Chapter 1

INTRODUCTION AND OVERVIEW

1.1. BACKGROUND AND INTRODUCTION

The scheduling of a manufacturing system is all about the planning and control of activities that should be performed for the manufacturing operations to be achieved in an orderly manner. Some of the activities that influence manufacturing might occur randomly. Manufacturing systems experiencing such random controllable factors are called stochastic manufacturing systems. The process of looking for the best set of states of those activities that influence stochastic production system are referred to as optimization of stochastic scheduling system in this report. This forms the theme of the present research.

The current business environments in many companies are characterized by markets facing tough competitions, from which customer requirements and expectations are becoming increasingly high in terms of quality, cost and delivery dates, etc. These emerging expectations are even getting stronger due to rapid development of new information and communication technologies that provide direct connections between companies and their clients. As a result, companies should have powerful control mechanisms at their disposal. To achieve this, companies rely on a number of functions including production scheduling. This function has always been present within companies, but today, it is facing increasing complexities because of the large number of jobs that must be executed simultaneously. Amongst many factors, it is time driven.

1.1.1. Scheduling

Time is the scarcest resource to humans, especially in this era. Scheduling is about making the most of a limited amount of this scarce resource, "time". Scheduling is very vital in almost all domains. This dissertation focuses on scheduling in manufacturing systems (commonly known as Production Scheduling). Before the existence of the proper formalization of the scheduling concept, there was a time when companies did not know when work was to start, where it was, how it moved through the shop floor, when it was to be completed as a final product and eventually shipped to the customer.

1.1.2. Production Scheduling

Production scheduling is a tangible plan. It usually tells shop floor personnel when things are supposed to happen. It shows the timing of certain activities (for example a Gantt chart) and answers questions such as “If all goes well, when will a particular event take place?” It is concerned with searching for an optimal sequence for processing jobs (Pinedo 2002). Production scheduling is an essential part of the management of production systems as it lies at the very heart of the performance of manufacturing organizations. Production Scheduling (PS) may be divided into two categories, namely: predictive and reactive scheduling (for more information refer to section 2.4.4). The former addresses jobs with deterministic or initially known parameters, e.g. known processing times, available machines throughout the scheduling horizon, etc. The latter addresses jobs with random parameters or unpredictable events such as random job arrivals, machine breakdowns, unavailable raw materials, etc.

Production schedules for manufacturing systems have been, to date, frequently generated based on the assumptions of static scenarios, with deterministic operation time, no machine failures, etc. In real life these assumptions may not be met since “disruptions” (or disturbance, unplanned break/stoppages, interruption, interferences) may occur leading to job flow patterns that are completely different from those predicted by original schedules. Some parts may arrive later and others earlier than their scheduled times at processing stations. Such disruptions lead to performances that are worse than planned. At the operational level, decisions have to be made on how to cope with these disruptions so that their effects on schedule performances are minimized. For example, one common decision to be made at each processing station is which job goes next for processing from all jobs pending to be processed. Traditionally, these operational level decisions have been the responsibilities of the shop foremen, who, based on their experience of the shop floor, decided the responses to the disruptions. However, such decisions call for a more detailed investigation than has been traditionally given to them.

Companies spend enormous amount of capital-intensive resources and efforts to generate business plans, production schedules based on demand, available resources, and other operational requirements so as to maximize profit. However, at the operational level, these plans are often affected by disruptions, which are largely unforeseen, such as unplanned demand changes, worker no-show, urgent or commonly called hot jobs, order cancellation, supply shortage, machine breakdowns, etc. These disruptions make a deviation from the initial schedule to be inevitable and make the original production schedule obsolete. If not managed properly and promptly, such deviations may severely affect the companies' performance in terms of overall revenue, operational efficiency, customer satisfaction, market competitiveness, and overall on-time delivery.

1.2. PROBLEM STATEMENT AND DEFINITION

Scheduling has generally been perceived by researchers to be a mathematical and programming problem. To enable the modelling and solving of the problem in a mathematically feasible way, many researchers greatly simplified the scheduling problems. It turned out that analytical solutions to the scheduling problems were not applicable to complex problems, (King 1976). This is because most problems were assumed to be known with certainty (i.e. as being deterministic and static) and many random disruptions were ignored. These assumptions greatly reduced the applicability of the results from these techniques in practice. The focus of this present research is on proposing an optimal approach that may deal with scheduling after random disruptions.

Efforts have been made for the past few decades to solve scheduling problems optimally by using conventional optimisation methods (Ignall & Schrage 1965). This type of problems has generally been reported as being strong non-deterministic polynomial hard (NP-hard), which are analytically intractable problems in terms of their complexity (Lin & Cheng 2001). They should even become more complex when other variables such as random disruption variables are included. To practically cope with this, most companies of the world rely purely on methods/policies such as Dispatching Rules, Enterprise Resource Planning (ERP) systems and

Capacity Requirement Planning (CRP). These methods and their respective shortcomings are elaborated in the following sections.

1.2.1. Dispatching Rules

Dispatching rules played a very vital role in dynamic contexts. Dispatching rules (or local control policies) and pull mechanisms are traditionally used to control production flow mostly without a production schedule, i.e. for example, when a machine becomes available it chooses from among the jobs in its queue by using a dispatching rule that sorts the jobs by some criteria (e.g. First In First Out (FIFO), Last In First Out (LIFO), Shortest Processing Time (SPC), etc.). Common dispatching rules employ processing times and due dates as universal measuring criteria. Dispatching rules are easy, simple and one can reasonably find solutions rapidly. Nonetheless, the main setback is that the quality of the solution is usually poor due to their myopic nature. These local control policies are useful but limited only to static conditions; however, the main shortcoming is that jobs with longer processing times may never be processed, if jobs with shorter lead times keep on arriving to the production line. For this reason, they are not deemed useful for a production process with stochastic settings.

1.2.2. Enterprise Resource Planning (ERP) Systems

It has been remarked that ERP systems do not have sufficient capabilities to provide detailed scheduling and rescheduling solutions for dynamic production systems in the presence of disruptions (Soffer *et al.*, 2003). ERP systems solutions are effective and only limited to static situations where all parameters are known with certainty. These limitations partly emphasize the importance of researching more on non-deterministic situations or systems characterized by random variables.

ERP systems mainly use the concept of Master Production Scheduling (MPS), which is a tool that assists schedulers to prioritize scheduled work. MPS groups the actual demand (customer orders) and forecast demand for finished goods stock keeping units (SKU's) or major assemblies. It compares this against the available finished goods stock and scheduled expected receipts from the production schedule. This is done using the concept of time buckets (usually weekly). Any surprise shortages in this process are used to tell the scheduler when they need to create new work orders. Unfortunately there is a major problem with MPS: it assumes that purchase orders and work orders will be completed at the date that they are planned and has no mechanism for adjusting to any random disruptions such as a late shipment from a supplier or a work center that is scheduled to about 100% capacity, etc. Lastly, the limitations of capacity requirement planning are discussed below.

1.2.3. Capacity Requirement Planning

In an attempt to address production-scheduling problems, Capacity Requirements Planning (CRP) module was also employed. CRP module in this context refers to the process of determining the amount of labour and machine resources required to accomplish the tasks of production. It is aimed at establishing, measuring and adjusting production capacities (Howard *et al.*, 1993). The CRP module is unable to accurately calculate the projected demand and utilization of capabilities as it uses a number of techniques that have serious limitations such as; infinite capacity, backward scheduling and time buckets. Various techniques that cause inaccuracies are discussed below:

- The CRP module cannot calculate projected impact of an overloaded work center on the capacity of downstream work centers as it uses the concept of infinite capacity,
- Because it uses backward scheduling, the CRP module does not provide a mechanism to remedy the effects of any change on either available capacity or on the scheduled completion dates of orders. The best that CRP can do is to give companies an exception message, which tells them that they have a problem.
- The CRP module uses the concept of time buckets to calculate the projected demand for capacity. Time buckets are useful for summarizing and reporting data, but they are inadequate when it comes to calculating available capacity or for scheduling orders for the following reasons (Howard *et al.*, 1993):
    - Time buckets don’t know if an event takes place at the end or the start of the time bucket, so the impact on downstream resources cannot be predicted,

- Time buckets do not take into consideration the impact that the sequencing of orders can have on capacity,
- Time buckets cannot accurately calculate the time an order will wait in a queue and so the concept of average queue times is employed,
- There is no mechanism to determine the impact/effect on the capacity or on the scheduled completion date of an order when raw materials are shipped late or machines goes down/breakdown,
- If there’s a delay during first operations, there is no way to determine how subsequent operations will be affected.

From the above discussions, it becomes apparent that CRP and scheduling tools built-in ERP systems do not have ability to predict downstream consequences of a change of any kind, i.e. they have no tools to help them intelligently prioritize their workload, they have no ability to accurately estimate the promised date of a new order and they have no way to synchronize material and capacity constraints. Given these limitations, the question that arises is how do companies stay in business? The only way that most companies survive is to build-in huge buffers of materials and finished goods. These buffers have cost implications. Furthermore, it is apparent that the methods employed in the past to address the disruption problems did not meet the expectations of the practical problems because they are inflexible (Leitao & Restivo 2007) and some of the researchers concentrated principally on machine breakdowns and new job arrivals (Jain & Elmaraghy 1997; Leitao & Restivo 2007; Henseler 1995; Sabuncuoglu & Kutanoglu 2006; and Dutta 1990). Various studies on real production systems point out that disruptions affecting production systems may occur frequently and randomly which may make the original schedule to be obsolete (McKay *et al.*, 1988; Jain & Elmaraghy 1997; and Leitao & Restivo 2007).

The aforementioned shortcomings clearly prove that economies of the world are notably affected by random disruptions. Company-layouts have different benefits as well as demerits; for that reason, it should be beneficial to explore the economic implications of disruptions on all company-layouts. Furthermore, it is fair to say that there is a need to articulate or propose an approach that should be employed to handle the dynamic and unforeseen natures of the real production systems that are affected by many factors occurring individually or simultaneously. In fact, Knight (2003) identified the need for an optimal model for scheduling that involves different factors that may cause disruptions. Knight (2003) suggests that with the application of such an approach, most people on earth will live the same standard as that set by the west.

1.3. RESEARCH QUESTIONS, MOTIVATIONS, OBJECTIVES AND METHOD

1.3.1. Research Questions

Although many approaches and efforts have been put on resolving scheduling problems with uncertain disruptions, much still have to be done because the optimal solution is still far-fetch. The questions of this present research include:

- How can a scheduling model that unifies the different factors that cause disruptions be established?
- How can a simple and yet efficient or optimal production scheduling approach that streamlines the entire process after a disruption be dealt with?
- What should scheduler do following a disruption?
- When and how to reschedule?
- Are the current methods of rescheduling production sufficient for solving the problem?
- What is the recovery production schedule with a minimum or reasonable amount of deviation from the initial schedule that works reasonably well under the changed environment caused by a disruption?
- What are the implications of various random disruptions on different company layouts?
- What are the monetary implications at a national level of various disruptive factors?

1.3.2. Motivation of Research

Most previous researches on production schedule assume that there will be no disruptions during the process execution (i.e. the classical scheduling problems have been considered). The inclusion of the process disruptions in schedules makes the problems more practical, but more complex and more challenging to solve optimally. These disruptions create discomfort in the production environments as they move the planned optimal process away from its optimum settings and thus reduce overall outputs (i.e. the impacts of deviation are enormous). Hence, researching on reducing the impact of random disruptions on production systems is imperative. Despite the extensive research carried out in this area as stated by Ashton *et al.*, (1989), Halsall *et al.*, (1994), Pinedo (1995), many companies still continue to experience difficulties related to production scheduling problems after disruptions.

1.3.3. Research Objectives

The primary objective of this research is to propose an optimal scheduler's guide that may be used for rescheduling following random disruptions caused by different factors. The specific objectives of this research are to:

- establish a model for performance measure that unifies different factors that may cause random disruptions
- collect data so as to test the proposed model
- establish the impact of different forms of disruptions on different company layouts
- find a recovery production schedule with a minimum or reasonable amount of deviation from the initial schedule that works reasonably well under the changed environment caused by a disruption
- unearth the monetary implications of some example disruptions on different types of company layouts and the overall nationally
- propose an optimal guide to be used by schedulers following random disruptions caused by different random factors

1.3.4. Research Method Summary

Impacts of production outputs are used in this paper to measure production disruptions. The most basic measure of production is productivity. In this report the knowledge of multifactor productivity is applied to unify the impacts of various factors that bring about the disruptions.

Since disruptions may necessitate the deployment of extra capacity or resources, the theory of line balancing is used to identify the optimal number or amount of resources that should be deployed following disruptions. Since disruptions may occur randomly in time and with different production facilities, the tools of Ito's stochastic differential rule and equation of moments are used since they offer ability to handle field variables. Furthermore the Bernoulli's theory is also employed to explore the actual behaviour of products passing through a production system at various production phases i.e. where there may be bottlenecks since disruptions of workstations along production line would create bottleneck situations. Since disruptions can be viewed as a sign of workstation breakdown (total plant stoppage) the theory of reliability and failure analysis are also employed. Furthermore, because disruptions may affect companies of various layouts differently, the impacts of disruptions on different company layouts and their monetary implications are dealt with.

1.4. DOCUMENT STRUCTURE

These methods listed above as the approaches of addressing the research problem were achieved through article-format. As such chapter three is a compilation of the different articles that have been published by the current author.

Chapter 1 dealt with the introduction of the topic, the identification of the problem, a presentation of the objective and specific objectives, and then a summary of the various methods deployed to address the problem. To motivate the need for the current research, the limitations of the commonly used methodologies or policies as found in the literature are presented.

Chapter 2: This chapter discusses literature in areas related to the current research problem. It starts by discussing the key contributions of individuals who completely revolutionized the entire production-scheduling field. This is followed by an overview of scheduling problems and related methodologies. A comprehensive review of literature dealing with various disruption factors is also presented. Some of the mathematical constructs that are deemed necessary to be used in addressing the problems (such as the Ito's stochastic differential equations and equations for moments) are also elaborated.

Chapter 3: brings together all the different articles that have been published by the current author. Furthermore, threshold concept and rescheduling interval concepts are proposed and discussed. This concept shall assist and guide schedulers during rescheduling of operations.

Chapter 4: deals with the overall discussion of the results and findings, i.e. a unified model which is a core focus in this study, followed by discussions on company layouts, supply chain value systems and Bernoulli's theory.

Chapter 5: this chapter deals with concluding remarks, directions for future studies and a comprehensive guide to schedulers (what schedulers should do following occurrence of random disruptions); followed by list of references and publications.

Chapter 2

LITERATURE REVIEW

2.1. PRELIMINARY LITERATURE REVIEW

Disruptions considered by the great majority of the current literature are principally machine breakdowns, late arrival or shortages of raw materials and employee absenteeism. Unfortunately, they have been studied in isolation i.e. most of the papers study the negative effects of only one type of disruptions on the production system, which is completely different from realistic situations where several types of events may affect production systems simultaneously. A body of standard practices, procedures, and rules to be employed when dealing with multifactor dynamic and stochastic manufacturing settings does not exist according to the best of the current author's knowledge.

To aid in solving this problem, it is important to understand the origins of production scheduling and trends following its inception. For this reason, works carried out by individuals who gave shape or birth to production scheduling concepts are given, i.e. 1) Frederick Taylor defined the key planning functions and created a planning office; 2) Henry Gantt provided a useful Gantt charts to improve scheduling decision-making for production scheduling, and finally, 3) Samuel Johnson initiated the mathematical analysis of production scheduling problems.

2.1.1. Production Scheduling Origins

2.1.1.1. The Planning Office

Frederick Taylor's most important contribution to production scheduling is the creation of the planning office. Planning office became critical as manufacturing organizations grew in complexity. It established the view that production scheduling should be a distinct decision making process in which individuals should share information, make plans and react to unexpected events such as all forms of disruptions which resulted in rescheduling.

In keeping with the idea of specialized work, there were many different jobs in Taylor's planning office: from route clerk to the inspector (Thompson 1974). Wilson (2000) lists fifteen different positions in the planning office. Brief descriptions of some of the positions that are most closely related and/or that affect scheduling are presented. The route clerk created and maintained routings that specified the operations required to complete an order and the components needed. The instruction card clerk wrote job instructions that specified the best way to perform the operations. The production clerk created and updated a master production schedule based on company orders and capacity. The balance of stores clerks maintained sheets with the current inventory level, the amount of components on order, and the quantity needed to satisfy customer orders. The work clerks issued material release to the shop. The recording clerks kept track of the status of each order by updating the route charts and also creating summary sheets. The superintendent of production determined the relative priority of different orders.

An interesting feature of the planning office was the bulletin board, with one in the planning office, and another on the production floor (Thompson 1974). The bulletin board had space for every workstation in the shop. The board showed for each workstation, the operation that the workstation was at that time performing, the orders currently waiting for processing, and future orders that would eventually need processing on that workstation.

The rise of information technology has not eliminated the planning functions defined by Taylor: it has simply automated them using even more complex software that is typically divided into modules that perform the different functions more quickly and accurately than Taylor's clerks could, i.e. ERP systems (discussed in detail in section 1.3.2).

2.1.1.2. Gantt Charts

Henry Gantt described scheduling, especially in the job shop environment, and discussed the need to coordinate activities to avoid interferences (Cox *et al.,* 1992). To improve managerial decision-making, Gantt created charts for visualizing planned and actual production. According to Cox *et al.,* (1992) a Gantt chart is "the earliest and best known type of control chart especially designed to show graphically the relationship between planned performance and actual performance." Gantt used time (not just quantity) as a way to measure tasks. Gantt used horizontal bars to represent the number of parts produced (in progress charts) and to record working time (in machine records). Gantt progress charts have a feature found in project management software today: the length of the bars (relative to the total time allocated to the task) showed the progress of tasks. Gantt's work on charts reflects the decision-making perspective, which is the view that scheduling is a decision that a scheduler must make.

Gantt charts were designed so that workers and supervisors could quickly know whether the production was on schedule, ahead of schedule, or behind schedule. Gantt charts were improvements to the forms that Taylor developed for the planning office. Notably, Gantt created charts for the personal use of supervisors in a portable format that can be carried at all times (unlike Taylor's bulletin board, which was only useful for personnel near central locations). Gantt created many different types of charts and gave two principles for these charts: 1) measure activities by the amount of time needed to complete them; and 2) use the space on the chart to represent the amount of the activity that should have been done in that time.

Clark (1942) provides an excellent overview of the different types of Gantt charts, including the machine record chart and the man record chart, both of which record past performance. Of most interest in production scheduling is the layout chart, which specifies "when jobs are to be begun, by whom, and how long they will take." According to Clark (1942), Gantt charts were deemed useful and should be ever-present in production scheduling and project management.

2.1.1.3. Mathematical model of Flow-Shop Scheduling Problems

A brief description of the operation of the flow-shop system is provided in this section. Following a bookbinding problem, Johnson (1954) analyzed the properties of an optimal solution and presented an elegant algorithm that constructs an optimal solution. The published paper by Johnson considered problems with three or more stages and identified a special case for the three-stage problem. The paper inspired a great deal of work on other versions of the production scheduling problem and set a foundation for the analysis of production scheduling problems of all kinds from the very beginning. Smith (1956) generalized Johnson's results for a two-machine production-scheduling problem. The most important and best known result of the flow-shop problem is Johnson's non-preemptive algorithm for optimising the make span in two-machine flow-shop. In this problem, there are two machines and *n* jobs simultaneously available at time zero where the objective is to determine a schedule to complete all jobs within a minimum make span.

2.2. PRODUCTION PLANNING AND CONTROL

The majority of the published literature on this scheduling area deals with the problems under idealized conditions, which are predictive in nature. But, reactive scheduling is unavoidable and efficient controls are also important for the successful implementation of scheduling systems. In what follows, research papers that are related to reactive-scheduling and those most relevant to the topic of rescheduling after system disruptions are reviewed and criticized.

2.2.1. Rescheduling and Impact of Disruptions

Studies conducted by Farn and Muhlemann (1979), and Muhlemann *et al.*, (1982) suggests that the rescheduling period affects the system performance more when there is greater disruption and that managers need to explore the trade-off between cost of rescheduling and the benefits of more frequent rescheduling. Rescheduling period affects the number of jobs being considered in schedule revision. A longer rescheduling period means that more jobs will be considered for scheduling problem, which ultimately increase the computational and human effort needed to create the production schedule. Vieira *et al.*, (2000) show that frequent rescheduling can significantly affect overall system performance. A lower rescheduling frequency lowers the number of setups and reduces time wasted on setups but increases manufacturing cycle time and work-in-progress (WIP).

A number of researchers have proposed rescheduling approaches for a variety of scheduling environments. In general, there are three major types of study approaches: 1) methods for repairing a schedule that has been disrupted, 2) methods for creating a schedule that is robust with respect to disruptions, and finally, 3) how rescheduling policies (which specifies when rescheduling is done) affect the performance of the dynamic manufacturing system.

To a scheduler and those interpreting a plan on a shop floor, disruptions are not just a stochastic concept confined to one parameter of the problem. Dynamic manufacturing situations are complex phenomenon, i.e. variability in processing speed has a different impact on the situation if the variation occurs early in the shift or close to the end of the shift. Disruptions experienced during night shift may have more impact than the same disruption encountered during the day when additional support staff and management are available for problem solving.

Bean *et al.,* (1991) discuss a matchup scheduling procedure that repairs a production schedule when disruption occurs. Results show that matchup scheduling is an optimal approach when disruptions are infrequent enough to allow the system to get back on schedule before the next disruption. Jain and Elmaraghy (1997) studied the impact of disruptions on schedule execution in a flexible manufacturing system (FMS) only for machine breakdowns, and left out other forms of disruptions. Jain *et al.*, (2002) further report that off all five selected factors for experimental study, the duration of disruption affects the impact of disruption significantly. The impact of a disruption at a bottleneck machine was found to be much higher than a disruption in a non-bottleneck machine. This agrees with the theory of constraints (TOC) by Goldratt (2004).

Leon *et al.,* (1994) analyze how a single disruption delays a floor shop schedule and present substitute measures for estimating that delay. A genetic algorithm for finding a robust schedule that minimizes expected delay and make span was presented. Byeon *et al.,* (1998) and Wu *et al.*, (1993) presented approaches to create a robust partial schedule for a floor shop that is subject to disruptions. The incomplete portions of the schedule are resolved at the appropriate time, giving the shop floor some flexibility for disruptions handling. Results showed that in a range of situations, such a schedule leads to better system performance than dispatching rules. However, as the amount of processing time variability increases, dispatching rules led to better performance. This however, does not address the dynamic aspects of the manufacturing system. Similarly, Mehta and Uzsoy (1998) present an approach to create predictive schedules that include inserted idle time as a means to reduce the impact of disruptions. Overall, the schedule was deemed robust but not accounting for performance measures optimisations such as minimization of completion times, make-span, and flow time, etc.

2.2.2. Disruptions Classification

As previously mentioned; the actual performance of manufacturing settings often differs from the planned or scheduled one. The majority of the deviations are negative, i.e. they negatively affect system performance leading to deterioration or infeasibility. The unforeseen disturbances that affect the normal operations of real-life manufacturing settings have been classified into two big categories (Stoop & Wiers 1996; Cowling & Johansson 2002; and Vieira *et al.,* 2003):

- Capacity disruptions: i.e. disturbances related to manufacturing resources like machine breakdowns, unavailability of tools, operator’s absence, etc.
- Order disruptions: i.e. job related disturbances like rush jobs, job cancelation, raw material shortage, priority change, rework, etc.

When disruptions upset system performance or lead to infeasibility, rescheduling is required to be triggered to reduce the impact (refer to Figure 1 for a detailed depiction). Hence, these unexpected events are often defined as rescheduling factors (Dutta 1990). Typical disruptions frequently encountered in manufacturing facilities are, amongst others: machine failures, rush orders, order cancellations, priority and due date modifications, workforce unavailability, material arrival delays, raw materials shortage, delay in transport, rework, variation of process times, variation of set-up times, outsourcing, machine performance deterioration, etc. Disruptions are sensitive and should be managed as effective as possible.

(a): Partial disrupted flow   (b): Disrupted/broken flow

Figure 1: Disrupted Flow

Disturbances can be divided into three categories:

- Disturbances regarding the capacity
- Disturbances related to orders
- Disturbances related to the measurement of data

An overview of disturbances, which is by no means exhaustive, is given in Table 1. A general characteristic of the first two types of disturbance is that they may be random. Therefore, other pre-planned occurrences that may influence the performance negatively (such as vacation, training of operators and preventive maintenance) are not considered to be real disturbances because a scheduler can take them into account when populating a production schedule.

Table 1: Common Disruptions

Types of disruptions	**Examples**
Capacity	Machine Breakdowns Illness of operators Unavailability of tools
Orders	Unavailability of materials and drawing Fulfilment of sequencing rules Extra orders caused by scrap, rework Rush orders
Measurement of data	Differences between pre-calculated and actual processing time Capacity efficiencies

Disruptions can be equally categorized into two groups, namely: (i) environmental disruptions, and (ii) system disruptions (Ho, 1989). Environmental disruptions include disruptions beyond the production process, such as demand disruptions, power failure, supply disruptions, etc. Whereas system disruptions are related to disruptions within the production process, such as failure of production system, quality defects, rush jobs, to mention a few.

2.2.3. Supply Chain Value System

"When you can measure what you are speaking about and express it in numbers, you know something about it; and you cannot manage what you cannot measure" (Root *et. al.*, 2000). These are two statements that demonstrate why measurements are important, yet it is surprising that organizations often overlook this function. Senior management in most companies tends to focus more on measurable performance indicators because of the financial implications they reflect. Measuring a company's performance is important, but it is equally important to measure the implications of disruptions. Unfortunately, many top executives are not comfortable or familiar with disruptions metrics so as to know how to assess their impacts. The ability of organizations to measure and track the impact of random disruptions, as well as changes in trends over time are essential if they want to effectively manage and control supply chain disruptions. It must be emphasized that supply chain disruptions include all potential disruptive factors from receipt of an order to shipment. Supply chain can be seen as the entire network of entities, directly or indirectly interlinked and interdependent in serving the same customer. It is comprised of the vendors that supply raw material, producers who convert the material into products, warehouses that receive and store raw materials, distribution centers that deliver to the retailers and retailers who bring the product to the ultimate user. Producers compete with each other only through their "supply chains", and no degree of improvement at the producers end can make up for other deficiencies along the supply chain which reduce the producer's ability to compete. This entire process is referred to as "supply chain value system". A broken or disconnected chain (as in the Figure 1) does not serve the purpose as compared to that of the unconstrained flow of materials and information. Some disruptions are acceptable whilst others are not, i.e. disruption is not extreme in Figure 1 (a) at least as compared to Figure 1 (b).

Loss of productivity is the key outcome for most supply chain disruptions, i.e. if companies do not have the right raw materials at the right time and location when required, subsequent workstations come to a complete stand still. Failure for SA Manufacturing sectors to deliver consistent and reliable service to customers results in significant loss in market share. The success of manufacturing industry at large is greatly dependent on its ability to deliver reliable service to the customers on time, i.e. due to the nature of new businesses, nowadays manufacturing industries need to produce products with less lead times, and meet delivery dates.

2.3. RESCHEDULING ENVIRONMENT

Rescheduling in practice is overshadowed by many unforeseen disruptions, with common ones given below (section 2.3.1.). To better understand these manufacturing disruptions, it is crucial to first explain an environment with which these disruptions take place.

2.3.1. Static and Dynamic Environment

Most of the proposed scheduling approaches are often impractical in dynamic real-world environments where there are complex constraints and a variety of unexpected disruptions. In most practical environments, scheduling is an on-going reactive process where the presence of real-time information continually forces reconsideration and revision of pre-established schedules.

Most scheduling researches have previously ignored these problems, focusing instead on optimisation of static univariable system. Until very recently the problem of scheduling in the presence of disruptions, termed dynamic scheduling, has been largely neglected and not more research have been done in this area (Fahmy *et al.,* 2008). The primary concern is the issue of how to handle and well manage impacts of disruptions during the execution of the initial schedule so that performance does not deviate significantly from that predicted by the original production schedule.

An unexpected disruption certainly brings changes to the performance/efficiency of the production process. In many situations, *how well the new recovery plan suits the new environment* should not be the only criterion to measure the schedule's effectiveness, since there is also a considerable amount of penalties associated with the new schedule's deviation from the initial schedule. Making abrupt schedule changes always requires more efforts to be spent in adjusting machine setups, crew assignments, etc., than it is needed when these changes have been laid out in the initial schedule. Therefore, a good recovery schedule has to suit, not only the changed environment brought about by the disruptions, but also has to be as close to the predetermined optimal schedule as possible in terms of profit, performance efficiency, and other performance measures, so as not to cause too much customer dissatisfaction or inconvenience to the downstream operations.

2.3.2. Manufacturing Process, Planning and Control

Production is a process of converting raw materials into final products (as depicted in Figure 2). Production is the driving force or element upon which other critical factors react. Among other elements, inventory exists because of the needs of production. Production function can be measured as the difference between the value of inputs and outputs. Production function encompasses activities such as procurement, allocation and utilization of resources, processing process, etc. The main objective is to produce products demanded by the customers in the most economical way. Thus, efficient management of the production function is crucial to achieve this objective.

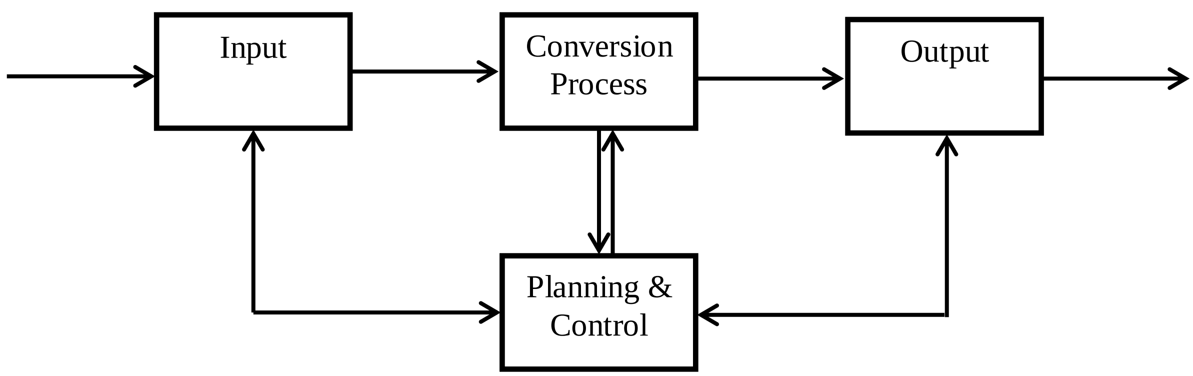


Figure 2: Production System Framework

The performance of a production system depends purely on the quality of Manufacturing Planning and Control (MPC) systems that are being used to plan and control or manage the flow of work. MPC includes on-going monitoring and reporting techniques for knowing what has happened, ideal status of production orders, as well as activation and notification techniques for indicating when work should start, how much to produce, the amount of inventory requirements, expected delivery dates for raw materials, etc. An example is a barcode reading technology and sensors. The manufacturing system control technology also includes the logic and analysis behind all of the production control process for determining what is needed when and the best way of doing it. The MPC system provides information upon which organizational personnel should make effective decisions, i.e. the MPC system does not make decisions nor manage the operations on their own: Managers do make these decisions; and the MPC system provides the support to manage decisions effectively. The development of an effective MPC is the key to the success of any manufacturing organization.

Like all MPC problems, the problem considered in this work starts with a specification of customer’s demand that is to be met. Limited production resources further complicate the problem that optimal rescheduling seeks to address. In most contexts, future demand is at best only partially known and often not known at all. Consequently, one relies on forecasts for the future demand.

2.3.3. Production Scheduling Environment

2.3.3.1. Flow-Shop Scheduling

Flow-shop scheduling problem can be described as follows: work piece flow from an initial machine, through several intermediate machines and ultimately to a final machine before completion. Each machine may have an input buffer in front, containing jobs to be processed. The jobs may be broken down into tasks called operations, and each operation is performed on a different machine. In this context, a job is a collection of all operations with a special precedence structure. In particular, each operation after the first has exactly one direct predecessor and each operation before the last has exactly one direct successor, as shown in Figure 3 and 4. Thus, each job requires a specific sequence of operations to be carried out for the job to be complete.

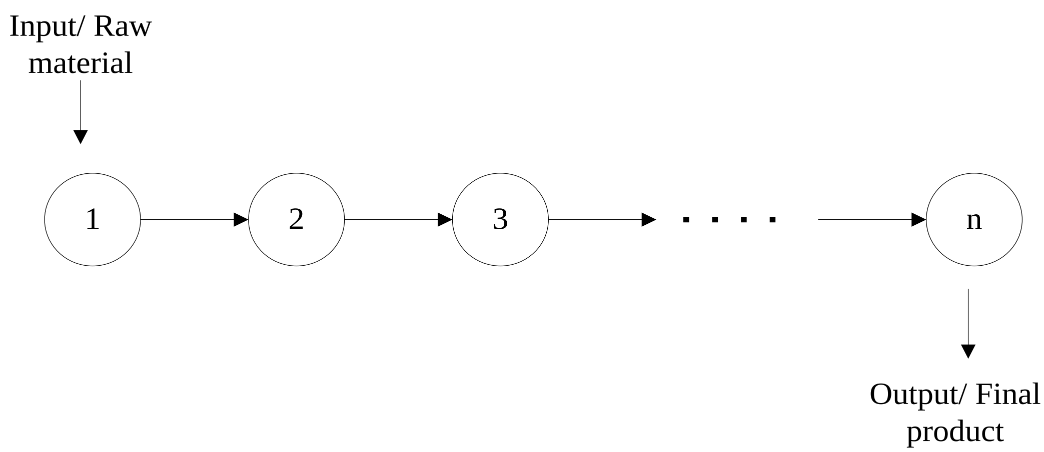


Figure 3: Precedence structure of a job in a flow-shop (serial unit process)

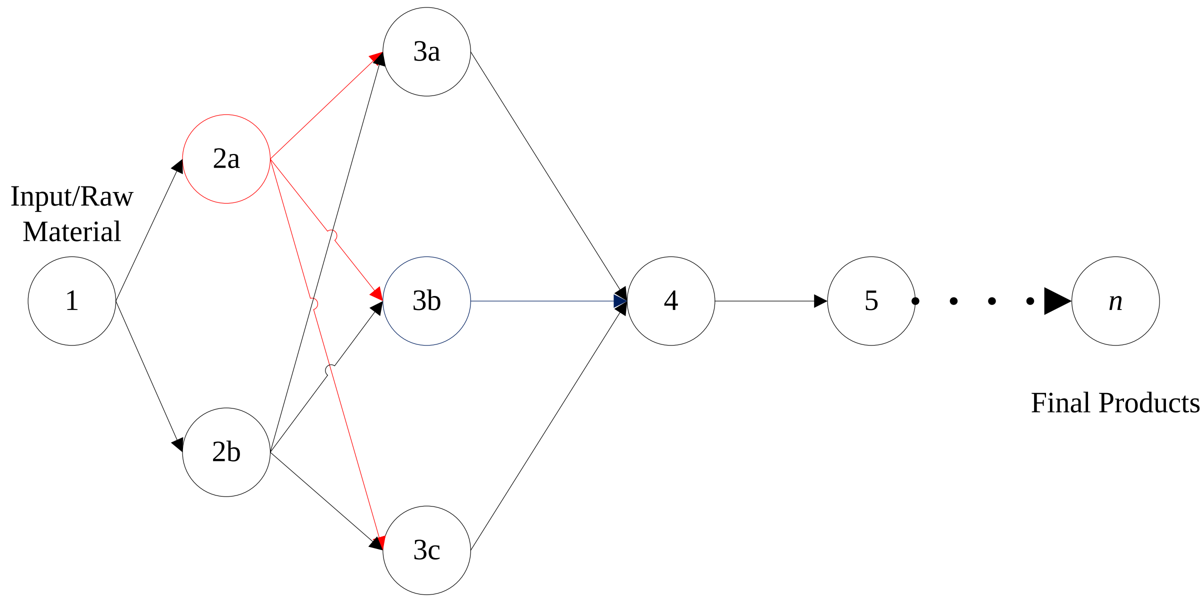


Figure 4: Precedence structure of a flow-shop (generalized serial/ parallel process)

2.3.3.2. Predictive Scheduling: "commonly known as Scheduling"

As already mentioned, predictive production scheduling is about allocating the limited resources to the required manufacturing tasks and to identify the sequence and timing parameters to accomplish these tasks. The output of this decision process is effective utilization of time, machine or operation assignments. In the scheduling literature, the objective is generally to minimize undesirable functions such as make-span, tardiness and flow time; or to maximize functions such as productivity, overall equipment efficiencies, etc.

Predictive scheduling is effective only in static conditions where job flow as anticipated and machines perform without failure. In many manufacturing industries, scheduling systems operate in dynamic and uncertain environments in which random disruptions prevent the execution of a pre-planned schedule exactly as it was developed. Examples of such disruptions are machine failures, rush orders, etc. Variation in processing times and other stochastic events further increase the variability in the system, which in turn deteriorate the scheduling performance.

The relationships or dependencies between tasks and resources are referred to as constraints (Beck 1998). Furthermore, limited capacity of resources is also constraint. Due to these constraints, not all the resource-allocation decisions are feasible in practical situations. Even though actual scheduling problems are dynamic and stochastic in real life, most of the existing literatures still continue to address static and deterministic versions. Nevertheless, even these simplified problems are NP-hard or analytically intractable.

Production schedules are often represented as Gantt charts (Gantt 1919). A Gantt chart is a two-dimensional chart, showing times and the resources along the horizontal axis and planned tasks along the vertical axis. Each rectangle on the chart represents a manufacturing task that is allocated to a certain resource in a certain time slot, and it does not account for disruptions. An example of the Gantt chart is shown in Figure 5 below. In this example, the chart represents the generated schedules for three orders A, B, C that are planned for processing on Machines 1 to 3. The tasks for these orders are depicted as $A1 \rightarrow A2 \rightarrow B1 \rightarrow B2 \rightarrow B3 \rightarrow C1 \rightarrow C2$, respectively.

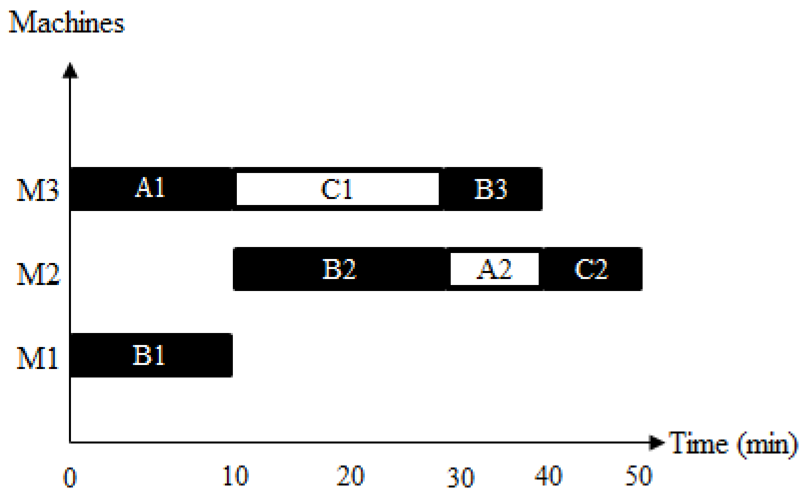


Figure 5: Example of Gantt Chart

2.3.3.3. Reactive Scheduling: "Rescheduling"

After a predictive schedule is generated, manufacturing operations begin by assuming that nothing would go wrong. Out-of-the-blue (impromptu) during a production process, disruption may emerge which calls for a rescheduling process to take place. Rescheduling updates an existing production schedule in response to disruptions or other changes (for more about rescheduling, see Vieira *et al*., 2001). Rescheduling is also referred in the production scheduling literature as 'reactive scheduling' or 'disruption management' (Morton & Pentico 1993), 'predictive-reactive scheduling' (Vieira *et al.*, 2003), 'real-time scheduling', or 'dynamic production planning' (Song 2001). Rescheduling is important for the success of manufacturing systems. Bean *et al.*, (1991) define rescheduling as a dynamic approach that responds to disturbances, whereas Herrmann *et al.*, (1993) defines rescheduling as the process of updating an existing production schedule in response to those disturbances. Thus, reactive scheduling is aimed at updating the existing schedule in response to the changes in the production environment and demand during the production process (Zweben 1994).

In the real-world environments, rarely do things go as expected. The system may be asked to do additional tasks that were not anticipated or planned, or to adapt to changes on several tasks, power failure, machine breakages, and sometimes allowed to omit certain tasks due to change in priorities. In other words, the resources available to perform these tasks are also subject to change. That is, certain resources may become unavailable and additional resources may be introduced. The start times and the processing times of tasks may also be subject to variation. A task can take more or less time than anticipated and tasks can arrive early or late. An optimal schedule generated after considerable effort may rapidly become obsolete because of unforeseen dynamic situations on the shop floor. Therefore, a new schedule has to be generated to restore optimal performance: logic presented in Figure 6.

Figure 6 depicts a conceptualized diagram of a typical production scheduling system, modelled as a feedback control system. The input to the production scheduling system is the set of jobs (perishable raw materials) that need to be processed. The order release function checks the status of the jobs and releases jobs that are ready. The schedule update function takes an existing production schedule, any changes to the state of the jobs, information about the state of the shop floor and creates a new production schedule, which the shop floor follows as best as possible in the face of disruptions.

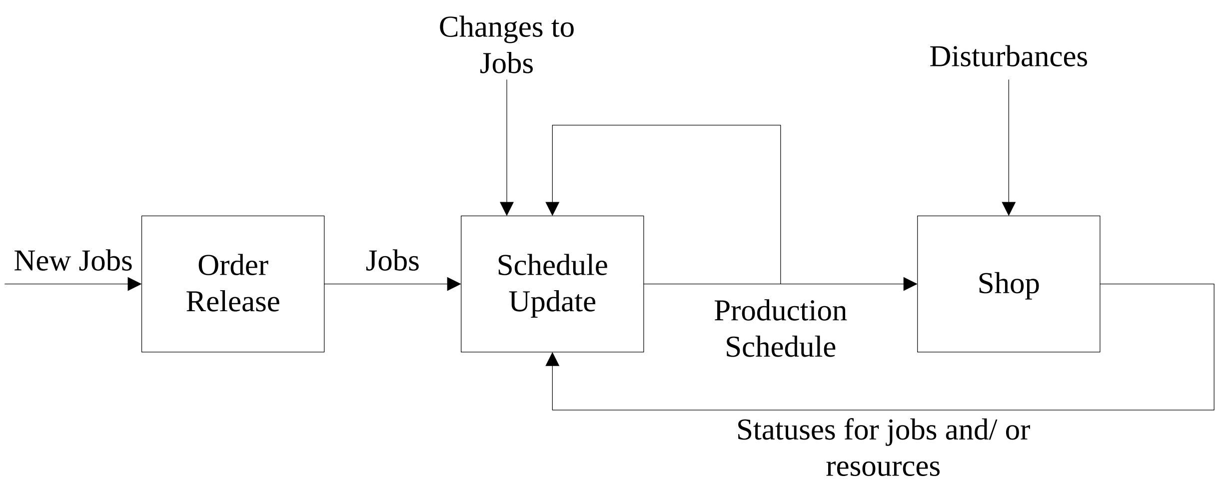


Figure 6: Production scheduling as a feedback control system

From this description, production schedule process flow looks fairly simple, but it is practically complex because the process of reacting to disruptions by updating the state of the manufacturing system and generating updated production schedules cannot be easily expressed as a mathematical function (mathematically intractable). This is an exception in static situations where disturbances do not occur randomly. Rescheduling of operations is driven by two pressing questions: when to reschedule and how to reschedule? These questions are elaborated in the following sections.

2.3.3.3.1. When to reschedule?

"When to reschedule" has to do with the timing of scheduling decisions and is triggered only when a system is upset following various unforeseen disruptions. It determines system response to various kinds of disruptive factors. There are several ways to decide on the timing of scheduling decisions (Sabuncuoglu & Karabuk 1999), namely; periodic scheduling, continuous scheduling and adaptive scheduling. Periodic scheduling schedules the system periodically; the period length can be constant or variable. In the constant case that is often used in practice, revisions are made at the beginning of each fixed-time interval. However, according to the variable-time interval method, scheduling decisions are made after a certain amount of schedule is realized. Another alternative could be to 'revise the schedule following a certain number of random events'. For example, the schedule can be updated after each major machine breakdown, or when a new important job arrival occurs. This method of scheduling is called continuous scheduling (Raman *et al.*, 1989). Another method is adaptive scheduling; the decision is triggered following a predetermined amount of deviation from the original schedule. For example, a revision is made when the total difference in completion times between the initial and actual schedules exceeds some threshold value, say 30 minutes (refer to section 3.5). Similarly, schedules can be revised after a certain amount of deviation from the planned throughput, flow-time, tardiness or any other performance measure.

2.3.3.3.2. How to reschedule?

"How to reschedule" determines the ways in which schedules are generated and/or updated. There are four related issues: the first one has to do with scheduling scheme. It can either be offline scheduling, online scheduling or a combination of the two (i.e. hybrid). Offline scheduling refers to the scheduling of available jobs for the entire scheduling period, before executing the schedule. In online scheduling, decisions are made one at a time, during the execution of schedule (Sabuncuoglu & Hommertzheim 1992). Dispatching rules in a dynamic environment serve as good examples of online scheduling.

Another issue is the amount of information available during the rescheduling process. When all the required information is available, the scheduling is said to be full scheduling, and it is called partial scheduling when there is low confidence about the accuracy of the future information. In this case only near future information is used to populate the revised schedule. With this policy, the system scheduler leaves the system to recover on its own from disruptions. Sabuncuoglu and Bayiz (2000) report that full scheduling is superior to partial scheduling in a static environment because of its global perspective and avoidance of myopic decision-making. On the other hand, the relative performance of full scheduling and partial scheduling in a dynamic and stochastic environment is needed for stability measure.

2.4. RESCHEDULING MANUFACTURING SYSTEMS

Manufacturing facilities are complex, dynamic, and stochastic in nature. From the beginning of organized manufacturing, workers, supervisors, engineers and managers have to develop many clever and practical methods for controlling production activities. Although dispatching rules, Kanban cards, and other decentralized production control policies are in use, many manufacturing facilities generate and update production schedules. Such policies are usually quick but myopic in nature as they do not use global information.

Note that, after a schedule is generated, manufacturing operations begin. Managers and supervisors want the shop floor to follow the schedule for optimal performances. In practice, operators may deviate from the schedule. Ideally, the schedule is followed as closely as possible. Small deviations from scheduled start times and end times are expected and usually ignored (the definition of small depends on the facility in question). Larger deviations or changes to the sequence occur when unexpected events disrupt the initial schedule. Even if the managers and supervisors do not explicitly update the schedule, schedule repair occurs as the operators react to the disruptions, delaying tasks or performing tasks out of order.

Rescheduling studies have considered many types of manufacturing systems, including single machine systems (Smith 1956), parallel machine systems (Zhang *et al.*, 2009; Vieira *et al.*, 2001), flow shops (Dudek *et al.*, 1992), job shops (Ashton & Cook 1989; Mehta & Uzsoy 1998), and flexible manufacturing cells and systems (Sabuncuoglu & Hommertzheim 1992; and Jain & Elmaraghy 1997). Many papers have addressed flexible manufacturing systems because they require tight synchronization between the shop floor and the planned procedures in order to reach the efficiency they are expected to have. Nof and Grantt (1991) review approaches for scheduling (but not rescheduling) and control of flexible manufacturing systems.

Unexpected events (disruptions) can change the system status and affect performance. If they cause significant deteriorations in performance, rescheduling is triggered to reduce the impact. For this reason, these events are called rescheduling factors. The following are the most common disruptive factors identified in rescheduling studies:

- Machine failure
- Urgent (rush or hot) job arrival
- Job cancellation
- Due date change (delay or advance)
- Delay in the arrival or shortage of materials
- Change in job priority
- Rework or quality problems
- Union Strikes (Figure 7)

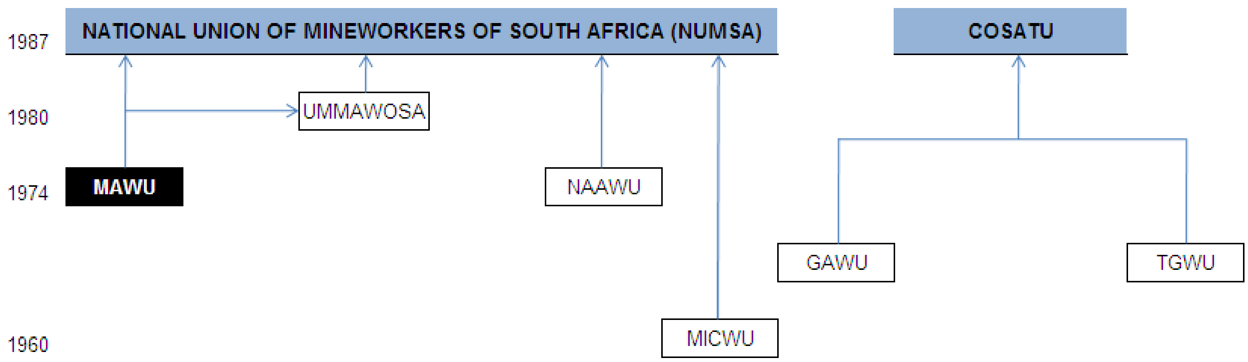


Figure 7: National Strikes

The above events may trigger other actions (listed below) that, in turn, suggest rescheduling:

- Overtime
- In-process subcontracting
- Process change or re-routing
- Machine substitution
- Limited manpower
- Setup times
- Equipment release

2.5. DYNAMIC SCHEDULING TECHNIQUES: Existing Research on Scheduling with Disruptions.

Over the last two decades a significant volume of research on the issues of scheduling with executional disruptions has begun to emerge. Manufacturing systems are 'dynamic' in nature which depending on severity level can change system status and affect the performance. As for dynamic scheduling four categories have been defined (Mehta & Uzsoy 1999; Vieira *et al.*, 2000): completely reactive, predictive reactive, robust predictive reactive and robust proactive scheduling. The latter of these is by far the most studied, and therefore examination of a number of specific issues related to this approach in more detail.

2.5.1. Completely Reactive Scheduling (CRS)

With this type of scheduling, a production scheduling is generated in advance and decisions are made locally in real time. Priority dispatching rules such as Short Processing Time (SPT), Earliest Delivery Date (EDD), First In First Out (FIFO), etc., are commonly and frequently used. Dispatching rules are used to select the next job with the highest priority to be processed from a set of jobs pending processing on the next machine. Dispatching rules are deemed quick, and intuitively easy to implement. However, centralized based global scheduling has the potential to significantly improve shop performance as compared to localized dispatching rules, where it is difficult to predict the overall system performance as decisions are made locally in real-time and does not account for performances in downstream operations.

Dispatching rules played a very vital role in dynamic contexts. Dispatching rules are used to control production mostly without a production schedule. For example, when a machine becomes available it chooses from among the jobs in its queue by using a dispatching rule that sorts the jobs by some criteria. Common dispatching rules employ processing times and due dates as universal measuring criteria. Dispatching rules are easy, simple and can reasonably find solutions rapidly. Nonetheless, the main setback is that the quality of the solution is usually poor due to their myopic nature. These local control policies are useful but limited only to static conditions; however, the main shortcoming is that jobs with longer processing times will never be processed if jobs with shorter lead times keep on arriving to the production line.

Of all the varieties of the dispatching rules in the literature, it was found that no rule performs well for all criteria. It has however been noted that process time based performs better under tight load conditions, while due date rules perform better under light load conditions. Dispatching rules are proved to be efficiently mostly when considering performance measures in isolation and locally. Many investigations were carried out towards recognizing a good combination of several dispatching rules to find a system state in which the performance of each rule is highest. Panwalkar and Iskander (1977) presented a list of dispatching rules and categorized them into five classes: simple dispatching rules, a combination of simple rules, weighted priority indexes, heuristic scheduling rules, etc.

2.5.2. Predictive-Reactive Scheduling

This is one of the most common approaches used in manufacturing systems. Most of the researches in dynamic scheduling are based on this approach. With this approach, schedules are revised in response to emerging disruptions. Predictive-reactive scheduling is a two-step process. Firstly, a predictive schedule is generated in advance with a common objective of optimising plant performance without considering potential disruptions on the shop floor. A schedule is then revised when a disruption emerges with the same objective of optimising shop floor performance.

The first study in this area is due to Holloway and Nelson (1974) who implemented a multi-pass procedure in a shop by generating schedules periodically and concluded that a periodic policy (scheduling/rescheduling periodically) is effective in dynamic environments. Later, Farn and Muhlemann (1979) compared dispatching rules and seeking algorithms for the static and dynamic single machine scheduling problems. Again, new schedules are generated periodically in a dynamic environment. Results indicate that the best heuristic solution for a static problem is not necessarily the best for the corresponding dynamic problem, i.e. Farn and Muhlemann (1979). In addition, Muhlemann *et al.*, (1982) analyzed the periodic scheduling policy in a dynamic and stochastic system, with experiments indicating that more frequent revisions are needed to obtain better scheduling performance.

Church and Uzsoy (1992) consider periodic and event driven (periodic revision with additional considerations on tight due date jobs) rescheduling approaches in a single machine production system with dynamic job arrivals. The results indicate that the performance of periodic scheduling deteriorates as the length of rescheduling period increases and the event driven method achieve a reasonably good performance. Yamamoto and Nof (1985) study a rescheduling policy in a static scheduling environment with random machine breakdowns. Rescheduling is triggered whenever a machine breakdown occurs. The results indicate that the proposed approach outperforms the fixed sequencing policy and dispatching rules. Also, Nof and Grantt (1991) develop a scheduling or rescheduling system and analyze the effects of process time variation, machine breakdown and unexpected new job arrival in a manufacturing cell. In this scheduling system, monitoring is performed periodically and either rerouting to alternative machines or order splitting policy is activated in response to unexpected disruptions.

Bean *et al.*, (1991) consider the rescheduling of the shop floor with multiple resources when unexpected events prevent the use of a pre-planned schedule. Rescheduling is performed to match-up with the schedule at some point in the future whenever a machine breakdown occurs. The match-up approach is compared with the response policy and several dispatching rules. The results of the test problems indicate that the proposed system is more advantageous. Later, Akturk and Gorgulu (1999) apply this approach to the modified flow-shop. The results indicate that the match-up approach is effective in terms of schedule quality, computation times and schedule stability.

Several approaches based on Heuristic Methods, Artificial Intelligence, Neural Networks were developed over the past years (Raheja & Subramaniam 2002) to successfully repair the predictive schedules during disruptions. Among the heuristic based approaches the Right–Shift Rescheduling (RSR) and Affected Operation Rescheduling (AOR) (Szelke & Kerr 1994) heuristic were most common or customary. The RSR heuristic essentially shifts the job operations forward in a time scale to accommodate disruptions, whereas the AOR heuristic reschedules only cover the affected job operations. The underlying concept in the AOR is to move the start times of the affected jobs forward in time scale while adhering to the constraints. This is performed to maintain the initial job sequence.

2.5.3. Robust Predictive-Reactive Scheduling

Shop floor efficiency has only been the common objective of this type of scheduling approach. A revised schedule may notably deviate from the predetermined schedule, which can seriously affect other planning aspects that are based on the original schedule and may lead to poor performance of the entire plant. Thus, generating a deemed robust predictive schedule is desirable. The need to create a robust schedule was recognized over two decades ago by Graves (1981). There is still little research in the literature to find out how a robust schedule can be generated in a dynamic environment.

The most common performance measure from previous researchers is shop floor efficiency. Therefore a potential solution to this problem is to reschedule considering both shop floor efficiency and deviation from the initial schedule known as stability, simultaneously. Stability measures the deviation from the original predictive schedule caused by rescheduling to quantify the undesirability of making changes to the initial schedule. Wu *et al.*, (1993) defined a bi-criterion robustness measure for one machine-rescheduling problem with only machine breakdown as a potential candidate of disruption. The criteria include the minimization of the make span and the impact of schedule change (stability). For stability, two measures are investigated: the deviation from the original job starting times, and the deviation from the original sequence. The experimental results showed the effectiveness of the robustness measure in that the schedule stability can be increased significantly with little or no reduction in make span.

2.5.4. Robust Proactive Scheduling

Robust pro-active scheduling approaches focus on building schedules that satisfy performance requirements predictably in a dynamic environment (Mehta & Uzsoy 1999; Vieira *et al.,* 2003). The main problem with this approach is the determination of predictability measures. Mehta and Uzsoy (1999) proposed a predictable scheduling model for a single machine subject to a single commonly considered disruption 'machine breakdown' with an objective of minimizing the maximum lateness. The effect of disruption is measured by the deviation between times of the original predictive schedule and the revised schedule. The deviation is reduced by inserting additional times (referred to as idle times) in the predictive schedule with the objective of achieving high predictability. Extensive computational experiments showed that predictable scheduling provides significant improvement in predictability at the expense of very little degradation in the maximum lateness. Davenport and Beck (2000) examined a variety of strategies for generating robust pro-active schedules based on the insertion of temporal slack with the objective to minimize the job tardiness. The main idea was to provide each operation of a job with extra processing time (allowance) to absorb some level of disruption without rescheduling.

2.6. STOCHASTIC OPTIMAL CONTROL

A major difficulty that has to be resolved when modelling a stochastic dynamic system is how to treat information regarding future events. Several modelling approaches are suggested for stochastic optimal control (Boukas *et al.,* 1996; Sethi *et al.,* 1998; & Bertsekas 2000). Yet, the effects of future information on the decision-making process within a finite planning horizon are not fully understood (Neck 1984). The large body of literature that deals with the modelling of stochastic optimal control has revealed common difficulties in the representation of uncertain future events. Elhafsi and Bai (1997) selected variable of the production system to be a random variable whose expectations are estimated. Such a selection is problematic since the distribution of the variables strongly depends on a priori unknown optimal control.

Neck (1984) suggests the division of the analytical modelling of stochastic optimal control into two approaches namely: 1) stochastic optimal control, and 2) pseudo-stochastic. The stochastic optimal control is concerned with models where the state variables are distributed stochastically. In these models, the dynamic equations are often approximated by Ito's differential equations that include additional components such as (i) the expected outcome of random variables; (ii) the control function; and (iii) a white-noise Weiner process that represents the environmental changes.

2.7. SUMMARIES OF APPROACHES DEPLOYED TO ADDRESS THE CURRENT PROBLEM

The following subsections outline tools that have been used in this study to address present problem (i.e. that of managing production systems following disruptions). The tools and functions are considered to address this problem: productivity (or multifactor productivity), reliability function, line balancing, company-layouts, Ito's stochastic differential rule and Bernoulli's theory.

2.7.1. Stochastic Theory

Stochastic theory is used in this paper to solve or address subjects that contain an element of random or stochastic behaviour, i.e. for a system to be stochastic, one or more parts of the system have randomness associated with it, unlike in deterministic systems (a system where all parameters are known with certainty). For example, a stochastic system does not always produce the same output for a given input: it is subject to change. A few components of a system that can be stochastic in nature include stochastic inputs, random time-delays, random disruptions, and also stochastic dynamic processes. If production flow is frequently subject to random disruptions; Ito's stochastic differential equation and Ito's stochastic differential rule can be deemed useful.

2.7.1.1. Ito's stochastic differential equation

Ito's stochastic differential equation deals with the expression for the increment of the random process (i.e. increments of the impact of random disruption e.g. productivity, I_p(w,t)). For random process, I_p(w,t), the expression for its increment including both continuous and discrete changes is given as, (Gikhman & Skorokhod, 1972; Arnold, 1974; Snyder, 1975 and Gardiner, 1985):

$$dI_p(\omega,t) = a(I_p(\omega,t))dt + b(I_p(\omega,t))dI_pW(t) + c(I_p(\omega,t))dV(t) \tag{2.1}$$

where I_p is the impact of disruption on productivity, $a(I_p(\omega,t))$ is drift term, $b(I_p(\omega,t))$ is diffusion term, $c(I_p(\omega,t))$ is the jump term, dW(t) and dV(t) are, respectively, the increments of Weiner process (or Brownian Motion) and stochastic counting process within an infinitesimal time interval [t,t+dt], $b(Z(\omega,t))dW(t)$ and $c(I_p(\omega,t))dV(t)$ respectively account for the random fluctuation in $I_p(\omega,t)$ due to the diffusion (continuous) process and the jump (discrete) process.

2.7.1.2. Ito's Differential Rules

Consider an arbitrary function $h(\mathbf{I_p}(\boldsymbol{\omega},t),t))$ of the production system, $\mathbf{I_p}(\boldsymbol{\omega},\text{t}),t)$ and of time t. Jump of magnitude p_α in the α-component of $V_\alpha(t)$ of the generating source process at the time t results in jump of $dI_p(\boldsymbol{\omega},t) = \mathbf{c}_{\boldsymbol{\alpha}}(I_p(\boldsymbol{\omega},t),t)p_\alpha$ of the production system which impart on the function h a jump of magnitude of, (Gikhman & Skorokhod, 1972; Arnold, 1974; Snyder, 1975 and Gardiner, 1985), given by

$$dh(\mathbf{I}_p(\boldsymbol{\omega},t),t) = \left(h\left(\mathbf{I}_p(\boldsymbol{\omega},t) + \mathbf{c}_{\boldsymbol{\alpha}}(\mathbf{I}_p(\boldsymbol{\omega},t),t)p_\alpha, t\right) - h\left(\mathbf{I}_p(\boldsymbol{\omega},t),t\right)\right)$$

$$= \frac{\partial h(\mathbf{I}_p(\boldsymbol{\omega},t),t)}{\partial t} dt + \sum_{i=1}^{n} \frac{h(\mathbf{I}_p(\boldsymbol{\omega},t),t)}{\partial I_{p_i}} \left(a_i(\mathbf{I}_p(\boldsymbol{\omega},t),t)dt + \sum_{\alpha=1}^{m} b_{i\alpha}(\mathbf{I}_p(\boldsymbol{\omega},t),t)dW_\alpha(t) \right)$$

$$+ \frac{1}{2} \sum_{i,j}^{n} \frac{\partial^2 h(\mathbf{I}_p(\boldsymbol{\omega},t),t)}{\partial I_{p_i} \partial I_{p_j}} \sum_{\alpha=1}^{m} b_{i\alpha}(\mathbf{I}_p(\boldsymbol{\omega},t),t) b_{j\alpha}(\mathbf{I}_p(\boldsymbol{\omega},t),t)dt$$

$$+ \sum_{\alpha=1}^{l} \left\{ h\left(\mathbf{I}_p(\boldsymbol{\omega},t) + \mathbf{c}_{\boldsymbol{\alpha}}\left(\mathbf{I}_p(\boldsymbol{\omega},t),t\right)\mathbf{p},t\right) - h(\mathbf{I}_p(\boldsymbol{\omega},t),t) \right\} dN_\alpha(t) \tag{2.2}$$

where *dN(t)* is the number of jump processes within the infinitesimal time interval [t, t+dt].

2.7.1.3. Equations for Moments

The moments are obtained by taking the expectation of both sides of the expression of the Ito's Differential Rule above, (Gikhman & Skorokhod, 1972; Arnold, 1974; Snyder, 1975 and Gardiner, 1985), i.e.

$$\frac{d}{dt}\mathbf{E}\left[h(\mathbf{I}_p(\boldsymbol{\omega},t),t)\right] = \mathbf{E}\left[\frac{\partial h(\mathbf{I}_p(\boldsymbol{\omega},t),t)}{\partial t}\right] + \mathbf{E}\left[\sum_{i=1}^{n} \frac{h(\mathbf{I}_p(\boldsymbol{\omega},t),t)}{\partial I_{p_i}} \left(a_i(\mathbf{I}_p(\boldsymbol{\omega},t),t)\right)\right]$$

$$+ \mathbf{E}\left[\frac{1}{2} \sum_{i,j}^{n} \frac{\partial^2 h(\mathbf{I}_p(\boldsymbol{\omega},t),t)}{\partial I_{p_i} \partial I_{p_{\setminus j}}} \sum_{\alpha=1}^{m} b_{i\alpha}(\mathbf{I}_p(\boldsymbol{\omega},t),t) b_{j\alpha}(\mathbf{I}_p(\boldsymbol{\omega},t),t)\right]$$

$$+ \mathbf{E}\left[\sum_{\alpha=1}^{l} \left\{ h\left(\mathbf{I}_p(\boldsymbol{\omega},t) + \mathbf{c}_{\boldsymbol{\alpha}}\left(\mathbf{I}_p(\boldsymbol{\omega},t),t\right)\mathbf{p},t\right) - h(\mathbf{I}_p(\boldsymbol{\omega},t),t) \right\} dN_\alpha(t)\right] \tag{2.3}$$

The tools of Ito's stochastic differential rule and equations for moments are employed since they offer the ability to handle the local or global random dynamic responses (i.e. the responses of individual or combined factors) and can be used to predict future responses.

2.7.2. Productivity or Multifactor Productivity

One can see productivity as a measure of the efficiency of production. Productivity function can be measured as a ratio of output to input functions, whereas, production is the difference between both functions. Note that the word “output” in the definition of productivity is different from the market demand, but it stands for the ability to produce per given input. In this report (section 3.2), the theory of multifactor productivity is employed to unify all the impacts from various factors that cause disruptions into a single model. Multifactor productivity values are calculated for both production systems without disruptions and for those with random disruptions. The differences between them should enable us to measure the impacts of disruptions and how systems should respond to various disruptions.

2.7.3. Reliability

One of the best ways of determining impacts of disruptions is through reliability. Disruptions may be considered to be equivalent to failure of the system or a section of a system. The failure rate of the system can be easily translated to the reliability of the system or a section of the system mathematically. Thus, in this report the probabilities of failure are used as indicators of disruptions, and the theory of reliability is then applied.

2.7.4. Line Balancing

Line Balancing is about levelling the workload across all processing stations (or workstations) in value stream (or production lines) so as to remove bottlenecks and excess capacity. The principles of line balancing are used to determine the required number of resources (in the production line) that minimize bottlenecks. A workstation that is not fully capacitated slows down processes and results in downstream operations waiting for the job and on the other hand, excess capacity results in absorption of fixed costs.

2.7.5. Types of Company-Layouts

Plant layout design (or systems configurations) and production flow are important factors when managing random disruptions. This is because the way facilities are positioned relative to each other has an important effect on so many aspects of operations, which ultimately has an effect on disruptions management. Firstly, it affects the total distance travelled by materials or information as they move through the operations. An effective layout should try to minimize the distance covered. Secondly, a layout can affect quality: for example if materials or information or materials are continually being handled from one part of the operation to another, then there may be many points at which damage can occur. Thirdly, a layout may affect throughput time: the further the distance travelled, the longer it takes to get through the operation. Fourthly, a layout can affect how much space is necessary for the operation(s): space costs money, e.g. the cost of operations in a high cost location such Sandton Central Business District (CBD). Every square meter is important: so a company layout can save costs.

The types of company-layouts considered are as follows: 1) fixed-position layout, 2) product family, 3) production line, and 4) process department. Tompkins *et al.*, 2000 defines these company layouts as follows (also illustrated in Figure 8 below):

Fixed-position layout: production resources are brought to the products
Product family: machines processing similar raw materials are grouped together
Production line: made up of machines in series working on the same raw material
Process department: resources performing similar function are grouped together

In view of the aforementioned considerations, another objective of this work is to study the impacts of disruptions under the different types of company-layouts. This also facilitates the determination of monetary implications of various disruptive factors at a national level from real-world companies.

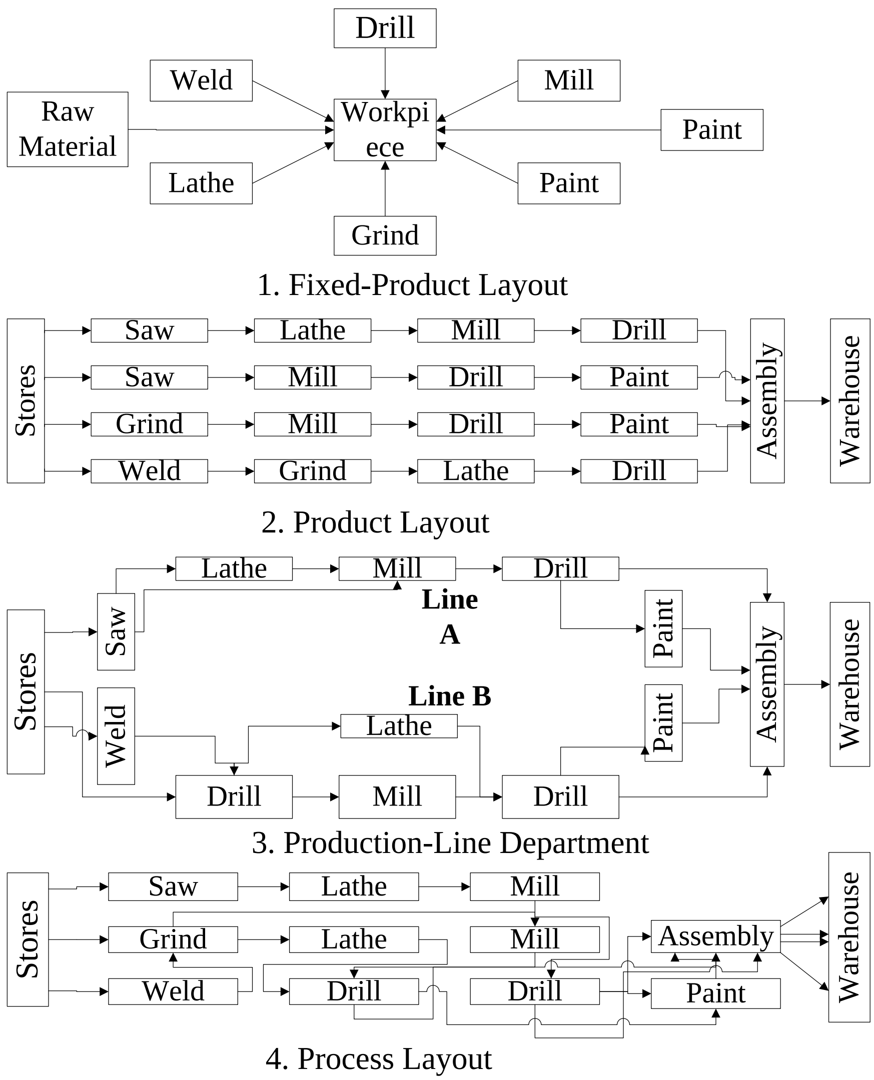


Figure 8: Different Types of Company-Layouts (Tompkins *et al.*, 2000)

2.7.6. Bernoulli's Principle

From its original introduction, Bernoulli's principle involves the movement of a fluid through a pressure difference, i.e. a fluid moving in the horizontal direction that encounters pressure difference. Pressure difference results in a net force, which by Newton's law will cause an acceleration of the fluid. The fundamental relation is that work done is the same as the change in kinetic energy. In this report, production and resource capacity are converted to pressure to be compatible with Bernoulli's equation. Pressure, in Bernoulli's language, is considered as any factor that contributes to the urgency of the job or a factor that cause bottleneck in production environment.

In this report, Bernoulli's principle is employed to explore the behaviours of products passing through a production system at various production phases (e.g. instances where demand is less than production capacity and secondly where demand surpasses production capacity: bottleneck situations). The effects of the production velocity (commonly known as TAKT time) and pressure are determined.

As materials with varying processing times pass through production resources with different capacities, production velocity (rate of production) and pressure also vary. In the production environment, as production capacities become limited (i.e. bottleneck operations), production flows slowly (Goldratt 2004), which is not the case with Bernoulli's principle. Bernoulli’s indicates the exact opposite with fluid flow: “as fluid flow more quickly through the narrow sections, the pressure actually decreases rather than increase” (Clancy 1975).

Chapter 3

RESEARCH DESIGN AND RESULTS: Approaches to address the problem

The current research project was carried out in the article format. Thus, this chapter is a compilation of the various articles that has been published by the present candidate to address problems considered herein. Because of some (minor) overlaps between the articles, (for example, with introductions, rationales and some elements of the conclusion), the present researcher has done his best to minimise the overlapping. Thus, the articles are not presented here in the exact format that they were published.

Recall that the issue at hand has been that of addressing production scheduling problems or rescheduling following random disruption caused by many factors. Note that disruption itself cannot be measured, but its impact can be measured. In this report, the impacts of disruptions are measured by the effects that they have on the productivities. The theory of multifactor productivity has been employed to unify the various factors that may cause disruptions. Because those factors causing disruptions may occur randomly as time progresses, the time increment of the multifactor productivity expression is obtained, and then made stochastic by the addition of fluctuation term. This leads to stochastic differential equation which is further modified by the theory of line balancing to obtain the stochastic model of the optimal amount of resources required to meet the production demand following random disruptions. Furthermore, in this report, since disruption can be viewed as a failure of a section of the production plant or the entire production plant, attempts to address the current problem at hand is also dealt with by employing the theory of reliability engineering. Depending on the layout of the production facilities, a failure of one section may or may not affect other sections of the plant. Thus, the theory of reliability engineering is tested on different company layouts. Disruptions can also effectively be viewed as bottlenecks or as an agent of an increase bottleneck. Thus, in this report the theory of Bernoulli's principle is applied to study the effect of production bottlenecks. This chapter is concluded on recommendations on how a scheduler should react following random disruptions.

3.1. MULTIFACTOR PRODUCTIVITY, ITO STOCHASTIC THEORY AND LINE BALANCING

Manufacturing system should normally produce products based on market demand (i.e. demand triggers production to commence). Knowing that the amount of raw materials needed to meet the market demands can be obtained through scrap estimation, the input functions can serve as a production command to available machines, i.e. a machine breakdown along a production flow-line may hold down other machines along the line. The occurrences of disruptions on the manufacturing systems should affect the productivities of the companies involved. Thus, the starting point of the present analysis is (multifactor) productivity. Productivity function can be measured by both input and output functions. Note that the word "output" in the definition of productivity is different from the market demand. It stands for the ability to produce per given input: market demand is commensurate to output of the final or exiting workstation. In practise, the multifactor productivity values should be calculated for both ideal production systems without disruptions and for those with random disruptions. The differences between them should enable us to measure how systems should respond to various impacts of disruptions, illustrated by:

$$Productivity_{ideal\,state} - Prod._{\,under\,stochastic\,conditions} \xrightarrow{yields} Impact of Disruption \qquad (3.1)$$

The multifactor productivity (Groover, 2008) can be calculated as follows:

$$P = \frac{O}{\sum I_i} = \frac{O}{I} \qquad (3.2)$$

Where "P" is representing a productivity function, "O" is the output quantity, and "I=$\sum I_i$" is input Quantity. Note that I = $\sum I_i$ should be interpreted as valid for a system that is affected by many production factors as well as systems affected by a single factor. It follows from expression (3.2) that:

$$O = PI \qquad (3.3)$$

By applying general laws of mathematical differential rule, expression (3) can be written as:

$$dO = IdP + PdI \tag{3.4}$$

Expression (3.4) can be made stochastic by the addition of fluctuation term, after taking the time derivative of both sides of that expression. The time rate of change of the output given in expression (3.4), in the stochastic sense, (i.e. by applying the Ito's stochastic theory (Gikhman & Skorokhod, 1972; Arnold, 1974; Snyder, 1975 and Gardiner, 1985),) is given as:

$$\frac{dO}{dt} = \frac{dP}{dt}I + P\frac{dI}{dt} + b(0,t)\,dW(t) + c(t)dN(t) \tag{3.5}$$

Where *b(0,t)* is generally called the drift term. Further differentiation of expression (3.4) or (3.5) above, give the following expression:

$$\frac{d^2O}{dt^2} = 2\frac{dP}{dt}\frac{dI}{dt} + I\frac{d^2P}{dt^2} + P\frac{d^2I}{dt^2} + \frac{db(t)}{dt}dW(t) + \frac{dc(t)}{dt}dN(t),\ since\ \frac{ddW(t)}{dt} = 0\ and\ \frac{ddN(t)}{dt} = 0 \tag{3.6}$$

Expression (3.6) and that of higher order moments are the general expressions needed for all the parameters of the distribution of the impact of disruptions. The "first integral" solution to this main expression (3.6) indicates the evolution of output per given time due to disruptions. This solution (i.e. output per given time) is actually the productivity. If this productivity is that of the exiting/final workstation, then its reciprocal gives the TAKT time.

Dividing the TAKT time by the production cycle time gives the number of production resources required to production demand. Comparing this number of resources for the various workstations to their "average times" leads to information about the degree of balance of the line.

Expression (3.6) is the main expression under this subsection. It is made up of variations in inputs and variation in effective multifactor productivity. The variations of the input variables with respect to time may depend on the circumstance under consideration, which may be represented as depicted in the plots in figure below.

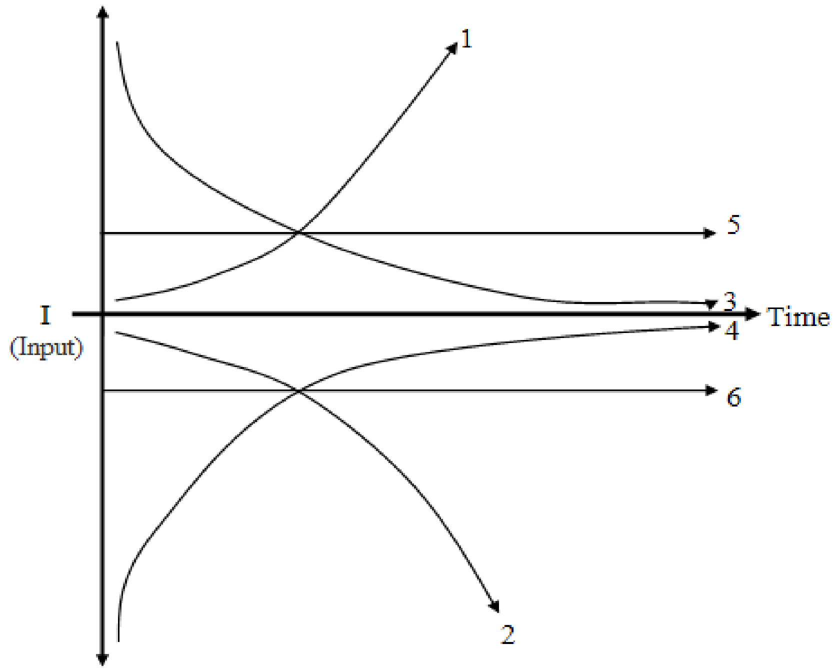


Figure 9: Time evolution of input functions due to various kinds of disrupting factors

The plots may be interpreted as follows:

Plot 1 can be interpreted as a case where a company and its suppliers are gaining production experience and the input variables such as raw materials are unlimited, i.e. the case of increasing availability of resources. Although the case of increasing inputs may not be perceived as disruption in the traditional sense, as more and more resources get available, it is necessary to reschedule the system in order to make good use of them. This is so that there should be high return on investment for the company to realize an increase share in the market through full utilisation of resource capacities.

Plot 2: This case can be interpreted as a situation where the input resources are "taken away" from the company such as through destructions following the disasters or workers' strikes or in product family layout. In this case the input does not serve the production purposes.

Plot 3: In this case, the input resources are getting depleted as time progresses. This can be because the employed resources are in the last phase of their life cycle, or that workers are on strike (workers not available to produce and deliver/transport) and inputs continue to diminish with time.

Plot 4 can be related to damages that are being repaired. Constant problems of inputs shortages are coming to an end, resulting in the company's operations picking up.

Plot 5 represents many common situations in which many companies operate, it depicts a constant parameter. It shows an ideal state where there's no disruption, every material flow is smooth with constant productivity.

Plot 6 depicts that the company is continually operating at a loss. Inputs have depleted.

The above input fluctuations can be combined into a unified mathematical expression by the theory of linear combination to:

$$I = a_1 t^{n_1} - a_2 t^{n_2} + a_3 t^{n_3} - a_4 t^{-n_4} + a_5 - a_6 \qquad (3.7)$$

In this unified expression (3.7), plot 1 is represented by the first term on the right hand side (RHS) of expression (3.7), plot 2 is represented by the second term, plot 3 by the third term, plot 4 by the forth term, plot 5 by the fifth term and plot 6 by the sixth term on the RHS of expression (3.7). Twice differentiating expression (3.7), so as to obtain expressions needed for substitution into expression (3.6), yields the following expression

$$\frac{dI}{dt} = a_1 n_1 t^{n_1 - 1} - a_2 n_2 t^{n_2 - 1} - a_3 n_3 t^{-n_3 - 1} + a_4 n_4 t^{-n_4 - 1} \qquad (3.8.1)$$

$$\frac{d^2 I}{dt^2} = a_1 n_1 (n_1 - 1) t^{n_1 - 2} - a_2 n_2 (n_2 - 1) t^{n_2 - 2} + a_3 n_3 (n_3 - 1) t^{-n_3 - 2}$$
$$- a_4 n_4 (n_4 - 1) t^{-n_4 - 2} \qquad (3.8.2)$$

If one let expression (3.7) to represent the amount of input required to produce a unit output, then it follows in the same vein that the production rate is given by (Groover 2008):

$$P = \frac{1}{T} = T^{-1} \tag{3.9}$$

Differentiating twice equation (3.10), so as to obtain expressions needed for substitution into expression (3.6), gives:

$$\frac{dP}{dt} = -\frac{1}{T^2}\frac{dT}{dt} \tag{3.10.1}$$

$$\frac{d^2P}{dt^2} = \frac{2}{T^3}\frac{dT}{dt} - \frac{1}{T^2}\frac{d^2T}{dt^2} \tag{3.10.2}$$

Unforeseen disruptions on the production line cause downtimes, with varying durations. These unforeseen events yield longer actual cycle time on the line. Therefore, the formulation of the actual production time can be expressed as follows (Groover 2008):

$$T = T_c + FT_d \tag{3.11}$$

Where T_c is the cycle time (min), T_d is the downtime (min), and F denotes a probability of failure or downtime frequency. The parameter that can be affected by random disruptions in expression (11) is F that can mathematically be represented, for the various cases of Figure 9, as follows:

$$F = b_1t^{m_1} - b_2t^{m_2} + b_3t^{-m_3} - b_4t^{-m_4} + b_5 - b_6 \tag{3.12}$$

By substituting expression (3.12) into expression (3.11), gives the following equation:

$$T = T_c + (b_1t^{m_1} - b_2t^{m_2} + b_3t^{-m_3} - b_4t^{-m_4} + b_5 - b_6)T_d \tag{3.13}$$

This expression should be substituted in expression (3.9). The drift term in expressions (3.5) or (3.6) may be given as:

$$b(0,t) = b_1t^{q_1} - b_2t^{q_2} + b_3t^{-q_3} - b_4t^{-q_4} + b_5 - b_6 \tag{3.14.1}$$

$$c(0,t) = c_1 t^{q_1} - c_2 t^{q_2} + c_3 t^{-q_3} - c_4 t^{-q_4} + c_5 - c_6 \qquad (3.14.2)$$

Expressions (3.7), (3.8), (3.9), (3.10) and (3.14) are substituted in the main equation, expression (3.6). The resulting equations are then solved with regard to time. The first integral gives the evolution of the rate of change of output, whose reciprocal is the TAKT time. The constant a_i, b_i, c_i, m_i, n_i and q_i are appropriately chosen to represent different real world scenarios or circumstances.

Information about the variable inputs with negative values is not considered in the present results i.e. plot2=plot4=plot6=0 or a_2=a_4=a_6=0. Furthermore, the increase in input due to disruption (i.e. increase in input with time) is also not considered (i.e. a_1=0). Similarly, the situations that generate negative values of frequency of downtime are not considered. This last consideration should not be misinterpreted. Remember that there may be situations where a random disruption (such as surplus supply) may reduce the frequency of machine idling. The parameters used are a_3=0.018, b_3=5x10^{-6}, m_3=2 and n_3=1.4. These parameters were chosen such that the trend matches or correlates with empirical data. Due to the fact that various types of disruptions made contribution to the input (polynomial) function, only the leading term was dealt without loss of generality. These values should actually depend on the operational needs or operational setback. The results of expression (3.1) to (3.14) are presented below.

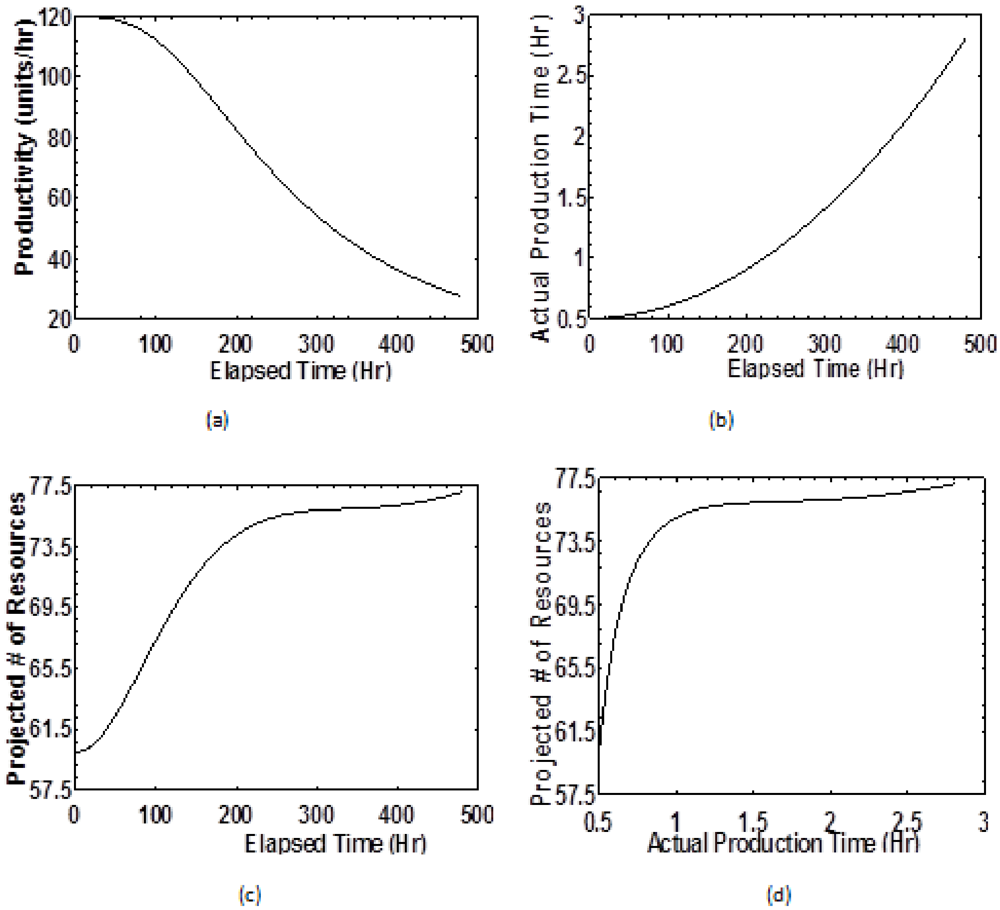


Figure 10: Time evolution of the (a) Productivity, (b) Production time, (c) No. of workstation required, and (d) Number of resources to meet demand

It can be observed in Figure (10a) as expected that if disruptions were to occur continuously with time, then the productivity will decrease as time goes on. Figure (10b) indicates that due to disruptions, the actual production time increases. Using the approach of line balancing which is used to determine the number of workstations (though not at the level of avoiding bottlenecks), the result of Figure (10c) is obtained. This plot indicates that as time goes on and following continuous disruptions, the number of facilities/resources required should increase. This increase in facilities/resources will account for the time lost due to disruptions so as to increase production rate. The scheduler should reschedule following the trend that is only predicted by the nature of disruption. Figure (10d) indicates that the relationship between the amounts of resources that should be rescheduled does not depend linearly on the actual production time.

3.2.RELIABILITY AND FAILURE

Since disruptions can be seen as failure of section of or the entire plant, and failure is directly related to reliability, one of the best ways of determining impacts of disruptions is through reliability. The probability of failure is expressed as a function of time. The expressions under this and the following sections are borrowed from the work of Mobley *et al.*, 2008. Different system configurations are considered, namely; system in series, parallel and combination of both. The relationship between reliability and failure is given as:

$$R(t) = 1 - \lambda = e^{-\lambda t} \tag{3.15}$$

Where λ is the system failure rate and R(t) is the reliability function. Reliability can also be given as "R". By considering a "series system or components in series", reliability is given as:

$$R_s = R_1 R_2 R_3 ... R_n = (e^{-\lambda_1 t})(e^{-\lambda_2 t})(e^{-\lambda_3 t})...(e^{-\lambda_n t}) = e^{-\sum_n \lambda n t} \tag{3.16}$$

where $R_n = e^{-\lambda_n t}$ from expressions (3.15) above. It follows that the overall failure also known as F is given by:

$$\lambda = F = \sum_{i=1}^{n} \lambda_n \tag{3.17}$$

Thus, for a system containing n independent components in series, the system failure rate becomes the sum of the individual components or system failures.

By considering a "parallel system or components in parallel", reliability is given as:

$$R_p = 1 - (1 - R_1)(1 - R_2)(1 - R_3)...(1 - R_n) \tag{3.18}$$

From expressions (3.15) and (3.18) it follows that the system failure is given by:

$$\lambda = F = 1 - \underset{k=1}{\overset{n}{\pi}} (1 - \lambda_k) \tag{3.19}$$

Machines or resource configurations may be in series or in parallel or a combination of both. The expression that can be used for this scenario where both series and parallel components operate in a single configuration can be given by:

$$R = w_s R_s \cup w_p R_p \tag{3.20}$$

Where w_s represent weight for series configuration and w_p represents weight for parallel configuration.

Since the impact of disruptions can be measured by the productivity, multifactor productivity can be expressed as previously presented in expression (3.2): see section 3.1, except that in this expression a function of time is introduced or considered.

$$P_i = \frac{O}{I} = \frac{O}{T} \tag{3.21}$$

Where T is the multifactor input function.

Considering expression (3.21) and the fact that reliability or failure rate is given as a function of time, productivity can be defined by the time that it takes to produce one unit. Disruption effect a change in production time as given by:

$$T_p = T_c + FT_d \tag{3.22}$$

Where T_p is the practical productive time, T_c is the ideal cycle time, F is the probability of failure and T_d is the average downtime

3.2.1. Company Layouts

3.2.1.1. Production Line Department

The classical production flow-line production considered herein is that of a series configuration set-up. The reliability or failure rate of such a layout has already been presented in expression (3.16) or (3.17) above. Expression (3.17) is that of the traditional upper bound approach where after failure emerged the part is damaged and is therefore removed from the production line. For the lower bound approach, when failure occurs parts are not damaged and as such would continue down the production line. When this is the case, the overall failure rate is given by expression similar to that of machines in parallel, or expression (3.19).

3.2.1.2. Product Family Layout

In this layout, machines and/or resources are configured in either series or parallel or the union of both. With the union of both configurations expression (3.20) is applicable. Expression (3.17) and (3.18) are applicable for series and parallel layout respectively.

3.2.1.3. Process department

In this layout resources performing similar functions are grouped together. Thus it can be assumed that the effective machines arrangement is in parallel. The assumption is due to the fact that the effective reliability of a series of machines can be obtained and can be called the reliability of that line (or that machine). Thus a reliability of a process line is given by first employing expression (3.16) for individual lines and then aggregating by employing an expression (3.18).

3.2.1.4. Fixed Position Layout

In this layout resources are brought to the product that is being processed. It can be viewed that there is only one workstation available. Thus expression (3.15) applies.

The following sections deal with applications of expressions (3.15) to (3.22) on different company layouts. Some of the top leading disruptive factors that affect different company layouts are listed in Table 3 below. These are the findings from employing expressions (3.15) to (3.22) presented above.

Table 2: Various disruptive factors per Company Layouts

Company Layout	Characteristics	Leading Disruptions
Production-Line Department	Made up of machines in a series working on the same raw material	Machine Breakdowns
		Material Shortage
		Employee Absenteeism
		Part Damages
		Order Changes
Product Family Layout	Machines processing similar products are grouped together	Machine Breakdowns
		Material Shortage
		Storage Facility
		Employee Absenteeism
		Part Damages
Process Department Layout	Resources performing similar function are grouped together	IT Outages
		Adverse Weather
		Machine Breakdowns
		Shift Changeovers
		Part Damages
Fixed-position Layout	Resources and materials are brought to the production of the product	Adverse Weather
		Order Changes
		Transportation Networks
		Storage Facility
		Machine Breakdowns
		Part Damages

Since disruption can be considered as failures and also considering the fact that a disruption of one type can cause a disruption of one type to occur (disruption in series) or disruptions can be independent (disruptions in parallel), the knowledge gained from expression (3.15)-(3.20) has been applied without loss of generality.

3.3.BERNOULLI'S PRINCIPLE

Production environment may be characterized by the dynamic and stochastic behaviour of different system parameters. These parameters include varying forms of pressure or force that affect production flow. Bernoulli's principle specializes mainly on work done by a fluid, where the density is considered to be constant, regardless of pressure variations in the flow, i.e. incompressible flow. Bernoulli's generic expression with constant gravity is given by (Clancy 1975):

$$A = \frac{v^2}{2} + gz + \frac{p}{\rho} \tag{3.23}$$

Where:

A is the energy of (or work done by) a fluid moving in a pipes,
v is the fluid flow speed,
g is the acceleration due to gravity,
z is the elevation of the point above a reference plane, with the positive z-direction pointing upward – so in the direction opposite to the gravitational acceleration,
p is the pressure at the point, and
ρ is the density of the fluid.

Expression (3.23) shows that in an ideal state pressure, *p*, and flow rate, *v*, are inversely related at a specific point: i.e. a slow moving fluid exerts more pressure than a fast moving fluid. The interpretation of expression (3.23) is such that the total energy of a constant-density and constant-temperature fluid at any point is constant. Within the production setting, the work done by a fluid is compared to the effort (i.e. investment) required to produce a product at a workstation. This is a function of the speed with which the product is processed at the workstation determined by the processing cycle time, the location of the workstation determined by the material handling efforts and the production demand of the workstation determined by the production quantity awaiting production. In the same vein, it can be interpreted that if the same amount of effort is to be dispensed for a workstation, then an increase in demand (or pressure) should be caused by a reduction in processing speed of that workstation and vice versa. This reduction in speed can be interpreted as failure of that workstation (such as machine degradation, worker absenteeism, etc.), and as such rescheduling has to take place. How would Bernoulli's principle apply to production scheduling?

3.3.1. Predictive or Static State

The production environment in this set-up assumes that all production parameters are known with certainty, i.e. supplier capacity is assumed to surpass demand of the manufacturer, known processing time, known production flow rates, etc. If the line is balanced, then it can be seen that the sum of all forms of efforts at any workstation is the same for each job because in a reservoir the effort per job mass is the same everywhere. Under the predictive or static state, it was found that when the production effort for a workstation was increased, then the speed of flow increased and the workstation pressure (determined production demand such as number of operators) also increased, see figure11. This is the case since the location of the workstation with respect to the starting point does not change. This is a typical situation where the production manager increases the investment at the workstation, either by increasing the number of operators then more jobs can be processed more faster.

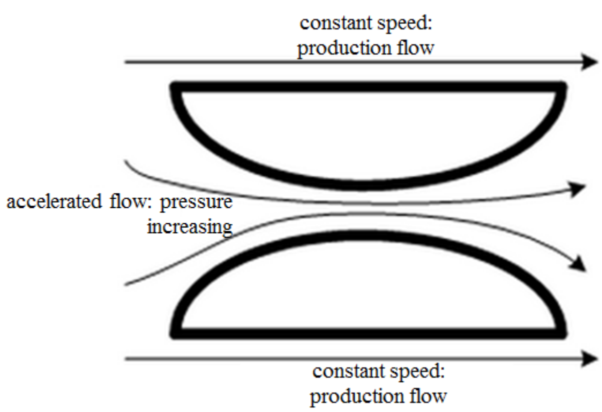


Figure 11: Change (Δ) in pressure and production flow rates

3.3.2. Dynamic or Unsteady State

In this situation, jobs are subject to random disruptions. Random disruptions bring about a reduction in production resources. This reduction in production facilities means an increase pressure on the limited number of remaining resources. Thus, in agreement with the Bernoulli's principle, it was found that the speed of flow at the workstation reduced following random disruption. It was the view of the operators that an indication of disruption was job pile-up that was subsequently associated with other operator(s) being absent or processing equipment breakdown; or operators being idle in the case of limited raw materials. The flow of job in an unsteady setting or following disruption can be depicted as shown in fig.12 and fig.13.

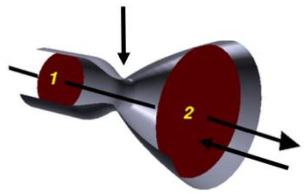


Figure 12: Production flow depiction

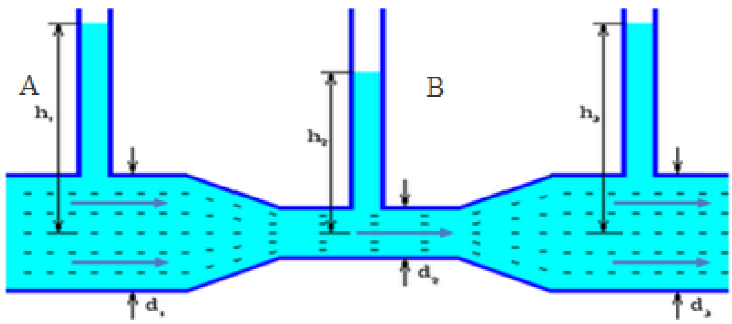


Figure 13: Production flow subject to pressure and varying capacities

Bernoulli's equation should then become the first starting point in operations planning (production scheduling) derivation. This principle should assist in levelling the workload on the production line: bottleneck operations.

3.3.3. Bottleneck Operation

This section discusses ways of handling and/or managing bottleneck operations through application of Bernoulli principle. Capacity as an important element in production flow can be visualized as a series of pipes (operations) of varying capacities and processing times, with smaller diameter pipe representing the bottleneck operation. Figure 14 depicts five pipes (departments or machines) with different diameter (or capacities). The output from one operation/pipe becomes input to the next operation until the finished product exits pipe number five. In the Figure 14, operation B is regarded as a bottleneck operation (i.e. high pressure on limited resources), as it cannot handle all the flow that pipe A can deliver, and therefore restricts the flow. This operation's limited capacity restricts flow from upstream operations and starves downstream operations.

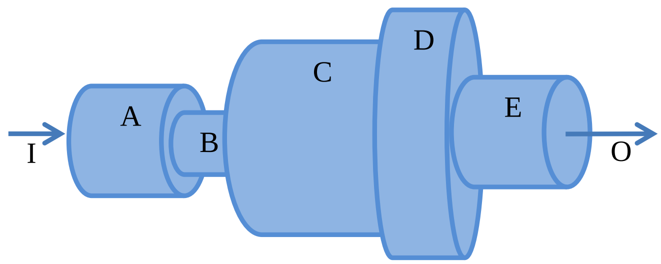


Figure 14: A Bottleneck Operation Flow

Workstations C, D and E can only process what workstation B has processed. This restriction is referred to as a bottleneck, and workstation B determines the system's capacity.

From Figure 14, let "I" be input and "O" represent output quantity. Identifying bottleneck station is of the essence in production planning, scheduling and control. Proposed approach to determine system capacities is discussed herein. The approach is illustrated in Figure 15 below.

Start at the beginning of the system and determine the capacity or pace of the first operation or department. The first workstation capacity becomes the pace (input) system capacity. The calculated capacity set the pace for the subsequent stations. Is the subsequent workstations well capacitated to handle incoming materials and process it completely? If it can, then the system capacity should not change. If it cannot, then the system capacity is reduced to match the capacity of that department. The procedure continues until the last operation if a system comprises of more than two operations. The system capacity can then be increased by adding extra resources to the bottleneck station. By doing this, bottleneck operation is balanced with less utilized operations (other parts) downstream. It should be remarked that a double increase of bottleneck operation does not mean a double productivity of the system. By doubling capacity, the bottleneck simply jumps to another part of the system (workstation). Thus, it is vital that process specialists should understand and carefully analyze the effect on the system of any increase in departmental capacity.

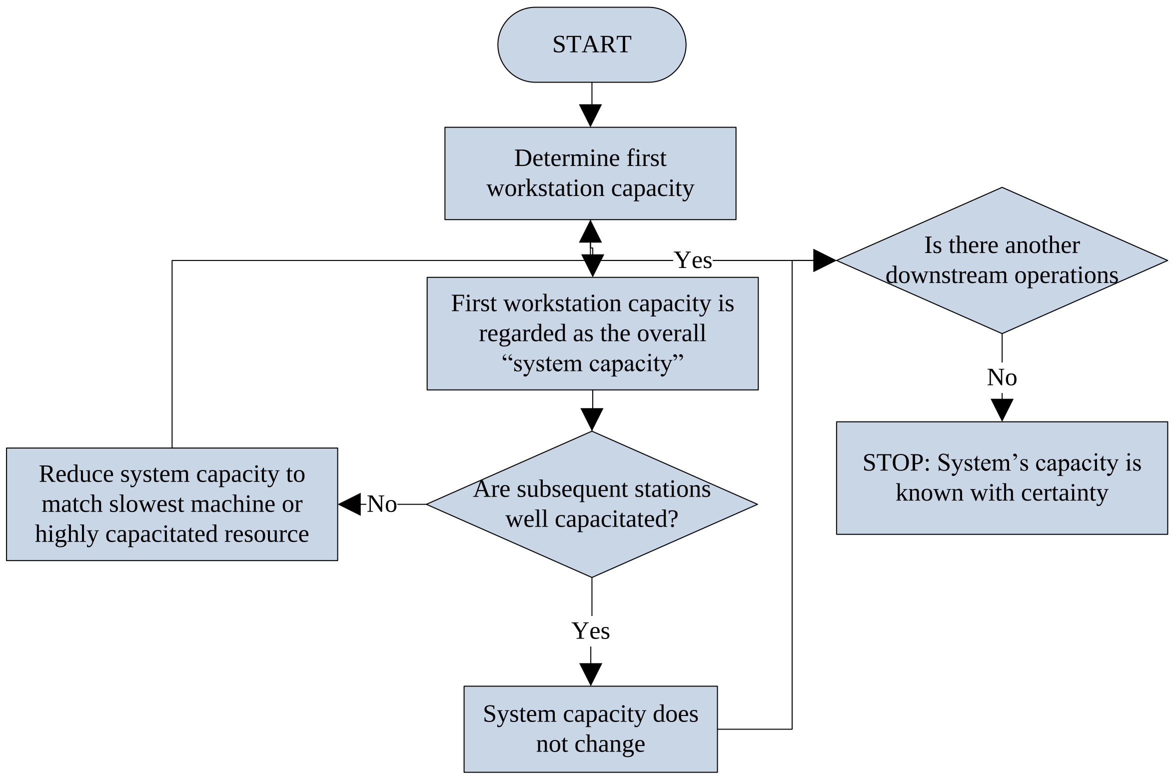


Figure 15: Proposed Approach for Determining Bottleneck Operation

The system capacity is proportional to the productiveness of the overall system. The proposed method serves as the foundation/starting point for bottleneck management. As in the above depictions, some workstations are well capacitated and thus attention should be given to the incapacitated or bottleneck operation with an emphasis of “amelioration”.

3.4. PROPOSED RESCHEDULING CONCEPTS OR APPROACHES

To help schedulers with effectual rescheduling of operations following disruptions, the proposed concepts presented below are vital; 1) threshold concept, and, 2) rescheduling interval. The former should help scheduler to know whether to reschedule or not. The latter should advice scheduler as to the type of rescheduling to consider, i.e. partial or complete rescheduling.

3.4.1. Threshold Concept

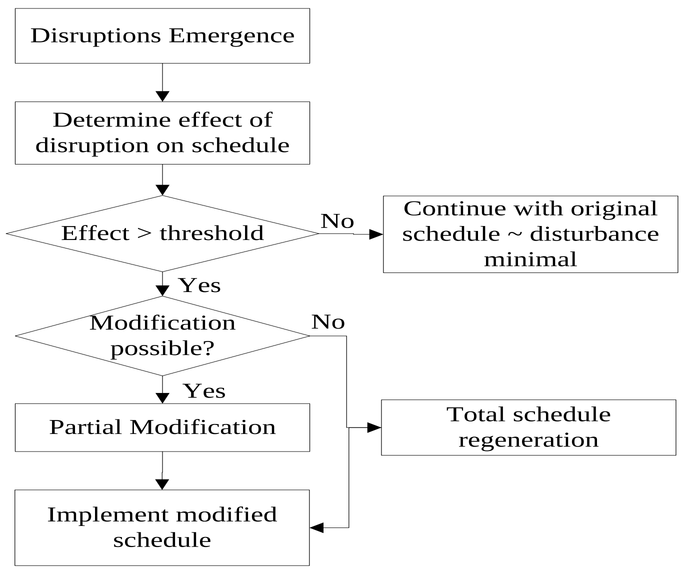


Figure 16: Basic decision flowchart following disruptions

In case of disruptions, the first rescheduling decision should be based on the estimated length of disruption. If the length is such that the schedule is not affected appreciably, then the decision may be to continue without changes. If, on the other hand, a disruption affects schedule performance drastically, alternative algorithms are executed with the objective of modifying the schedule in a way that minimizes the effect of disturbances. For example, multiple durations may be considered, i.e. 20 minutes, 1 hour, and 2 hours. This should be a random range selected with the expectation that disruptions shorter than 20 minutes may not always call for schedule modifications. Disruptions longer than 2 hours may frequently require regeneration of a new schedule. The potential modifications may include rescheduling of operations. If no acceptable solution is found, the scheduler regenerates a schedule. Decisive process flow is depicted in the

Figure 16. The threshold is an important decisive factor in rescheduling of operations as it determines whether to reschedule or not; and "not" to reschedule guarantees less impact on effective performances and stability measures.

3.4.2. Rescheduling Interval (RI)

Continuing from the above explanation, Figure 17 presents a concept of event-driven rescheduling policy where disruptive factors of both RI^1 and RI^2 are of varying degree, i.e. with RI^1 a new schedule is required as the impact is notably greater than the threshold, and for RI^2 an original schedule may still be followed since the impact is lower than the threshold value[1]. Practically, schedules should only be generated in every RI time interval. However, in real-life the scheduler should determine the feasibility of performing rescheduling activities following a logic presented above. Rescheduling is effected right after disruption "A" as in the diagram below. If disruption "B" is envisaged to have minor impact on operations downstream, then production rescheduling is not considered, i.e. rescheduling is neglected because the current schedule is still executable without notable degradation of the system performance. However, if disruption has severe impacts on the production system (e.g. in disruption "A"), then "complete rescheduling" is considered in which all jobs from the original schedule that remained unprocessed are included in the pool of jobs waiting for processing during rescheduling of operations.

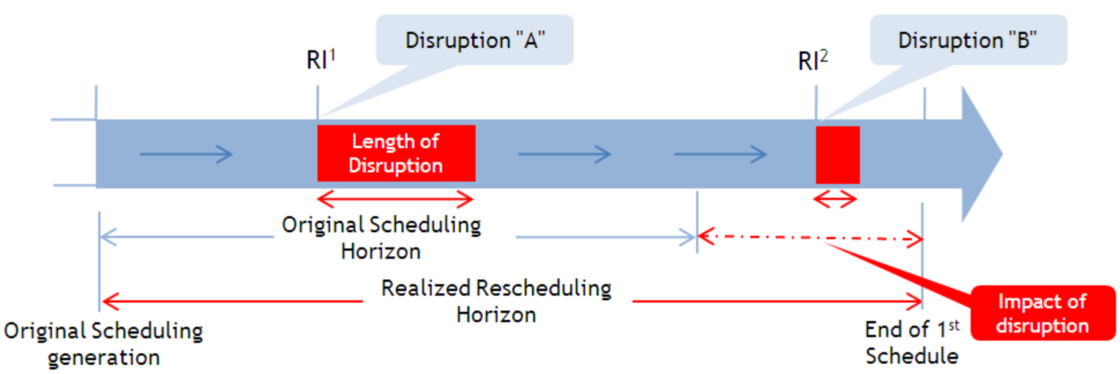


Figure 17: Impact of disruptions in manufacturing operations

[1] Threshold in this study is defined as the maximum value for non-reaction to random disruptions.

3.5.SUPPLY CHAIN DISRUPTIONS

Previous sections addressed disruptions at a micro-level (i.e. within manufacturing systems), and disruptions at a macro-level (i.e. supply chain systems) are discussed under this section.

The occurrences of disruptions on the supply chain systems affect productivities of the systems under consideration and have direct negative impact on the national economy. On the impact of disruption, productivity values are calculated for both ideal production systems (e.g. without disruptions) and for one obscured by random disruptions, and the difference between both states should enable the scheduler to measure how random disruptions affect supply chain systems, as illustrated by the expressions below:

$$P_{idealstate} - P_{withrandomdisruptions} \xrightarrow{yield} D_{impact} \tag{3.24}$$

The ideal state should be the target. The basic productivity function as given in section 3.1 is used.

To determine the severity or degree of the various impacts of disruptions, the disruption index is proposed and introduced. Mathematically, disruption index is given as the ratio of the performance factors on the number of days with disruptions and total number of days worked, as follows:

$$DI = \frac{P_{disrupted}}{P_{planned}} \tag{3.25}$$

Where "DI" represents a disruption index, "$P_{disrupted}$" is the actual production, and "$P_{planned}$" is the planned productivity.

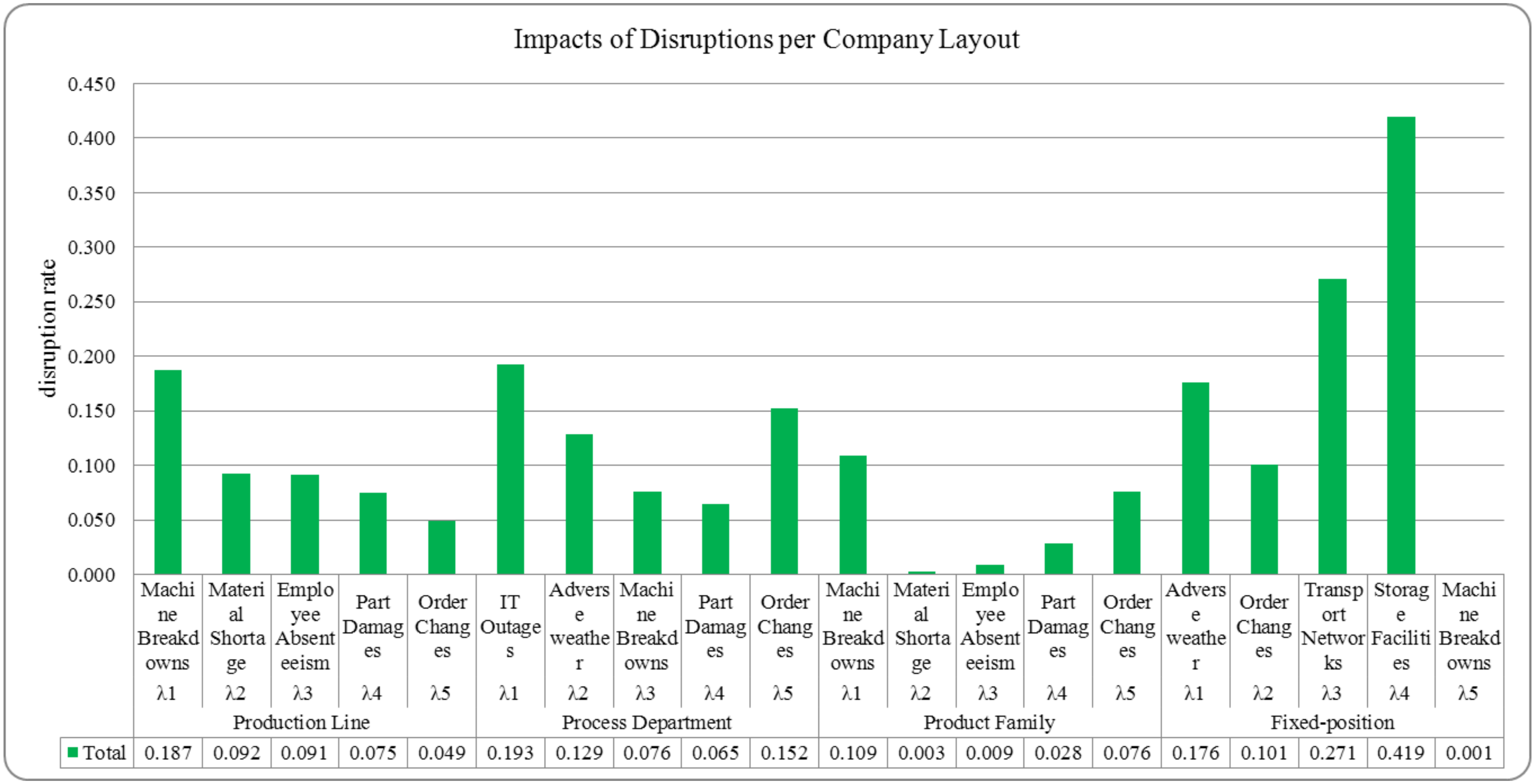
For the analysis, data was collected from several companies grouped by their similarities in company layouts. Since disruptions can, without loss of generality, be considered to be indications of failures, the average failure rate was obtained for each type of disruption factor.

The averaging was due to the fact that, for example, different companies producing similar type of products had machines of different ages and as such their reliabilities varied.

It can be seen from Table 3 below how different disruptions affect the system's performance per company-layout. For the sake of comparison and clear depiction the results are presented graphically as in Figure 18 below.

Table 3: Company-Layout Disruption Indices

Company Layout	**Lambda (λ)**	**Leading Disruptions per Company Layout**	**Failure Rate**
Production Line	λ_1	Machine Breakdowns	0.187
	λ_2	Material Shortage	0.092
	λ_3	Employee Absenteeism	0.091
	λ_4	Part Damages	0.075
	λ_5	Order Changes	0.049
Process Department	λ_1	IT Outages	0.193
	λ_2	Adverse weather	0.129
	λ_3	Machine Breakdowns	0.076
	λ_4	Part Damages	0.065
	λ_5	Order Changes	0.152
Product Family	λ_1	Machine Breakdowns	0.109
	λ_2	Material Shortage	0.003
	λ_3	Employee Absenteeism	0.009
	λ_4	Part Damages	0.028
	λ_5	Order Changes	0.076
Fixed-position	λ_1	Adverse weather	0.176
	λ_2	Order Changes	0.101
	λ_3	Transport Networks	0.271
	λ_4	Storage Facilities	0.419
	λ_5	Machine Breakdowns	0.001



	Layout	Disruption	Total
λ1	Production Line	Machine Breakdowns	0.187
λ2	Production Line	Material Shortage	0.092
λ3	Production Line	Employee Absenteeism	0.091
λ4	Production Line	Part Damages	0.075
λ5	Production Line	Order Changes	0.049
λ1	Process Department	IT Outages	0.193
λ2	Process Department	Adverse weather	0.129
λ3	Process Department	Machine Breakdowns	0.076
λ4	Process Department	Part Damages	0.065
λ5	Process Department	Order Changes	0.152
λ1	Product Family	Machine Breakdowns	0.109
λ2	Product Family	Material Shortage	0.003
λ3	Product Family	Employee Absenteeism	0.009
λ4	Product Family	Part Damages	0.028
λ5	Product Family	Order Changes	0.076
λ1	Fixed-position	Adverse weather	0.176
λ2	Fixed-position	Order Changes	0.101
λ3	Fixed-position	Transport Networks	0.271
λ4	Fixed-position	Storage Facilities	0.419
λ5	Fixed-position	Machine Breakdowns	0.001

Figure 18: Impacts of Various Disruptions per Company Layout

As used in section 3.2, the parameter λ is given as a failure rate of the system. The aggregate results are presented below for different types of company layouts, i.e.; system failure rate for production line, process, product family and fixed-position layout are $\lambda_{PL} = 0.099; \lambda_{PR} = 0.123; \lambda_{PF} = 0.045; and, \lambda_{FP} = 0.194$ respectively. Considering the fact that these different types of company layouts are all found in South Africa (SA) and also assuming that the effective gross domestic product (GDP) is influenced by disruptions from the different company layouts, the following data can be derived. Losses per company layouts are as follows: fixed-position layout recorded a total of 42% followed process department at 27%, then by production line department at 21% and 10% recorded for product family layout (*for more see discussions in section 3.5.1*). Assuming further that these company layouts equally share R5.7 trillion SA's total turnover, then the monetary implications per each company layout are as follows (in tabular form):

Table 4: Company-Layouts Loss Breakdown

Production Line	Process Department	Product Family	Fixed Position Layout
R 0.141 trillion	R 0.175 trillion	R 0.064 trillion	R 0.276 trillion

From respective failure rates results above, approximately R 0.656 trillion is lost annually by SA economic system due to unforeseen disruptions.

The results reveal that fixed-position layout suffer more due to disruptions than other company layouts, followed by process department, production line and product family layout as the last one. It can be observed that adverse weather, order changes, transport networks and storage facilities are the leading candidates of disruptions on fixed layout (for more see table 3). Machine breakdown was recorded to have the least disruption impact on fixed layout, when compared to the impact it has on other company layouts. It can be seen from the figure above that disruption of one type (e.g. machine breakdown) may not greatly affect productivity of a certain company layout, whilst similar disruption can have devastating effects on another type. Machine breakdown, material shortages and employee absenteeism are found to be the most leading disruptions candidates in the production line department. Product-family layout is not tied down by material shortages, because if material is finished at a particular workstation, it can be sourced from workstations within the group.

3.5.1. Supply Chain: Impact of Disruptions

Since production systems are subject to a variety of random disruptions, it is important to find out per company layout how these disruptions affect them. Supply chain encompasses all different types of company layouts. For this reason different companies were considered for analysis grouped by their similarities. The results apparently indicate that leading sources of disruptions might vary from industry to industry. For financial service industries and call-centers, unplanned outage of IT, telecom systems and unanswered calls are the most common causes of disruptions. In service industries like hospitals, shortage of medication and shift changeovers are recorded as the most common causes of disruption. In manufacturing industries, machine breakdowns, raw material shortages and employee absenteeism are the frequent causes of disruptions. For retail and wholesale, IT and communications; adverse weather, transport networks and storage are the most common causes of disruption. Supply chain disruptions are identified as the primary causes of productivity losses. Productivity is indirectly proportional to supply chain disruptions, i.e. an increase in supply chain disruptions yields a loss in productivity. It was found that for any company layout experiencing worsening degrees of distress and disruptions, loss of productivity proved to be greater.

For production line department, product family and process department the most recorded disruption is employee absenteeism, followed by machine breakdowns at less than 1.5% of the total time and then by perishable raw materials shortage following late deliveries by suppliers. Employee absenteeism may occur more often, but it’s not as expensive as machine breakdown and late deliveries because in some companies employees are cross-trained to operate or work on other production lines. With a fixed position layout where all processes and materials required for production are brought to a product; severe weather conditions proved to be costly and leading disruptions in raining seasons, e.g. construction of a new building – work comes to a complete halt or standstill.

As presented in the previous sections, disruption impacts can also be assessed by determining disruption index using expression (3.38). Disruption index is the ratio of the production on days when the disruption occurred and the average planned daily production performances without disruptions. The results of disruption indices are presented succinctly in Table 5 and 6. Companies encounter many disruptive factors, and only top “A” rated or leading disruptions are presented.

Table 5: Manufacturing Process Industry

Company Layout	Disruption Indices					Total
	Machine Breakdown	Material Shortage	Employee Absenteeism	Order Change	Rework	
Production	0.338	0.229	0.111	0.009	0.000	0.68
Process	0.469	0.493	0.546	0.099	0.130	1.73
Product	0.475	0.312	0.410	0.090	0.179	1.46
Fixed	0.275	0.217	0.095	0.762	0.325	1.67

Below are highlights of various leading disruptions per company layout. This is also presented graphically in Figure 19.

Table 6: Various Leading Disruption Types per Company Layout

Leading Disruptive Factors’ per Industry					
Process	Production Line		Product Layout		Fixed-Position
Outage of IT	Shift Change-Over	Stock-outs	Stock-Outs	Transport Networks	Adverse Weather
0.944	0.959	0.752	0.742	0.322	0.543
0.341	0.462	0.354	0.235	0.347	0.995
0.529	0.509	0.280	0.521	0.152	0.139
0.897	0.916	0.599	0.438	0.094	0.793

As can be seen from table 5, machine breakdown is a leading source of disruption occupying 28% of the total disruptions (*calculated as a ratio of specific disruption index and the total disruption index*), followed by raw materials shortage at 22%, then employee absenteeism by 21%. In this case, overall production performances dropped massively by 29% due to random disruptions.

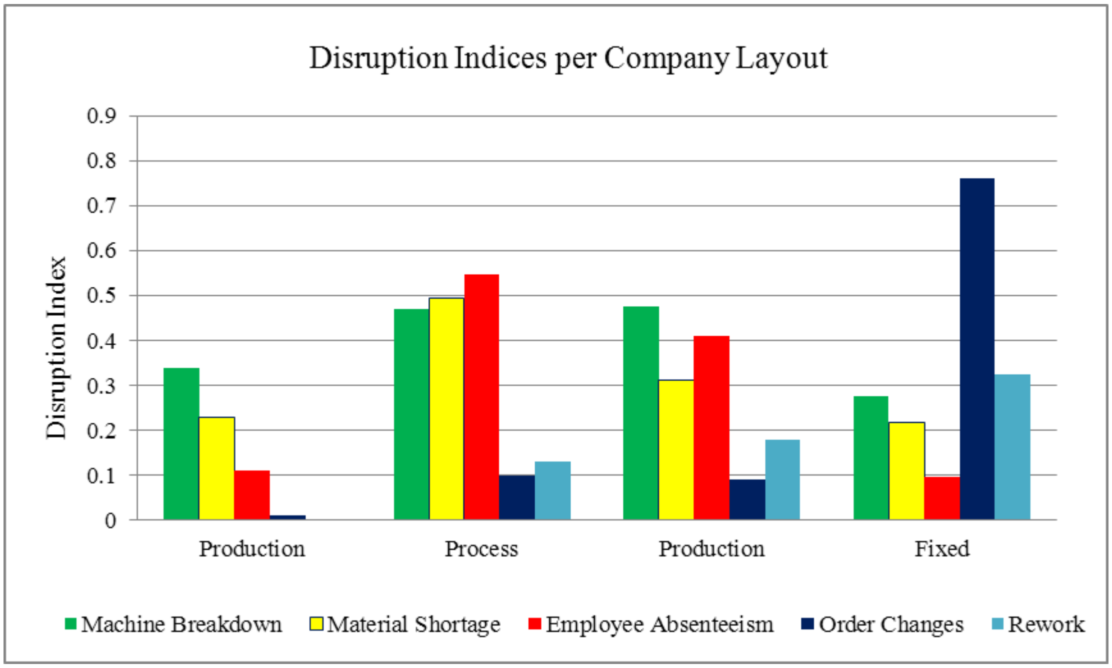


Figure 19: Disruptions Indices per Company-Layout

3.5.2. Production Performance: Strike

A research was conducted to assess impacts of disruption on the production system. Total operating time per day derived from the summation of actual processing times and transportation or material handling times is given as:

$$\text{Operating time per day} = \sum(\text{actual processing times}) + \sum(\text{transportation times}) \tag{3.26}$$

$$\text{Output rate} = \frac{\text{Operating time per day}}{\text{Cycle time}} \tag{3.27}$$

From the above expression, it follows that cycle time can be calculated as follows:

$$\text{Cycle time} = \frac{\text{Operating time per day}}{\text{Output rate}} \tag{3.28}$$

The numbers in Table 7 depicts production performances for a manufacturing company for two states, namely; 1) under ideal conditions, and 2) with random disruption parameters. Productivity for ideal state is primarily calculated with an assumption of a perfect system to enable us to measure how systems responded under stochastic states. The actual performances for the first four weeks (Week 24 to 27) prior to industrial action (i.e. strikes which are most common in manufacturing industries) were recorded, followed by substandard performances for the last two weeks (recorded during the strike period).

Table 7: Production Throughput per Week

Week #	Actual State	Actual
Week 24	Ideal	78
Week 25	Ideal	85
Week 26	Ideal	88
Week 27	Ideal	98
Week 28	Disrupted	13
Week 29	Disrupted	25

Production rates per week for both ideal and stochastic states were calculated as the ratio between total actual production and the number of days worked given by:

$$\text{Production Rate}_{\,Ideal\ State\ \&/or Disrupted State} = \frac{\text{Total Production}}{\text{Number of weeks}}\ (\text{units/week}) \tag{3.29}$$

Results are as follows: weekly performance $_{\text{ideal state}}$= 87 units per week, and weekly performance $_{\text{disrupted}}$= 19 units per week. It follows that a company lost 68 units per week, which is about 78% of the average planned throughput per week as compared to the ideal state. It is apparent from this results that the presence of unplanned disruptions has negative impacts on the performance and organizational profitability.

At this stage, it was imperative to calculate the aggregate efficiency of the production line. The highest production rate was used to represent an optimal (or ideal) production rate (as in Table 9) of the entire line and is used to: 1) determine an optimal or near-optimal target for the shop, and 2) to analyze various impacts of disruptions per given time.

Table 8: Monthly Actual Performances

Month	Reject Reason	(A) Values Sum of Actual	(B) Sum of Rejects	(C) Potential Actual Production
Jan		987	2	989
Feb		1261	9	1270
Mar[2]		1483	16	1499
Apr		902	6	908
May		1274	7	1281
Jun		1264	4	1268
Jul[3]		611	2	611
Aug		1081	4	1085
Grand Total		**8863**	**48**	

Production rate under ideal state equates to 1499 units (optimal production output) per month.

Table 9: Production Rates

Month	Values Sum of Actual	Sum of Rejects	Potential Actual Production	Potential Lost Production	Disruption factors Rejects	Strike	Aggregate Impact of disruption
Jan	987	2	989	510	0.20%	-	34.02%
Feb	1261	9	1270	229	0.71%	-	15.28%
Mar	1483	16	1499	0	1.07%	-	0.00%
Apr	902	6	908	591	0.66%	-	39.43%
May	1274	7	1281	218	0.55%	-	14.54%
Jun	1264	4	1268	231	0.32%	-	15.41%
Jul	609	2	**611**	888	0.20%	53.24%	59.24%
Aug	1081	4	1085	414	0.37%	-	27.62%
Grand Total	8861	50	48				

Production performance during strike period (2 weeks) = 0. This plant is fitted with complex, state-of-the-art equipment, which can only be operated by trained operators. This further accentuate that the plant has not implemented lean principles, i.e. where each machine in the plant should have a user manual or standard operating procedures on how to operate it.

[2] Highest possible production quantity per month: a figure is used as a baseline to determine various impact of sdisruptions
[3] Worst performance (disrupting factors are further analyzed).

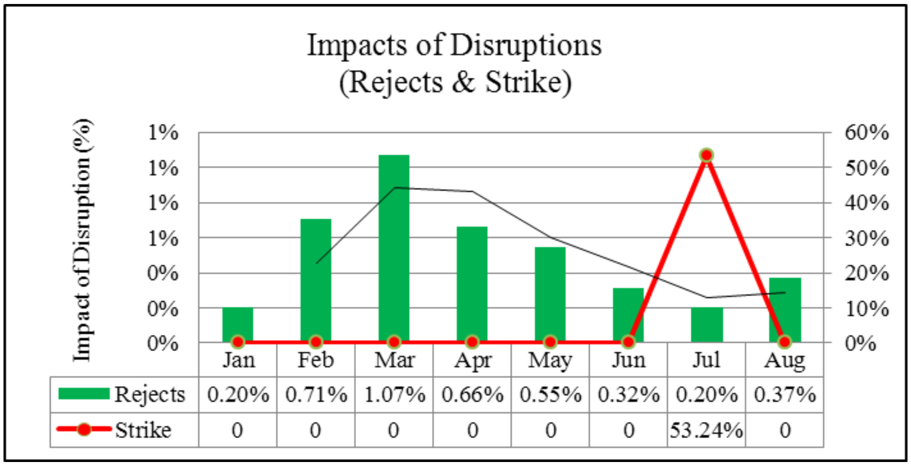


Figure 20: Impacts of disruptions per month

Weekly performance under ideal state = 375 units per week (1499 per month). As a result of this disruption under consideration, a company lost production for 375 units per week. Impact of disruption as a result of the strike is at extreme. It is apparent from below graphical depiction that South African economic system and other countries are losing their well-deserved share due to random disruptions. Global economic growth is solely based on how companies of the world respond, manage and control this unforeseen disruption. It is equally a disturbing issue in supply chain value systems.

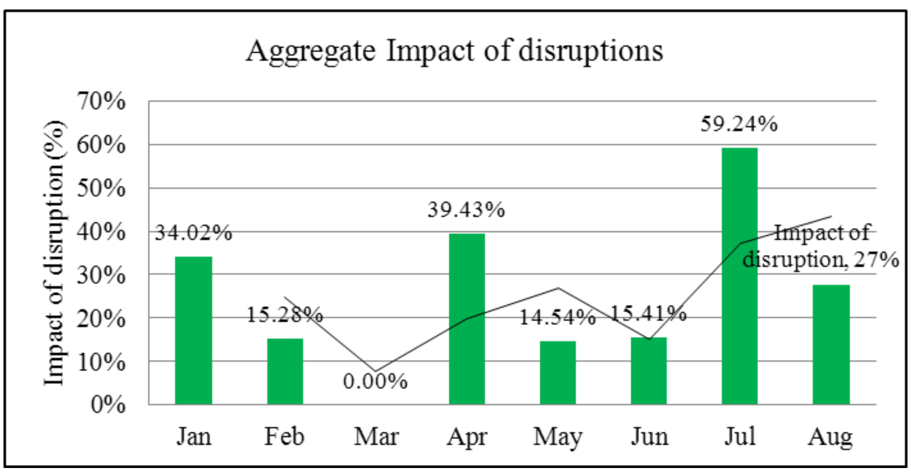


Figure 21: Aggregate Impact of disruptions per month

It was also observed that disruptions experienced mainly on the night shift have a major cost impact than the same disruption encountered during the day when additional support staff and management were available for instantaneous problems solving.

Chapter 4

SUMMARISED DISCUSSIONS

In this study, various methodologies were employed to address production-scheduling problems. In what follows, the respective findings and results are discussed, i.e. a unified model which is a core focus in this study, followed by discussions on company layouts, supply chain value systems and Bernoulli's theory. The conclusion, comprehensive guide to schedulers and future endeavours are presented in the next chapter. Since disruptions cannot be quantitatively measured, this present study focused on the impacts as a driving tool for managing disruptions.

4.1. UNIFIED MODEL

In this study, several disruptive factors were unified into a unified model by the application of the tool of multifactor productivity. Because disruptions occur randomly, the tools of stochastic have been applied to predict the impact of disruptions. To optimise the response to disruption (i.e. to propose an optimal reschedule following random disruption), the knowledge of line balancing was employed.

Results indicate that the amount of resources needed after disruption depends on the nature of disruption. It can further be concluded that due to the disruption, the scheduler should plan for "increasing" number of facilities, following a trend that is only predicted by the nature of disruptions and its associated impact. For companies operating shifts, disruptions experienced mainly during night shift have more impact than the same disruptions encountered during the day when additional support staff and management are available for instantaneous problems solving.

4.2. COMPANY-LAYOUTS

In this section, problems of dynamic situations under different types of company layouts are discussed below.

- **Production-line department,** machine breakdown proves to have a major impact on productivity. This is because a machine that has broken down tends to stop flow of products along the line. Though sometimes, managers recommend the use of storage buffers between production line machines, such introduction of workstation has its cost implication that tend to reduce the (multifactor) productivity.
- With **process layout**, setups are more frequent, hence higher setup costs. The span of supervision is small due to job complexities (routing, setups, etc. Since there are multiple machines available, process layouts are not particularly vulnerable to frequent equipment failures like other company layouts. But machine failure was not seen to have drastic impact on the productivity since other machines were always available to process the job that was meant for the machine that is down.
- **Product-family layout**: Labour specialization results in reduced training time and cost. A wider span of supervision also reduces labour costs and probable reworks or rejects. Unlike other company layouts, raw materials shortage is not a problem with this layout.
- For many **fixed-position layouts**, it is shown that as a result of disruption, the work area may be crowded so that little storage space is available which causes material handling problems (i.e. forklifts congestion) and difficult coordination. These may cause poor utilization transport facilities leading to high costs. This is because most materials are big and not easy to transport, thus, only special transports are hired that are not put to use, hence escalated production costs. It was also found that severe weather conditions have severe impacts on the company's productivity.

It is shown that disruption of one type may not greatly affect productivity of a certain company layout, whilst similar disruptions can have devastating effects on another type. It is further concluded that the impacts of disruption are dependent on the company layouts. The results reveal that an impact disruption due to "severe weather" for example is worse for a fixed company layout than other company layouts.

It is also shown that effects of order changes on productivity depend on how far down the production line an order is. The study shows that disruptions occurring towards the end of the production cycle are likely to cause complete line stoppages (as parts being processed will be withdrawn from the system) at least as compared to disruptions occurring at the beginning of the production process.

In the flow line production layout, it was found that failure might cause damage or not. In the case where failures occur due to disruption, the productivity decreases significantly as compared to the case where damage may not occur.

4.3. SUPPLY CHAIN DISRUPTIONS

It is shown that leading sources of disruptions may vary from industry to industry; i.e. for financial service industries and call-centers, unplanned outage of IT, telecom systems and unanswered calls are the most common causes of disruptions. In service industries like hospitals, shortage of medication and shift changeovers are recorded as the most common causes of disruption. In manufacturing industries, machine breakdowns, raw material shortages and employee absenteeism are the frequent causes of disruptions. For retail and wholesale, IT and communications; adverse weather, transport networks and storage are the most common causes of disruption. Supply chain disruptions are identified as the primary causes of productivity losses. Productivity is inversely proportional to supply chain disruptions, i.e. an increase in supply chain disruptions yield loss in productivity. Any company layout experiencing worsening degrees of distress and disruptions, loss of productivity proved to be greater. Disruptions increase supply chain costs which negatively affect countries' economic systems. It is proved that SA economic system is losing close to R5.7 trillion due to these random disruptions.

4.4. BERNOULLI'S THEOREM

A good starting point in process or system improvements is understanding dynamics associated with the system itself. With Bernoulli's theory, it is proven that as pressure of different forms increases the product cycle times also decreases. Thus, the physical cause of high pressure may be machine deterioration or degradation or disruption. When pressure was interpreted as the need to perform jobs as instructed by managers in the presence of the managers, the use of Bernoulli's equation in this study shows that the lower the pressure, the slower the rate of flow, and the faster the rate of flow; the higher the pressure. When job flows through a small cross section, it gains velocity and kinetic energy. To conserve total energy it must lose pressure according to Bernoulli principle, which is not the case with production situation. Thus, Bernoulli's law is sufficient to explain measures for production planning and control and aid in solving bottleneck situations.

Bernoulli principle in physical production setting can be re-established for managerial pressure as follows: where the velocity of a job is high, the pressure is also high and where the velocity is low (subject to random disruptions), the pressure is also low. As jobs move from a wider (incapacitated) resource to a narrower (capacitated) one, the volume of that job moves a given distance in a given time period does not change (constant). But since the width of the narrow resource is smaller, the job must move faster in order to achieve the results. This principle can be related to theory of constraints and organizational nightmare "bottleneck operations".

Given the criticality of bottleneck operation management and control as given in Bernoulli's expression, system capacity can be increased by considering additional resources to the bottleneck station. By doing this, bottleneck operation is balanced with less utilized stations downstream. Customer demand should in essence drive or determine the production rates. With this in mind, companies should produce only when the products are required to avoid many more complications and unnecessary costs, i.e. rusted components that end up being scrapped, etc.

Chapter 5

CONCLUSION, RESCHEDULING GUIDE AND FURTHER STUDY

Under this section, the conclusion is made, directions for future study are explained and a comprehensive guide to schedulers is presented: what process controllers or schedulers should do following occurrence of random disruptions. The objective is centered on the fact that schedules' deviation should be controlled such that company's performances, in terms of its revenue and other important measurable or parameters, are not notably affected.

5.1. CONCLUSION

In this study several disruptive factors were unified into a single model to solve scheduling problems after disruptions using stochastic theory and multifactor productivity. The theory of line balancing was employed to project the optimal amount of resources required following disruption. Results indicate that the amount of resources needed after disruption depends on the nature of disruption. It can further be concluded that due to the disruption types considered, the scheduler should plan for "increasing" number of facilities, following a trend that is only predicted the nature of disruptions.

With company layouts, it is shown that similar disruption affects company layouts differently, i.e. disruption of one type may not greatly affect productivity of a certain company layout, whilst similar disruptions can have devastating effects on another type. It is shown that leading sources of disruptions may vary from industry to industry; i.e. for financial service industries and call-centres, unplanned outage of IT, telecom systems and unanswered calls are the most common causes of disruptions.

In the flow line production layout, it was found that failure might cause damage or not. In the case where failure occur due to disruption, the productivity decrease significantly as compared to the case where damage may not occur.

When pressure was interpreted as the demand, it was found in agreement with Bernoulli's principle that an increase in pressure brings about a reduction in production velocity. When pressure was interpreted as the presence of managers, it was found by employing the theory of Bernoulli that contrary to the Bernoulli's principle that in production setting where the velocity of a job is high, the pressure is also high, and where the velocity is low (subject to random disruptions, i.e. absence of managers), the pressure is also low. Thus, Bernoulli's law is sufficient to explain measures for production planning and control and aid in solving bottleneck situations. This principle was related to the theory of constraints and "bottleneck operations". Given the criticality of bottleneck operation as given in Bernoulli's expression, system capacity was increased by considering additional resources to the bottleneck station. By doing this, bottleneck operation is balanced with less utilized stations downstream. Customer demand should in essence drive or determine the production rates. With this in mind, companies should always produce only when the products are required to avoid complications and unnecessary costs, i.e. rusted components that end up being scrapped, etc.

5.2. RESCHEDULING GUIDE

It is proven that if disruptions were to occur continuously with time, without being effectively controlled or managed, then productivity will decrease as time goes on (for more refer to figure 10). Below are some guidelines that schedulers should use when random disruptions occur in manufacturing systems. Among other objectives, these guidelines answer the questions raised earlier in the paper, namely; "*when to reschedule"* and *"how to reschedule*"?

5.2.1. Rescheduling (operational level)

The impacts or intensity of random disruptions varies per company layout. In case of any random disruptions, the first decision when it comes to rescheduling should be based on the length of disruption, i.e. how long disruptions affect the smooth flow of products. If the length is short that the schedule is not affected appreciably, the decision may be to continue without making the changes. If, of the other hand, a disruption affect schedule drastically, alternative algorithms are executed with an objective of modifying the schedule in a way that minimizes the effect of disruptions by following logic presented in section 3.4 (figure 15 & 16).

Parallel to the logic presented above, schedulers should also understand the intensity of the disruption and timings of respective scheduling decisions. Projected amount of deviation should be determined, and if the total difference in completion times between the planned and actual schedule exceeds some (or set) threshold value, then rescheduling is considered and not if otherwise. This proposed concept is discussed in section 3.4.

5.2.2. Rescheduling (strategic planning)

At the managerial level, Bernoulli's theorem should be employed to intensely explore the behaviour of materials passing through an imbalanced production system at various production phases. It is only applicable where customer demand is higher than production capacity with bottleneck operations. The effects of production velocity should be determined. Parallel to this, TOC principles is equally employed to further understand the dynamics associated with production delays caused by bottleneck operations. Various models as discussed above (chapter 3) should be used to determine the incapacitated operations and respective additional workstations required to balance the production line through line balancing principles. By using this multi-phased approach, workload is then levelled throughout the production line.

Before actual rescheduling can be carried out, schedulers should try and project outcomes of the impact of disruptions. This should advice schedulers on the number of the additional amount of resources needed to counter the disruption. Due to the disruption types considered, the scheduler should plan for "increasing" number of facilities, following a trend that is only predicted by the nature of disruptions.

Furthermore, it is shown that another way of determining impacts of disruptions is through reliability function. The probability of failure is expressed as a function of time. Mathematical constructs presented in section 3.2 should be employed during rescheduling activities to add to knowledge the probable impacts of disruptions under varying system configuration, namely;

system in series, parallel and combination of both. The relationship between reliability and failure is given as (section 3.2).

5.3. FUTURE ENDEAVOURS

While making use of the time evolutions of the input function due to various kinds of disruptive factors to be used in the multifactor productivity analysis (figure 9), other "natures" of disruptions were not considered such as cases where raw material gets depleted, resources taken away from the factory, constant input, etc. A model that considers all the various natures of disruptions as given in expression 3.7 (i.e. neither of the a_i, b_i, c_i are not equal to zero) might reveal interesting results. This future unified model should not be misinterpreted with the unification model dealt with in this report where it was assumed that all the disruption types fall under a single nature of disruption. In the single model considered in this report, all forms of disruptions bring about a reduction in the input variables.

Research on sensitivity analysis has just emerged in the area of production scheduling. Efforts to seek answers to the various types of ‘‘what if ...’’ questions in a manufacturing systems setting still need to be initiated, and would offer useful information to production planning and control management field.

Vehicle and driver scheduling in public transportation systems in South Africa are complex and interconnected problems requiring extensive knowledge of transit operations. This issue is further complicated when disruption such as traffic congestion is likely to occur. The problems should be solved iteratively or simultaneously, because finding independent solutions to each does not necessarily guarantee a cohesive solution for the transport system as a whole. It is a global problem, and literature survey show no records associated with this kind of research. It will be very interesting to research on the dynamics associated with this problem.

Online approach accommodates considerable flexibility in the schedule to compensate for unforeseen system disturbances but lacks the global perspective provided by an offline approach. Therefore, analyzing both approaches' strengths and weaknesses and identifying the circumstances under which one performs better than the other should be an interesting problem for the future research community. From literature surveys and investigations, it has been proved that offline scheduling is superior to online scheduling in a static and deterministic environment. However, a further analysis of offline scheduling and online scheduling methods is needed in a dynamic and stochastic environment. It is recommended that future researchers should focus or deal with this issue in more detail.

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