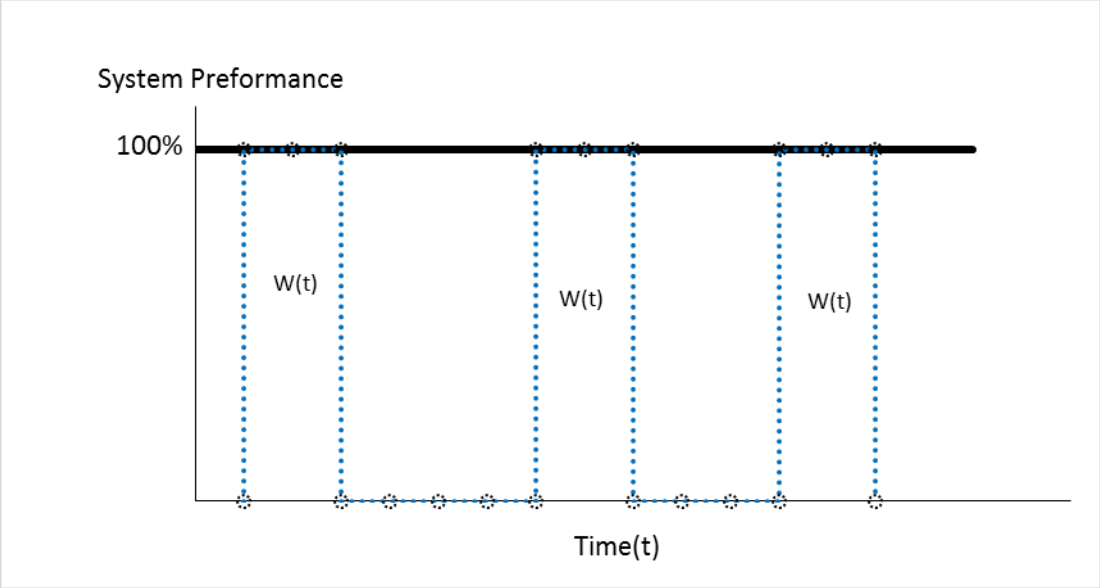


Figure 3.5. Machine performance

Figure 3.5 shows the relation between the workload and the capacity in the job shop, where the machine sometime is available but it has to wait for the job to be finished at another machine and that waiting time is called the idle time. In a job shop, there are two types of effects if a machine fails. The first effect is on the work on the machine that failed, and the second is the remaining work on the job sequence that waiting for the machine failure. The resilience of a machine is calculated by taking into consideration the influence of failures of other machines which in turn influences the schedules and hence the productivity of the machine under study.

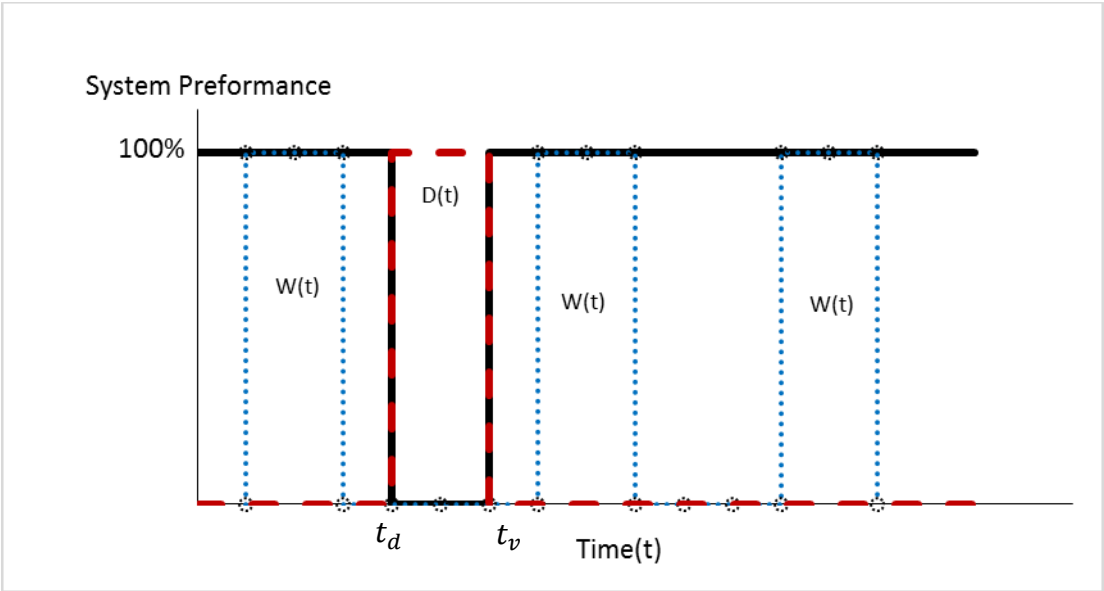


Figure 3.6. Machine performance when disruption occurred

When a disruption occurs at time t_d as seen in Figure 3.6, the machine moves to the down-time state. The productivity of the machine from that moment is zero until time t_v. T_v is the time at which the machine repair is complete.

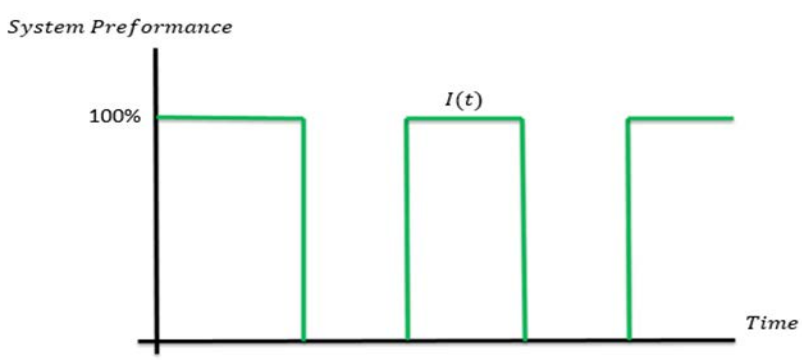


Figure 3.7. Idle Time

Figure 3.7 represent the curve of the idle time (green line) for machines, where the machine is avilable but there is no product assigned to the machine. Also, the idle time depends

on the amount of productivity that is assigned for the machine and the machine speed, and that will vary from machine to another.

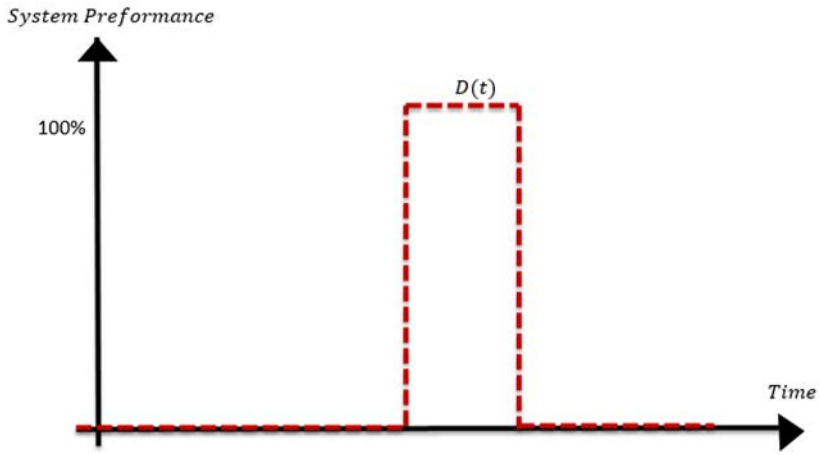


Figure 3.8. Disruption Time

A typical resilience curve for a machine is shown in Figure 3.8 for the disruption time event. In a job shop, when a disruptive event such as a breakdown affects a machine, the performance typically degrades to a non-working machine and hence the productivity of the machine is zero, and disruption breakdown is at 100% level where is no product can be assigned to the machine. Thus until the machine is repaired, the slope for productivity of the machine is zero. On the other hand, typical resilience studies and curves for non-machine type systems show a trend of declining performance until it reaches the point where recovery is initiated.

3.5 Numerical Example:

For illustration purpose, the job shop contains four machine and the shop has three different jobs. The number of jobs are fixed, so there is no need to calculate the inter-arrival time of jobs. The goal is to measure the resilience for each machine for the static scenarios.

Table 3.1. Machines processing times

Jobs	Machine Sequence	Processing Times
1	1,2,3	U[4,5]
2	3,2,1,4	U[4,5]
3	4,3,1	U[4,5]

Table 3.1 represents the sequence and processing time for each machine. The sequence is different from one machine to another and the time required for each machine is also different.

3.5.1 Modeling the System:

3.5.1.1 Simulation:

The job shop scheduling problem (JSSP) is practical in nature and is widespread in both supply chain management and manufacturing. Notably, job shop scheduling is a process of assigning specific tasks for optimizing particular objectives. A successful optimization is possible if the machines have a satisfactory performance in the context of predetermined resource limitations. In general, these objectives are as follows: (a) shortening the time of production, (b) decreasing maximum lateness, or (c) reducing the number of delayed jobs. Thus, the JSSP for the amount of machines ≥ 2 is among common NP-hard problems. This implies that the increase in the number of orders determines the exponential increase in the quantity of potential schedules.

There are *m* machines and *n* jobs in the JSSP. A fixed processing route it a part of each job, and this route encompasses certain machines or all the machines available in accordance with a prearranged scheme. An operation of the job is a manufacturing process pertaining to one machine. Hence, the minimization of completion time is the primary goal that is taken into

consideration during the operations' scheduling. A range of problem assumptions claims attention:

1. Processing times are conditioned.
2. All jobs are prone to processing at time *t0*.
3. Processing of one job is possible on a machine during a certain period.
4. Generally, one job is assigned to each machine.
5. The setup times for each job are incorporated in the processing time.
6. The time needed for transportation between machines is not taken into consideration.
7. Setup times required for each job.
8. Causes except for machine breakdown are not acceptable for interrupting machines.
9. Machine breakdowns are permitted.

Because of the random nature of breakdowns, the use of stimulators in terms of machines' disrupting the operations is justifiable. Herein, we point out the ways in which we address the challenges posed by the simultaneousness of flexible job shop scheduling and machines' undergoing stochastic breakdowns for optimizing the objectives that are based on the anticipated time of production and the anticipated mean tardiness through the implementation of simulation.

The given system is modeled in ARENA Simulation software. Figure 3.9 describe the Arena model for the job shop, consisting of three main segments:

1. Job processing time

2. Job sequence

3. Machines setup time

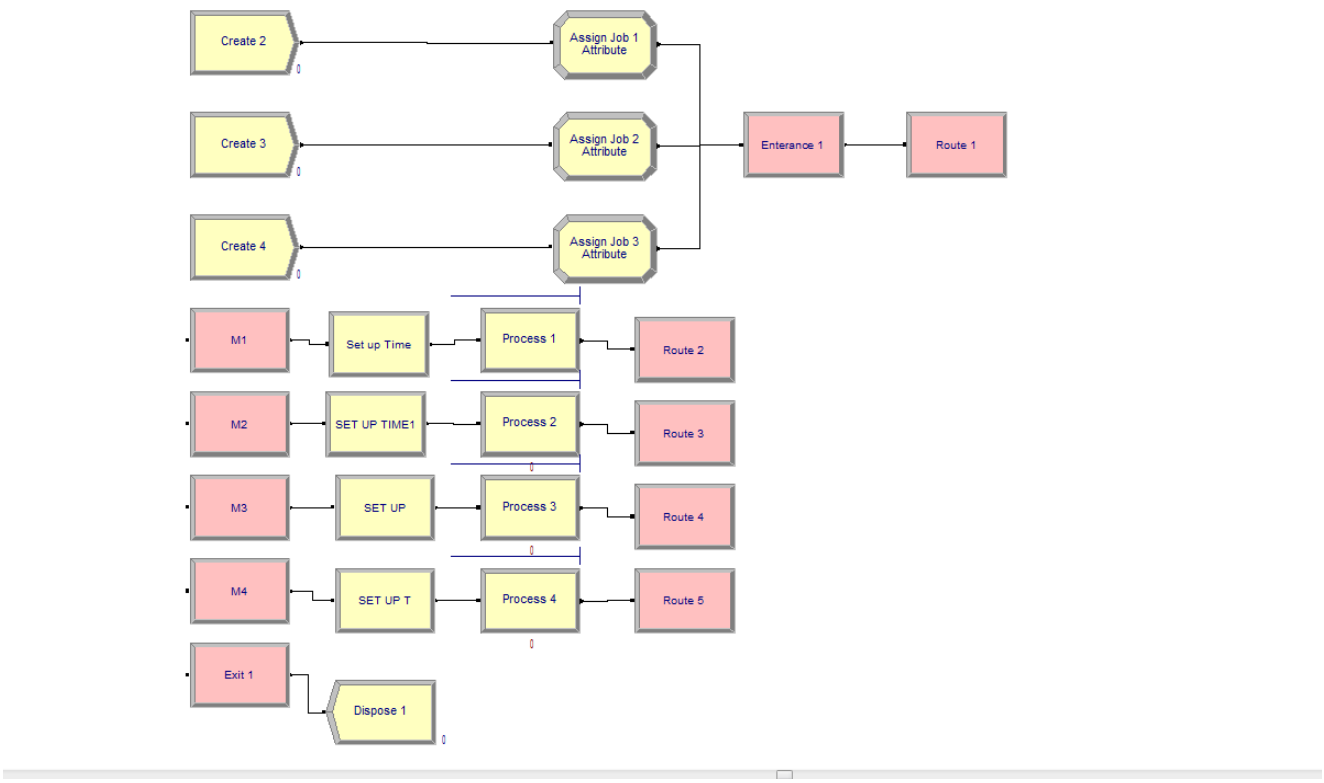


Figure 3.9. Arena Model for Manufacturing Job Shop

The following section will be a segment-by-segment through the model

Create a Job:

This part includes the section of create a jobs. The segment is shown in Figure 3.10.

Figure 3.10. Job Segment

A job entities are created in the Create module, called Create Jobs whose dialog box is displayed in Figure 3.11. Sine this model is a static model the time between arrivals will be constant.

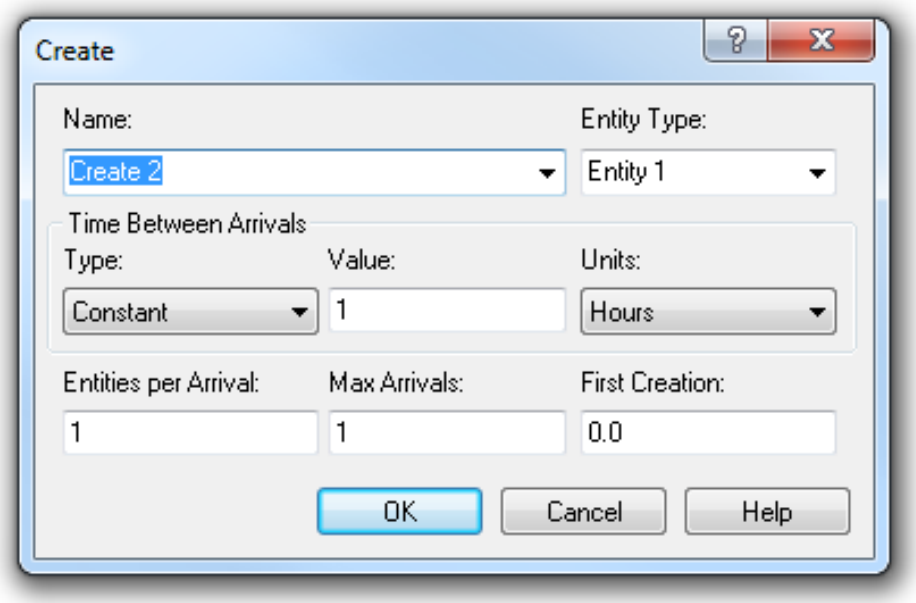


Figure 3.11. Dialog box of the create a jobs

The entity next enters the Assign module called Assign Job Type and Sequence, whose dialog box is displayed in Figure 3.12. The Arena attribute Entity Sequence is assigned the value

of the Type attribute. This attribute acts as an index that associates a job type with the corresponding operations sequence.

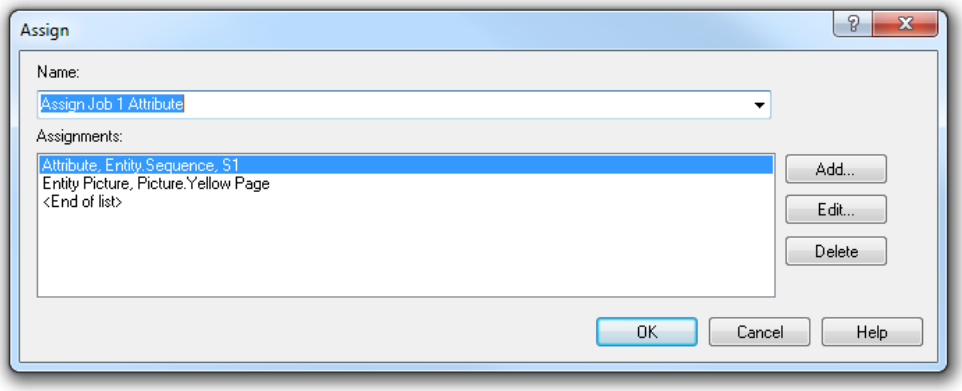


Figure 9. Dialog box of the assign module

Figure 3.13 shows the segment that includes the actual processing of the job. The job processing segment encompasses sets of process modules, each modeling an operation in the sequence, from machine one to four. The Seize Delay Release option from the action domain is used to model job delays at this process

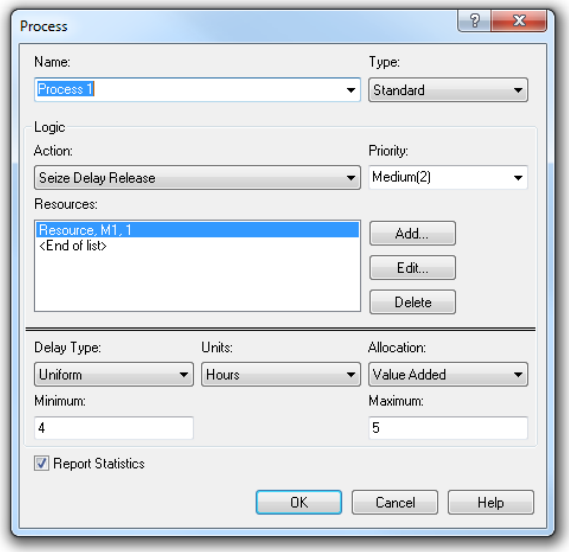


Figure 3.13. Dialog box of the Process module

Arena computes Failure times of machines among Station modules based on their down time and up time. Figure 3.14 introduces Failure into the model and specifies their parameters in the Failure module spreadsheet. These include columns for a Name field to specify the Failure set, a Type field (Time or count), up time field for specifying the time of machine working and similarity for down time.

Failure - Advanced Process

	Name	Type	Up Time	Up Time Units	Down Time	Down Time Units	Uptime in this State only
1	DN Time and Repair	Time	1.0	Hours	EXPO(0.2)	Hours	

Double-click here to add a new row.

Figure 3.14. Dialog spreadsheet of Failure module

This segment showing in Figure 3.15 called the transport of finished jobs from job shop to outside. Eventually the job entity arrives at the Station module, called Shop Exit, which is always the last location in each operations sequence.

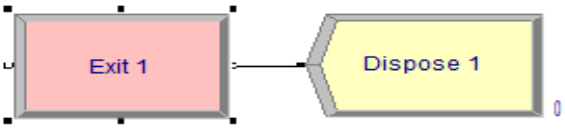


Figure 3.15. Job Departure Segment

Figure 3.16 shows the job shop set up model and it was simulated for 16 hours. Parameters like number of replications and hours per day are given in Run Setup.

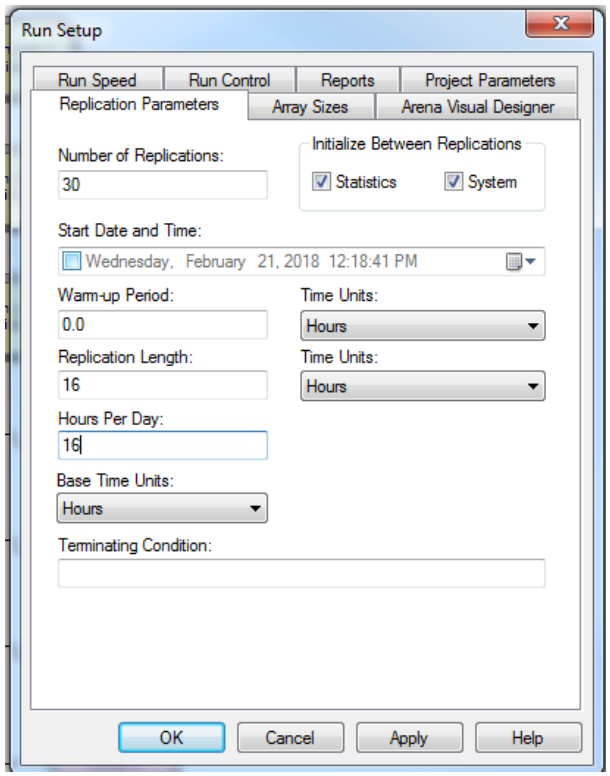


Figure 3.16. Dialog box of Run Setup

3.5.1.2 Result and Discussion:

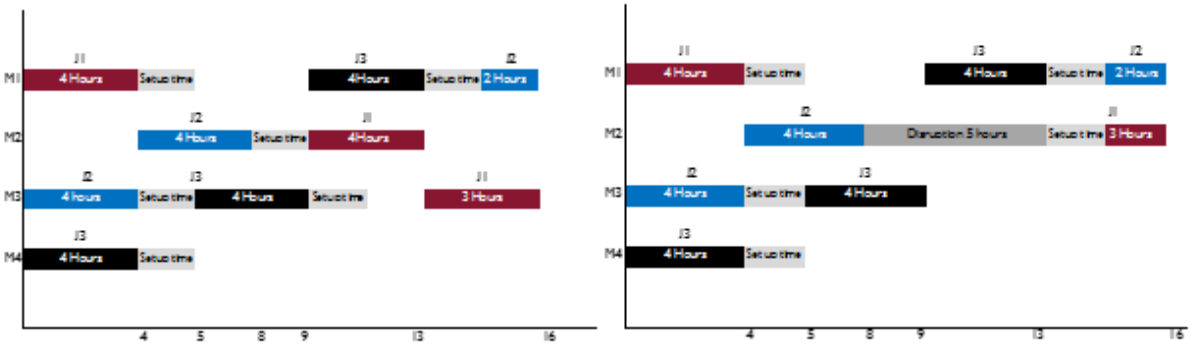


Figure 3.17. Gantt Charts for Job shop

In the static model, the chart shows the time it takes to complete all the three jobs based on shortest process time (SPT) rule. If there is a disruption on Machine ‘m2’ for job ‘j2’ as

shown in Figure 3.17 then machines M1, M3, and M4 will also be affected along with machine M2 because of job 'J2 and J1 sequence.

Table 3.1. The process time based on SPT

	performance of the machine in the absence of disruptions		**performance of the machine with the disruption**		
	$\boldsymbol{p(t)}$	$\mathbf{I(t)}$	$\boldsymbol{p(t)}$	$\mathbf{I(t)}$	D(t)
M1	16	6	16	6	0
M2	16	8	16	4	5
M3	16	5	16	8	0
M4	16	12	16	12	0

The vales in Table 3.3 are showing the resilience in the terms of percentage. For example, machine 1 and 4 are fully resilience and that mean either these machines are not affected by the disruption or the time period was enough to handle the disruption.

Table 2.3. Results of resilience

	Performance Area for the baseline (unit area)	Performance Area after the disruption	Resilience
M1	10	10	100%
M2	8	7	87.5%
M3	11	8	72.7%
M4	4	4	100%

To compare which machine is more resilient based on the simulation result, the resilience metric was used. It calculates the resilience by comparing the system performance when there is no disruption (baseline) with the resilient performance after the disruption. Table 3.4 shows the average process time for each machine before and after the disruption with same period time of 16 hours. The results of the simulation study are obtained by taking the mean of mean values of 30 replications for both scenario in order to calculate the expected resilience and assuming the disruption for the second scenario will happen in machine 1. The MTTR and MTBF are exponentially distributed.

Table 3.3. The process time of two different scenario

	performance of the machine in the absence of disruptions		**performance of the machine with the disruption**		
	$\boldsymbol{p(t)}$	$\mathbf{I(t)}$	$\boldsymbol{p(t)}$	$\mathbf{I(t)}$	D(t)
M1	16	4.8	16	4.8	0
M2	16	7	16	4.1	4.4
M3	16	3.8	16	7.1	0
M4	16	11.5	16	11.5	0

The values in Table 3.5 showing the resilience in the terms of percentage. For example, machine 1 and 4 are fully resilience and that mean either these machines are not affected by the disruption or the time period was enough to handle the disruption. However, machine 2 and 4 are effected by the disruption, machine 2 is where the disruption occurred and machine 3 is effected because of the job sequence.

Table 3.4. Results for expected resilience

	Performance Area for the baseline (unit area)	Performance Area after the disruption	Resilience
M1	11.2	8.9	100%
M2	9	7.5	84%
M3	12.2	9	74%
M4	4.5	4.5	100%

3.6 Conclusion:

In this chapter, we proposed resilience measures for machines in a job shop under a disruptive event. The measure for the static and dynamic model was based on the proportion of the areas that are below the curve representing system performance. Also, the disruption event is defined as the length of time it takes to repair the machine. The resilience analysis discussed here illustrates a quantitative approach to resilience as proposed in this paper. Resilience behavior can differ among varying machines, workloads, and repair times. The example illustrates the benefits of implementing the most appropriate restoration action, and indicates that it is possible to arrive at an ‘‘optimal resilience strategy’’ that would enable the system to bounce back quickly and efficiently.

Just like many other fields and domains, the field of manufacturing has been the target of many uncertainties and disruptions. Resilience in relation to the maintenance and management of job shop systems has not yet received significant consideration or adequate study. Yet resilience is increasing in usage within engineering fields, although its application varies from one system to another. In a job shop, machines are considered most important, and they are always the most

susceptible to disruptions during different kinds of operations. A disruptive event in a machine causes errors in the machine workload, operations, and the job shop system. This chapter proposed a new definition for resilience in a job shop and used a sample case study to show how it can be measured.

CHAPTER 4: JOB SHOP RESILIENCE BASED ON RELIABILITY AND RESTORATION

4.1 Introduction:

The design of most manufacturing systems involves a passive and fixed design capacity. For this reason, the reliability of these systems remains questionable under adverse circumstances. Currently, the design of manufacturing systems implies system redundancies for the achievement of the desired system reliability under adverse circumstances. Nonetheless, increased levels of system redundancy lead to the increase in life-cycle cost of a system. The research on resilience in a number of non-manufacturing areas has made it possible to achieve sustainable development. However, the problem of resilience in job shop design is unsolved. Additional theoretical material is required for acquiring a better understanding of the ways in which resilience is achieved in the context of a manufacturing system. Moreover, it is needed for developing generic resilience principle that would be effectively applied in manufacturing design.

Several circumstances can explain the need for new design tools aimed at the development of sustainable, low-cost, and high-reliability job shop systems. Firstly, the growing system complexity is challenging for designers since it makes it difficult to consider all potential failure models that could take place during the operation of the system. Secondly, the tendency of building long-term use systems will ultimately result in challenges associated with projecting the system's environmental usage impacts, as retrofitting events are unavoidable. In addition to the above-mentioned challenges related to the development of complex systems, one should consider the significance of resilience since this concept is of paramount importance for finding new approaches to coping with systems and addressing system failures with the help of preventive measures, as well as recovery efforts. The concept of resilience in the context of a

manufacturing system applies a system's ability to recover from an undesired change in automatic mode or adjust to this change without serious outcomes and any significant loss. Multiple innovations and inventions are the outcomes of inspiration determined by natural systems. One of the best examples confirming this assumption is an ecosystem's ability to recover after various kinds of damage.

4.2 Literature review:

Mainly promoted by scientists in the academic area of environmental sustainability, ecology-related resilience represents a parameter of speed required for an ecosystem to come back to its state of balance after some disturbance (DeAngelis, 1980). The concept of coming back to the so-called "equilibrium" made a huge impact on developing original engineering resilience philosophy (Walker, Holling, Carpenter, & Kinzig, 2004). In context of engineering, speed of recovering towards the state of balance or equilibrium is directly attributed to such characteristics: (1) how fast a system designed may adjust to disturbance; and/or (2) how fast a system designed might recover from its disorganized conditions (Yodo & Wang, 2016). Engineering-based resilience is the principle that blends resilience capacities with real engineering experiences. Such type of resilience presumes the capability of a system designed to identify and react to negative influences in health, resist failure incidents, and restore from the impact of unexpected scenarios in an autonomous way (Yodo & Wang, 2016b). Based on tenets of the U.S. Department of Defense, it is stated that a resilient system should be an entity that incorporates certain resilience qualities, including capability to reject, withstand, or assimilate; capability to restore; and precondition for adjustment and adaptation. There is a survey regarding various definitions of resilience from multiple disciplines placed in the following References (Francis & Bekera, 2014; Righi, Saurin, & Wachs, 2015). Resilience has been introduced as an

alternative option or some addition to the conventional perspective on system security to cope with potential risks (Hollnagel, Nemeth, & Dekker, 2008; Steen & Aven, 2011). The resilience of systems designed has been described in a variety of ways, resulting into dramatic progress of engineering sub-discipline titled “engineering resilience”, also known as “resilience engineering” within the community of engineering experts. The uninterrupted ambition to create a more sophisticated, secure, and longstanding system has provoked an essential increase in comprehensiveness and scopes of the engineering systems (Neches & Madni, 2013). Prepared to function in terms of unpredictable and uncertain environment, comprehensive engineered systems definitely demand extremely high security measures in design to consider any unpredictable failures, including natural disaster risks. Nevertheless, in the early phase of design, it is quite complicated and even impossible for engineers to define and cover all the risks possible. For this reason, engineering resilience has been scrupulously considered for being integrated into systems designed to manage system risks and unpredictable failures.

Conventional studies have concentrated on designing a system with high reliability parameters to prevent risks. Even though reliability was a concept that enhanced system performance to a certain extent, it is not widely used today because of two central reasons. First, achieving reliability is a costly solution. Enhancing system’s reliability is associated with backup, excessive, or standby systems and/or their elements. Eventually, extra expenditures are inevitable in this case. The costs on enhancing reliability would get significantly higher towards approaching maximum level of reliability in the system. In this sense, reliability has become less cost-efficient for enhancing systems, mostly due to the principle of diminishing returns. Second, it is impossible to avoid all risks in context of engineering, no matter of system reliability level (Yodo & Wang, 2016). For example, a failure with zero possibility might still take place in term

of engineering, which is supported by basic probability theory. Moreover, there are contexts where the damage from an accident cannot be either controlled or prevented, which is typical to natural disaster events. Engineering-based resilience has become a cornerstone in current research field that aims at seeking more progressive ways of facing and managing risks typical to engineering practices. As long as reaching higher reliability of a system is not economically rational and risks are unavoidable, engineering-based resilience proposes options to withstand risks and rather quickly recover from damage caused. Resilience is extremely suitable for systems that must resist and then quickly restore from low frequency-high impact destructive events(Uday & Marais, 2015).

To become resilient against damage or possible risks, system should have two vital qualities before or after an event. The first quality is the system's capability to continue its performance without errors, relating to system reliability. The second quality is the system's capability to restore from disruptions, which is known as system recovery. Both properties are essential to resilience, which means they should be considered and integrated into the system engineered to actually engage failure resilience mode. Factors of reliability and recovery have been interpreted as passive and proactive resistance parameters (Rafi, Steck, & Rokhsaz, 2012; X. Wang, Qi, Wang, Si, & Zhang, 2015). Static and dynamic resilience attributes (Ayyub, 2015), or absorptive/adaptive capacities (Steen & Aven, 201).

Aside from reliability and recovery qualities, other resilience properties have also been examined in literature: for instance, the system's capability to supervise its operation cycle, forecast possible risks, respond to threats, and learn lessons from errors (Dessavre, Ramirez-Marquez, & Barker, 2016). The system's capability to supervise refers to methods of change tracking during the performance. It also includes monitoring over the environment, computation

and forecasting over a risk, and offering options to avoid it or reduce its effects. When a risk is expected, then more consistent, well-planned, and adequate strategies the system is able to offer. If the system proposes quite unfavorable options, then the system should be capable to learn from failures and past lessons to improve quality of its response.

4.2.1 Resilience Metrics Based on Reliability and Restoration:

As mentioned before, a resilient system incorporates the capability to withstand and restore from the potential disruption caused by some destructive event. The system's resilience is identified as the capability to anticipate and resist negative effects and restore from any damage inflicted by the destructive events (Cimellaro, Fumo, Reinhorn, & Bruneau, 2008). To measure the system's resilience and its qualities (reliability and recovery), a mathematical formula has been developed. In the system, reliability means system's capability to continue its functionality and performance exceeding a security limit for a selected period of time under established conditions. In the meantime, recovery calculates the system's capability to restore its full functionality by identifying, forecasting, and moderating the effects caused by destructive events and risks. This leads to mathematic representation (Yodo & Wang, 2016a):

$$\Psi = \text{Reliability}(R) + \text{Restoration}\ (p) \tag{4.1}$$

Where recovery is defined as (p) and can be viewed as the reliability-recovery degree. Both recovery and reliability can be presented as a series of hypothetical likelihoods.

The system's reliability refers to capability of measuring special functions for a selected time without failing, which in turn defines the scope of likelihood. When analyzing system's reliability, failure is rather identified with reference to system performance of interest (p), which commonly indicates of the system's functions with random variables and in random areas, where p is below 0. Technically, 0 is equal to system failure. Regarding the interest of application,

measurements are viewed as extremely dependent, ranging between deterministic-probabilistic and static-dynamic categories. The random input area is split into two principal dimensions, such as safe dimension and failure dimension. It is defined by the integral function P = 0 (Li & Lence, 2007; Z. Wang & Wang, 2014). The random input variables likelihood is relating to safe dimension, introduced as reliability parameter. Respectively, the likelihood of these variables for reaching failure dimension is presented as the likelihood of failure. Given the likelihood and measurable reliability of failure, resilience is introduced as the system's failure recovery, with considering its nature of probability. Keeping in mind that system failures were at time (t1) and the recovery of failures took place after some time (t2), resilience can be derived from two points' t1 and t2 in the following way (Li & Lence, 2007):

$$\Psi(\mathrm{t1}, \mathrm{t2}) = \mathrm{pr}[\mathrm{P}(\mathrm{t2}) \geq 0, \mathrm{P}(\mathrm{t1}) < 0] \tag{4.2}$$

Where Ψ (t1, t2) is the conditional likelihood referred to the system failures at t1 and restoration at t2. Given P_{FS} (condition-based transition likelihoods) between the reliable and failure conditions, in addition to the failure likelihood (P_F), resilience can be further calculated as (Attoh-Okine et al., 2009; Li & Lence, 2007):

$$\Psi = \frac{P_{FS}(t1, t2)}{P_F(t1)} \tag{4.3}$$

The formula of reliability based on performance parameters or scope of damage is also available, presenting a lot of various resilience metrics. The measurement of resilience is illustrated as Pr(A/i) relating the conditional likelihood that explains the system's attempt to fit performance criteria (A) after i, which is a title for destructive event (Attoh-Okine, Cooper, &

Mensah, 2009). Also, Attoh-Okine et al presented the performance criteria incorporate (r*) as robustness and speed properties (t*). In this perspective, robustness is the maximum extent of damage that the system is able to endure and resist. Moreover, speed is the maximum limit of time necessary for system to withstand disruption or recover its functionality at full. After the destructive events, the r_o (original damage) and the t_n (time of full restoration) should not exceed the performance criteria presented in Figure 4.1. Formally, r_o>r* and t_n<t*. Considering the available resilience data and metrics, objective functions of resilience introduced as Pr(A/i) have to meet the reliability goals of r* presented as follows:

$$\Psi = \Pr(\mathrm{A/i}) = \Pr(r_o < \mathrm{r^*} \text{ and } t_n < \mathrm{t^*})$$

$$\Psi = \Pr(\mathrm{A/i}) \geq R^* \tag{4.4}$$

Equation 4.4 proposes resilience measurements by considering very specific destructive events. When events are multiple and diverse, conditional resilience measurements were offered by (Han, Marais, & DeLaurentis, 2012), which engages the system functionality percentage with taking destructive events into account. Even though these competencies have been widely examined to date, the measurements of the engineering systems are subject to important standards.

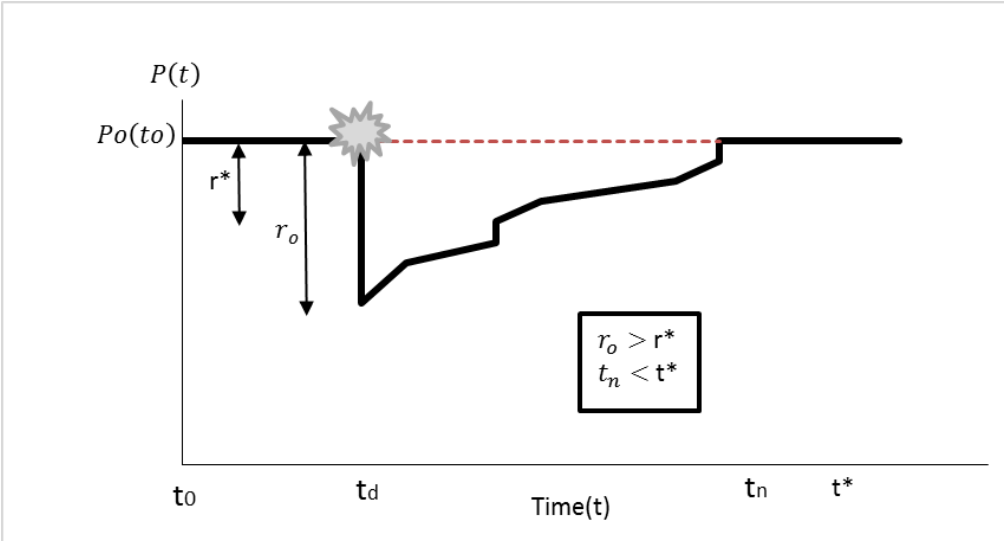


Figure 4.1. Robustness performance measures (Chang & Shinozuka, 2004)

In the meantime, resilience has also been measured on the basis of proportion of functionality impairment which is recovered from system's corrupted conditions (Henry & Ramirez-Marquez, 2012):

$$\Psi(\mathrm{t} \mid e_i) = \frac{P(\mathrm{t} \mid e_i) - P(t_{vs} \mid e_i)}{P_o(t_{o)} - P(t_{vs} \mid e_i)} \tag{4.5}$$

Where $P(\mathrm{t} \mid e_i)$ is the proportion of the functionality function restored from its corrupted conditions titled $P(t_{vs} \mid e_i)$ (Fig. 27). In context of a destructive event *ei*, original time to a damaged condition t_{vs}, time to recovery t_{vf}, and time t(t_{vs}, t_{vf}), the resilience measurements depicted in equation (4.6) are also associated with the quotient resilience (Dessavre et al., 2016).

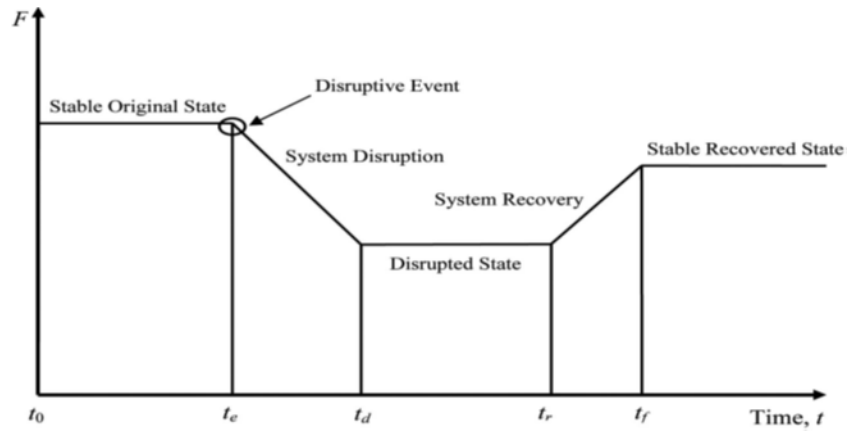


Figure 4.2. Resilience as function of time. (Henry & Ramirez-Marquez 2012)

In the same way, a resilience measurement was derived as the coefficient of capacity recovery over the original functionality states (Francis & Bekera, 2014):

$$\Psi = S_p \frac{F_r}{F_o} \frac{F_d}{F_o} \tag{4.6}$$

Where S_p is the speed of restoration factor; F_r is the functionality at the specific restored condition; F_d is the level of functionality right after the damage; and F_o is the initial state of the system functionality before the damage. F_d/F_o and F_r/F_o can be described as the absorptive/adaptive capabilities of the system, as discussed by Francis and Bekera (2014). In this context, absorptive capability is equal to reliability; meanwhile, the adaptive capability refers to recovery from damage.

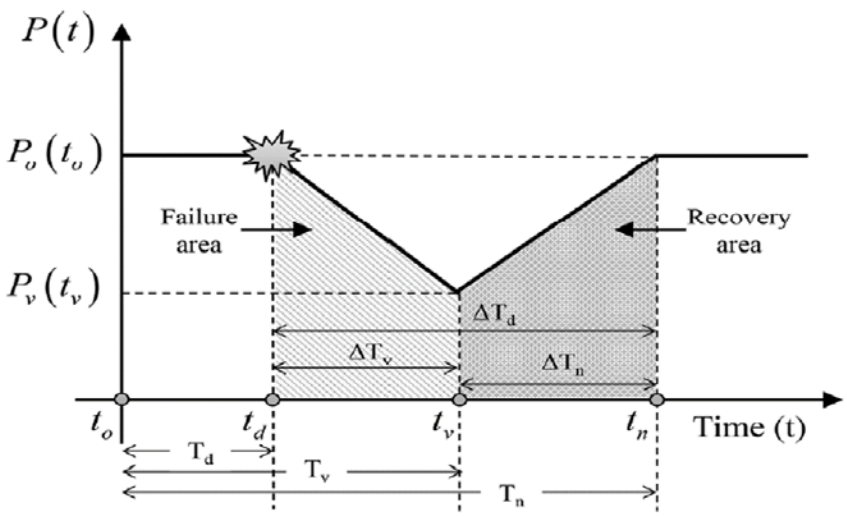
The resilience curve based on metrics (discussed in Chapter 3) has also been used to compute the scope of reliability and recovery. A resilience metrics were calculated by Ayyub (2015) as follows:

$$\Psi = \frac{T_d + F\Delta T_v + pT_n}{T_d + \Delta T_v + T_n}$$

$$F = \int_{t_d}^{t_v} f\, dt \Big/ \int_{t_d}^{t_v} P(t)dt$$

$$p = \int_{t_v}^{t_r} p\, dt \Big/ \int_{t_v}^{t_r} P(t)\, dt \qquad (4.7)$$

Where failure profile (F) and recovery profile (p) are gauged on the basis of failure event (f) and recovery event (p), accordingly, in terms of existing functionality P(t). The time indicators have been tagged in Figure 4.3, respectively.



T_d = Time to incident	ΔT_d = Disruption duration (t_n-t_d)
T_v = Time to failure	ΔT_v = Failure duration (t_v-t_d)
T_n = Time to recovery	ΔT_n = Recovery duration (t_n-t_v)

Figure 4.3. Notations for Eq. 4.7 (Ayyub, 2015)

In addition, the system's performance before the destructive event (E_0) is supposed to have an impact on the recovery phase. Resilience has been measured by Franchin and Cavalieri (2015) paying attention to urban infrastructures facing earthquake, as well as the recovery over the loss of functionality by considering E_0, the indicators of damage caused (P_d) after an event, and the metrics pertaining to the recovery process (P_q), accordingly. The eventual resilience measurements were presented in the following way:

$$\Psi = \frac{1}{P_d E_0} \int_0^{P_d} E(P_p)\, dP_d \tag{4.8}$$

4.2.2 Scale:

Even though resilience has been measured in various perspectives for diverse goals as mentioned in the previous section, it is still important to find a consensus on a scale of the designed system's resilience and ways it can be calculated. This condition prompts further resilience analysis and additional evaluation of resilience efficiency for various types of system. A resilience scale guarantees quantifiable measurements showing to what extent resilience is achieved within a selected system. According to experts, the majority of resilience measurements proposed a resilience scale between 0 and 1 (Cimellaro, Reinhorn, & Bruneau, 2010; Henry & Ramirez-Marquez, 2012; Yodo & Wang, 2016). Sometimes, it can be showed as a percentage value, ranging from 0% to 100%. Measuring resilience with reference to different system functionalities of interest with a help of a universal scale between 0 and 1 could, in theory, optimize the complexities posed by all available resilience metrics, thus creating a commonly pragmatic instrument of measurement.

Since resilience is viewed as one of the vital system's properties, it is preferable to measure resilience at a relative scale that accounts for performance alterations prior to and after a destructive event. Moreover, in case of uncertainties during a completion of resilience analysis, probabilistic resilience measurements are to be utilized with incorporating a likelihood value between 0 and 1. By relying on a resilience scale, a final resilience value would be derived considering system performance recovery after a destructive event. It can also be based on the probabilistic theory, identifying whether the system is generally able to withstand or recover from the event. For instance, a system incorporating a resilience value equal to 0.9 is viewed as the entity with 90% of resilience against a selected destructive event. In addition, it might represent 90% probability, meaning that the system will withstand a specific event or restore to the original system functionality within an established time after the destructive event.

The objective of this paper to examine and analysis the resilience of manufacturing systems design, determine the best level of system redundancy that lead to the increase in life-cycle of a system, and evaluate the resilience by using reliability analysis approach.

4.3 Resilience Metric and Definition in job shop:

It is obvious that resilient activities related to non-manufacturing fields can be beneficial for engineering design when it comes to dealing with multiple failures and establishing manufacturing systems that are characterized by resilience and sustainability.

Definition of Resilience. The purpose of this subsection is to propose a conceptual definition of manufacturing resilience that will make it possible to simplify its generic formula's derivation concerning reliability. System capacity's ongoing degradation, as well as systems' poor performance determined by adverse events, is a typical outcome of non-resilient system designs. To the contrary, resilient system designs are characterized by the ability to restore their

system capacity, and therefore, a successful recovery from critical health states is one of their advantages.

Job shop resilience is defined as the degree of a passive survival rate (reliability) in conjunction with a proactive survival rate (restoration). From a mathematical perspective, the resilience measure is the conjunction of reliability and restoration, which can be represented as follows (Yodo & Wang, 2016a):

$$\text{Resilience} \triangleq \text{Reliability(R)} \oplus \text{Restoration}(\rho) \tag{4.9}$$

From abstract algebra $\oplus$ is the direct sum, and $\triangleq$ means is equal to by definition. It is worth noting that the aforementioned definition makes job shop resilience a quantifiable property, and thus, one can evaluate a manufacturing system's resilience potential. A detailed discussion of reliability and restoration – two hallmarks related to resilience – is of immense significance for understanding this concept.

Reliability: Reliability quantifies a job shop system's ability to maintain its performance and capacity without overcoming safety limits during a certain period under specified conditions. Consequently, resilience implies an adequate level of capacity and performance regardless of fatal events. We point out that reliability should be referred to as an essential feature that has a positive impact in terms of resilience in the context of a system's self-preservation.

Restoration: Restoration means the measurement of the system's ability to restore performance/capacity with the help of detection, prediction, mitigation, and recovery from adverse events and other negative effects that might occur in different parts of the system. In other words, restoration is a manufacturing system's ability to alter performance/capacity in the

context of adverse circumstances. Such adaptability is beneficial in terms of the system's sustaining its adaptive reliability throughout its lifetime.

The capacity restoration (ρ) refers to the degree of reliability recovery. The capacity restoration is understood as a joint probability of an event of a system failure (E_{sf}), a correct prognosis event (E_{cd}), a correct diagnosis event (E_{cp}), and a mitigation/recovery event of action success as shown below (Yodo & Wang, 2016a):

$$\rho(R, A_p, A_D, \kappa) = Pr(E_{sf}E_{cd}E_{cp}E_{mr}) = Pr(E_{mr} | E_{sf}E_{cd}E_{cp}).$$

$$(E_{cp} | E_{sf}E_{cd}).(E_{sf}E_{cd}E_{cp}E_{mr} | Esf).(Esf)$$

$$= \kappa . A_p . A_D . (1-R) \tag{4.10}$$

Where A_p, A_D, and κ are the M/R action success conditional capabilities as well as correct diagnosis and prognosis. The system failure probability is identified as (1_R). The value of κ in this study, is constant by assuming that the maintenance actions, M/R, are performed on a consistent basis.

Rather than separately considering the A_p, A_D, and κ measures, it is noted that a combined measure is derived, and is identified as

$$\Lambda = \kappa . A_p . A_D \tag{4.11}$$

In this case Λ, which is the component efficiency**,** refers to as the capability of system restoration measure given an event of a system failure. Mathematically, this event is the conditional probability to store the system via successful prognosis, successful diagnosis, and

successful M/R action. For instance, 0% λ is a representation of an extreme case, which the component lacks capability to restore.

4.4 A General Framework of Modeling Job Shop Resilience:

This section is aimed at highlighting a general framework that could be applied for facilitating the modeling stage of job shop resilience. The structure of the general framework involves the reliability block diagram (RBD) approach. To achieve this purpose, RBD is first highlighted in the following section. Afterwards, the utilization of RBD for developing a general framework for manufacturing resilience is discussed.

4.4.1 Reliability Block Diagram:

The reliability block diagram is an inductive technique applied for the analysis of systems and assessment of their reliability. RBD uses a graphical representation for analyzing the probability of system failure, and in such a way, this diagram represents the entire system and its distinctive components in particular. The blocks, which represent the system's smallest undividable elements, are arranged in relation to their impacts on the system. Thus, the system and the blocks' components represent sets of smaller components.

Components in Series: The fact that a system's individual components are linked in series is indicative of a probable failure of the entire system if any component fails for some reason. To be more precise, the system fails if one block fails. The parallel placement of a system's individual components is a context in which all components' failures make the system fail. Figure 4.5 shows an RBD of a system that contains *n* components connected to each other in series. If R_i represents the event, which implies component C_i operating at time *t*, then one can write the system's reliability in the following way:

$$R = (R_{i1} * R_{i2} * \ldots * R_{ij}) \tag{4.12}$$

Figure 10. Reliability block diagram with n components in series

Parallel Components: Figure 4.6 shows an RBD of a system that contains *n* parallel components. If R_i represents the event, which implies component C_i operating at time *t*, then one can write the system's reliability in the following way:

$$R = 1 - \prod_{i=1}^{n} 1 - R_i \tag{4.13}$$

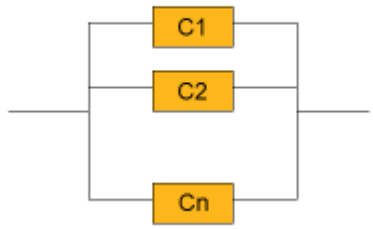


Figure 4.6. Reliability block diagram with n parallel components

In general, to simplify reliability calculation, we can assume that the equipment is in the bathtub curve's constant hazard rate phase, where failure rate λ is constant and the failures do not depend on time and will not undergo quantitative changes determined by the equipment's age. The failure density function is referred to as a negative exponential. During this phase, MTTF is equal to MTBF. MTBF is constant over time if only the failure distribution remains exponential.

An RBD shows network relationships by using block diagrams. In such a way, it analyzes large and complex systems' availability and reliability. The structure of an RBD delineates the logical interaction between failures found in a system. As a result, the sustainability of system operation is achieved. The effectiveness of operational systems is determined by the presence of at least one well-maintained pathway between input and output. The description of the minimum combination of failures that makes the entire system fail is implemented with the help of Boolean algebra expressions. The minimum number of failures that contributes to a system failure is represented by minimal cut sets. An RBD is a drawing, and a calculation tool applied to model complex systems. An RBD is a set of images (blocks) that represent different parts of a system. The calculation of the system's availability, failure rate, reliability, and MTBF can take place once a proper configuration of the images (blocks) occurs. Any change in the diagram's configuration leads to an immediate change in calculation results. An RBD often corresponds to the placement of the system's components, although this rule is not applicable in certain cases. For example, a parallel placement of two resistors means that a system failure is inevitable if one of the resistors fails. In the case of such system, the RBD aimed at the "fail short" mode of failure would consist of two sets of blocks. However, the RBD implies two parallel blocks in the case of other modes of failure (e.g. an "open" failure mode). A network diagram's logical flow originates from an input node at the diagram's left hand side and is directed toward an output node at the diagram's right hand side. Blocks are set in series, as well as parallel arrangements between input and output nodes of the system. Noteworthy, the connection between blocks is directed in the RBD module, and therefore, it is important to consider this fact if preference is given to the creation of undirected connection representations of RBD.

Formally, reliability, from machines' perspective, is a system's ability to perform necessary functions under certain conditions for a certain period. Indeed, reliability is a thoroughly investigated topic in contemporary literature. Multiple methods have been developed and are frequently used in the design of reliable systems/components.

4.4.1 Framework:

This section highlights a generic framework for modeling and evaluating resilience in the context of complex systems that are based on RBDs. It has been pointed out that the assessment of complex systems' resilience is based on such essential attributes as reliability and restoration.

A system can be referred to as a downgraded one if failures related to its reliability occur. Once a specific adverse event takes place, the restoration of a system to an optimal operating level is required. Notably, the probability of a system's reliability before a disturbance, as well as the likelihood of a system's characteristics being worsened because of disturbances, determines the probability of system restoration. Hence, the system specific characteristic node and the reliability node precede the restoration node. The system specific characteristic node applies the proposed framework and is aimed at involving the difference in characteristics (subsystems' logic connections, system structures, and the system's interaction with the environment) of specific system applications.

In this resilience assessment RBD structure, the likelihood of system resilience is highlighted as a function of the likelihood of system reliability and the likelihood of system restoration. One can represent the resilience as a function of time by using the RBD approach for reliability and recovery capacity ratio related to the machines that are subject to restoration.

4.5 Numerical example:

4.5.1 Case 1:

In what follows, the system resilience and RBD will be analyzed in details to evaluate the job shop based on its reliability and restoration. For explanation purposes, we provide a job shop of a series-parallel system as shown in Figure 4.7. Each cell contains a number of machines M_{ij}, of the same type, where i is the number of machine and j is the shop number. This section presents a numerical example for the design of a job shop to demonstrate the effectiveness of RBD approach in modeling and quantifying manufacturing resilience.

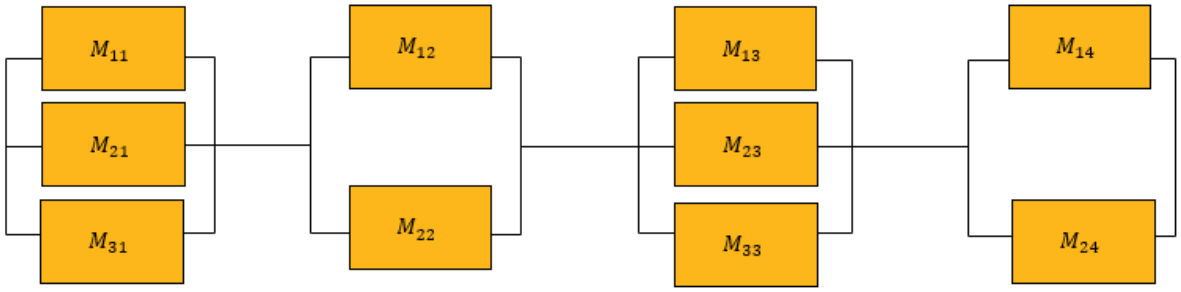


Figure 4.7. Job shop problem for a series-parallel system

4.5.1.1 Data:

Figure 4.8 shows the hypothetical data for the reliability and efficiency for each machine, $\acute{\Lambda}$ is the capability of system restoration measurement of a system failure event, which mathematically is the conditional probability to store the system via successful prognosis, successful diagnosis, and successful M/R action. R is the reliability of the machine and it can be calculated by the following:

$$\mathrm{R(t)} = \mathrm{e}^{-\mathrm{t/MTBF}} \tag{4.14}$$

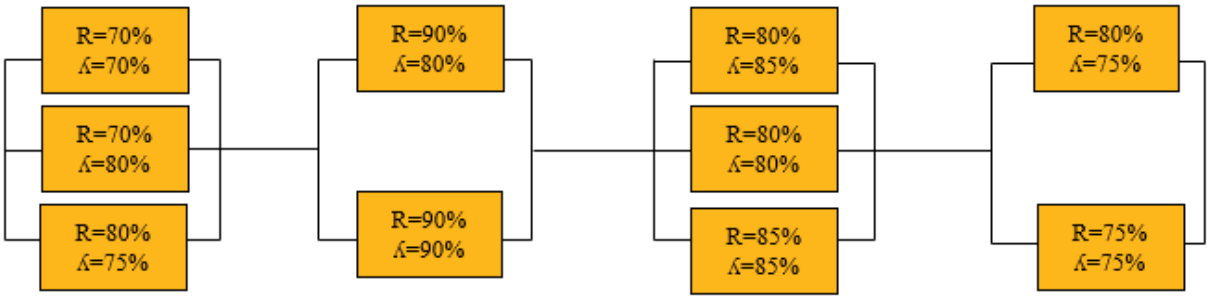


Figure 4.8. Reliability and efficiency for machines

4.5.1.2 Result and Discussion:

Figure 4.9 presents the resilience measure for each machine. The results vary from one machine to another, and these results differ according to the number of machines and their evaluation. In Figure 4.9, the resilience of each cell is calculated based on Equation (4.9) and the structure of the shop. If we look at the third cell we find that it contains the highest degree of flexibility. Note that the second cell has a higher reliability rate, but the third element is superior in flexibility because it contains more machines and the restoration ratio is higher. We can see from Figure 4.9 the impact of machine configurations on system resilience.

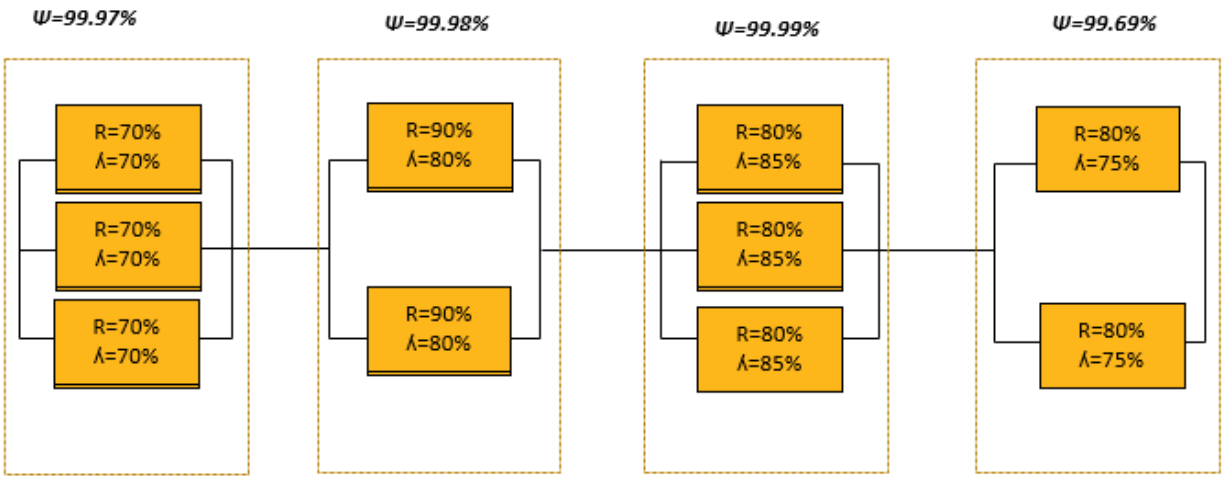


Figure 4.9. Resilience for every component

The goal of designing a resilient system is to mitigate the effect of system failure, and in this example we can see how the system is highly resilient and that because of the system configuration and the evaluation value. After calculating the resilience for the parallel system, the design of the job shop will be as series system of four cells (Figure 4.10) and the resilience of each cell has been calculated. In the case of a job that goes through all four cells, then the resilience will be the multiplication of the four resilience value based on RBD approach for series component, and the resilience value is Ψ=99.63%.

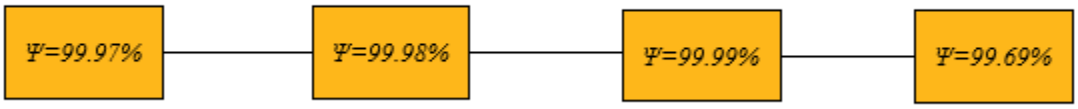


Figure 4.10. Series system resilience

If we use the same example from Chapter 3, in which the job shop contains four cells and three jobs. The goal is to measure the resilience for each job based on the job sequence. Table 4.1 represents the sequence for each machine. The sequence is different from one job to another.

Table 4.1. Machines sequence

Jobs	Machine Sequence
1	1,2,3
2	3,2,1,4
3	4,3,1

Since the jobs sequence is different and not all jobs are required to go through all cells, then the resilience is based on the number of cells that the job is processed through. Table 4.2 shows the resilience for all jobs. It can be seen that job 2 has the same result of resilience as the above value because job 2 is processed in all four cells and job 1 and 3 are different because these jobs are not required to be processed in all cells.

Table 4.2. Resilience based on job sequence

Jobs	**Resilience**
1	99.94%
2	99.63%
3	99.65%

4.5.2 Case 2:

For explanation purposes, we provide a job shop of system in series as shown in Figure 4.11. Each shop contain one machine (M_{ij}), where i is the number of machine and j is the shop number.

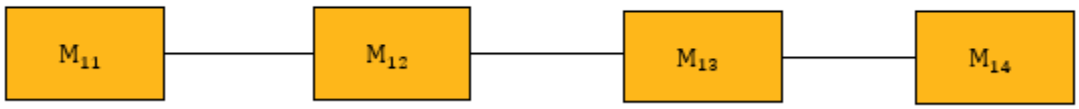


Figure 4.11. Series job shop

Figure 4.12 shows the hypothetical data for the reliability and efficiency for each machine, Λ is the capability of system restoration measurement of a system failure event, which mathematically is the conditional probability to store the system via successful prognosis, successful diagnosis, and successful M/R action. R is the reliability of the machine.

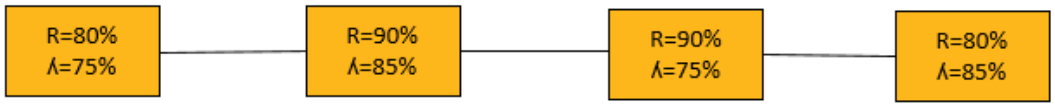


Figure 4.12. Reliability and efficiency

After calculating the resilience for the series system (Figure 4.13) and assuming that the job will go through all four cells, then the resilience in this case is the multiplication of the four resilience values based on RBD approach for series and the resilience value will be Ψ=86.67%.

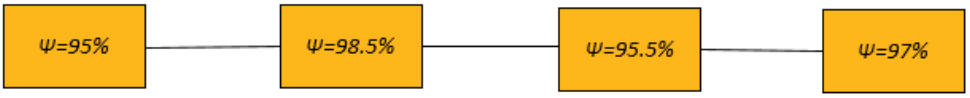


Figure 4.13. Resilience measurement for Series system

4.6 Conclusion:

In this paper, manufacturing systems' resilience measures are proposed. Numerical studies are conducted to analyze how these measures are affected by the configuration of systems. RBD has been used to analyze the probability of system failure. The system indicates that the built-in flexibility as well as redundancy can improve the performance of system resilience. When it comes to systems lacking flexibility or redundancy, the resilience of parallel configurations are above that of serial configurations. As a result, this assists the system designer to determine the flexibility and redundancy optimal level in building the manufacturing systems in order to ensure the system is both cost-effective and resilient. Today, the growing system complexity is challenging for designers. Hence, we should consider the significance of resilience, since this concept is of paramount importance for finding new approaches to coping with systems and addressing system failures.

CHAPTER 5: RESILIENCE OF MACHINES WITH CHANGING PRODUCTIVITY

5.1 Introduction:

Conventional service and maintenance procedures include repair, upgrade, and replacement practices (Chen and Feldman, 1997; Wang, 2002). Nevertheless, there are multiple other activities aside from these traditional experiences that are applied to maintenance management to deal with failure or machine impairment. For example, if a machine is seriously impaired and damaged, the machines' throughput capacity gets rather lower, making a machine less capable to carry on its original functions. This in turn leads to its degradation and reduction of performance. With a slow degradation process, a machine can still be active, yet at the lower level of performance. In this case, maintenance operation is necessary. Maintenance, whether it is repair, replacement or upgrade, should happen in a more preferred period of time, providing maintenance specialists with a bigger scope of opportunities to prepare their resources and get the appropriate results. With good expertise and rational time, maintenance would definitely become more productive and cost-efficient, requiring less labor and/or time, by making a machine more prepared and fit for further enhanced use.

Any shift in throughput can be quite useful for achieving certain production objectives, especially when unexpected events take place in the system causing havoc in the established production plan. In case of traditional production facilities, - automotive manufacturing plans, for instance - production plan is often prepared offline based on market demand and manufacturing capacities. The planning process's final goal is the establishment of the daily production tasks for each unit. Evidently, the factory's management is responsible for preparing all production equipment to meet the goals identified (Yang, Djurdjanovic, & Ni, 2007). Given the contemporary maintenance and production planning approaches and probability of

unexpected production failures (a machine breakdown, for example), the system will be able to continue its functionality when the maintenance service is completed. The waiting time to complete maintenance procedure is viewed as the lost operational time, which means that the idle time of the daily operational cycle will not suffice to fulfill all established objectives without applying extra resources and time windows.

It is important to note that most American automotive plants are working in compliance with 60–70% of operational efficiency (Yang, Djurdjanovic, & Ni, 2007). Therefore, once an emergency occurs, plants are prepared to set system production throughput to a higher level to satisfy the established production objectives within the remaining timeline. In this sense, alignments made within the operational throughput are interpreted as another maintenance procedure responding to a dynamic and unexpected change within the production framework. It leads to a more flexible and reactive maintenance decision-making mechanism that definitely outperforms a traditional model of maintenance. The central issue is to arrange a proper speed of replacement, repair and production in context of changes to eventually optimize combined benefits from continued production gain and cost spent on maintenance.

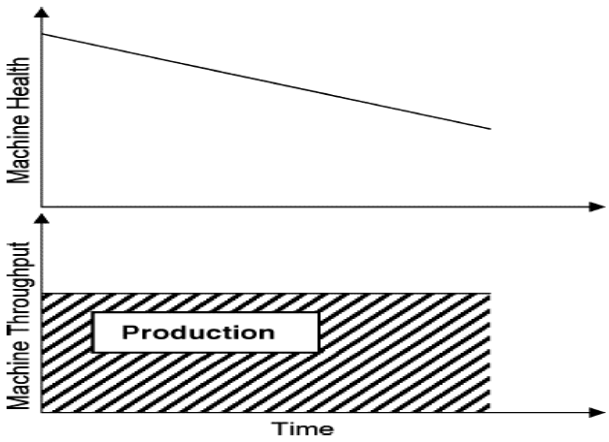


Figure 5.1. Relation between machine health and production (Yang, Djurdjanovic, & Ni, 2007)

Figure 5.1 shows one potential impairment pattern for a machine working at a regular throughput degree. If the throughput configurations are altered from one time period to another, which is depicted in both pictures (Fig. 5.2 and 5.3), a machine state curve will definitely change its form over time. As illustrated in Figure 5.2, the machine's impairment process will be slowed down once the machine gets decreased throughput loading, thus increasing the machine's chance for technical survival for a longer time of exploitation. Still, the shift of throughput configurations in any episode will also influence the level and scope of production. Reduction of machine throughput will lead to decreased productivity extent. It can be argued that, in this case, the machine's survival is reached at the expense of degraded production capacity. In contrast, when the throughput configurations are increased to secure more manufacturing capacities, machine state and its deterioration will intensify, guaranteeing extra risks of equipment failure and related downtime in terms of original production process. The second case is demonstrated in Figure 5.3.

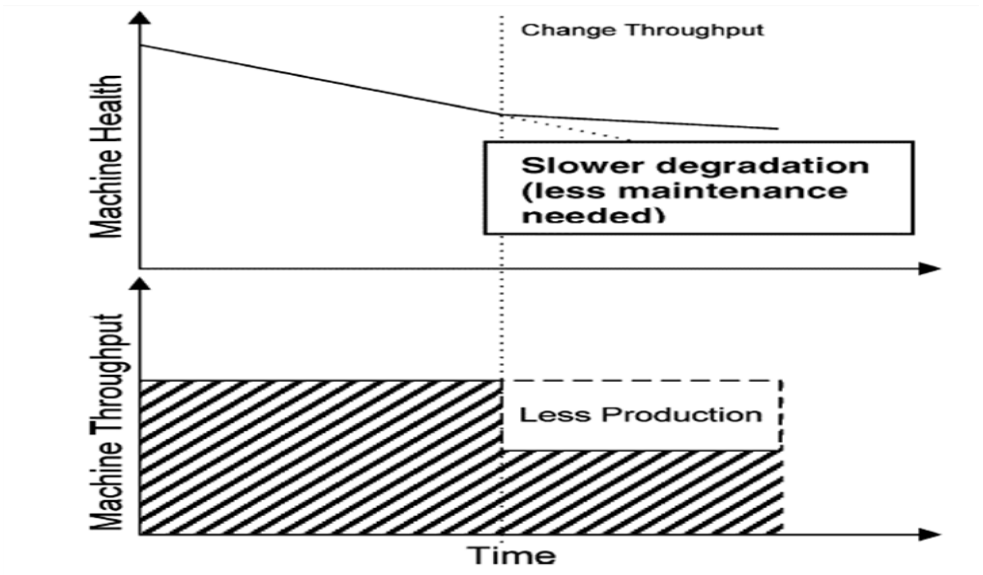


Figure 5.2. Throughput decrease on machine health (Yang, Djurdjanovic, & Ni, 2007)

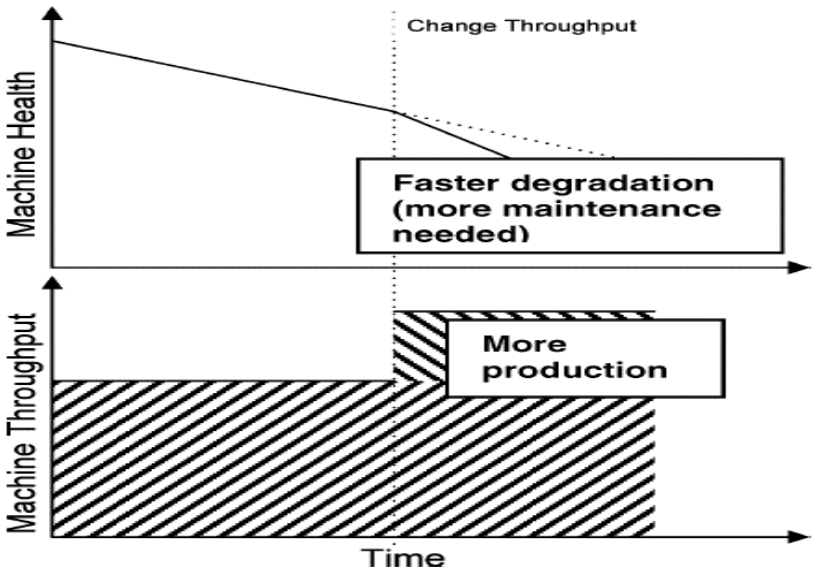


Figure 5.3. Throughput increase machine health (Yang, Djurdjanovic, & Ni, 2007)

Some compromise should be reached between the maintenance intervention and changes in throughput configurations to optimize benefit from production gain and costs spent on maintenance. Reaching such a compromise stands as a vital task, especially for organizations whose profitable manufacturing process depends on factors others than just producing more products. Order-based production systems are typical examples of these organizations, as they need only a specific number of products and it is necessary to avoid over-production that can be lead to inefficiency.

Because of inseparable interconnections between the maintenance management and throughput capacities, solving the productivity requirements problem becomes quite a challenging task. This is especially true for large manufacturing systems, in which multiple machines may have degradations or improvements in performance, which in turn leads to changed throughput specifications. This paper aims at measuring the resilience for

manufacturing systems in relation to maintenance procedures and changed throughput configurations, given the importance of these outcomes for the entire system functionality.

A hypothetical one-machine system can be taken as an example. The machine incorporates two vital throughput configurations. It is linked to an extremely large supply network to secure delivery of raw materials and a huge buffer to receive completed items. For preserving analytical flexibility, it is supposed that the machine's time of operation between two adjoining maintenance procedures (i.e., time to failure) follows a specific exponential distribution. The time to fix the machine follows quite a diverse exponential distribution trend. It is also estimated that an adjustment maintenance strategy is applied to this one-machine system (maintenance takes place only in case of real failure) and the machine health status will not be influenced by the maintenance intervention. It is also implied that maintenance procedures do not depend on alterations in throughput configurations, nor additional expenditures or time losses are needed to fix the throughput parameters. Ultimately, it is implied that idle times does not affect the machine in any way, meaning that machine is engaged in neither manufacturing or maintenance.

5.2 Resilience Quantification Metrics:

A typical resilience curve for a machine is shown in Figure 5.4 and 5.5. In a job shop, when a disruptive event such as a breakdown affects a machine, the performance typically degrades to a non-working machine and hence the productivity of the machine is zero.

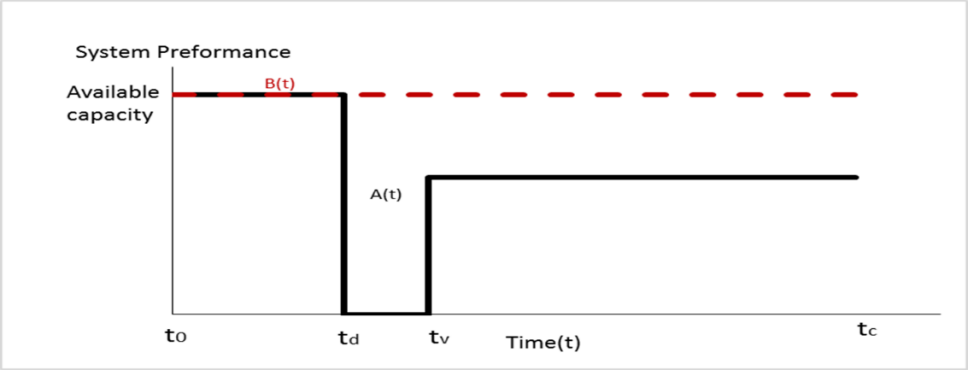


Figure 5.4. System performance with decreasing in productivity level

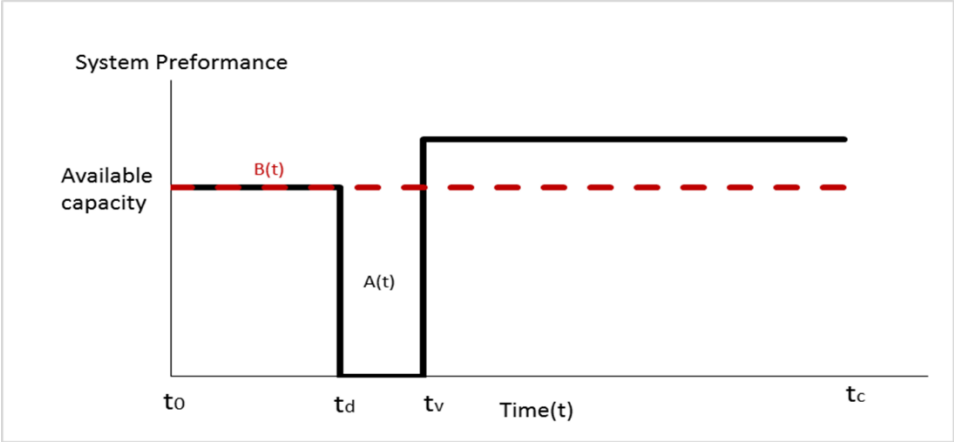


Figure 5.5. System performance productivity level

Figure 5.5 shows curves of hypothetical systems performance for machine with the disruption effects A(t), and without the disruption effects B(t). The general overview, shows time-dependent system performance as well as illustrates the essence of time during the systems response. It is expected that, under the disruption effects, there is degradation of performances. This performance with respect to the disruption time occurrences can be divided into stages that are mutually exclusive namely the pre-distribution ($t_o<t_d$), during the disruption ($t_d<t<t_v$) and, lastly, post-disruption ($t>t_v$) periods. In the first stage, the system functions under the normal conditions whereby the systems' capacity as well as demand are not impacted by the disruption. This time or period starts at the time of reference, t_0, and terminates at the occurrence t_d

disruption time. In the period between, which is the time when the machine is hit by the disruption, t_d, as well as when the disruption terminates, the system does not operate as a result of the disruption influence.

Resilience can be measured as the ratio of the areas that are below the curve representing system performance after a failure *A(t)* over the system's baseline response *B(t)* from time *t0* the long period of time *T*. Mathematically, this can be shown as the following :

$$\boldsymbol{\Psi} = \frac{\int_{t_0}^{T^*} \boldsymbol{A(t)\, dt}}{\int_{t_0}^{T^*} \boldsymbol{B(t)\, dt}} \tag{5.1}$$

B(t) is characteristic of the performance of the system in the absence of disruptions from time t_0 to time *T**. In turn, *A(t)* is characteristic of the system response in case a failure occurs from time t_0 to time *T**.

In job shop, the system's baseline response can be defined as the proportion of the areas of workload time for the machine during the time-period. So, B(t) can be formulated as follows:

$$\int_{t_0}^{T^*} B(t)\, dt = \int_{t_0}^{T^*} P(t)\, dt \; - \int_{t_0}^{T^*} I(t)\, dt \tag{5.2}$$

P(t) represents the productivity level of the machine in the absence of disruptions, and I(t) is the idle time for the machine without disruption, and both are from time t_0 to time *T**.

Areas that are below the curve representing system performance after a failure can be formulate as the following equation:

$$\int_{t_0}^{T^*} A(t)\, dt = \int_{t_0}^{T^*} P(t)\, dt \; - \int_{t_0}^{T^*} I(t)\, dt - n \int_{t_0}^{T^*} D(t)\, dt \tag{5.3}$$

5.3 Numerical Example:

5.3.1 Case 1:

For illustration purpose, the job shop contains three machines and the shop has three different jobs. Each machine in the shop can process only one operation at a time on any selected job, and the job can be processed by only one machine. When the job starts on the machine, it must be finished before another job can start on the same machine. If a machine breaks down, no operation can be performed until the machine is repaired. When a machine breaks down, its repair starts immediately. Repaired machine works at twice the productivity as compared to the machine productivity before disruption. The number of jobs are fixed, and hence the inter-arrival time of jobs is not necessary. The goal is to measure the resilience for each machine for both scenario.

Table 5.1. Machines processing times

Jobs	Processing Times
1	$p_{11}=6$, $p_{21}=5$, $p_{31}=4$
2	$p_{32}=4$, $p_{22}=6$, $p_{12}=5$, $p_{42}=6$
3	$p_{43}=4$, $p_{33}=4$, $p_{13}=4$

Table 5.1 represents the sequence and processing time for each machine. The sequence is different from one machine to another and the time required for each machine is also different.

Figure 5.6 shows the Gantt charts for this shop. Where in this model, the chart shows how long it takes to complete all the three jobs based on shortest process time (SPT) rule.

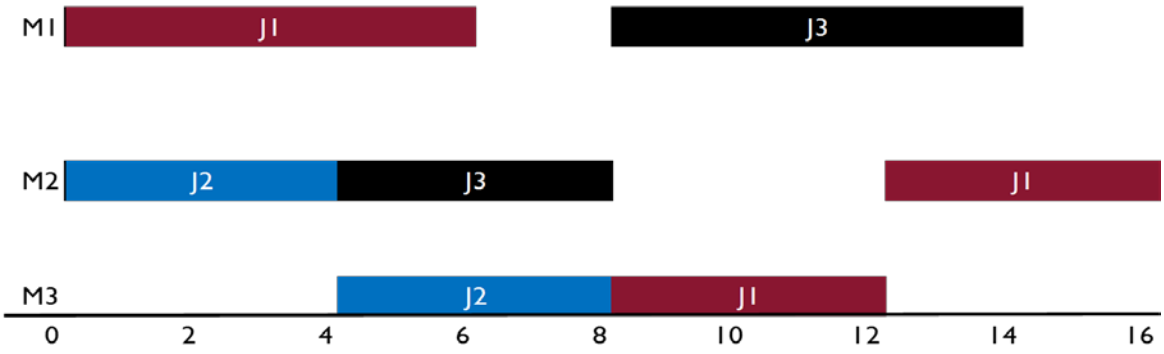


Figure 5.6. Gantt Charts for Job shop

If we assume there will be a disruption on the Machine 2 for 8 hours, and the disruption happened after finishing the first job which is in this case job 2. In addition, it is assumed that the productivity level increases by a factor of two after maintenance.

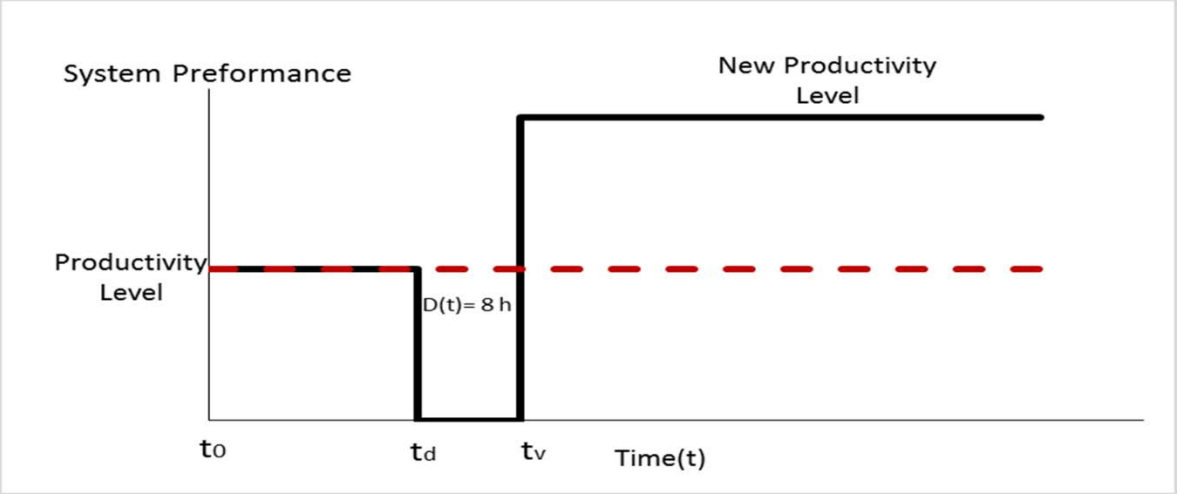


Figure 5.7. Machine 2 disruption

5.3.1.1 Results and Discussion:

It can be seen from Figure 5.8, that the disruption in machine 2 has an effect on the machine 1. If we assume that the time period for analysis is 16 hours, then the effect of this disruption is felt only on machine 1.

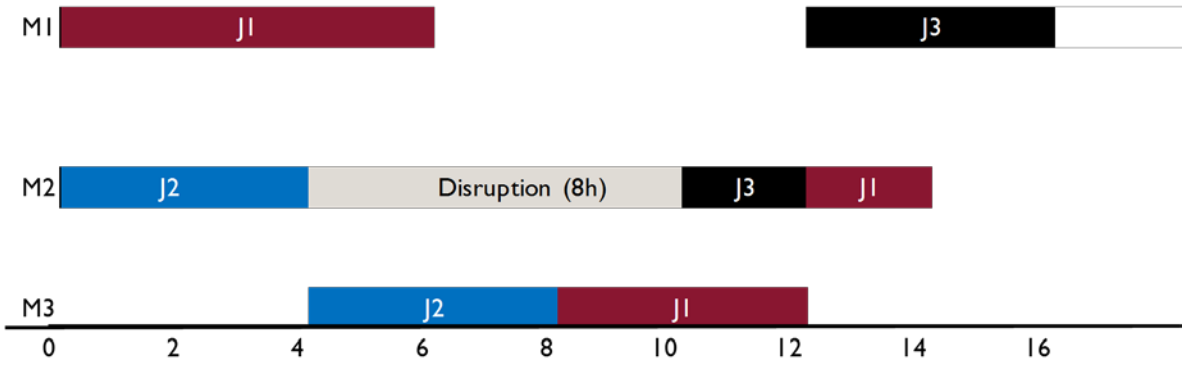


Figure 5.8. Gantt Charts After disruption in M2

Table 5.2 shows the performance of machines in the presence of disruption as well as the absence of disruption during the same time period of 16 hours.

Table 5.2. Performance of machines

	performance of the machine in the absence of disruptions		**performance of the machine with the disruptions**			
	P(t)	**I(t)**	P(t)		**I(t)**	D(t)
M1	16	4	16		6	0
M2	16	4	10	12	4	6
M3	16	8	16		8	0

The resilience values are shown in Table 5.3. For example, machine 1 is found to be 83.3% resilient, and machine 2 and 3 are fully resilient and that mean machine 3 is not affected by the disruption and machine 2 can handle the impact of the disruption within the same time period because of the increase in the productivity level.

Table 5.3. Resilience under a disruption of M2

	Performance Area for the baseline (unit area)	**Performance Area after the disruption**	**Resilience**
M1	12	10	83.3%
M2	12	12	100%
M3	8	8	100%

5.3.1 Case 2:

In this case, the productivity level for machine 2 decreased by 25 % after two hours of maintenance. Figure 5.9 shows the Gantt charts for this shop based on SPT rule.

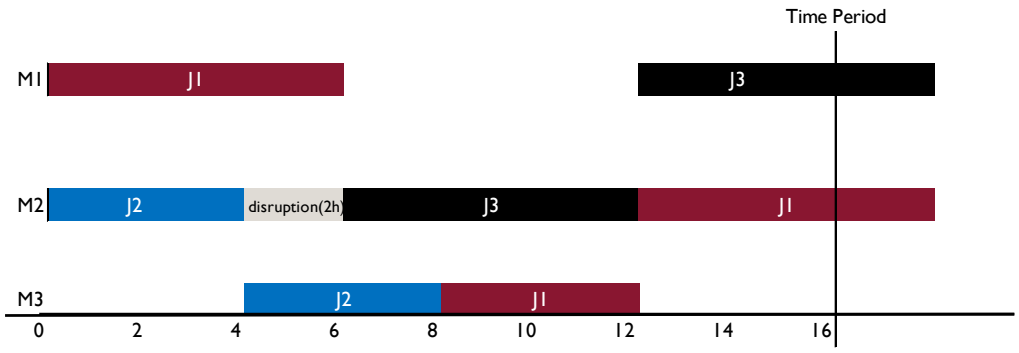


Figure 5.9. Gantt Charts second scenario

5.3.1.2 Results and Discussion:

Based on Figure 5.10 it can be seen that the disruption on machine 2 affected machine 1 as well. For the 16 hour time period under study, the effect of this disruption will be on machine 1 and 2. Table 5.3 shows the performance of machines with and without disruption with for the same period time of 16 hours.

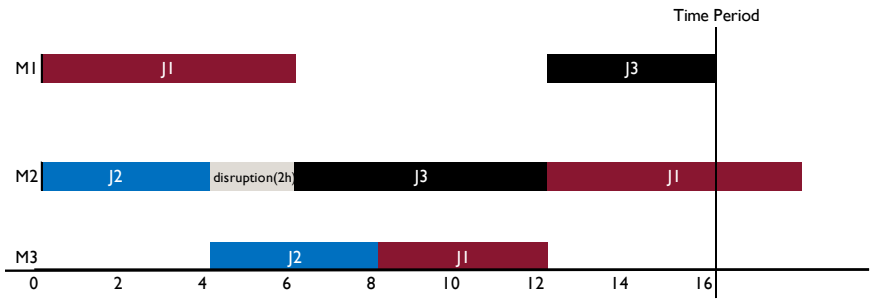


Figure 5.10. Gantt Charts After decreasing the throughput

Table 5.3 Performance of machines with throughput changing

	performance of the machine in the absence of disruptions		**performance of the machine with the disruptions**			
	P($\boldsymbol{t}$)	**I(t)**	P($\boldsymbol{t}$)		**I(t)**	D(t)
M1	16	4	16		6	0
M2	16	4	6	7.5	0	2
M3	16	8	16		8	0

Table 5.4. Resilience of machines with throughput decreasing

	Performance Area for the baseline (unit area)	**Performance Area after the disruption**	**Resilience**
M1	12	10	83.3%
M2	12	10.5	87.5%
M3	8	8	100%

Table 5.4 shows the resilience of each machine. For example, machine 1 is found to be 83.3% resilient, and machine 3 is fully resilient. The resilience for machine 2 is 87.5 because of the disruption that happened and the decreased productivity level.

5.4 Conclusion:

In this chapter, we proposed resilience measures for machines in a job shop with adjustable throughput. As mentioned before, the throughput can be changed after the repair depending on the machine status and machine health resulting in changed throughput. Job shop needs to keep specific targets of throughput that help the firm to meet the demand. If the system throughput decreases after disruption, demand cannot be met and deadlines have to be rescheduled by planners. This situation causes manufacturers to lose money and customer satisfaction. However, the planner can make a decision on the throughput decrease if the utilization of the machine is low, and that may lead to faster repair times. On the other hand, when the throughput is increased which results in higher productivity, the repair times may be larger. The difference in the throughput will affect the repairing time and the probability of breakdown.

CHAPTER 6: CONCLUSION AND FUTURE WORK

6.1 Conclusion:

Most of the studies in manufacturing have focused on production capacity and flexibility in planning. However, there are not enough studies of resilience in the field of manufacturing. Manufacturing, like many other fields, is subject to disturbance and uncertainties. Resilience in relation to the maintenance and management of job shop systems has not yet received significant consideration or adequate study. In a job shop, machines are considered most important, and they are always the most susceptible to disruptions during different kinds of operations. A disruptive event in a machine causes errors in the machine workload, changes the dynamics of the operations and results in a less productive job shop system. This dissertation proposed a new definition for resilience in a job shop and analysis frameworks.

In this dissertation, the measurement of resilience was used for machines in a job shop under a disruptive event. The machine curve was applied to illustrated the resilient behavior to describe the overall variation of machine disruption during disruptions. The measurement was based on the proportion of the areas that are below the curve representing machine performance. The resilience of a machine was calculated by taking into consideration the influence of failures of other machines which in turn influences the schedules and hence the productivity of the machine under study. Also, the disruption event is defined as the length of time it takes to repair the machine.

In addition, manufacturing systems' resilience measures were proposed based on reliability and restoration of the machines. RBD approach was used to represents the entire system based on the manufacturing configuration. The systems indicated that the built-in flexibility as well as redundancy can improve the performance of system resilience. As a result,

this assists the system designer to determine the flexibility and redundancy optimal level in building the manufacturing systems in order to ensure the system is both cost-effective and resilient.

Resilience was calculated for machines in a job shop with adjustable throughput. The throughput can be changed after the repair depending on the machine status and machine health for different throughput. The measure was based on the proportion of the areas that are below the curve representing system performance after changing in the productivity level. A quantitative approach was used to evaluate the performance of the machines in a manufacturing system when disruption occurs. The metrics were defined based on machine curve and restoration and reliability.

6.2 Future Work:

The quantitative approach of resilience metrics is calculated based on resilience curve, pre- and post-disruption performances, and restoration and reliability. In this research, the measurement of resilience is based on resilience curve, restoration and reliability. Therefore, pre- and post-disruption performances of the machine or job shop can be considered for calculating resilience. In addition, the resilience definition in the job shop can be developed based on the recoverability cost, recoverability time, and budget limitations. An optimization problem can also be proposed in which there are conflicting objectives such as due date, cost of repairs and maintenance costs can be used to satisfy multiple objectives. These conflicting objectives will be helpful to achieve the desired tradeoffs for a system, and hence, a comprehensive design based on the resilience can also be developed.

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