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Development of a Capacity Deployment Model for Disrupted Supply Chain Networks

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DEVELOPMENT OF A CAPACITY DEPLOYMENT MODEL
FOR DISRUPTED SUPPLY CHAIN NETWORKS

by

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The increasing complexity of modern supply chains is widely accepted as one of the many drivers of risk that can leave organizations vulnerable to the effects of a disruption. This acceptance has contributed to an emerging interest in Supply Chain Resilience in the literature. Resilient supply chains are able to both resist the effects of a disruption and recover efficiently if the disruption is severe. This new body of literature is still in a formative phase and has thus far focused on defining Supply Chain Resilience, proposing frameworks for its implementation, exploring factors that contribute to resilience, and investigating methods to design resilient supply chains. Among the most accepted factors of resilience is redundancy, which refers to the auxiliary resources and capacity of a supply chain that can be called upon during a disruption. Furthermore, the ability of managers to efficiently navigate the recovery process is believed to be central to overall resilience. Unfortunately, relatively few studies have sought to align the tools and methods of recovery with the findings from the broader Supply Chain Resilience literature. This research aims to narrow this gap by developing and validating a mathematical supply chain network model that integrates the known resilience construct of redundancy into its formulation in a flexible manner to support managerial decision-making at the beginning of a disruption.

The value of the model stems from its efficiency in deploying redundant capacity throughout a supply chain to minimize the impact of a disruption and from its ability to provide sensitivity information relating to that deployment. The deterministic formulation incorporates common supply chain structures from contemporary literature. Numerical studies were performed to examine the behavior of simulated networks under disruption and to assess the ability of the model to achieve the desired objectives. The findings of this research support the proposition that the model is able to efficiently distribute capacity throughout a supply chain to support a recovery effort. The provision of sensitivity analysis relating to incremental capacity deployment decisions is able to provide insights for managers who are responsible for balancing the trade-offs between demand and costs during a disruption.

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The completion of this dissertation marks the end of a season. As seasons change it is good to reflect so that we may understand our journey and show gratitude to those who have walked with us along the way. Upon reflection, I realize that there are many who have contributed to this work and deserve acknowledgement in this short space. I will do my best.

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James D. Burns

TABLE OF CONTENTS

Table of Contents - Continued

Table of Contents - Continued

Table of Contents - Continued

CHAPTER

LIST OF TABLES

LIST OF FIGURES

List of Figures - Continued

List of Figures - Continued

CHAPTER I

INTRODUCTION

Historical Background of the Problem

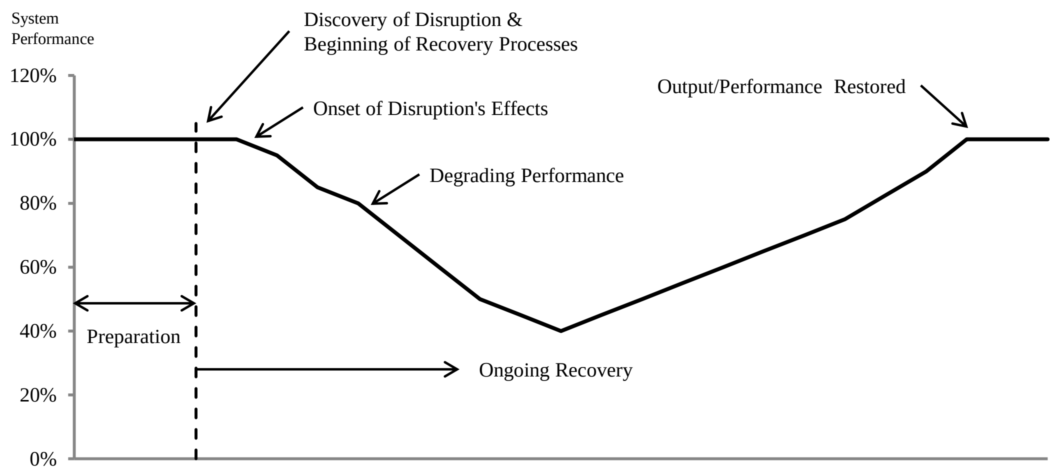
Researchers and business leaders agree that complexity within modern supply chains is increasing and that this increased complexity is a primary driver of supply chain risk (Christopher & Peck, 2004). The consensus on increasing complexity along with several high-profile disaster events, such as the 2011 Japanese tsunami, Hurricane Katrina, and the September 11th terrorist attacks, has helped to spur on an acceleration of research activity in the area of Supply Chain Risk Management (SCRM). Although SCRM is an evolving discipline in its own right (Ghadge, Dani, & Kalawsky, 2012), there is agreement that certain topics within the SCRM research area deserve special focus. Among them is the development of methods that will improve resistance to, and recovery from, supply chain disruptions (Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007; Hu, Li, & Holloway, 2013; Macdonald & Corsi, 2013). In the literature, a supply chain that is able to recover effectively from a disruption and quickly return to normal functions is known as a Resilient Supply Chain (Christopher & Peck, 2004), and the ideas of preparation, resistance to disruption, and recovery are at the heart of the emerging Supply Chain Resilience research stream.

Disruptive Events

A supply chain is a network of organizations that are connected by the physical flow of materials with the goal of meeting customer needs for a product or service within a specified time period (Craighead et al., 2007). Supply chains themselves have become increasingly exposed to risks from several different areas. Globalization has caused modern supply chains to lengthen, exposing them to social and economic turmoil abroad. Lean production systems, which are a hallmark of modern supply chains and can be highly efficient, contribute to volatility and risk by focusing on the reduction of inventory (Ghadge, Dani, & Kalawsky, 2012; Pettit, Fiksel, & Croxton, 2010; Sheffi & Rice Jr., 2005), which is a known buffer against disruptions. Additionally, the shortened product life cycles that have accompanied rapid changes in technology leave managers with little margin for error when facing a disruption. These risks often manifest themselves as disruptions through natural disasters, extreme weather events, and supply and demand fluctuations. Guarding against these disruptions is central to risk management. Unfortunately, some disruptive events, such as a terrorist attack, may require an entirely new and previously unconsidered operating paradigm for an organization. Other disruptions may originate from known sources of risk but feature a new means of exposure. For instance, a lightning strike in the year 2000 at a key supplier in Albuquerque, New Mexico resulted in a major disruption for Ericsson's mobile phone business. The fire that ensued led to a $400 million loss for Ericsson that year and reportedly influenced the firm's decision to leave the mobile phone market entirely (Norrman & Jansson, 2004). Presumably the firm, which was headquartered in Sweden, did not account for the possibility that a single lighting strike in the United States could have such a devastating impact. Their supply chain was exposed, unprepared, and in retrospect did not manage the disruption well. Ericsson's competitor Nokia, who was also affected by the

disruption, by all accounts managed the event more successfully, and the effects were much less devastating.

A basic definition of a supply chain disruption is any unplanned event or action that degrades performance or interrupts the normal flow of goods (Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007). In this regard, the a supply chain disruption can originate at the operational level of a single organization in a supply chain, or from an industry- level event. Disruptions are often characterized by increased costs, and in some cases the knowledge of the impacts and timing of a disruption may be known about in advance. An example of this would be when a firm realizes that a planned maintenance activity originally scheduled to occur in six months must be done within the next month. The firm understands the impacts and has advanced warning, but the event itself is still unexpected and is therefore a disruption. Other times a disruption may not be discovered until well after the triggering event has taken place, such as when a previously undiscovered quality defect is found by a customer, leading to a product recall. The time prior to a disruption occurring (or being discovered) has been described as the preparation phase (Sheffi & Rice Jr., 2005), which is the time where risk planning activities take place. Once a disruption occurs, preparation becomes action, and the recovery phase begins. Although there are varying perspectives on what might signal the actual beginning and end of a recovery, it can best be described as beginning once a disruption is discovered and continuing on until steady-state planning activities resume. The end of the recover process may also depend on the circumstances surrounding the disruption, the characteristics of the supply chain, and the perspective of those managing the recovery process. In other words, recovery is not necessarily when output is restored to normal. Figure 1 provides a graphical representation of the phases of a supply chain disruption as described above.



Adapted from (Sheffi & Rice Jr., 2005)

Figure 1: Conceptual Disruption Profile

A supply chain at risk of disruption can be thought of as one that is vulnerable to some event which may originate from either an anticipated or unanticipated source. To reduce vulnerability organizations engage in risk management activities either to mitigate negative impacts if the event occurs or to reduce the likelihoods of disruptive events occurring. Because the scope of potential disruptive events is practically boundless, researchers have worked to classify events broadly rather than to enumerate them. Terms such as *natural*, *man-made*, *intentional*, *accidental*, *external*, and *internal* have been used to describe disruptive events in the literature (Macdonald & Corsi, 2013). Using Macdonald and Corsi's classifiers, the fire caused by lightning at Ericsson's supplier in Albuquerque can be described as a *natural*, *internal* event. Conversely, a labor dispute at an international shipping port that causes ripples to propagate through the global transportation system may affect deliveries around the globe. To a firm that does not engage in shipping goods internationally this would be considered a *man-made*, *external* event. However, it is

generally accepted that absolute prevention of all disruptions is impossible, and even with predictable risks there is usually some degree of uncertainty related to the probability of its occurrence (Sheffi & Rice Jr., 2005). There is also uncertainty as to what appropriate responses for any given disruption might be, so even the best mitigation plans will be unable to fully control potential negative impacts.

The impact of a disruptive event is usually measured in terms of direct and indirect financial costs, but can also extend to the loss of goodwill or lost opportunities (Table 1). Because the significance of financial and service-related impacts is highly dependent on the industry, size of the firm, and organizational context, disruptions are normally broadly classified in the literature according to their consequences (*light* or *severe*) (Sheffi & Rice Jr., 2005) and duration (*short or long*) (Macdonald & Corsi, 2013). Unfortunately, just as it is difficult to ascribe significance to objectively quantified financial costs, it is also difficult to interpret the meaning of other types of objective measures for severity or duration. Nevertheless, there is agreement in the literature that these measures are currently the most appropriate to quantify the impact of a disruption. Extending this idea to the notion of Supply Chain Resilience, the severity and the length of time until the supply chain recovers from a

Table 1: Impacts of Disruptive Events

Criteria	Description
Financial	The monetary cost associated with the disruption. Includes lost sales and cost associated with response and recovery.
Service	Non-financial costs associated with failing to meet customer demand.
Duration	Length of time a supply chain's performance is degraded.

disruption are also two of the best measures of resilience (Macdonald & Corsi, 2013).

Resilience and Recovery

Although Supply Chain Resilience is a relatively new area of study within the larger scope of SCRM (Ponomarov & Holcomb, 2009), there is already general agreement regarding its conceptual nature in the literature. Several definitions have been put forth in the literature, and in spite of a few subtle differences they all reflect the basic definition of resilience, which is an ability to recover from or adjust easily to misfortune or change (Resilience [Def. 2], n.d.). The following definition authored by Ponomarov and Holcomb (2004) using a multi-discipline perspective is perhaps the most useful for understanding the essence of Supply Chain Resilience:

> The adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function.

However, the agreement on the conceptual definition of resilience has not yet produced a full understanding as to what actions organizations may take to develop resilience in their supply chains. Recent studies investigating the antecedents of resilient supply chains (Scholten, Sharkey, & Fynes, 2014) outlined a resilience framework as a cyclical four-phase process: preparation, immediate response, recovery, and mitigation. Preparation describes the steps taken prior to a disruptive event, and in layman's terms can be described as the risk analysis, response plan development, and risk-avoidance phase. The immediate response is an organization's reaction to a disruption from a managerial perspective, including

operationalizing contingency plans made during the preparation phase. Recovery and mitigation phases include both returning the system to a normal state and taking steps to improve risk-avoidance plans. At this time, the preparation phase begins again. Like many frameworks, this description is useful for conceptualizing Supply Chain Resilience as a high-level process, but more operational guidance is needed.

Researchers have also identified a host of organizational capabilities that are thought to contribute to resilience. The three ideas shown in Table 2 stand out among the most prominent in the literature: having and making use of redundant capacity, possessing a comprehensive knowledge of the structures of a supply chain, and flexibility (Pettit, Fiksel, & Croxton, 2010) (Ponomarov & Holcomb, 2009) (Ponis & Koronis, 2012) (Christopher & Peck, 2004) (Blackhurst, Dunn, & Craighead, 2011). The first of these ideas, redundancy, refers to reserve inventory, spare assets, or underutilized assets that may be deployed to buffer the effects of disruptions (Hu, Li, & Holloway, 2013). Because redundancy is usually associated with increased costs, its presence within a supply chain is seen as a negative by managers and modern production theories. Structural knowledge refers to the level of understanding an organization has regarding the physical supply chain, and some authors include in it the level of information managers have regarding the status of the individual

Table 2: Selected Supply Chain Resilience Factors

Factor	Description
Redundancy	Extra capacity or inventory above minimum required (e.g., safety stock).
Structural Knowledge	Awareness of the physical and informational structures of a supply chain.
Flexibility	Ability to respond and change quickly.

components (Ponomarov & Holcomb, 2009). In this way, structural knowledge is closely associated with another conceptual factor, supply chain visibility, which is an understanding of the current state of a supply chain. The terms are frequently used together in the literature. The third prominent idea in the Supply Chain Resilience literature, flexibility, often refers to the ability to quickly adapt to changes taking place both inside and outside of the supply chain (Ponomarov & Holcomb, 2009) (Pettit, Fiksel, & Croxton, 2010) (Scholten, Sharkey, & Fynes, 2014). Like structural knowledge, flexibility is difficult to objectively quantify. Conversely, redundancy offers organizations a means to objectively measure a resilience factor (e.g., utilization of equipment). In the context of Supply Chain Resilience, flexibility is frequently discussed alongside the notion of agility, which has been described as an outcome of a flexible supply chain (Scholten, Sharkey, & Fynes, 2014).

Resilience requires organizations to accept the inevitability of disruptions and the fact that no amount of planning will fully insulate a supply chain from either the direct or indirect effects of disruptive events. In other words, absolute prevention of a disruption is not possible. This leaves supply chain managers with two basic strategies: investing time and resources in activities to avoid disruptions when possible, and preparing to respond effectively when disruptions do occur. The first method is of course preferred and involves pre-disruption mitigation to reduce the probability of a disruption through effective design and risk-avoidance. Effective response strategies complement efforts to prevent disruptions by enhancing the ability to recover in a quick and controlled manner. Unfortunately, research addressing recovery from a mathematical supply chain modeling perspective is fragmented, incomplete, and not yet fully aligned with management literature. The aim of this dissertation is to help bridge the gap between factors that are known to support Supply Chain Resilience and mathematical techniques that will aid managers in developing and executing

operational recovery plans.

Research

The primary focus of this research is the development and validation of a mathematical model that assists managers in designing disruption recovery strategies by offering the ability to model a wide range of supply chain configurations and by providing information related to trade-offs in resource allocations. As illustrated in the previous section, there are two basic research streams of literature that relate to Supply Chain Resilience. The first stream is found in management literature and is comprised of investigations that employ retrospective techniques such as interviews and surveys. These research efforts seek to qualitatively develop and test conceptual constructs of Supply Chain Resilience. As with definitions of Supply Chain Resilience, the findings of the studies that comprise this research stream are generally aligned and are discussed in Chapter II. The second stream of research relates to the use of mathematical models in assessing Supply Chain Resilience relative to objective criteria such as operational costs, lost demand or recovery time. This literature can be further divided into research related either to models that inform on the design of a supply chain relative to its ability to recover from a disruption, or to models that control the operation of a supply chain during a disruption. Because mathematical models focusing on designing a supply chain are of little practical value during a disruption, their usefulness in this research is limited. However, models focused on controlling the flow of goods through a supply chain are quite relevant, because they are tactical in nature and can directly affect resilience by mitigating the impact of a disruption. Unfortunately, these recovery models are often constructed according to narrowly defined supply chain or production system configurations and do not provide managers with

information related to trade-offs in resource allocation decisions.

The most recent resilience frameworks in the literature define factors outlining strategic business processes that are thought to lead to effective planning and recovery (Scholten, Sharkey, & Fynes, 2014). There is, however, little guidance related to the application of these frameworks at the tactical or operational level. The research that is available, which proposes tactical or operational guidance for recovery strategies, has yet to be validated or applied broadly by supply chain managers (Hishamuddin, Sarker, & Essam, 2012) (Hu, Li, & Holloway, 2013) (Schmitt, 2011). Because Supply Chain Resilience is a relatively new area of study, this type of validation might not be available for many years. It is reasonable that research into methods that simplify the application of resilience frameworks might help to validate their appropriateness. This notion is supported in the literature through assertions that developing a solid base of research to better understand the relationships between resilience factors should be a near-term objective (Macdonald & Corsi, 2013). The mathematical model developed and validated in this dissertation contributes to the larger body of research through a modeling approach that links resilience factors with the needs of managers during the disruption recovery process.

Objectives

This research investigated how incorporating the Supply Chain Resilience factor of Redundancy into a mathematical supply chain modeling formulation might be useful in improving the ability of supply chains to recover from a disruption. One objective of the research were to develop and validate a supply chain modeling approach based on a linear network flow formulation that efficiently deploys redundant capacity to a disrupted supply

chain. A second objective was to leverage the ability of linear programming formulations to provide sensitivity information regarding capacity deployment to establish a method that guides supply chain managers in the selection the best sources of redundant capacity.

These objectives were based on a proposition that *structural knowledge* of *redundancies* within the supply chain, when properly considered, can improve *flexibility* and mitigate the effects of a disruption. The research shows that the sensitivity analysis obtained in solving the model can be useful in identifying the most effective and efficient manner to deploy redundant capacity. Contemporary research suggests that redundant capacity allocation decisions are important in the disruption recovery process, and this research demonstrates that the decisions can be summarized from a managerial perspective by answering the following three questions:

1. Should a source of redundant capacity be utilized?
2. How much of the redundant capacity should be utilized?
3. When should the redundant capacity be deployed?

Importance

The findings of the literature review presented in Chapter II demonstrate the importance of this research, and can be summarized in the following five points:

1. All supply chains are at risk for disruption (Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007).

2. The ability to recover from a disruption is a critical component of resilience (Macdonald & Corsi, 2013) (Hu, Li, & Holloway, 2013) (Pettit, Fiksel, & Croxton,

2010).

3. Redundancy, Structural Knowledge, and Flexibility of the Supply Chain are among the chief factors that contribute to resilience (Christopher & Peck, 2004) (Blackhurst, Dunn, & Craighead, 2011) (Ponis & Koronis, 2012).

4. The coordination of resources and managerial influence prior to and during a disruption is important to managing a disruption (Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007) (Macdonald & Corsi, 2013) (Scholten, Sharkey, & Fynes, 2014).

5. The recovery models found in the literature are not sufficiently able to accommodate redundant capacity decisions in a flexible manner across a variety of supply chain configurations.

Research Questions

To achieve the primary objective of this research, a generalized linear programming model for a supply chain was used to answer the following research questions:

Q1: Can a comprehensive understanding of a supply chain's redundant capacity improve the ability to recover from a disruption?

Q2: Can the timing of a manager's decision to begin utilizing a supply chain's redundant capacity affect its ability to recover from a disruption?

Q3: Can a solution procedure for the generalized linear programming model for a supply chain provide reliable insights into capacity acquisition decisions?

Q4: Can sensitivity information from the model's solution procedure provide reliable insight into locations within the supply chain that would benefit from additional resources or redundant capacity?

Q5: Do the findings in Questions 1-4 differ when applied to an assembly network versus a serial network?

Organization of the Document

This document is organized into six chapters as described below:

Chapter I – Introduction. A brief discussion of the topics that frame the research, and a description of the research objectives.

Chapter II – Literature review. A review of contemporary and relevant historical literature related to the main topic areas, plus a review of relevant mathematical techniques that form the basis of the research methods. Focus areas include:

1. Supply chain disruption and resilience.
2. Current perspectives and needs relating to supply chain recovery.
3. Current mathematical approaches for supply chain recovery.
4. Gaps in the existing research.

Chapter III – A description of the problem and discussion of the methods and procedures used in the research. This chapter includes descriptions of important network structures, and a description of the experimental design.

Chapter IV – Results and analyses.

Chapter V – Case study. Application of the modeling formulation applied in a case study format for a manufacturing organization that is facing a disruption.

Chapter VI – Discussion, implications, and future directions.

CHAPTER II

REVIEW OF LITERATURE

This chapter contains a review and discussion of literature that is relevant to the topic area and to the objectives of the study. The purpose of this review is to frame the research problem in terms of the Supply Chain Risk Management (SCRM) discipline, the concept of Supply Chain Resilience, the needs of organizations, and the efforts thus far to address those needs. This chapter is organized into sections that discuss supply chain disruptions, Supply Chain Resilience, current perspectives on disruption recovery, mathematical approaches to recovery, and gaps identified in the existing research. The objective of this review is to illustrate the need for a mathematical model to assist supply chain managers in recovering disrupted supply chains.

Supply Chain Disruption and Resilience

Disruption

In SCRM literature the assumption is that disruptions are born out of some underlying vulnerability, and the impacts of disruptions have the potential to severely affect a supply chain's function (Ponomarov & Holcomb, 2009). Recovering from a disruptive event is a central theme of resilience, and it follows that understanding the nature of disruptive events is a prerequisite for building resilient supply chains. Because disruptions themselves are nothing more than realized risk, it is possible to classify and characterize them much in the same manner that supply chain risks are classified. Several studies have described

disruptions in terms of three basic characteristics: *Severity*, *Duration*, and *Origin*.

In the literature, a severe disruption has been described in multiple ways. One description states that a severe disruption is one that hampers the ability of the supply chain elements to ship or receive goods (Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007). Another description of a severe disruption is an event that interrupts the flow of goods, thereby exacting a financial penalty or another tangible penalty on the supply chain (Macdonald & Corsi, 2013). The distinction between the two descriptions is that the first does not explicitly cite a financial implication as a component of a disruption. Craighead et al. (2007) postulated that the severity of supply chain disruptions was positively correlated to three design characteristics (Density, Complexity, and Node Criticality). They also believed that the ability to quickly identify and recover from disruptions would mitigate the severity of the disruption, suggesting that the severity of a disruption is related to both the physical design of the supply chain and how it responds to a disruptive event. A subsequent study by Macdonald and Corsi (2013) concluded that the circumstances surrounding the disruptive event can influence how a firm perceives its severity. For instance, they found that a team that was seen as dysfunctional by its supply chain manager resulted in a negative perception of the recovery efforts of the team. Additionally, their findings suggested that the speed at which a disruption was discovered had a moderating effect on the perception of a disruption's severity if its source was external to the firm. Craighead et al. (2007) proposed the same connection of discovery and severity but did not distinguish effects related to the origin of disruption.

Classifying a disruption's duration has proven to be difficult because the literature is relatively silent on whether the classification should refer to the event itself or merely the

impacts on the supply chain. In the case of Ericsson, a ten-minute fire resulted in months of disturbed shipments (Norrman & Jansson, 2004). However, the origins of a disruption are relatively easier to classify, and a number of authors have put forth schemes to do so. As stated before, because disruptions can be thought of as realized risk it is reasonable that their classification descriptors are somewhat similar to those of SCRM. Among these is a useful three-category scheme recounted by Macdonald and Corsi (2013). The three categories are *Internal Man-Made Events*, *External Man-Made Events*, and *Natural Events*. These classifications are similar to those discussed earlier regarding supply chain risk, and the illustrative events mentioned previously are useful here as well. This classification scheme is detailed in Table 3 along with examples.

Resilience

Supply Chain Resilience is a relatively new subset of SCRM research, and so it can be thought of as an emerging concept within an emerging field. Whereas Supply Chain Risk

Table 3: Classifications of Disruptions

Disruption Type	Example 1	Example 2	Example 3
Internal, Man-Made Events	Supplier bankruptcy due to default.	Machine breakdown.	Recall related to quality defect.
External, Man-Made Events	Strike at an international port.	Unexpected change in regulations or laws.	Terrorist attacks.
Natural Events	Earthquake that affects the productive capacity of suppliers in a region.	Lightning strike at an electrical substation.	Flood that closes a major transportation corridor.

Management literature proposes frameworks that center on identifying and quantifying risk factors and then eliminating or reducing likelihood of their occurrence, Supply Chain Resilience presumes that disruptions are unavoidable and is therefore geared toward recovery (Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007). The term Supply Chain Resilience began appearing in the literature early on in the 21st century. This research tended to focus on its definition, proposing frameworks and exploring their underlying constructs, and differentiating it from similar concepts such as Robustness (Christopher & Peck, 2004). Several authors have put forth definitions meant to clarify the underlying ideas, and the four most prominent definitions are shown in Table 4. Ponomarov and Holcomb (2009) presented what is perhaps the most holistic definition by reviewing and comparing existing supply chain research to the fields of Ecology, Social, Psychological, Economic, and Organizational perspectives. Their definition incorporates all phases of a supply chain disruption, and

Table 4: Definitions of Resilience from a Supply Chain Perspective

Author(s)	Definition
Ponomarov and Holcomb (2009)	The adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function.
Christopher and Peck (2004)	The ability of a system to return to its original state or move to a new, more desirable state after being disturbed.
Sheffi and Rice (2005)	The ability to bounce back from a disruption.
Ponis (2012)	The ability to proactively plan and design the Supply Chain network for anticipating unexpected disruptive (negative) events, respond adaptively to disruptions while maintaining control over structure and function and transcending to a post-event robust state of operations, if possible, more favorable than the one prior to the event, thus gaining competitive advantage.

centers on the idea of control. The definition also implies purposeful action on the part of the supply chain managers. Christopher and Peck (2004) also put forth a definition that is frequently cited in contemporary literature. Their more concise definition also implies purposefulness with a reference to establishing an improved state after recovery. Because resilience has been previously defined in other contexts, much of the current Supply Chain Resilience research centers on themes that recur in other disciplines.

Supply Chain Resilience is also closely related to the idea of disaster or emergency management, and although one is not clearly a subset of the other in the literature there is some overlap in terminology. Disaster management, the more mature discipline, is concerned with the resilience of networks that serve communities and is characterized by highly proactive planning processes. Supply Chain Resilience is not so narrowly focused in this regard as it concerns itself with both minor and catastrophic disruptions. Scholten et al. (2014) argued that examining the processes of disaster management can provide insight into how general Supply Chain Resilience can be enhanced, and they recommended the proactive establishment of networks and infrastructures prior to a disruption occurring in order to mitigate its impacts (Scholten, Sharkey, & Fynes, 2014). This mirrors many of the findings in Supply Chain Resilience literature, in particular the idea that managers should have a comprehensive structural knowledge of the supply chains they manage.

In addition to clarifying the overall definition of Supply Chain Resilience, a goal of recent literature has been to understand the relationships between supply chain attributes (e.g., Flexibility and Agility) or organizational activities (e.g., risk planning and effective communication) that might affect resilience. Several authors have proposed frameworks based on either conceptual or empirical justification (Blackhurst, Dunn, & Craighead, 2011)

(Pettit, Fiksel, & Croxton, 2010) (Ponis & Koronis, 2012). However, there are few meaningful differences in the central arguments or themes, and the only distinguishing features are the number of factors identified and the arrangement of various elements that comprise the factors. For instance, the framework proposed by Blackhurst et al. (2011) contained three broad elements and thirteen sub elements, whereas Pettit et al. (2010) used sixteen elements, and Ponomarov (2009) discussed seven aspects in the development of a resilience capabilities matrix.

Ponis (2012) uses a literature review to form a framework based on four elements (Agility, Redundancy, Collaboration, and Physical and Informational Structure), arguing that more of an element will improve resilience. In this work, Flexibility was identified as a component of Agility. Similarly, Pettit et al. (2010) identified sixteen resilience capability factors. In their work, the flexibility was comprised of two factors (Flexibility of Sourcing and Flexibility of Production), and the elements that Ponis used to define Physical Structure were distributed between other factors such as Dispersion and Visibility. Collaboration appeared in both works, with no significant differences in its underlying elements. Pettit et al. (2010) also uses seven vulnerability factors which are said to degrade resilience, and they propose that effective Supply Chain Resilience strikes a balance between capabilities and vulnerabilities to avoid eroding profits or becoming overexposed to risk. This mirrors the approach by Blackhurst et al. (2011), which organizes a framework around Resilience Enhancers and Reducers in a 2x2 matrix. They propose that balancing Supply Chain Resilience is achieved by increasing the level of Enhancers and lowering the level of Reducers.

For the purposes of this literature review, these common factors have been condensed

to: *Redundancy*, *Structural Knowledge of the Supply Chain*, *Flexibility*, *Visibility*, and *Risk Management Activities*. Table 5 provides a basic definition of each factor, along with an indication as to whether or not it was explicitly or prominently featured in the foundational works listed. This research proposes that the first two factors listed, Redundancy and Structural Knowledge of the supply chain are both central to recovery from disruptions and related to mathematical models that may be used to formulate improved recovery policies.

Ponomorov and Holcomb (2009) acknowledged that flexibility was a formative element of Supply Chain Resilience, and stated that it was a product of a coherent logistics structure with the ability to respond to disruptions. In this way, flexibility is seen both as a physical characteristic of the supply chain and as a trait that the supply chain exhibits. In

Table 5: Resilience Factors in Literature

Factor/ Element	Description/Definition	Paper Number				
		1	2	3	4	5
Redundancy:	Spare capacity within a supply chain. Includes redundant capital resources and excess capacity or idle time.	X	X	X	X	X
Structural Knowledge:	Understanding of the physical structure of the supply chain and the connections between its elements.	X	X	X	X	X
Flexibility:	Ability to quickly change configuration to adapt to new conditions	X	X	X		X
Visibility:	Awareness of the status of supply chain elements and customer demand.	X	X	X	X	X
Risk Management Activities:	Activities undertaken to identify risks, and work done to prepare for or prevent risks from becoming manifest.	X	X		X	X

Paper Index: [1] (Pettit, Fiksel, & Croxton, 2010), [2] (Ponomarov & Holcomb, 2009), [3] (Ponis & Koronis, 2012), [4] (Blackhurst, Dunn, & Craighead, 2011), [5] (Christopher & Peck, 2004)

“X” Indicates the presence of the factor or element in the research.

their overview of resilience, flexibility and agility were listed as elements of the same construct. Conversely, Ponis (2012) suggested that Flexibility was an antecedent of Agility, and a supply chain must possess flexibility in order to demonstrate agility. Christopher and Peck (2004) saw flexibility as a physical property and an output of effective design and management of redundancies within the supply chain. Pettit et al. (2010) identified flexibility in sourcing and flexibility in order fulfillment as separate resilience capability factors, which are more aligned with physical properties of the supply chain than traits of its function. Stevenson and Spring (2007) stated that flexibility in and of itself is a multi-dimensional construct that has yet to be fully clarified in the larger supply chain literature but that it is a capability that does not have to be demonstrated to exist. It has also been suggested that in addition to improving resilience, flexibility has benefits in the normal course of operations (Sheffi & Rice Jr., 2005). Although there is no empirical method to measure flexibility across supply chains, the literature reviewed suggests that flexibility is not a function of the physical characteristics of the supply chain, but is rather a description of its operation and a trait that can be exhibited.

There is considerable alignment in the literature in regard to redundancy, which can take on many forms. Safety stock, backup capital equipment, reconfigurable equipment, open capacity, multiple suppliers, reserve workforce, and multiple routings are all sources of redundant capacity. Some studies discuss redundancy in general terms, calling it a primary factor or capability of resilience (Pettit, Fiksel, & Croxton, 2010). Others cite the benefits of specific forms of redundancy, such as safety stock, but see it as a less important component of Supply Chain Resilience (Blackhurst, Dunn, & Craighead, 2011). Nevertheless, redundancy is discussed frequently in Supply Chain Resilience literature, and it represents a

paradox for practitioners in terms of Supply Chain Resilience because it imposes an incremental cost on a supply chain (Sheffi & Rice Jr., 2005) and is frequently driven out of the supply chain by modern production theories such as Lean Manufacturing, which often involves highly specialized processes and low levels of inventory.

Structural knowledge of the supply chain and its underlying themes were specifically highlighted in each of the resilience frameworks in the studies reviewed. Some frameworks deemed structural knowledge to be a “fundamental prerequisite” or primary factor of Supply Chain Resilience (Christopher & Peck, 2004). Others described it as an antecedent of resilience but not a primary factor (Ponis & Koronis, 2012). The common theme of structural knowledge of the supply chain can be summarized as an understanding of the physical and informational connection between the individual elements (Choi & Hong, 2002), and an understanding of where pinch points, risks, and critical paths reside within a system (Christopher & Peck, 2004). It is believed that this understanding leads to more effective disruption preparation and mitigation. In their framework, Pettit et al. (2010) placed these elements under the factors of Dispersion, Collaboration, and Adaptability. In their descriptions, Dispersion and Collaboration represent an awareness of both physical and informational structures, while Adaptability is the ability to act in a manner that mitigates the impact of a risk. Blackhurst et al. (2011) characterized the idea of structural knowledge as a monitoring of risks at each node of the supply chain, and as the ability to quickly redesign the physical supply chain. Blackhurst et al. (2011) also discussed structural knowledge in terms of redundancy by highlighting that the location and amount of safety stock in a supply chain was important to improving resilience.

Measuring Resilience

One problem in regard to Supply Chain Resilience is that researchers have yet to develop and validate a method to objectively quantify it across supply chains. Pettit et al. (2010) extended their own earlier work to develop an assessment tool and measurement model based on their sixteen capability factors and seven vulnerability factors (2013). Soni, Jain, and Kumar (2014) developed a deterministic model for measuring Supply Chain Resilience based on an amalgamation of resilience factors found in the literature. Both studies propose fixed scales (0%-100%) that are sufficient for assessment within and across supply chains, but the methods have not been validated through comprehensive empirical studies.

Because the process of recovering from a disruption is central to Supply Chain Resilience, characteristics of the recovery process are often used as a proxy for resilience in the literature. As discussed previously, measurements such as financial impact and duration are only meaningful when placed into the context of a specific supply chain and disruptive event. Those measurements, however, are the primary method for investigating methods to improve resilience and are illustrated in the following section, which discusses supply chain recovery.

Supply Chain Recovery

Although there have been several supply chain and operational recovery models put forth in the literature, there have been few that seek to develop general models for the purpose of recovering from a disruption. Recovery models to date usually center on very

specific operational conditions and assumptions, meaning they are not easily adapted to other configurations. Furthermore, this review has found little evidence in quantitative literature that factors of resilience, beyond spare inventory or production capacity, have been effectively integrated into modeling techniques. This is not necessarily surprising, considering that the study of Supply Chain Resilience is still in its infancy and that new research is continually shaping how academics and practitioners understand resilience. Also, much of the literature related to recovery policy predates recent foundational work in identifying resilience factors. Another problem is that many of the quantitative studies that are specific to a particular type of network design seek to find a long-run mathematical optimum relative to operational costs, which is known to be only one of many components to an effective recovery. This suggests that recovery in a Supply Chain Resilience framework involves more than finding optimal solutions using network modeling.

Macdonald and Corsi (2013) cited the lack of post-disruption research currently available as a problem and suggested that a better understanding of managing recovery processes would be of value. This, along with their findings that the severity of a disruption and its impact on an organization are subject to firm-specific circumstances, suggests that the process of recovery is more akin to a tactical or operational process than an overarching strategic process. Scholten et al. (2014) reinforces this idea with their assertion that managers ought to preemptively establish networks and infrastructures so they may “direct and prioritize resources accordingly” during a disruption. In doing so, managers will stand a better chance of influencing the effectiveness of the recovery, as well as the organization’s perceptions of the disruption and recovery process. In a similar finding, Ponomarov and Holcomb (2009) thought a thorough understanding of the supply chain (Structural

Knowledge) was important when responding to a disruption, because by understanding the capabilities and connectedness of its elements, managers are able to make decisions with increased effectiveness and confidence. The importance of managerial decision-making and influence is not often addressed in recovery models, but is clearly an important component of resilience and recovery.

Recovery Models

Most mathematical recovery models found in the literature investigate specific supply chain design configurations and treat disruptions as random "shocks" to the system. These shocks are normally in the form of lost capacity or a supply shortage for a period of time. The effectiveness and efficiency of the recovery are usually based on objectives that center on minimizing costs associated with production, inventory, and lost sales. Although the volume of research that has been conducted precludes an exhaustive exploring of this research stream, recovery models can be generalized into two broad categories: 1) models that optimize recovery costs for an existing supply chain configuration that has been disrupted, or 2) models that seek to optimize the configuration of a supply chain to improve its propensity to recover quickly. Because this research is centered on recovery as opposed to design, emphasis is given to the first category.

One of the simplest supply chain configurations is that of a single machine under predictable demand, which can be managed using an Economic Order Quantity (EOQ) approach. Tang and Lee (2005) developed a strategy for recovering a two-product, single machine system that experiences probabilistic breakdowns. Their solution procedure involves a manager selecting a strategy to pursue once the machine is returned to service

(e.g., continue running the current product vs. switching products). They found that generalized rules could be formulated to guide the manager in selecting the best approach. Their objective was to return the production schedule to normal in terms of inventory levels so that the original scheduling strategy could be resumed. In this least-cost approach, the best strategy was largely a function of holding costs and inventory levels of products. Backorder and lost sales costs were not considered. Similarly, Hishamuddin, Sarker, and Essam (2012) investigated a recovery model for a single-stage production and inventory system under random disruption occurrence and duration. The solution algorithm developed for this work produced both optimal lot sizes and the number of production cycles needed to return the system to the normal schedule. Their objective was to minimize total cost over the recovery period when considering setup, inventory holding, backorder, and lost sales costs. Although the model allows for advance notice of a disruption's occurrences, a limitation of their approach is that it stipulates that sufficient idle time be available in the system to absorb the shock. In other words, there is no means to supplement production with redundant capacity that may be available. Eisenstein (2005) investigated a similar condition, the case of cyclical production on a single machine, using a dynamic Produce-Up-To (PUT) policy for recovering from disruptions. This work also leveraged the inherent idle time of the system to adjust PUT parameters when disruptions produce either an inventory shortfall or an inventory surplus through single or multiple shocks. The objective of the approach is to determine the efficient sequence and PUT levels for the next jobs as the current job's production cycle ends. Performance in this research is measured in terms of cost and stability of the inventory levels compared to a steady-state.

Chen, Zhao, and Zhou (2012) developed a model for periodic review systems with a

single backup supplier (a source of redundant capacity) to describe optimal replenishment policies for cases when the usual supplier is unable to fulfill demand due to a disruption. In their formulation, an assumption is that the backup supplier has limited capacity, larger fixed and variable costs, and longer lead times relative to the preferred supplier. Their formulation incorporates this source of redundant capacity into the supply chain structure, and utilizes a probabilistic assessment by a manager for the availability of the primary supplier to arrive at an ideal quantity to order from the backup supplier for the period in question.

Other approaches have been extended to cover more complex situations. Schmitt (2011) developed a network model for a multi-echelon system which might face disruptions at any level and also incorporated a strategy to employ backup facilities and inventories. These strategic backup resources represent both reactive and proactive approaches to mitigating disruptions, and the study investigated important relationships between the model's parameters, such as the amount of inventory held in strategic reserve and the number of planning periods required for backup facilities to begin contributing to demand. The limitation of this study was that the objective was maintaining a long-run service level requirement.

The most comprehensive work to date in modeling supply chains for the purpose of improving resilience was performed by Hu (2013) and consisted of the modeling of manufacturing enterprises. In this work, a mathematical model for generic manufacturing structures was developed to determine optimal production and inventory policy when one area of the enterprise experienced a disruption. Unlike prior research, which is limited by the specific configuration(s), the general model presented in this research is able to describe almost any production-inventory system. Additionally, the model incorporated a

comparatively wider array of cost structures than has been considered in previous research and included production, storage, backorder, and setup costs. The underlying purpose of the model was to provide a minimum cost solution for inventory levels once a disruption's occurrence became known.

Another important aspect of supply chain recovery that is not frequently mentioned in the literature is that the actual state of a supply chain at the beginning of a disruption will reasonably influence the recovery strategy chosen by managers. Inventory levels, resource availability, and the speed at which a supply chain's entities can physically respond to a disruption will all likely carry great influence over the recovery strategy pursued by managers. Although some recovery models, such as Eisenstein (2005), have the ability to integrate some state variables into a solution procedure, the ability to tailor the networks parameters is not adequately addressed in current recovery formulations. To illustrate, consider the proposed model of Hishamuddin et al. (2012), which stipulates that there be sufficient capacity in the system to absorb a shock in order to solve for a recovery plan. It is conceivable that a system that is able to absorb a shock when inventory levels are high might not have sufficient idle capacity to absorb the same shock when inventory levels are low, meaning the usefulness of the model is dependent upon the state of the system. In contrast, the formulations developed in this research are structured to allow for feasible solutions regardless of the state of the supply network.

Gaps in Existing Research

These and other studies relating to supply chain recovery conceptually demonstrate the effects of disruptions on a system, but are rigid in their configurations and assumptions.

Researchers have suggested that generalized models with few rigid assumptions would be useful in practice (Schmitt, 2011). It is also likely mathematical models will not find widespread use until such a model is developed and validated. Furthermore, although optimizing long-run operational parameters is practical, recovery models within the context of Supply Chain Resilience should also be designed to provide clear information to managers regarding the trade-offs of their decisions. This is a gap between the needs of supply chain managers and the available tools for managing the recovery. This research aims to narrow this gap by addressing the following problems:

1. Despite agreement in the literature that traditional supply chain metrics are favorable for solving supply chain recovery problems, researchers have yet to develop a general model that is both useful for the supply chain recovery process and adaptable to a variety of supply chain configurations.

2. Existing models have not provided a means for, or guidance relating to, the necessary interaction between supply chain managers and the recovery models. This research proposes that the most pressing needs in this regard are the ability to:

    a. Integrate sources of redundant capacity that are outside of the usual supply chain into the recovery process, and allow managers to choose recovery strategies that access those sources according to their preferences or needs.

    b. Assess trade-offs between different strategies for deploying redundant capacity, or trade-offs within a specific strategy in regards to recovery costs, while maintaining the ability to pursue optimal strategies.

CHAPTER III

METHODS AND PROCEDURES

Problem Description and Modeling Approach

As discussed in Chapter II, current literature suggests that research efforts for recovery models thus far have been primarily geared toward the adaptation of preexisting supply chain and production models to the recovery problem. As a result, the models available to practitioners are restricted to narrowly defined supply chain configurations, and they often do not consider the important resilience factor of redundancy in the formulation. Findings from the Supply Chain Resilience literature have also indicated that the disruption recovery process requires more than just modifications to existing planning methods. More specifically, the efficient deployment of redundant capacity at the opportune time and location appears to be central to the recovery of disrupted supply chains. Furthermore, research suggests that managerial decisions early in the recovery process are vital to recovery, meaning models that only provide optimal solutions without providing information regarding capacity trade-offs or pinch points in the supply network might be of limited practical value during a disruption.

Guided by the findings of the literature review, a Linear Programming (LP) model was developed to integrate these important characteristics and facilitate a flexible approach that is suitable for modeling a wide variety of supply chain configurations. Numerical experiments were used to validate the model and to test hypotheses related to the research

questions presented in Chapter I. The underlying structure of the model is that of a Minimum Cost Network Flow Problem (MCNFP) formulation, which was chosen for its ability to effectively represent a variety of supply chain network configurations. Side constraints were used to augment the standard model and accommodate different network configurations. Binary variable constructions were used to control decisions related to acquiring redundant capacity, resulting in a Mixed Integer Programming (MIP) formulation for the final model. Modifying the MIP formulation by removing binary decision variables and adjusting the Right-Hand Side (RHS) values for specific constraints in the formulation allowed the model to be solved as an LP relaxation to yield valid sensitivity information for redundant capacity decisions. This chapter discusses important characteristics of the network structures used in the development of the mathematical formulation for this research and describes the experimental procedures used to validate the model.

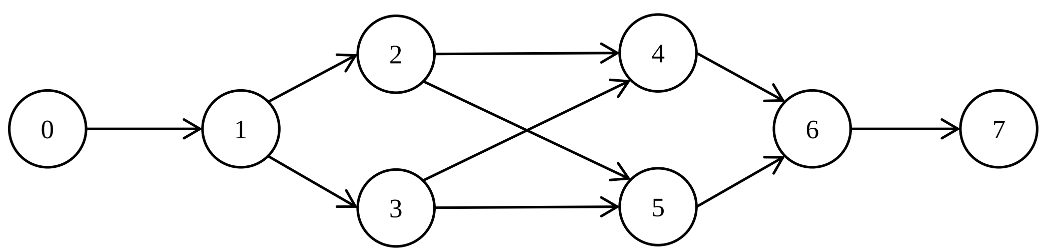
Network Structures

Basic Flow Network Structure

One of the most basic flow networks is the minimum-cost network flow model (Figure 2). The MCNFP formulation is a generic network form that has been useful in modeling a wide variety of supply chain configurations. The objective of the formulation is to send flow from source nodes, which represent the supply chain's resources, to a sink node representing customer demand. Flow is routed through the arcs of the network according to decision variables that relate to managerial decisions. The model's constraints and parameters represent the design and structure of the supply chain itself and include those for

productive capacity, storage capacity, and demand. When solved, variables, constraints, and parameters provide a least-cost solution. The value of the MCNFP is that the formulation can be tailored to accommodate a wide array of network conditions through the addition of side constraints.

In terms of a supply chain, the nodes of an MCNFP network can represent machines, factories, warehouses, customers, or can be indexed to accommodate discrete time periods. The network's arcs can represent both the production of goods and the movement of material



$$\min z = \sum_{all\ (i,j)} c_{i,j} X_{i,j} \tag{1}$$

s.t.

$$\sum_j x_{i,j} - \sum_k x_{k,i} = b_i \qquad \forall\, i \tag{2}$$

$$l_{i,j} \le x_{i,j} \le u_{i,j} \qquad \forall i,j \tag{3}$$

$x_{i,j} = number\ of\ units\ of\ flow\ sent\ from\ node\ i\ to\ node\ j\ through\ arc\ ij$
$x_{k,i} = number\ of\ units\ of\ flow\ sent\ from\ node\ k\ to\ node\ i\ through\ arc\ ki$
$b_i = net\ supply\ (outflow - inflow) at\ node\ i$
$c_{i,j} = cost\ of\ transporting\ 1\ unit\ of\ flow\ from\ node\ i\ to\ node\ j\ through\ arc\ i,j$
$l_{i,j} = Lower\ bound\ on\ flow\ through\ arc\ i,j$
$u_{i,j} = Upper\ bound\ on\ flow\ through\ arc\ i,j$

Figure 2: Basic Network Flow Model

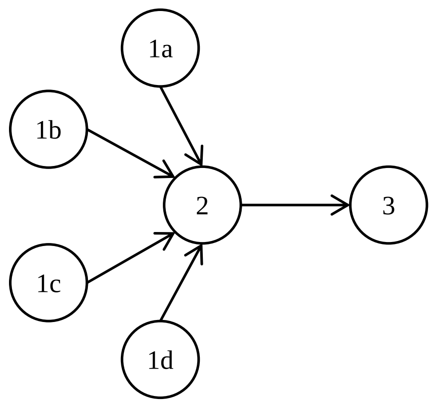
between machines, factories, warehouses, or time periods. The presence and direction of the network's arcs relative to its nodes dictate the function of the node itself. Nodes that only have arcs originating from them are source nodes, which supply the network with flow. These nodes are usually, but not necessarily, the physical structures of the network. Nodes that only have arcs terminating at their location are sink nodes, which accumulate all the flows of the network. Nodes with arcs in both directions are transshipment nodes and represent the physical structures of the network. It is often the case that a network contains a single source and a single sink, referred to as a global source or sink. The formulation developed for this research incorporates a global sink node to accumulate all customer demand that has either been filled or left unmet. The formulation uses multiple source nodes, which either represent the beginning of the supply chain or provide additional flows necessary to fill demand that is left unmet by the supply chain.

Supply Chain Structures

Although the MCNFP formulation is capable of solving a wide array of network problems, it often requires that its structure be modified for specific conditions. This generally involves the addition of side constraints but may also involve changes to the basic constraint structure. Structures that are featured prominently in the supply chain literature include those for accommodating multiple production sources, assembly operations, multi-period planning, and the scaling of flows, as well as the ability to accommodate late or unmet demand.

The first structure illustrates a scenario where flow within a supply chain arrives from

more than one location, as is the situation when multiple facilities or machines can be used to meet demand (Figure 3). In the general case, the production volume at any location is determined by the relationship of its associated cost parameters to the other resources. The nature of the minimization formulation forces the lower cost option for filling demand to be utilized first. However, it is also possible that the use of multiple sources occurs only in special situations such as a capacity disruption. In these cases a decision is necessary and



$$\min z = 1{,}000 y_{1d,2} + 5x_{1a,2} + 5x_{1b,2} + 8x_{1c,2} + 7x_{1d,2}$$

s.t.

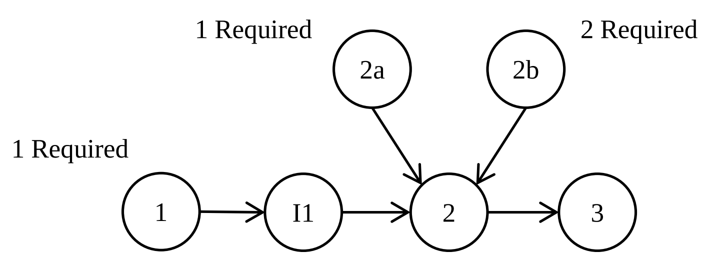
$$x_{1a,2} \le 10 \quad (4)$$
$$x_{1b,2} \le 10 \quad (5)$$
$$x_{1c,2} \le 10 \quad (6)$$
$$x_{i1,2} \le 10 \quad (7)$$
$$x_{1a,2} + x_{1b,2} + x_{1c,2} + x_{1d,2} - x_{2,3} = 0 \quad (8)$$
$$x_{2,3} = 25 \quad (9)$$
$$x_{1d,2} \le M y_{1d,2} \quad (10)$$
$$x_{ij} \ge 0 \qquad \forall i,j \quad (11)$$
$$y_{1d,2} = 0{,}1 \quad (12)$$

Figure 3: Network Example with Multiple Sources

additional constraints are needed to allow the redundant source to contribute when some criteria is met, such as the benefits of its use outweighing a fixed charge. In many redundant capacity situations, this fixed charge is required to access the redundant capacity. Both of these situations are illustrated in the network configuration shown in Figure 3, in which three primary source nodes, 1a, 1b, and 1c, supply transshipment Node 2 through arcs $X_{1a,2}$, $X_{1b,2}$, and $X_{1c,2}$. Their individual capacities, which are illustrated in constraints (4) through (7), are usually able to at least meet the demand of Node 3 (25 units of flow through arc $X_{2,3}$) . Node 1d is an auxiliary node that will only contribute if the binary variable $y_{1d,2,}$ representing a decision, is set equal to 1 in constraint (10), which will happen only in cases where the savings achieved by utilizing Node 1d are sufficient to overcome the fixed charge associated with the $y_{1d,2}$ variable in the objective function. Therefore, the binary variable represents a decision to utilize the capacity of that node, and constraint (10) is necessary to prevent the solution procedure from routing flow through Node 1d instead of 1c, which is a more expensive option.

Another situation common in modeling supply chains occurs when one location receives flow from more than one source and then passes flow on to other nodes downstream in the supply chain. When the flow into a node is not the same as the flow leaving the node, additional constraints are required to maintain the proper proportion of flows in and out of the node. This is typical in networks for assembly operations or when the flow out of a location must be adjusted to account for losses incurred in the normal course of operations (e.g., fallout due to quality control activities). Figure 4 illustrates an assembly operation, where Node 2 collects flow from three sources and then passes flow on to Node 3, which is

downstream. Nodes 1, 2a, and 2b produce flows that are "assembled" at Node 2. Node I1 is a transshipment node. To produce 1 unit of flow for Node 3, Node 2 must receive 1 unit each from Nodes I1 and 2a, and 2 units from 2b. In this research, assembly operations are accommodated by adding one additional side constraint for each additional resource involved in the operation. The total flow demanded by Node 3 is 25 units, shown by constraint (15). The assembling of flows requires Node 2 to balance while considering the flows for Nodes I1, 2a, and 2b by way of constraints (16), (17), and (18). In other words, all three constraints must hold true when passing flow on to Node 3. Constraints (19) and (20) are capacity limits



$$min \sum_{all\ (i,j)} c_{i,j} x_{i,j}$$

s.t.

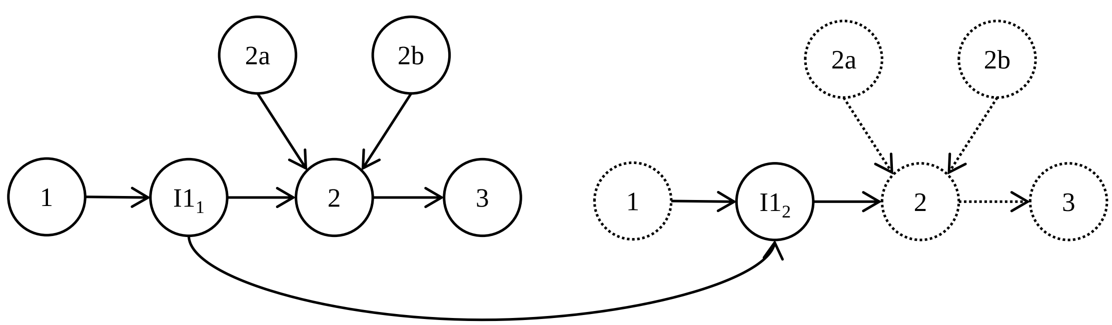
$$x_{1,I1} \leq 25 \tag{13}$$
$$x_{1,I1} - x_{I1,2} = 0 \tag{14}$$
$$x_{2,3} = 25 \tag{15}$$
$$x_{I1,2} - x_{2,3} = 0 \tag{16}$$
$$x_{2a,2} - x_{2,3} = 0 \tag{17}$$
$$2x_{2b,2} - x_{2,3} = 0 \tag{18}$$
$$x_{2a,2} \leq 75 \tag{19}$$
$$x_{2b,2} \leq 110 \tag{20}$$
$$x_{i,j} \geq 0 \quad \forall i,j \tag{21}$$

Figure 4: Network Example with Assembly Operations

for Nodes 2a and 2b respectively.

The previous example considered only a single planning period, but in most supply chain applications constructing models that span several planning periods is desirable. Multi-period planning can be accomplished by indexing the set of nodes and arcs for multiple discrete time periods and then creating links between the periods with transhipment nodes. In this research inventory nodes are constructed as transhipment nodes to allow for inventory to be held from one period to the next. The constraints for each resource are indexed to account for each period, and the links between periods are made by appropriately modifying constraints for transshipment nodes. Figure 5 illustrates this technique by indexing the network in Figure 4 for a second period and adjusting constraint (14) to link the periods. After adjusting, the new constraint is of the form shown in constraint (14a).

Another use of multi-period supply chain models is the ability to fullfill demand in



$$x_{1,I1_1} - x_{I1,2} - x_{1,I1_2} = 0, \tag{14a}$$

$$x_{I1_1,I1_2} \leq 25 \tag{22}$$

Figure 5: Time-Phased Supply Chain

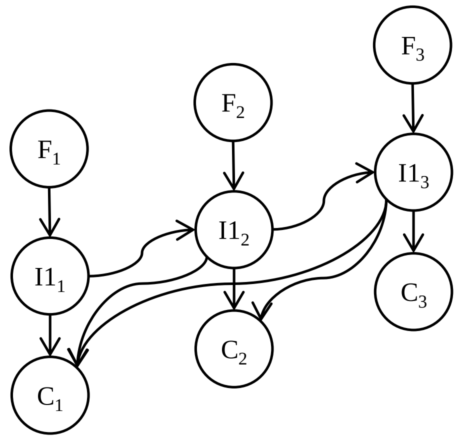


Figure 6: Multi-Period Supply Chain with Backordered Demand

subsequent periods through backorders. Figure 6 depicts a 3-period supply chain comprised of the single factory (F) and inventory location (I1). A customer, Node C, demands product in all three periods. If the capacity at F_1 plus the available inventory at the inventory location I_1 are unable to meet demand for Period 1, that remaining demand may be filled in subsequent periods through the arcs that connect inventory nodes for Periods 2 and 3 (I_2 and I_3) to the customer demand in Period 1 (C_1).

Model Formulation

Basic Model Formulation

This section modeling formulation and notation developed for this research, hereafter referred to as the Supply Chain Recovery Formulation (SCRF). Parameters and coefficients of the model represent demand, costs, and capacities of the network activities, and the nodes

of the network represent the networks resources, inventory location, customers, and global source and sink nodes used to balance and accumulate flows. The network's arcs represent activities such as the production or storage of goods, the filling of demand, and the holding of inventory. An important aspect of the model's structure is the handling of redundant capacity, which is not normally utilized in an undisrupted supply network but is accessed during periods of disruption. This is accomplished through the addition of a binary decision variable structure. In the formulation, resources are comprised of nodes in set P ∈ (1, . . . p) and are indexed with *i*. Redundant resources are comprised of the set D which is a subset of P (D ⊂ P). Inventory locations are comprised of nodes in the set V ∈ (1, . . . v) and are indexed with *j*. Notations for nodes, arcs, and parameters are described in individual sections below for clarity, with the structures dedicated to modeling redundant capacity decisions residing in their own section.

Parameters

N	Number of planning periods
t	Planning period index
k	Planning period index, forward-looking ($k = t+1, . . N$)
i	Resource node index
j	Inventory node index
r_{it}	Capacity limit for Resource R_i in Period t
$\lambda_{I_jR_i}$	Scaling factor for Resource R_i drawn from Inventory I_j
$\lambda_{R_iI_j}$	Scaling factor for Inventory I_j drawn from Resource R_i
i_{jt}	Inventory holding limit for Inventory I_j from Period t to Period $t+1$
i_{j0}	Initial inventory level for Inventory I_j

d_t Customer demand in Period t

Cost Coefficients

$\alpha_{R_{it}I_{jt}}$ Cost of flow from Resource R_i to Inventory I_j in Period *t*

$\beta_{I_{jt}}$ Cost of flow from Inventory I_j, Period *t* to Period *t*+1

$\delta_{I_{jt}}$ Cost of filling demand for Period *t* from Inventory I_j

δ_{tSI} Cost of filling demand in Period *t*

$\omega_{tI_{jk}}$ Cost of unmet demand for Period *t*, filled from Inventory I_j in Period *k*

ω_{SOt} Cost of unmet demand for Period *t*, primary cost

ω_{tSI} Cost of unmet demand for Period *t*, secondary cost

Nodes

R_{it} Resource R_i in Period *t*

I_{jt} Inventory Location I_j in Period *t*

D_t Customer demand for Period *t*

U_t Unmet or late customer demand for Period *t*

SO Source node for unmet demand

SI Sink node for both met and unmet demand

Arcs

$X_{R_{it}I_{jt}}$ Flow from Resource R_i to Inventory I_j in Period *t*

$I_{I_{jt}R_{it}}$ Flow from Inventory I_j to Resource R_i in Period *t*

$I_{I_{j(t+1)}}$ Flow between Inventory I_j, Period *t* to Period *t*+1

$D_{I_{jt}}$ Fulfilled demand for Period *t* from Inventory I_j

$U_{tI_{jk}}$ Unmet demand for Period t, filled from Inventory I_j in Period k

U_{SOt} Flow from source to unmet demand for Period t

I_{jSI} Flow from Inventory I_j from the last Period t to the Sink

D_{tSI} Fulfilled demand for Period t

U_{tSI} Unmet or late demand for Period t at the end of the planning horizon

Redundant Capacity Decision Variable, Cost Coefficient, and Right Hand Side parameter

Y_{R_i} Decision variable to use Redundant Resource R_i

γ_{R_i} Cost to activate Redundant Resource R_i

b_{R_i} Right Hand Side parameter (total capacity) for Redundant Resource R_i

M_i Large number, greater than $\sum_{t=1}^{N} r_{it}$ for Redundant Resource R_i

The basic SCRF formulation is described as follows: The objective function (23) minimizes the overall cost of the production plan over the planning horizon. Constraint (24) controls the decision to utilize or not utilize redundant capacity. Flow balancing constraints are shown in Equations (25) through (28). Constraint (25) balances inventory nodes, constraint (26) balances demand nodes, constraint (27) balances unmet demand nodes, and constraint (28) balances resource nodes. Constraint (29) sets the capacity for resources, and constraint (30) sets the inventory storage capacity from one period to the next. Constraint (31) establishes the initial inventory levels. Constraint (32) requires that all demand is either met or unmet at the end of the planning period. Constraint (33) addresses the binary nature of the decision to access redundant capacity.

$$\min z = \sum_{i \in D} \gamma_{R_i} Y_{R_i} + \sum_{t} \omega_{SOt} U_{SOt} + \sum_{t} \omega_{tSI} U_{tSI} + \sum_{t} \sum_{j} \delta_{I_{jt}} D_{tSI} + \sum_{t} \sum_{i} \sum_{j} \alpha_{R_{it} I_{jt}} X_{R_{it} I_{jt}} + \sum_{t} \sum_{j} \beta_{I_{jt}} I_{I_{j(t+1)}} + \sum_{t} \sum_{j} \delta_{I_{jt}} D_{I_{jt}} + \sum_{t} \sum_{k=t+1}^{N} \sum_{j} \omega_{tI_{jk}} U_{tI_{jk}} \tag{23}$$

s.*t*.

$$\sum_{t} \sum_{j} X_{R_{it} I_{jt}} - \mathrm{M}_i \mathrm{Y}_{R_i} \leq \mathrm{b}_{R_i} \qquad \forall\, i \in D \tag{24}$$

$$\sum_{i} \lambda_{R_i I_j} X_{R_{it} I_{jt}} + I_{I_{j(t-1)}} - \sum_{i} \lambda_{I_j R_i} I_{I_{jt} R_{it}} - I_{I_{j(t+1)}} - D_{I_{jt}} = 0 \qquad \forall\, j \in V,\ t \tag{25}$$

$$\sum_{j} D_{I_{jt}} - D_{tSI} = 0 \qquad \forall\, t \tag{26}$$

$$U_{SOt} + \sum_{k=t+1}^{N} U_{tI_{jk}} - U_{tSI} = 0 \qquad \forall\, t \tag{27}$$

$$\sum_{j} \lambda_{I_j R_i} I_{I_{jt} R_{it}} - \sum_{j} \lambda_{R_i I_j} X_{R_{it} I_{jt}} = 0 \qquad \forall\ i \in P,\ t \tag{28}$$

$$\sum_{j} X_{R_{it} I_{jt}} \leq r_{it} \qquad \forall\ i \in P,\ t \tag{29}$$

$$I_{I_{j(t-1)}} \leq i_{jt} \qquad \forall\, j \in V,\ t \qquad (30)$$

$$I_{I_{j0}} = i_{j0} \qquad \forall\, j \in V \qquad (31)$$

$$D_{tSI} + U_{tSI} = d_t \qquad \forall\, t \qquad (32)$$

$$\mathrm{Y}_{R_i} = Binary \qquad \forall\, i \in D \qquad (33)$$

Scaling Factor

A parameter (λ) is utilized in this formulation to facilitate both the modeling of assembly networks and the changes to flow volumes that occur in many supply chain operations. This parameter functions as a scaling factor for flows passing through a node and is able to help control the aggregation, magnification, and reduction of flows. The parameter may be applied to the flow balancing constraint or constraints for any resource or inventory location as necessary. For an assembly operation, the scaling factor $\lambda_{I_i R_i}$ represents the number of input units required from inventory location I_{it} for a single output unit at the assembly Resource R_{it}. For instance, if an assembly operation occurring at a production node R_D requires two units of component A, three units of component B, and a single unit of component C to produce a single assembled unit D, three balance constraints in the form of Equation (23) are needed. Using the notion described above and assuming that the assembled units are passed to an inventory location designated I_D and that flow arrives to R_D from inventory locations I_A , I_B , and I_C , the resulting set of three constraints in the first period would be:

$$I_{I_{A1}R_{D1}} - 2X_{R_{D1}I_{D1}} = 0$$

$$I_{I_{B1}R_{D1}} - 3X_{R_{D1}I_{D1}} = 0$$

$$I_{I_{C1}R_{D1}} - X_{R_{D1}I_{D1}} = 0$$

The scaling factor can also be applied to accommodate for other flow reducing supply chain characteristics, such as losses that occur due to quality control activities. For example, if a product is tested using destructive methods that result in a 5% loss, the scaling factor $\lambda_{I_i R_i} = 0.95$ may be applied to constraints in the form of Equation (28). Consider this situation where a resource R_A supplies an inventory location I_A in the first period of the planning horizon, and goods will then be sent on to a downstream resource R_B. The flow balance constraint for the production resource R_B in this situation may be written as:

$$0.95 I_{I_{A1}R_{B1}} - X_{R_{B1}I_{B1}} = 0$$

Sensitivity Analysis

The SCRF formulation is solved as an MIP to provide a global optimal solution with a set of least-cost decisions for the deployment of redundant resources, for the production levels of both redundant and existing resources, and for inventory levels. The variables in the model also provide information related to late and unmet demand. Altering the formulation slightly allows the model to be solved as an LP, from which sensitivity information can be obtained. To solve as an LP, the objective function described in Equation (23) is replaced with Equation (23a), and the constraint described in Equation (24) is replaced with Equation (24a).

$$\min z = \sum_t \omega_{tSI} U_{tSI} + \sum_t \delta_{I_{jt}} D_{tSI} + \sum_t \sum_i \sum_j \alpha_{R_{it} I_{jt}} X_{R_{it} I_{jt}} + \sum_t \sum_j \beta_{I_{jt}} I_{I_{j(t+1)}} + \sum_t \sum_j \delta_{I_{jt}} D_{I_{jt}} + \sum_t \sum_{k=t+1}^{N} \sum_j \omega_{tI_{jk}} U_{tI_{jk}} \tag{23a}$$

$$\sum_t \sum_j X_{R_{it} I_{jt}} \leq \mathrm{b}_{R_i} \qquad \forall\, i \in D \tag{24a}$$

These alterations consist of removing binary variables and large number coefficients M_i that are associated with redundant resources. In the LP relaxation, the activity of a redundant resource and its overall capacity level becomes subject to the Right Hand Side (RHS) parameter b_{R_i} of Equation (24a). This equation limits the total capacity available in all periods, while the individual capacity constraints for a given resource regulate its ability to produce in any given period.

Because optimal solutions to network flow problems are often degenerate in practice, obtaining accurate shadow prices for incremental decisions is usually not possible. However, these modifications provide the ability to obtain shadow prices and allowable increases. Sensitivity information, derived by using the Capacity Evaluation and Deployment Algorithm (CEDA) developed for this research, provides a framework for making decisions for any resource modeled using the redundant resource structures. The algorithm considers both the incremental cost of production and the fixed costs associated with bringing the resource online. While the intention of the CEDA algorithm is to determine the location of the network where additional capacity would have the greatest impact on the objective function,

its structure is well-suited to evaluating decisions based on managerial preference and discretion. Notation for the CEDA algorithm approach to sensitivity analysis is introduced below.

SP_{R_i}	Shadow Price for a Redundant Capacity Source R_i,
AI_{R_i}	Allowable increase in b_{R_i} for a Redundant Capacity Source R_i
AD_{R_i}	Allowable decrease in b_{R_i} for a Redundant Capacity Source R_i
b_{R_G}	RHS of constraint for a Redundant Capacity Group R_G
SP_{R_G}	Shadow Price for a Redundant Capacity Group R_G
AI_{R_G}	Allowable increase in b_G for a Redundant Capacity Group R_G
γ_G	Cost for activating resources for a Redundant Capacity Group R_G
ε	A small number for perturbing RHS parameter b_{R_i} or b_{R_G}
C	The increase in capacity allotted to a Redundant Capacity Source or Group

The CEDA algorithm is developed to evaluate sources of redundant capacity according to their ability to impact the objective function of the model. Rather than investigating several constraints, which may be degenerate, to find the most effective location within the network to deploy additional resources, the decisions criteria are reduced to the evaluation of a single constraint for each redundant resource or group of resources that work together to improve the objective function. The evaluation is therefore simplified, because it is independent of the number of planning periods, the complexity of the network, or the location of the resources within the network.

Although in many cases the addition of capacity to a single resource will result in an improvement to the objective function, situations do exist where more than one resource is necessary to improve the flow through or within the network. Two examples illustrate

circumstances where a group of redundant resources may be necessary. Consider first, a case when complementary resources are disrupted concurrently, as might happen when two production cells are damaged during a severe weather event. Additional capacity for only one resource may be insufficient to improve flow if the production cells are in series. Another instance where a group of resources may be necessary occurs when multiple resources (either disrupted or undisrupted) are operating at full capacity. It is possible that increasing the capacity related to only one of the complementary operations will not necessarily increase flow or improve the objective function. Of course, these instances are not of great concern when solving the MIP formulation because the appropriate grouping of redundant resources will be found when the model is solved. However, groups of resources must be identified explicitly when solving the model using the LP formulation for the purpose of obtaining sensitivity information.

A pseudocode description of the algorithm is provided in Appendix A. The CEDA algorithm begins by formulating the problem as an LP model. Next, the RHS values (b_{R_i}) of constraints associated with redundant resources in the form of Equation (24a) are set equal to some initial allotted capacity. This value determines the maximum amount of capacity that the resource can contribute during all planning periods. The most reasonable value in most cases will be zero so that the algorithm itself can determine the appropriate increase in capacity. This is repeated for each redundant resource constraint, and the model is solved to determine an optimal solution, given these initial allotments.

Once an initial optimal solution is obtained, the iterative portion of the algorithm begins. The RHS values for each redundant capacity constraint in the form of Equation (24a) are individually increased, or perturbed, by some small amount ε. The model is then re-

solved, and valid sensitivity information for the perturbed constraint can be obtained. The shadow price (SP_{R_i}) and allowable increase (AI_{R_i}) for the resource are stored to produce a shadow price function using the equation described below. After developing the shadow price function, the RHS value of the constraint is returned to its initial value by subtracting the small value ε.

$$f(\mathrm{C}) = \mathrm{SP}_{R_i}\mathrm{C} - \gamma_{R_i}\mathrm{Y}_{R_i} \tag{34}$$

The variable Y_{R_i} in the shadow price function is a binary variable that is set equal to one if the value of b_{R_i} is equal to zero in the current optimal solution, indicating the resource has not been used. In the same manner as the MIP formulation, this variable applies to the fixed charge for the redundant resource if needed. The increase in capacity allotted to the resource (C) can be any value up to the allowable increase. In this research, the allotted increase is always set equal to the allowable increase ($\mathrm{AI}_{R_i} = C$). The process of perturbing constraints is repeated in order to develop shadow price functions for each resource.

Once shadow price functions for each redundant resource are obtained, the algorithm calls for the evaluation of any grouped resources being considered. Shadow price functions are obtained for grouped resources using a similar procedure as for individual resources. The first step combines each of the individual constraints in the group into a single constraint. The individual constraints are then removed from the formulation. Because RHS values for the individual constraints represent the allotted capacity for the resource, combining constraints by summing the RHS values for all resources in the group produces the total capacity of the group. Each of the individual resource's variables are included when constructing the Left Hand Side of the combined constraint in a process that essentially

collapses the individual constraints into one. A similar process of perturbation and evaluation is then performed on the grouped constraint to obtain sensitivity information.

Shadow price functions are obtained in the same manner as with individual resources, with the values for SP_{R_G} and C being obtained directly. A series of binary variables Y_{R_i} and fixed cost parameters γ_{R_i} are required for each resource in the group. The shadow price and allowable increase for the group of resources that are obtained represent the group as a whole, and as a result, any increase in capacity must be distributed between the individual resources of the group.

Once shadow price functions are obtained for each resource or resource group, the final values for each function are assessed to determine which redundant capacity source or group is to receive additional capacity. Although in this research the resource or group of resources that produces the greatest savings for the objective function is chosen, other criteria may also be used. The RHS value for the resource or group selected is then adjusted by the value C of the shadow price function. In the case where a grouped resource is chosen, the capacity must be distributed proportionally according to its required contribution to the flow of the network. This procedure is described in detail in the pseudocode contained in Appendix A and is illustrated in the example given in the next section. Once the new RHS value is obtained, the algorithm can be repeated until no more improvement to the objective function is possible.

CEDA Example

To illustrate the operation of the CEDA algorithm, consider the 2-resource, 4-period serial network modeled according to the SCRF formulation shown in Figure 7. Customer demand is satisfied on the arcs connecting I_{Bt} and DM_t for each Period *t*. Demand is equal to 100 units in each period ($DM_t = 100$). The total capacity of resources A_t and B_t are 100 units for any Period *t*, which is enough to satisfy demand under normal conditions. In this example, capacity is disrupted during the second period for both resources ($A_2 = 90$ and $B_2 = 80$), and Resource B is also disrupted during the third period ($B_3 = 80$). Redundant capacity is available as support for each primary resource at an incremental unit cost plus a fixed charge if the source is in fact utilized. The capacity and costs related to the four redundant resources are shown in Table 6. The CEDA algorithm is initialized by first

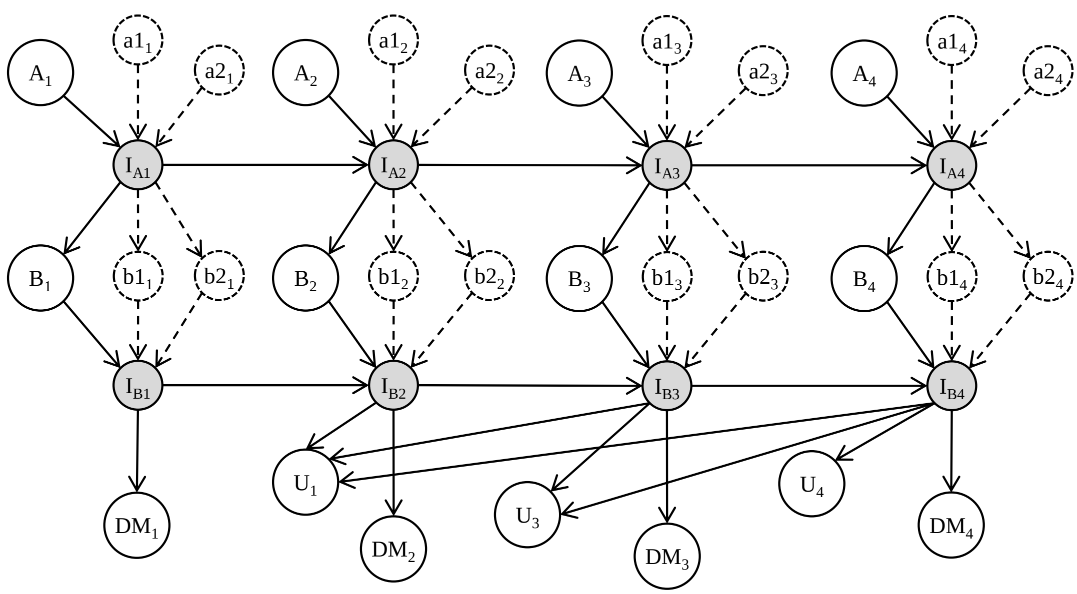


Figure 7: CEDA Example Network

Table 6: CEDA Example – Redundant Resource Characteristics

Primary Resource	Associated Redundant Resource	Fixed Cost	Incremental Cost	Capacity in Period			
				1	2	3	4
A	a1	750	10	0	5	5	5
	a2	1,000	12	15	15	15	15
B	b1	1,000	11	10	10	10	10
	b2	750	13	15	15	15	15

formulating the problem according to the SCRF formulation and then incorporating the changes described in Equations (29) and (30). The initial capacity allotment for all redundant resources are then set to zero (b_{R_i}=0).

The following series of graphics and tables illustrates the execution of the CEDA algorithm on an iteration-by-iteration basis until all demand is satisfied. There is no production on redundant resources in the first iteration of the algorithm, because values for all b_{X_i} are initially zero, leaving some demand unmet. Solving the formulation as a linear program produces the network state illustrated in Figure 8 and the sensitivity information in Table 7. Shadow price functions are obtained from individual shadow prices and allowable increases to determine the best location to add capacity for this network state. If a redundant resource currently has a RHS or final value of zero, its corresponding variable Y_{R_i} is set equal to one, and a fixed cost is incorporated into the shadow price function. When the benefit from adding capacity on a resource is sufficient to overcome its fixed charge, then adding the capacity is a net gain for the network in terms of cost.

For the first iteration, the shadow prices for Resources a1 and a2 are equal to zero, meaning that allotting additional capacity to those resources will not improve the current

objective function. Shadow prices for both b1 and b2 are negative, meaning that each unit of additional capacity allotted to those resources will improve the objective function by the value of the shadow price. From the shadow price function column, it can be found that increasing capacity of Resource b2 up to the allowable increase of 10 units will produce the greatest reduction to the objective function in the current state ($\mathrm{AI}_{R_G} = C$). The calculations for evaluating the shadow price function for Resource b2 at its allowable increase are as follows:

$$f(\mathrm{C}) = \mathrm{SP}_{R_i}C - \gamma_{R_i}\mathrm{Y}_{R_i} = (-5{,}183) * (10) - (-750) * (1) = -51{,}080$$

The RHS of the constraint associated with redundant Resource b2 is increased by 10 units, and the problem is again solved as a linear program to obtain new shadow prices and allowable increases. Figure 9 illustrates that the solution procedure for the LP formulation applies the 10 units of additional capacity to the network in Period 2, which in-turn increases the production from Resource A in Period 2 from 80 to 90 units, and the total demand met in Period 2 increases from 80 to 90 units.

Examining the values of shadow prices and shadow price functions in Table 8 shows that Resources b1 and b2 are the only resources for which additional capacity will result in a reduction of the objective function. As with the first iteration, grouping resources does not provide any advantage. The best decision for Iteration 2 is to once again allocate 10 additional units of capacity to Resource b2. The resulting solution for the third iteration is shown in Table 9, and Figure 10 illustrates that the additional capacity is allocated to Period 3.

Examining the diagram and table for Iteration 3 reveals that both Resources A and B

are now operating at the maximum level allowed by the disruption. As a result, adding capacity from any single redundant source in any period will be insufficient to meet any of the 10 remaining units of unmet demand from Period 2. However, it can be seen from the individual shadow prices in Table 9 that improvement to the objective function is possible through additional capacity on either Resource a1 or a2, or by adding capacity on Resource b1, even though the benefits do not outweigh the additional fixed costs.

Although individual resources improve the objective function by either deferring unmet demand to later periods or by using a resource with slightly lower incremental costs, adding capacity at two locations will allow the objective function to be reduced by eliminating unmet demand. The largest savings associated with grouped resources occurs when capacity is added at Locations a1 and b2, making this the best choice for additional capacity. To determine the amount of capacity to add at each location, the following calculations are performed. The increased capacity ($C = 10$) is divided proportionally between the resources in the group according to the procedure described in the CEDA algorithm. Proportions are driven by the scaling factors, which in this case are both equal to one. The calculations for the new b_{R_i} values for Resources a1 and b1 are as follows:

$$\text{For a1: } \mathrm{b}_{a1} = \mathrm{b}_{a1} + \left({\lambda_{I_{A1}a1}}\Big/{\lambda_{I_{A1}a1} + \lambda_{I_{B1}b2}} \times \mathrm{C} \right) = 0 + \left({1}/{1+1} \times 10 \right) = 5$$

$$\text{For b2: } \mathrm{b}_{b2} = \mathrm{b}_{b2} + \left({\lambda_{I_{B1}b2}}\Big/{\lambda_{I_{A1}a1} + \lambda_{I_{B1}b2}} \times \mathrm{C} \right) = 20 + \left({1}/{1+1} \times 10 \right) = 25$$

Distributing the capacity across the two resources results in additional capacity for both resources deployed in Period 2. Unmet demand in Period 2 is reduced by 5 units (Figure 11). The sensitivity information for Iteration 4 is shown in Table 10, and inspection reveals that the greatest reduction in the objective function can be produced by distributing 10 units of capacity between Resources a2 and b2. The repeating of this procedure to allocate capacity across multiple resources increases production in Period 2. The 5 remaining units of unmet demand in Period 2 are filled by holding inventory at the end of Period 1 (Figure 12). Examination of the new sensitivity table for Iteration 5 shown in Table 11 illustrates that although some shadow prices are negative, there are in fact no individual or grouped resources that will reduce the overall value of the objective function through additional capacity, and the algorithm is terminated.

The final solution produced by the CEDA algorithm is a local optimal solution for the redundant resources that are currently active. In this example, it can be seen from inspection that if the capacity allocated to Resource a1 were removed, it could be replaced by capacity from a2 for a slightly higher incremental cost.

Model Implementation and Testing

Numerical experiments were conducted on serial and assembly networks to validate the SCRF formulation and to test hypotheses related to the research questions in Chapter I. The multi-period network designs were tested under varying capacity configurations and disruption profiles to assess the model’s efficacy in determining a least-cost production and inventory strategy to overcome the disruption. The testing and evaluation process consisted of two phases. The first phase involved obtaining a least-cost production and inventory plan

for a given network configuration. In the second phase, least-cost plans were evaluated using Monte Carlo simulation techniques to observe their performance when subjected to variability. Additionally, Monte Carlo simulations were also used to validate the CEDA algorithm's ability to deploy redundant capacity in such a manner that improves overall performance of the network on an incremental basis.

Solving the SCRF formulation for an optimal solution as either a mixed-integer or linear programming form, which is necessary for execution of the CEDA algorithm, can be accomplished through a variety of open-source or commercial solver packages. In this research, solutions were obtained by constructing models in Microsoft Excel (Version 2010) and solved using both the OpenSolver (Version 2.7.1) platform and the Coin-OR CBC Optimization Engine (Version 2.9). Microsoft Visual Basic for Applications (Version 7.0) was used to streamline model construction and automate sensitivity analysis procedures. Monte Carlo simulation models were developed using Microsoft Excel and executed using Visual Basic for Applications.

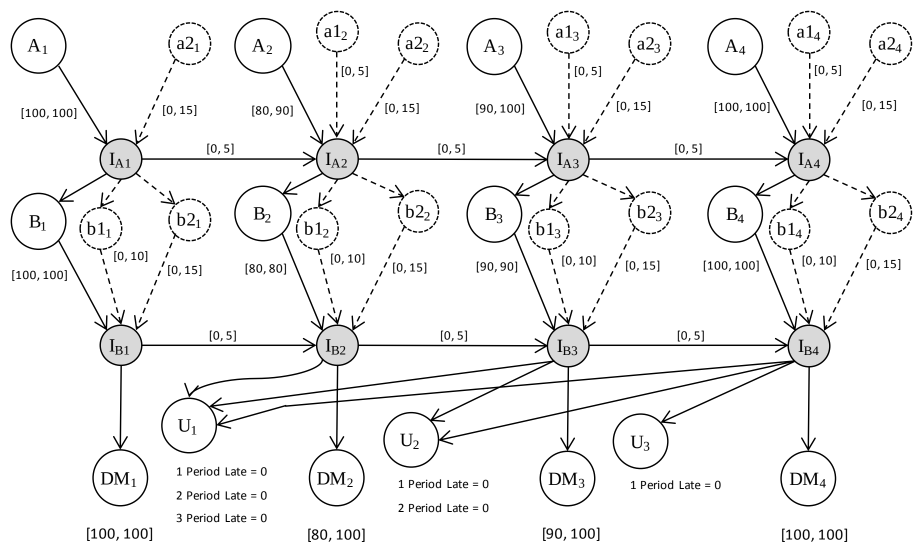


Figure 8: CEDA Example Network Diagram - Iteration 1

Table 7: CEDA Example – CEDA Example Summary Table – Iteration 1

R_i	Final Value	b_{R_i}	SP_{R_i}	AI_{R_i}	γ_{R_i}	Υ_{R_i}	$f(C)$
a1	0	0	0	Inf.	-750	1	750
a2	0	0	0	Inf.	-1,000	1	1,000
b1	0	0	-5,185	10	-1,000	1	-50,850
b2	0	0	-5,183	10	-750	1	-51,080
R_G	Final Value	b_G	SP_{R_G}	AI_{R_G}	γ_G	$\Upsilon_{R_1}, \Upsilon_{R_2}$	$f(C)$
a1 & b1	0	0	-5,185	10	-1,750	1, 1	-50,100
a1 & b2	0	0	-5,183	10	-1,500	1, 1	-50,330
a2 & b1	0	0	-5,185	10	-2,000	1, 1	-49,850
a2 & b2	0	0	-5,183	10	-1,750	1, 1	-50,080
	Optimal w/o Fixed Costs:	158,700			Optimal w/Fixed Costs:	158,700	

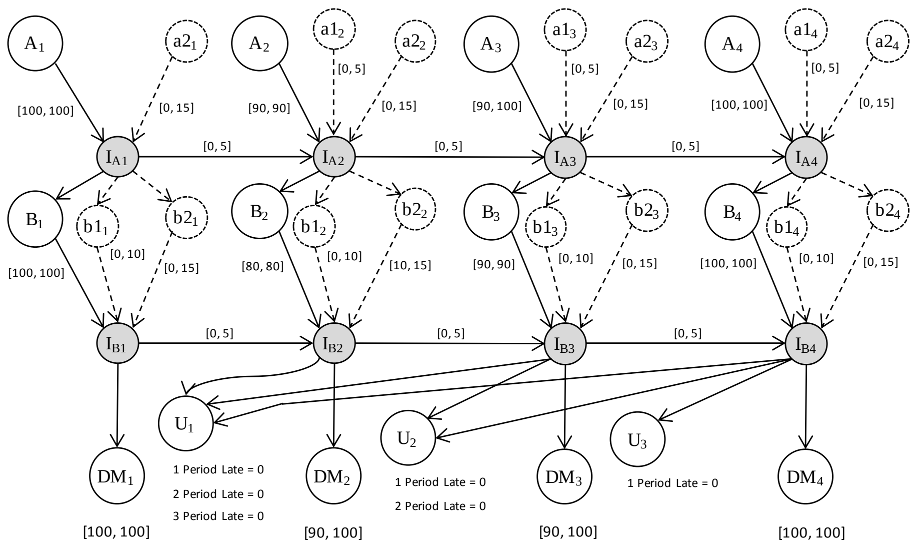


Figure 9: CEDA Example Network Diagram - Iteration 2

Table 8: CEDA Example – CEDA Example Summary Table – Iteration 2

$R_{i'}$	Final Value	$b_{R_{i'}}$	$SP_{R_{i'}}$	$AI_{R_{i'}}$	$\gamma_{R_{i'}}$	$\Upsilon_{R_{i'}}$	R_i
a1	0	0	0	Inf.	-750	1	750
a2	0	0	0	Inf.	-1,000	1	1,000
b1	0	0	-5,085	10	-1,000	1	-49,850
b2	10	10	-5,083	10	-750	0	-50,830
R_G	Final Value	b_G	SP_{R_G}	AI_{R_G}	γ_G	$\Upsilon_{R_1}, \Upsilon_{R_2}$	$f(C)$
a1 & b1	0	0	-5,085	10	-1,750	1,1	-49,100
a1 & b2	10	10	-5,083	10	-750	1,0	-50,080
a2 & b1	0	0	-5,085	10	-2,000	1,1	-48,850
a2 & b2	10	10	-5,083	10	-1,000	1,0	-49,830
Optimal w/o Fixed Costs: 106,870				Optimal w/Fixed Costs: 107,620			

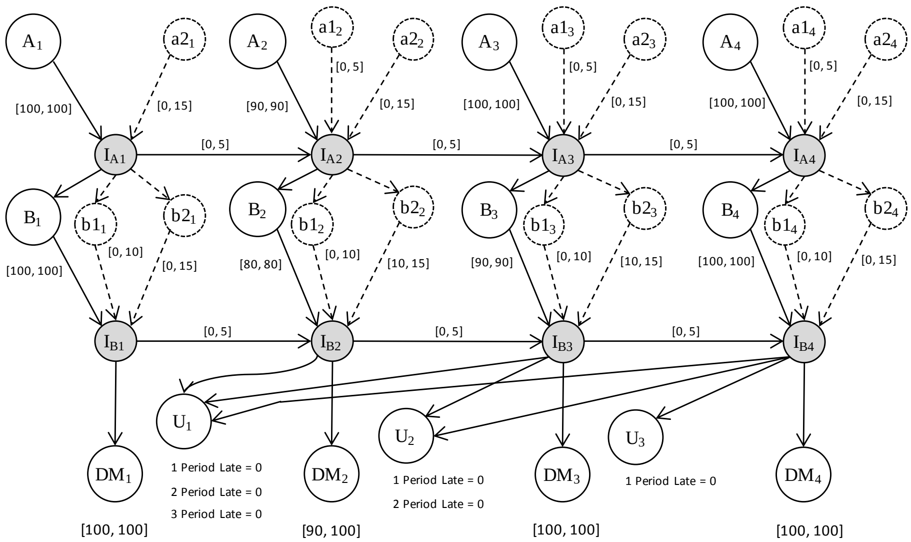


Figure 10: CEDA Example Network Diagram - Iteration 3

Table 9: CEDA Example – CEDA Example Summary Table – Iteration 3

R_i	Final Value	b_{R_i}	SP_{R_i}	AI_{R_i}	γ_{R_i}	Υ_{R_i}	$f(C)$
a1	0	0	-94	5	-750	1	280
a2	0	0	-92	5	-1,000	1	540
b1	0	0	-2	10	-1,000	1	980
b2	20	20	0	Inf.	-750	0	0
R_G	Final Value	b_G	SP_{R_G}	AI_{R_G}	γ_G	$\Upsilon_{R_1}, \Upsilon_{R_2}$	$f(C)$
a1 & b1	0	0	-2,590	10	-1,750	1,1	-24,145
a1 & b2	20	20	-2,589	10	-750	1,0	-25,135
a2 & b1	0	0	-2,589	10	-2,000	1,1	-23,885
a2 & b2	20	20	-2,588	10	-1,000	1,0	-24,875
Optimal w/o Fixed Costs: 56,040				Optimal w/Fixed Costs: 56,790			

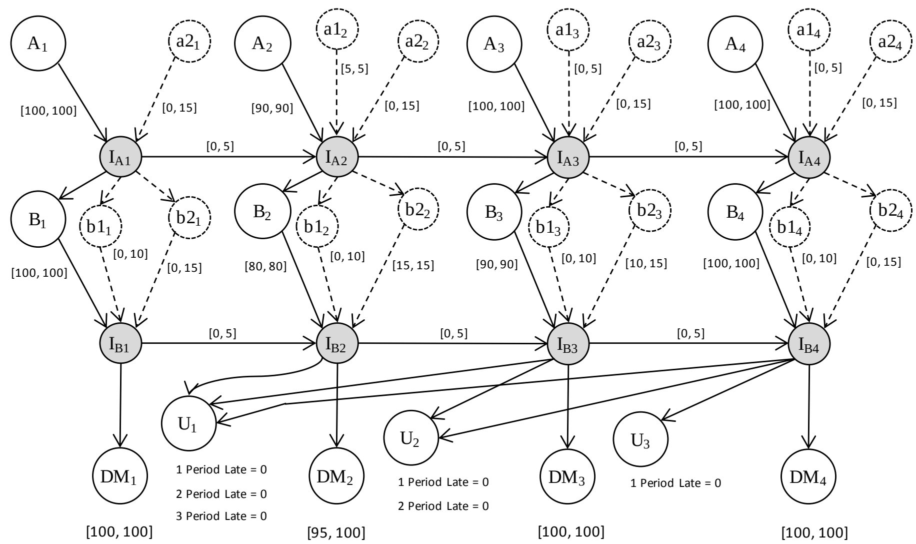


Figure 11: CEDA Example Network Diagram - Iteration 4

Table 10: CEDA Example – CEDA Example Summary Table – Iteration 4

R_i	Final Value	b_{R_i}	SP_{R_i}	AI_{R_i}	γ_{R_i}	Υ_{R_i}	$f(C)$
a1	5	5	0	Inf.	-750	0	0
a2	0	0	-92	5	-1,000	1	541
b1	0	0	-2	10	-1,000	1	980
b2	25	25	0	Inf.	-750	0	0
R_G	Final Value	b_G	SP_{R_G}	AI_{R_G}	γ_G	$\Upsilon_{R_1}, \Upsilon_{R_2}$	$f(C)$
a1 & b1	5	5	-2,487	10	-1,000	0,1	-23,870
a1 & b2	30	30	-2,486	10	0	0,0	-24,860
a2 & b1	0	0	-2,589	10	-2,000	1,1	-23,885
a2 & b2	25	25	-2,587	10	-1,000	1,0	-24,874
Optimal w/o Fixed Costs: 30,155				Optimal w/Fixed Costs: 31,655			

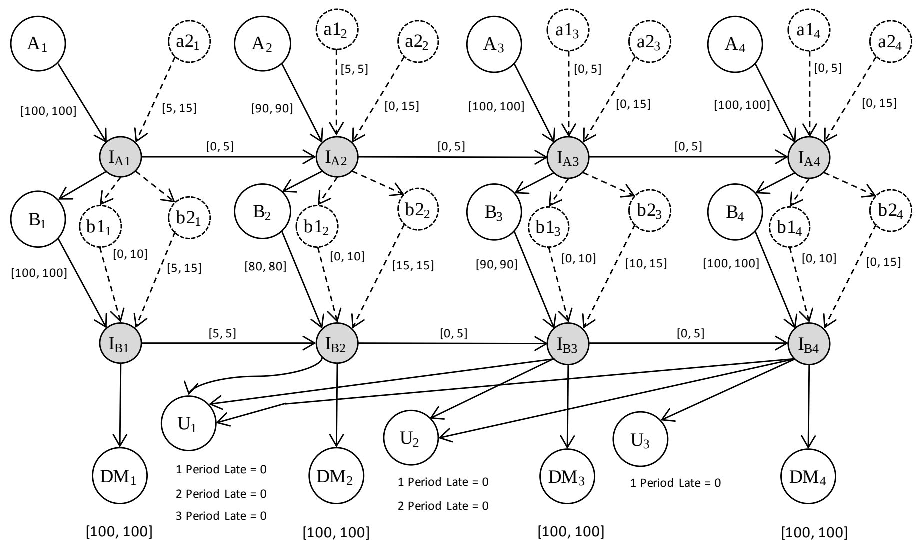


Figure 12: CEDA Example Network Diagram - Iteration 5

Table 11: CEDA Example – CEDA Example Summary Table – Iteration 5

R_i	Final Value	b_{R_i}	SP_{R_i}	AI_{R_i}	γ_{R_i}	Υ_{R_i}	$f(C)$
a1	5	5	0	Inf.	-750	0	0
a2	5	5	0	Inf.	-1,000	0	0
b1	0	0	-2	5	-1,000	1	989
b2	30	30	0	Inf.	-750	0	0
R_G	Final Value	b_G	SP_{R_G}	AI_{R_G}	γ_G	$\Upsilon_{R_1}, \Upsilon_{R_2}$	$f(C)$
a1 & b1	5	5	-2	5	-1,000	0,1	989
a1 & b2	35	35	0	Inf.	0	0,0	0
a2 & b1	5	5	-2	5	-1,000	0,1	989
a2 & b2	35	35	0	Inf.	0	0,0	0
Optimal w/o Fixed Costs: 4,281				Optimal w/Fixed Costs: 6,781			

Experiment

Network Design

The underlying structures of both serial and assembly networks, such as the planning horizons, the number of primary resources, and the number of inventory locations, were held constant for the experiments. Differences in the network configuration were introduced through changes to the characteristics of the network's redundant resources and cost structure. Figure 13 illustrates the generalized form of the serial network, and Figure 14 illustrates the generalized assembly network. A planning horizon of ten periods (t = 10) was used for both configurations. The serial network was comprised of six ($i = 6$) production resources ($\{A, B, C, D, E, F\} \in P$) and six corresponding inventory nodes ($\{I_A, I_B, I_C, I_D, I_E, I_F\} \in V$), and the assembly network consisted of nine ($i = 9$) production resources ($\{A, B, C, D, E, F, G, H, I\} \in P$) and nine inventory nodes ($\{I_A, I_B, I_C, I_D, I_E, I_F, I_G, I_H, I_I\} \in V$). The assembly network features two branches, $\{A, B, C\}$ and $\{E, F, G\}$, joining together at Location D and continuing on as $\{D, H, I\}$. In both networks, nodes identified by letters represent process activities with the flows moving downstream in alphabetical order. Customer demand for any period (DM_t) was supplied by the furthest downstream inventory location (Nodes I_F for the serial network and I_I for the assembly network). Nominal demand for each period was held constant at 100 units.

A total of six primary resources in each network type were subject to disruption. The network disruptions were modeled as a complete loss of capacity for a primary resource for a given number of periods. The onset of a disruption was uniformly distributed between the second and seventh planning period, and the duration of the disruption was uniformly

distributed between one and three periods. Disruptions occurred once per experiment combination, and the location of a disruption was treated as a factor in the experiment. Table 12 presents a summary of the general configurations and capacity parameters.

Primary resources in the network had a constant nominal capacity of 100 units per period when undisrupted. The unit cost for any given primary resource was treated as a uniformly distributed random variable and held constant for each period in a given configuration. The number of redundant resources (n_{R_i}) available to any primary resource in

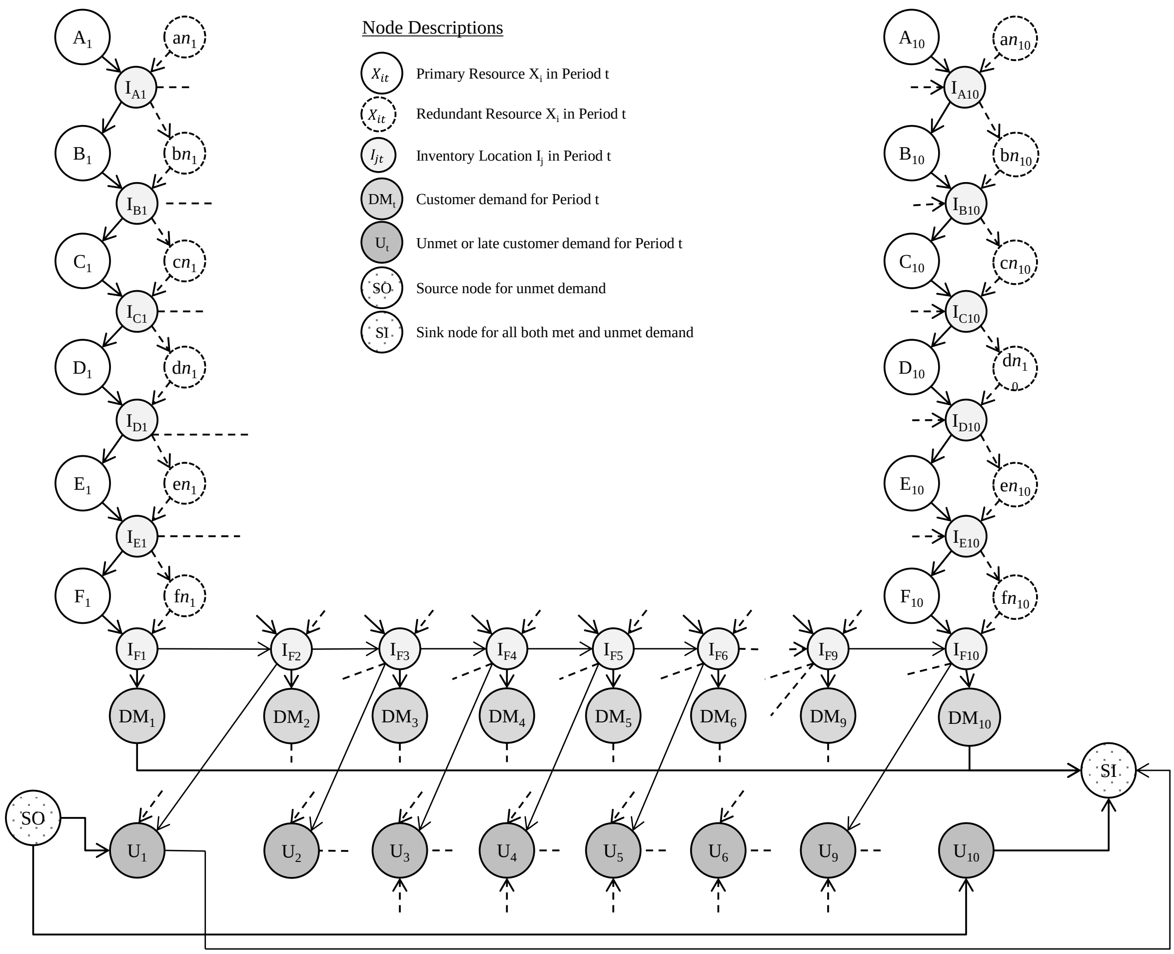


Figure 13: Serial Network Configuration

the network was dependent on its location relative to the primary resource being disrupted. Because a resource that is located closer in proximity within the network to a disrupted resource is more likely to require redundant capacity support during a disruption, a larger number of redundant capacity options were made available to those resources in the experiment. The characteristics for redundant resources were treated as uniformly distributed random variables and include a fixed charge to access the capacity, an incremental unit cost that was relatively higher than the corresponding primary resource's unit cost, and a

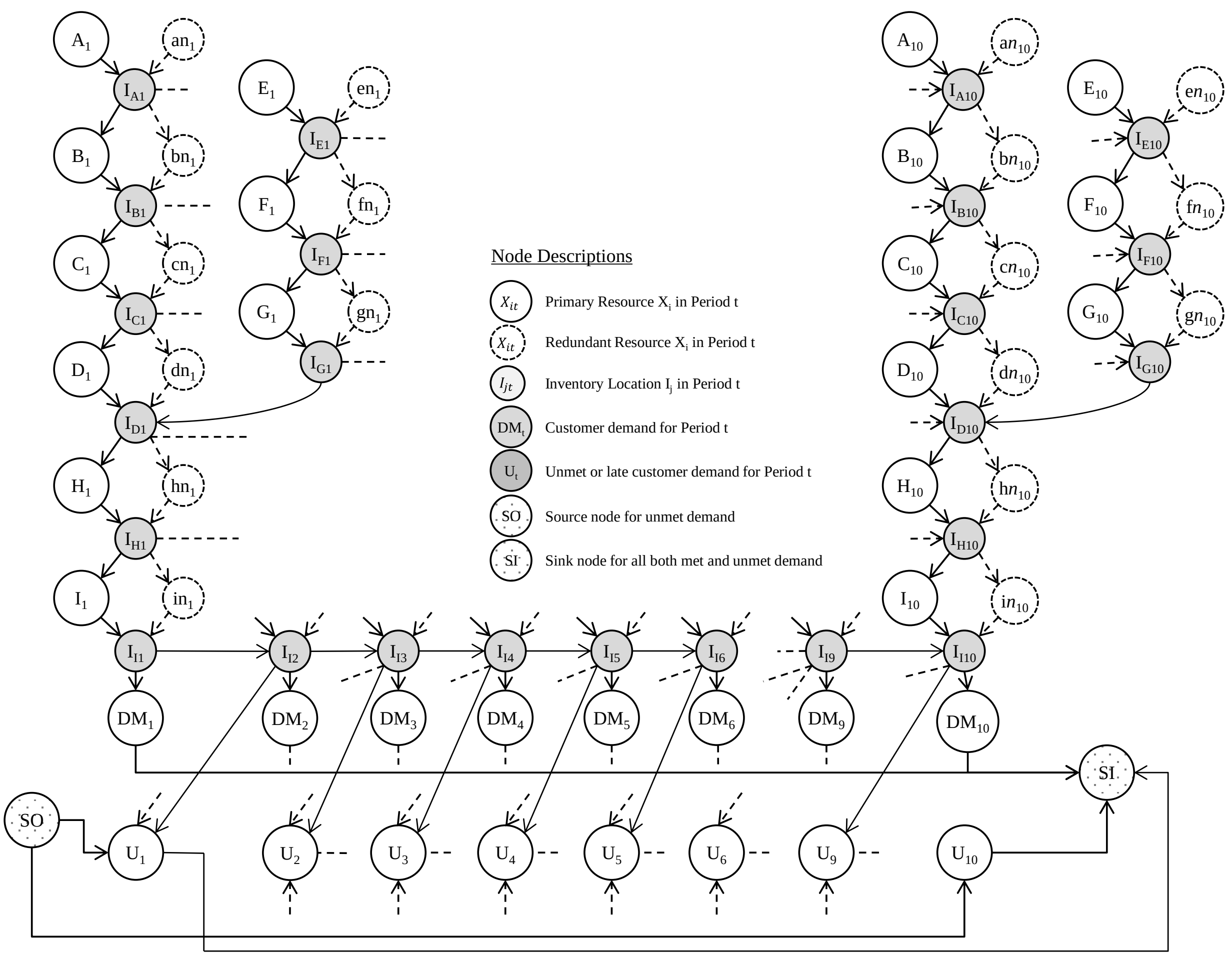


Figure 14: Assembly Network Configuration

Table 12: General Network and Primary Resource Parameters

Network	Planning Periods	Resource Nodes	Disruption Start	Disruption Duration	Resource Capacity	Resource Unit Cost	Inventory Holding Cost
Serial	8	{A*, B*, C*, D*, E*, F*}	$U(2,7)$	$U(1,3)$	100	$\alpha_{R_{it}I_{jt}}$ $U(8,14)$	$\beta_{I_{jt}}$ $U(0.1,0.4)$
Assembly		{A, B*, C*, D*, E, F*, G*, H*, I}					

* Location Subject to Disruption

delay-to-access that prevents the capacity from being accessed for some amount of time. Table 13 lists characteristics of the redundant capacity that were treated as random variables.

Inventory locations were included between each of the primary resources and were formulated as transshipment nodes to aggregate flow from both primary and redundant resources, and to transfer flow between periods. Each inventory node was incapacitated in terms of inventory flows within a given period, but had a constant capacity of 50 units for transferring between periods.

A natural objective in production planning is to eliminate or limit late and unfilled demand. These objectives are not explicitly addressed in the SCRF formulation, but are instead controlled by the relationships between cost parameters. Research investigating recovery models to date have not yet provided direct guidance as to an appropriate cost structure for recovery models. Therefore, cost parameters in this research for both late and unmet demand were constructed to ensure that their relative impact on the behavior of the networks was both consistent and limited through the use of a heuristic approach. The approach set costs in such a way so as to force a solution to have zero unmet demand if at all

Table 13: Redundant Capacity Node Variable Parameters

Network	No. of Redundant Resources n_{R_i}, by Disrupted Node	Unit Capacity	Fixed Cost	Unit Cost	Delay to Access
Serial	A: $n_{R_i}\{A,..F\} = \{12,12,10,10,8,8\}$ B: $n_{R_i}\{A,..F\} = \{10,12,12,10,8,8\}$ C: $n_{R_i}\{A,..F\} = \{10,12,12,10,8,8\}$ D: $n_{R_i}\{A,..F\} = \{8,10,12,12,10,8\}$ E: $n_{R_i}\{A,..F\} = \{8,8,10,12,12,10\}$ F: $n_{R_i}\{A,..F\} = \{8,8,10,10,12,12\}$	r_{it} $U(10,35)$	γ_{R_i} $U(800,$ $1{,}400)$	$\alpha_{X_{it}I_{jt}}$ $U(14,24)$	$U(0,4)$
Assembly	B: $n_{R_i}\{A,..I\} = \{12,12,10,10,8,8,8,8,8\}$ F: $n_{R_i}\{A,..I\} = \{8,8,8,10,12,12,10,8,8\}$ C: $n_{R_i}\{A,..I\} = \{10,12,12,10,8,8,8,8,8\}$ G: $n_{R_i}\{A,..I\} = \{8,8,8,8,10,12,12,10,8\}$ D: $n_{R_i}\{A,..I\} = \{8,8,10,12,8,8,10,12,8\}$ H: $n_{R_i}\{A,..I\} = \{8,8,8,10,8,8,10,12,12\}$	r_{it} $U(10,35)$	γ_{R_i} $U(800,$ $1{,}400)$	$\alpha_{X_{it}I_{jt}}$ $U(14,24)$	$U(0,4)$

possible, and to prefer that demand be backordered later in the planning horizon rather than earlier.

Cost parameters for unmet demand were set to be greater than the most expensive option for producing a part in the network by summing the upper bound on the distribution of fixed costs for each redundant resource, the upper bound on the unit costs for each redundant resource, and the upper bound of inventory holding costs from the first period to the last for all inventory locations. The summation of these costs was assigned to the cost parameter for unmet demand from the last period of the planning horizon. Cost parameters for unmet demand from each period earlier in the planning horizon were incrementally higher by a nominal amount greater than the summation of inventory holding costs. This procedure guarantees that unmet demand will only occur when there is no possible combination of primary and redundant resources that will mitigate the disruption.

Similarly, the cost parameter for late demand from the next-to-last period that is filled in the last period was determined in the same manner as the cost parameter for unmet demand in the last period, except that fixed charges for redundant capacity were not included. Cost parameters for filling late demand for periods earlier in the planning horizon increased incrementally by a nominal amount greater than the upper bound on the inventory holding cost distribution. This provides assurance that demand will not be left unmet when available capacity to meet demand exists anywhere in the network, but it is subject to the threshold created by the fixed costs of redundant resources.

Deterministic Experimental Design

Network configurations for validation of the SCRF formulation were created according to both the parameters discussed previously and the experiment design described in Table 14. Individual network configurations were constructed by fully randomizing primary resource cost structure, inventory holding charge structure, and all characteristics of the redundant resources available to the location being disrupted. The random network configurations were subjected to each of the factors discussed in the following section, and

Table 14: Network Configuration Factors

Set	*Locations*	*Awareness*	*Timing*
54	6	*Full* *Alternate* *90%* *80%*	*Early* *Late*

statistical analyses were conducted for each of the resource locations independently using regression techniques for linear models.

The primary factors of interest in the study are *Timing* and *Awareness*. The random factors of *Start* and *Duration* both exert significant influence on the overall variation in the experiment, and they were therefore treated as covariates. To test the supply chain resilience construct of Structural Knowledge, the factor *Awareness* was introduced, which relates to the probability that a supply chain manager was aware of a given source of redundant capacity. Under the level *Full*, all redundant resources are available to the model, and an optimal least-cost redundant capacity set is obtained. Under the level *Alternate*, any redundant resource used in the optimal set is made unavailable. Levels *90%* and *80%* represent the relative probability that any redundant resource that was not used in the optimal set is available. The availability of resources was determined through Monte Carlo sampling. If a redundant resource was determined to be unavailable, it was made unavailable in the SCRF formulation by setting the large number coefficient for that resource equal to zero ($\mathrm{M}_i = 0$). To examine the effect of delaying action to a disruption, the factor *Timing* is introduced with levels for *Early* and *Late*. *Late* shifts the disruption one period earlier but leaves the delay in accessing a source of redundant capacity unchanged.

Data for the experiments was generated and stored according to the flow diagram shown in Figure 15. A record of each experiment replication and model, including final values and randomly created data, was stored to facilitate the phase-two simulations and data analysis activities. A minimum of 54 network configurations (*Set*) were constructed for each location subject to disruption. Least-cost solutions were obtained for each combination of *Timing* and *Awareness*, yielding a total of 8 combinations for each *Set*. Configurations were

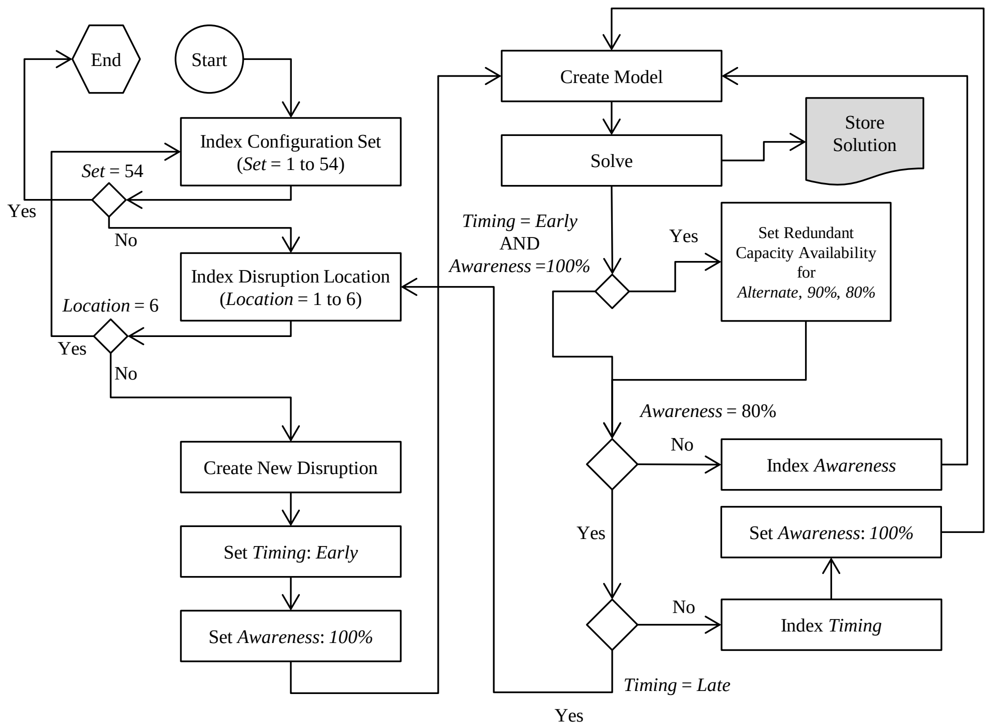


Figure 15: Deterministic Data Generation Flow Chart

randomly generated until three instances for each combination of *Start* and *Duration* were obtained.

CEDA Experiment Design

Serial network configurations were tested to evaluate the efficacy of the CEDA algorithm to improve solutions on an incremental basis. Table 15 presents network configuration parameters for the CEDA evaluation experiments. Ten networks were constructed for evaluation. Capacity allotments for each individual redundant resource were set to zero ($b_{R_i} = 0$) upon initialization of the CEDA algorithm, and capacity groups

Table 15: General Network and Primary Resource Parameters for the CEDA Experiment

Planning Periods	Resource Nodes	Disruption Start	Disruption Duration	Resource Capacity	Resource Unit Cost	Inventory Holding Cost
8	{A*, B*, C*, D*, E, F}	$U(3,5)$	$U(1,3)$	100	$\alpha_{R_{it}I_{jt}}$ $U(8,14)$	$\beta_{I_{jt}}$ $U(0.1,0.4)$

No. of Redundant Resources n_{X_i} by Disrupted Node	Unit Capacity	Fixed Cost	Unit Cost	Delay to Access
A: $n_{R_i}\{A,..F\} = \{2,2,2,2,0,0\}$ B: $n_{R_i}\{A,..F\} = \{2,2,2,2,0,0\}$ C: $n_{R_i}\{A,..F\} = \{2,2,2,2,0,0\}$ D: $n_{R_i}\{A,..F\} = \{2,2,2,2,0,0\}$	r_{it} $U(10,35)$	γ_{R_i} $U(800, 1{,}400)$	$\alpha_{R_{it}I_{jt}}$ $U(14,24)$	$U(0,4)$

* Location Subject to Disruption

consisted of pairwise groupings of redundant resources that were adjacent to one another within the network. Because each primary resource from A through D had two unique sources of redundant capacity, this pairing convention produced a total of 12 groups. For example, the redundant resources associated with A ($a1$, $a2$) produced four grouped pairs when combined with the redundant resources from the adjacent Resource B ($a1b1$, $a1b2$, $a2b1$, $a2b2$).

Capacity allocation decisions during execution of the CEDA algorithm were made by increasing capacity on resources that provided the greatest savings according to both incremental and fixed cost decisions, and the algorithm was executed until no improvement to the objective function was possible. Examination of the effectiveness of the capacity allocation was performed by comparing gains observed in three iterations of the algorithm leading up to termination with the simulation model.

Simulation Design

To validate the efficacy of the SCRF formulation and CEDA algorithm, the deterministic least-cost plans for each experiment replication were subjected to conditions of random variation in production volume relative to the intended production volume using Monte Carlo simulation models constructed with Microsoft Excel. Unlike deterministic least-cost plans, which are solved assuming perfect knowledge of production levels and are driven by the model's cost structure, variables, and constraints, the simulation model's operation is necessarily dependent on random production levels. For this reason, decision criteria for the relationships between production, inventory, and demand fulfillment were needed to replicate the *de facto* decision criteria created by the cost parameters under a given network configuration. In the simulation models, the actual production level for any given resource in Period t ($X_{R_{it}I_{jt}Actual}$) was random and was calculated to be either the lesser of 110% of its nominal capacity r_{it} , or the value of a normally distributed random variable with a mean of its target $X_{R_{it}I_{it}}$ and a standard deviation of $Cv * X_{R_{it}I_{it}}$, where Cv is the coefficient of variation for production. The formula for actual production at any location is:

$$X_{R_{it}I_{jt}Actual} = Min\left[N\left(X_{R_{it}I_{jt}}, Cv * X_{R_{it}I_{jt}}\right),\ 1.10 * X_{R_{it}I_{jt}}\right] \qquad (32)$$

Any resource having immediate predecessor resources is also limited in its production by the production levels and the available inventory of those predecessor resources. It follows that because primary and redundant resources draw from the same predecessors through an inventory location, the combined production of a primary resource and its corresponding redundant resources are limited. The calculation addresses this

requirement by limiting the overall production for the combined primary and redundant resources by subjecting them to the inventory available from their immediate predecessor. In the equation, $X'_{R_{it}I_{jt}Actual}$ represents the combined production level for a primary resource and its supporting redundant resources, and n is the number of combined primary and redundant resources. $Available\ Inventory$ includes flow from all predecessor resources in the same period as well as any flow transferred from prior periods. In a case where production on combined primary and redundant resources is limited by available inventory, it is assumed that all resources contribute at a level proportional to their planned production for the period.

$$X'_{R_{it}I_{jt}Actual} = Min\left[\sum_{i=1}^{n} X_{R_{it}I_{jt}Actual}, Available\ Inventory\right] \qquad (33)$$

This limitation applies only to resources having predecessor nodes. It is assumed that for those resources at the beginning of the network, any materials or goods needed to facilitate production are readily available. Additionally, any resource in any serial network will have at most one immediate predecessor location, whereas in an assembly network a resource may have several predecessors. In this research, only Resource D of the assembly network has multiple primary resources as predecessors, and the definition of $Available\ Inventory$ is therefore extended to include both predecessors.

By virtue of the cost structure of the SCRF formulation the ideal inventory level in a network with sufficient capacity to meet demand in every period will be zero. The inventory holding charge penalizes the objective function in a manner that forces demand, whether for an immediate downstream node, customer demand, or backordered customer demand, to be filled from capacity in that same period, if possible. Additionally, any inventory that is stored

according to the least-cost plan will be held as far downstream in the network and planning horizon as permitted by capacity constraints to reduce storage costs. It is therefore possible to model inventory control in the simulation models purely as a function of production and demand. Because it is not reasonable for a system to have zero running inventory, it is also assumed that a nominal amount of running inventory is held at each inventory location of the network except for the final location. This value is established as a uniformly distributed random variable between zero and five percent for each simulation replication. Initial inventory is calculated as a percentage of nominal demand.

$$Initial\ Inventory = I_{I_{j0}} = U(0.00, 0.07) * DM_t \tag{34}$$

The cost structure of the formulation also requires that decision criteria be applied to all inventory locations for the purpose of assigning priorities to flow. The decision criteria forces the simulation model to prioritize current period demands over demand that has been previously backordered, and to prioritize upstream inventory flows needed for the current period's production over the transfer of flows between periods. Two criteria are incorporated into the logic of the simulation model to accomplish this:

Any production resource will produce flow according to the least-cost plan, and inventory not consumed by an immediate successor will be carried forward to the next period. In other words, the production volume of any resource is not limited by the ability of an immediate successor to receive flow. Any current or backordered demand will be filled with production capacity and inventory, if possible, and inventory will not be carried forward if there is backordered demand that can be filled.

Each deterministic least-cost solution for both serial and assembly networks was

tested using simulation models according to the parameters shown in Table 16. The purpose of the simulation models was to validate that the findings and relative performance of the deterministic solutions were insensitive to variability associated with production output at resource nodes. The factors *Awareness* and *Timing* will produce suboptimal conditions that will in-turn result in increases of planned inventory within the network. Because variations in production yields have the potential to propagate throughout the network and because the placement of inventory in a production network can buffer variations, validation through simulation is a more effective means of assessing the actual differences between the factors. To align the simulation with the overall objective of the formulation, which is the ability to efficiently meet demand over a planning horizon containing a disruption, demand was not treated as a random variable in the model.

Response variables for the simulation models include actual cost of the least-cost plan (*ActCost*), average late demand (*ActLate*), and demand left unmet at the end of the planning horizon (*EndLate*). Actual cost of the plan is calculated by applying production levels from the simulation model to variable coefficients from its associated least-cost plan. The cost of late demand, which is a component of *ActCost*, was calculated using variable coefficients from the least plan model. However, due to the large values employed for the

Table 16: Simulation Experiment Parameters

Coefficient of Variation	*Replications*
5%	4

unmet demand penalty in the formulation's cost structure, the cost of unmet demand used in *ActCost* calculation was adjusted to make comparisons easier by bringing it in-line with the cost of late demand. Specifically, the cost of unmet demand was calculated to be incrementally higher than the cost of demand left unmet from the first planning period by a nominally small amount. The same value used to increment late demand costs from period to period was also used in this calculation. Values from the optimal solutions from the deterministic models (*OptCost*) were adjusted in the same manner to establish the variable *AdjOptCost*.

Analysis and Hypotheses Testing

Multiple linear regression analysis was used to examine the results of the deterministic and simulation experiments. Analyses were performed individually for each network disruption location against the outcome variables *ActCost*, *ActLate,* and *EndLate*. Analyses included examining the means and standard deviations of response variables relative to each other in graphical summaries, with special attention given to capacity deployment and inventory accumulation within the network relative to the disruption.

Factors in the regression analysis for both serial and assembly networks include the continuous variables *Start* and *Duration*, and the factors *Timing* and *Awareness*. Binary indicator variable coding was used in the analysis with levels *Early* and *Full* being reference groups. The indicator variable for *Timing* was *Late*, and the indicator variables for *Awareness* were *Alternate*, *90 Percent* and *80 Percent*. Indicator variables were also used for *Start* and *Duration*. For *Duration*, a 1-period disruption was the reference group, with variables *Duration2* and *Duration3* modeled for 2-period and 3-period disruptions

respectively. For *Start*, a disruption in Period 5 was the reference level, with variables *Start6* and *Start7* modeled for disruptions beginning in Period 6 and 7 respectively. To partition variability associated with network configurations (*Set*), the variables *NormAct* and *NormAveLate* were introduced. As a covariate, the value calculated for *NormAct* was the average value of *ActCost* for all simulation trials in the reference condition (*Timing* = *Early*, *Awareness* = *Full*) and was grand mean centered in the statistical model. *NormAveLate* was calculated as the average value of *AveLate* for all simulation trials in the reference condition and was also grand mean centered in the statistical model. The statistical models examined in this research are shown below. For each model, *i* is the response index for the experiment.

$$ActCost_i = \beta_0 + \beta_1 NormAct_i + \beta_2 Duration2_i + \beta_3 Duration3_i + \beta_4 Start6_i + \beta_5 Start7_i + \beta_6 Late_i + \beta_7 Alternate_i + \beta_8 90Percent_i + \beta_9 80Percent_i + \varepsilon_i \tag{35}$$

$$AveLate_i = \beta_0 + \beta_1 NormAveLate_i + \beta_2 Duration2_i + \beta_3 Duration3_i + \beta_4 Start6_i + \beta_5 Start7_i + \beta_6 Late_i + \beta_7 Alternate_i + \beta_8 90Percent_i + \beta_9 80Percent_i + \varepsilon_i \tag{36}$$

$$EndLate_i = \beta_0 + \beta_1 NormAveLate_i + \beta_2 Duration2_i + \beta_3 Duration3_i + \beta_4 Start6_i + \beta_5 Start7_i + \beta_6 Late_i + \beta_7 Alternate_i + \beta_8 90Percent_i + \beta_9 80Percent_i + \varepsilon_i \tag{37}$$

For the CEDA evaluation, the statistical model included a categorical variable for the individual iterations of the CEDA algorithm (*Iteration*), a blocking variable (*Network*) to partition variability associated with the randomly generated networks, and a covariate (*ExpLate*). *ExpLate* was calculated as the expected average number of units late from the deterministic plan for a given experimental combination. Statistical comparisons were made for responses of *AveLate* and *EndLate*. The objective of the analyses was to determine if successive iterations of the algorithm improved network performance. The reference group in the statistical models was the final iteration of the CEDA algorithm (*Iteration0*) and was the first randomly generated network configuration. The statistical models evaluated are shown below.

$$\begin{aligned} AveLate_i = \beta_0 &+ \beta_1 Network2_i + \beta_2 Network3_i + \beta_3 Network4_i + \beta_4 Network5_i \\ &+ \beta_5 Network6_i + \beta_6 Network7_i + \beta_7 Network8_i + \beta_8 Network9_i \\ &+ \beta_9 Network10_i + \beta_{10} Iteration3_i + \beta_{11} Iteration2_i + \beta_{12} Iteration1_i \\ &+ \beta_{12} ExpLate_i + \varepsilon_i \end{aligned} \tag{38}$$

$$\begin{aligned} EndLate_i = \beta_0 &+ \beta_1 Network2_i + \beta_2 Network3_i + \beta_3 Network4_i + \beta_4 Network5_i \\ &+ \beta_5 Network6_i + \beta_6 Network7_i + \beta_7 Network8_i + \beta_8 Network9_i \\ &+ \beta_9 Network10_i + \beta_{10} Iteration3_i + \beta_{11} Iteration2_i + \beta_{12} Iteration1_i \\ &+ \varepsilon_i \end{aligned} \tag{39}$$

The following statistical hypotheses were tested to address the research questions presented in Chapter I:

Reduced awareness of the redundant capacity in a network (*Awareness* = *Alternate*) will negatively affect the overall cost of a recovery plan, and the impact on the ability to meet demand will be marginal when redundant capacity is abundant.

$H_0: Alternate = 0$

$H_1: Alternate \neq 0$

Response Variables: *ActCost*, *AveLate*, *EndLate*

A delay in discovering or responding to a disruption (*Timing* = *Late*) will negatively affect the overall cost of a recovery plan, and the impact on the ability to meet demand will be marginal when redundant capacity is abundant.

$H_0: Late = 0$

$H_1: Late \neq 0$

Response Variables: *ActCost*, *AveLate*, *EndLate*

Successive iterations of the CEDA algorithm will positively affect the ability of the network to meet demand over the planning horizon and improve the cost effectiveness of the intermediate recovery plan.

$H_0: Iteration = 0$

$H_1: Iteration \neq 0$

Response Variables: *ActCost*, *AveLate*, *EndLate*

There is no difference in terms of the relationships between network types among the findings above.

Response Variables: *ActCost*, *AveLate*, *EndLate*

CHAPTER IV

RESULTS AND ANALYSIS

Introduction

This chapter contains a detailed summary of the analyses related to the experimental designs in Chapter III. Charts, tables, and graphics in this section are supplemented with complete information contained in the appendices of this document. The three sections of this chapter cover the analysis of experiments pertaining to the serial networks, the analysis of the assembly networks, and the assessment of the Capacity Evaluation and Deployment Algorithm (CEDA). Each section includes narratives of the data and summary interpretations of the results, with the narrative of the serial networks being more detailed in order to provide context for other two sections. Interpretation of the analyses related to the research questions along with the underlying themes of the research are both presented in this chapter.

Common themes that appear in the literature regarding Supply Chain Resilience, disruption management, and mathematical recovery are also found in the results of these experiments. One such theme is the magnifying effect that disruptions with shorter lead times can have on network performance. Past research has also shown that delays in accessing sources of redundant capacity can have an impact on the ability of a supply chain to recover (Schmitt, 2011). These delays in practice stem from lead times for planning, changeover of equipment, the procurement of capital assets, and the lead times of suppliers. The net result is that disruptions that occur with little warning will leave managers with comparatively fewer options for managing the recovery process. Finally, the physical

distribution of capacity and inventory throughout the network during a disruption features recurring patterns, similar to those found in previous research. Although not central to the objectives of the research itself, these findings provide support to the validity of the Supply Chain Recovery Formulation (SCRF) and provide context for applications in industry.

Serial Network

Overview

A variable that aggregates the capacity available to a network location prior to a disruption was introduced for the analysis. This variable (*PreDisCap*) represents the total amount of redundant capacity available prior to the onset of the disruption for the network location facing the disruption. Theoretically, if a location facing a disruption has sufficient redundant capacity to fully replace the capacity being lost, there will be no late or unmet demand resulting from the disruption. Because some sources of redundant capacity cannot be utilized immediately, there is relatively less capacity available in cases where the disruption strikes in earlier planning periods. Figure 16 illustrates that a greater amount of pre-disruption capacity is available when there is more time between the beginning of the planning period and the start of a disruption. In this research, the capacity lost during a disruption varies according to the length of disruption, reaching a maximum of 300 units in the case of a 3-period disruption. The figure also shows that that for Period 5 and beyond, there is sufficient redundant capacity on the disrupted resource to fully replace the capacity lost to the disruption prior to its onset. Conversely, disruptions beginning in Period 2 that have durations lasting longer than one period (i.e., with a capacity loss greater than 100 units) generally do not have sufficient capacity to buffer the disruption completely. In these cases,

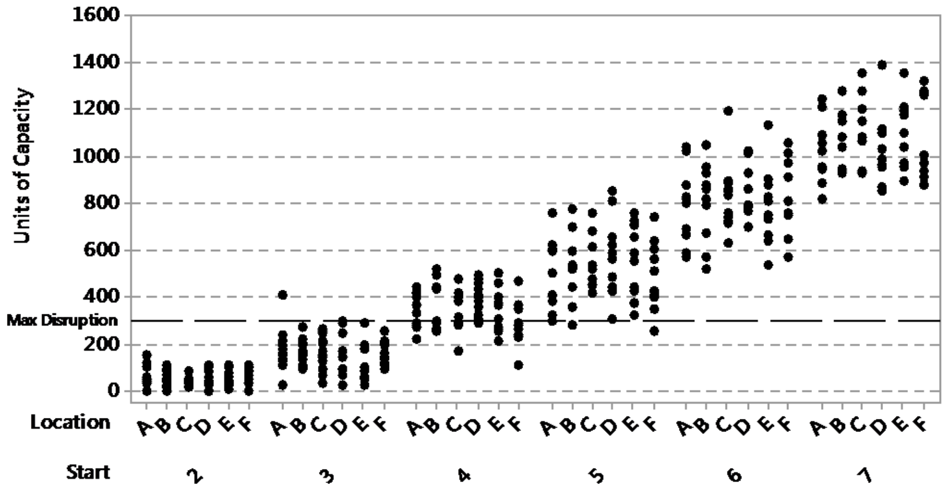


Figure 16: Serial Network, Predisruption Capacity by *Start* & *Location*

backorders are inevitable, and some demand will be filled in later periods. Figure 16 also demonstrates the high degree of correlation between *Start* and *PreDisCap*. Table 17 further illustrates the effect of early disruptions by comparing *AveLate*, which is an output variable of the simulation model, with the variable *ExpLate*, which is the expected number of late deliveries obtained from the deterministic plans. It can be seen that disruptions occurring earlier or with longer durations have higher overall levels of average and expected late demand. The largest response occurs when the disruption begins in Period 2 and lasts for three periods. It should also be noted that little distinction exists between the responses for each variable in Period 5 or later.

In an ideal situation, any disruption would be managed by replacing the lost capacity with some form of redundant capacity within the same period or periods in which the disruption occurs. In reality, simply replacing lost capacity during a disruption often proves to be infeasible or impractical. To illustrate, consider a situation where a lone source of

Table 17: Serial Network, *AveLate* and *ExpLate* by *Start* and *Duration*

	Duration					
	1		2		3	
Start	*AveLate*	*ExpLate*	*AveLate*	*ExpLate*	*AveLate*	*ExpLate*
2	39.58	7.11	67.67	12.80	84.86	15.89
3	26.37	4.16	43.33	7.71	57.64	10.80
4	19.44	1.68	22.46	2.63	24.59	2.85
5	17.05	0.42	17.85	0.64	17.03	0.38
6	16.54	0.20	16.25	0.07	17.57	0.34
7	16.51	0.25	16.49	0.22	16.15	0.00

redundant capacity is only able to produce at half the rate of the primary source. Full replacement of that lost capacity is theoretically possible but will take twice as many periods to accomplish. The preference in this case would be to deploy capacity early and store inventory in order to meet demand. Deploying capacity from other sources toward upstream operations may also be necessary in order to support the temporarily higher production rates. A second, less ideal option to manage the disruption involves deploying redundant capacity after the disruption begins, which may result in late shipments. This situation also results in higher production rates, potentially requiring alternate sources of capacity to be used on downstream operations in order to maintain adequate material flow. Each of these cases requires a net increase in the total capacity needed to manage the disruption and can be viewed as a measure of efficiency for the recovery. This idea and its relationship to disruption start time and duration can be seen in Figure 17.

Figure 17 presents mean and individual values for the overall capacity deployed for each experiment trial by *Start* and *Duration*. Values are shown as a ratio of the total amount of redundant capacity deployed for all network locations to the capacity lost from the disruption (see Appendix C for results versus network location). A global capacity ratio of 1.0 indicates that the disruption was managed through a direct replacement of the lost

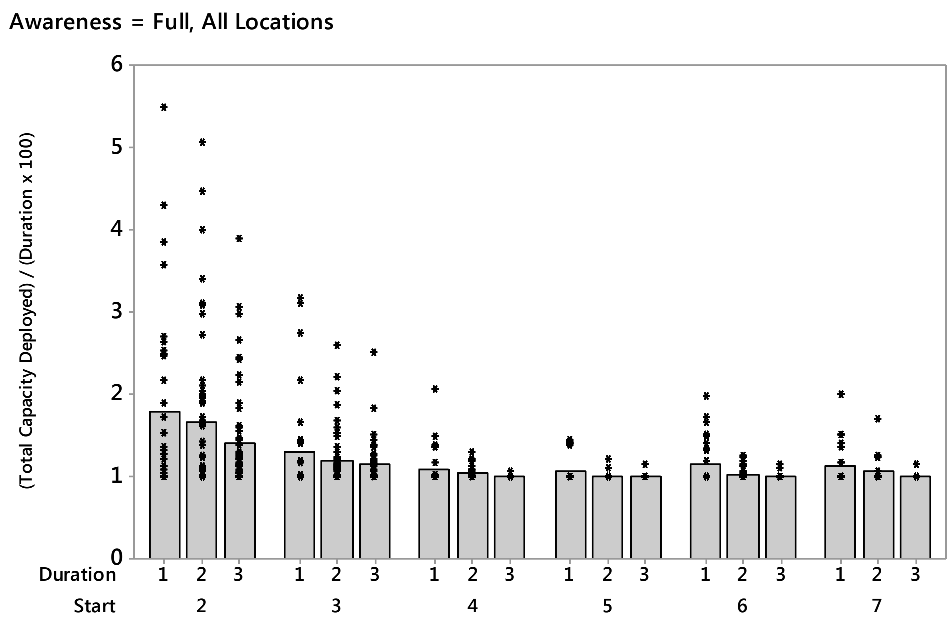


Figure 17: Serial Network, Global Capacity Deployed as a Ratio of Capacity Loss

capacity for the resource being disrupted. Because the SCRF formulation is a least-cost formulation, the replacement capacity for the disrupted resource will assuredly be no greater than its total capacity loss. In other words, the formulation will not allow overproduction when attempting to meet demand. Because a ratio above 1.0 indicates that a greater overall amount of capacity is being used, it is also certain that the additional capacity is being applied to either upstream or downstream resources. The figure shows that for disruptions with little advanced notice a greater amount of overall capacity is required.

Three implications stem from these results. The first is that early disruptions tend to require the deployment of redundant capacity to non-disrupted resources. Secondly, even in cases where full replacement of lost capacity is possible, optimal plans often include the deployment of redundant capacity on either upstream or downstream resources. This reinforces that the holding of inventory is an important option. Lastly, it can be seen in the

complete data provided in Appendix C that the position of the disrupted resource within the network influences the capacity deployed, with locations near the beginning or end of the network tending to have lower ratios.

Other characteristics exhibited by the serial network structure relate to the timing and placement of redundant capacity within the network. Figure 18 presents a capacity view with a normalized disruption timeline, where Time 0 indicates the onset of a disruption and Time -1 indicates one period prior to the disruption's onset (see Appendix C for a complete set of figures). The Y-axis of the figure represents the amount of redundant capacity deployed to a network location as a percentage of the capacity lost to the disruption. For example, in a case where a 2-period disruption results in a 200 unit capacity loss at Location C, a value of 35%

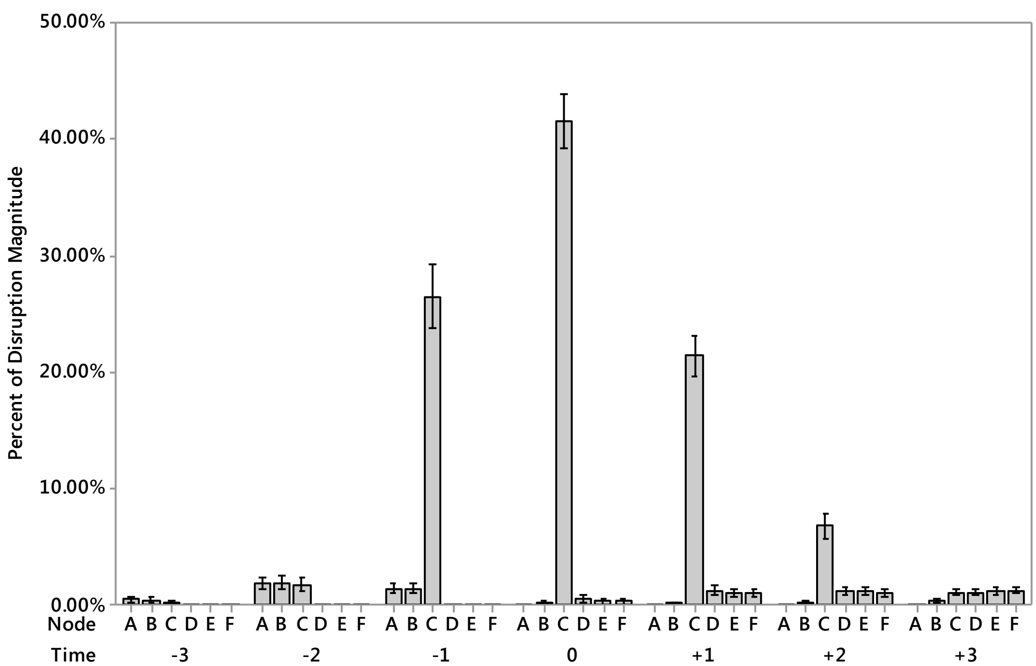


Figure 18: Serial Network, Capacity Deployed Relative to Disruption Start for Location C

for Location C at Time -1 indicates that 70 units of capacity were deployed at that time. Because simply replacing lost capacity is logically the most preferable strategy for managing a disruption, the majority of redundant capacity deployed occurs on the disrupted node at the onset of a disruption. It can also be seen that redundant capacity deployed prior to a disruption tends to occur either on or upstream from the disruption, and capacity deployed after a disruption tends to occur downstream from the disruption.

Disruptions occurring early in the planning horizon have comparatively fewer redundant capacity options due to the delay in accessing some resources, thereby reducing the ability of the network to build inventory ahead of the disruption. An alternate course of action for early disruptions is to minimize costs associated with late or unmet demand by using redundant capacity at downstream resources. This results in higher inventory flows, which are used to fill the backordered demand stemming from the initial capacity loss. A relatively smaller amount of upstream redundant capacity is needed to support these higher flows as a net surplus of upstream capacity is created by the disruption itself. For disruptions occurring later in the planning horizon, the cost structure that penalizes both late and unmet demand forces inventory to accumulate upstream from the disruption. Any inventory accumulated is then drawn down throughout the disruption period while the undisrupted downstream resources fill demand as it occurs.

Past research has demonstrated that for a specific type of serial network under disruption, inventory will accumulate at the node farthest downstream from the disrupted node which is the lowest storage cost (Hu, Li, & Holloway, 2013). However, these networks are rare in practice, and this rule can only be generalized if the network is mathematically transformed to represent the special-case network. In this research, a similar observation can

be made regarding the accumulation of inventory in that it tends to accumulate in the network according to the timing and location of the disruption. Figure 19 presents an example of the typical inventory accumulation pattern of the network in total units stored with a normalized time scale (see Appendix C for a complete set of charts). For any location in the network, inventory tends to accumulate upstream from the disruption and prior to the onset of the disruption. This built up inventory is then consumed throughout the disruption by downstream nodes.

Network Performance

Basic statistics of the primary variables of interest by disruption location (*Location*) for the serial networks are presented in Table 18. Little discrepancy exists in the overall

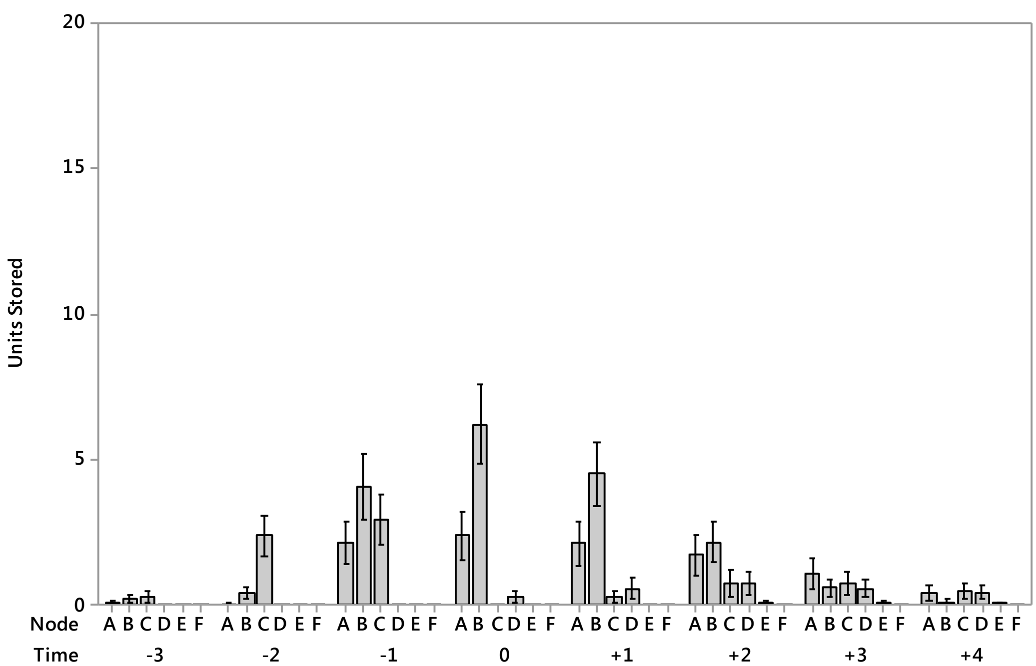


Figure 19: Serial Network, Inventory Storage Relative to Disruption Start for Location C

performance of the network in terms of cost or backorders when primary Resources B, C, D, E, and F are disrupted. A disruption on primary Resource A produced the lowest mean responses for both *ActCost* and *AveLate*. There is little difference between mean responses of *EndLate* at any location. Response variables of interest were also plotted against the main factors of interest, *Awareness*, *Timing*, *Start*, and *Duration*. The variable *ActCost* versus the primary factors of interest, *Awareness* and *Timing*, are shown in Figure 20 and Figure 21. *AveLate* versus *Awareness* and *Timing* are shown in Figure 23 and Figure 24. *EndLate* versus *Awareness* and *Timing* are shown in Figure 26 and Figure 27. Figure 22, Figure 25, and Figure 27 present *ActCost*, *AveLate*, and *EndLate* versus the *Start* and *Duration*. For context, an expected cost of network performance in an undisrupted state is identified on all figures relating to *ActCost*. Expected late and unmet demands are assumed to be zero.

The figures presented give insight into the effects the factors have on network performance and the ability to create efficient plans using SCRF formulation. In the

Table 18: Serial Network Summary Statistics

Disrupted Location	*ActCost*		*AveLate*		*EndLate*	
	Mean	SD	Mean	SD	Mean	SD
A	80,954	14,108	25.1	24.3	25.6	8.1
B	86,972	16,478	32.9	32.8	25.6	8.7
C	87,322	15,590	32.5	31.5	24.9	8.3
D	87,613	14,242	32.8	30.9	24.7	8.2
E	87,847	14,819	35.1	33.8	25.9	12.2
F	86,573	13,962	31.9	28.0	25.2	8.1
Overall	86,221	15,077	31.7	30.6	25.3	9.0

experiment, a network with access to all sources of redundant capacity (*Awareness* = *Full*), and one that also discovers and acts upon the disruption immediately (*Timing* = *Early*), will in theory have relatively lower costs and suffer fewer late or unmet orders compared to a network in a different situation. The objective of the analysis was in-part to determine if these hypothesized relationships remained true when the network was exposed to variability from the simulation model. Upon review, the relationships clearly are preserved.

For the factor *Awareness*, the level *Full* consistently produced the lowest mean responses of *ActCost* and *AveLate* regardless of the location of a disruption, and a disruption on Resource A produced comparatively lower mean responses versus the other resources for both variables. For *Timing*, the level *Early* produced lower responses of *ActCost* and *AveLate* than *Late* in every case, and mirrored *Awareness* in that Resource A had relatively lower costs than the other resources. There was no consistent pattern for responses of *EndLate* observed for any of the comparisons, indicating that the ability of the formulation to meet demand does not seem to be influenced by the factors considered.

As is expected, given the cost relationship between primary and redundant resources, longer disruptions produce comparatively higher values of *ActCost*, but that relationship is influenced by the starting time of a disruption. Disruptions beginning in Periods 2, 3, and 4 produce noticeably higher responses versus those beginning later in Periods 5, 6, and 7. This relationship repeats for values of *AveLate*, although differences in later periods are not readily apparent.

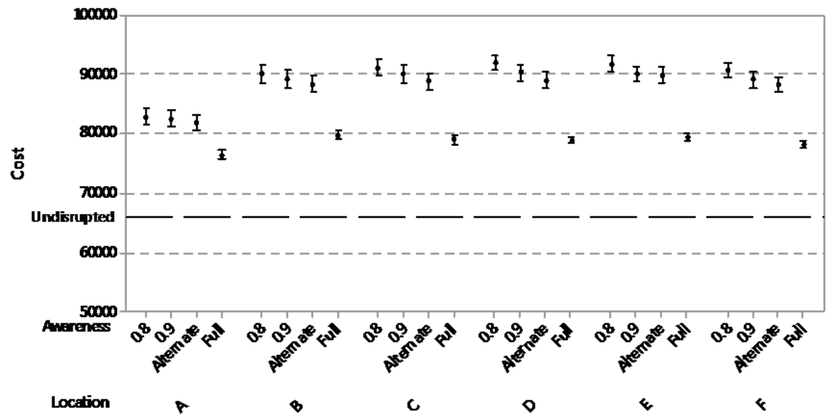


Figure 20: Serial Network, *ActCost* by *Location* and *Awareness*

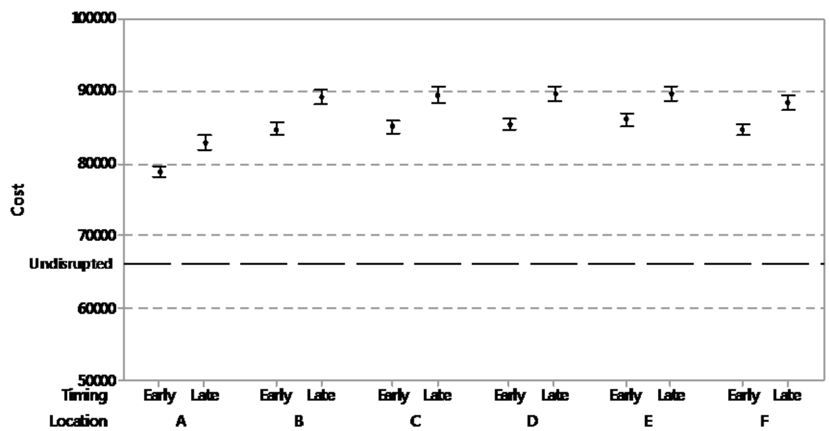


Figure 21: Serial Network, *ActCost* by *Location* and *Timing*

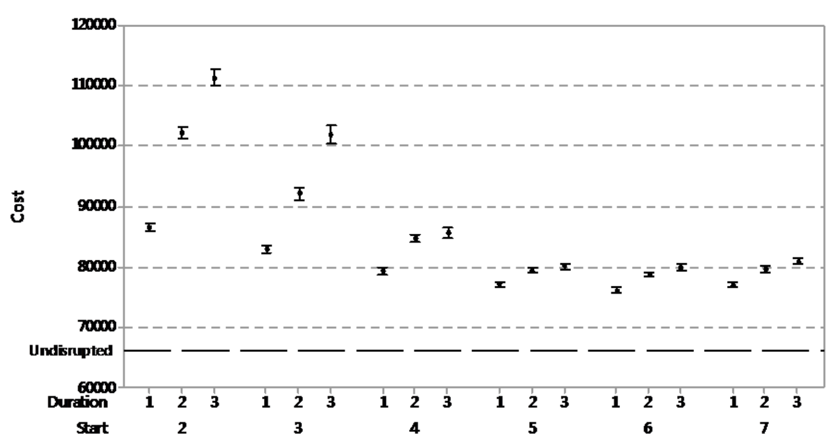


Figure 22: Serial Network, *ActCost* by *Start* and *Duration*

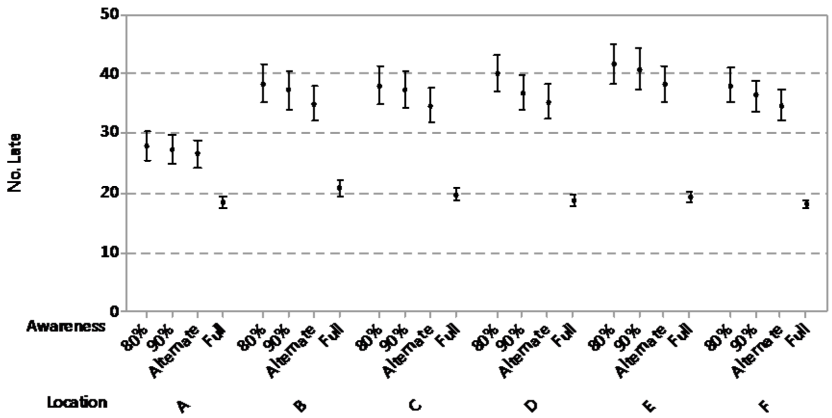


Figure 23: Serial Network, *AveLate* by *Location* and *Awareness*

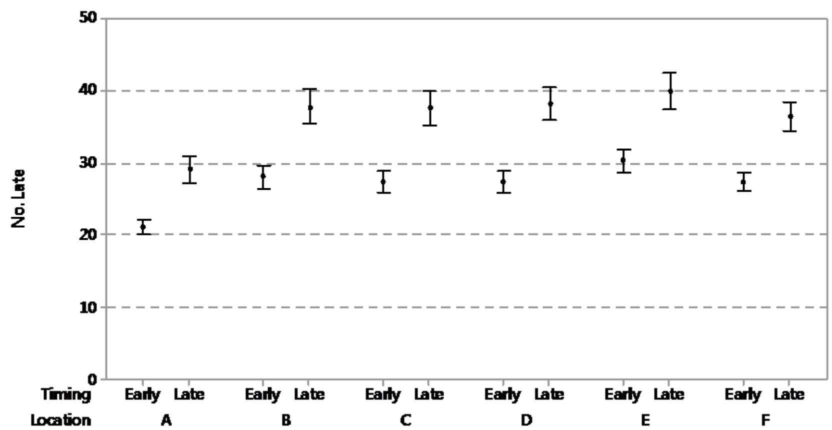


Figure 24: Serial Network, *AveLate* by *Location* and *Timing*

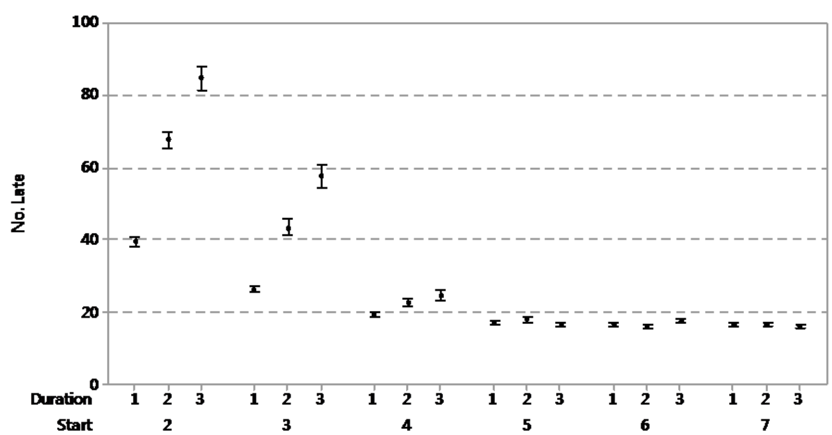


Figure 25: Serial Network, *AveLate* by *Start* and *Duration*

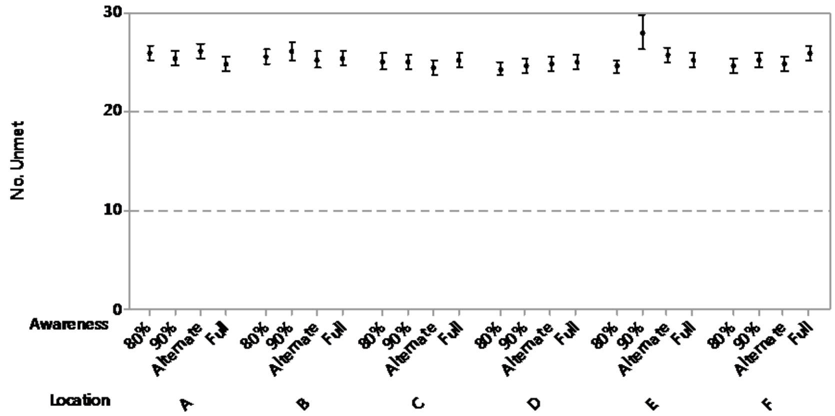


Figure 26: Serial Network, *EndLate* by *Location* and *Awareness*

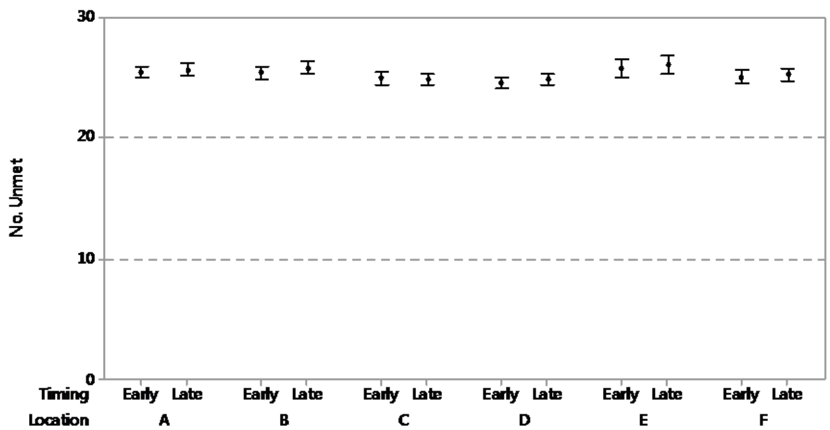


Figure 27: Serial Network, *EndLate* by *Location* and *Timing*

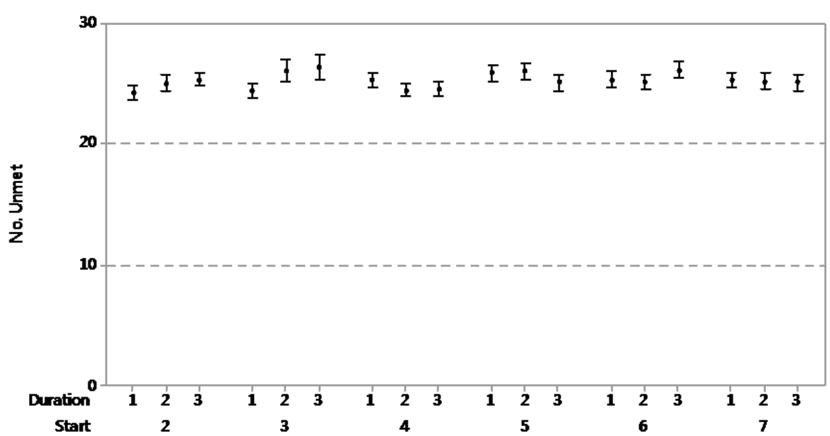


Figure 28: Serial Network, *EndLate* by *Start* and *Duration*

Statistical Analysis

The intent of the SCRF formulation is to determine a least-cost plan to fulfill demand requirements by deploying available sources of redundant capacity efficiently, and the purpose of this statistical analysis is to determine if the formulation is indeed able to do so. The previous figures reveal that in cases where redundant capacity is abundant (e.g., *Awareness* = *Full*), the formulation will have little trouble filling demand, and costs will be kept comparatively low. It is also clear that when disruptions occur earlier in the planning horizon, there is a negative impact on both cost and ability to meet demand. This degraded performance can be attributed to the limited amount of pre-disruption capacity (*PreDisCap*) available for disruptions beginning early in the planning horizon. These effects are the most pronounced in Periods 2, 3, and 4, with little distinction between costs or ability to meet demand observed in Periods 5, 6, and 7. It is also important to note that there is relatively less pre-disruption capacity available when disruptions are not discovered immediately (*Timing* = *Late*). From this, the central question for the statistical tests becomes whether or not the SCRF formulation is able to adequately deploy capacity to meet demand when redundant capacity is not abundant (*Awareness* ≠ *Full* and *Timing* ≠ *Early*).

Statistical comparisons were made for each of the variables of interest according to the statistical models described in Chapter III. The results discussed in this chapter center on comparisons of the variables *ActCost* and *EndLate*. All statistical comparisons in this research were performed using Minitab software (Version 17).

Table 19 presents a summary of the Analysis of Variance (ANOVA), variable coefficients, and *p*-values for tests associated with the primary factors of interest for the

Table 19: Serial Network, Selected Regression Coefficients by Location for *ActCost* and *EndLate*

Disruption Location	Factor	Level	*ActCost* Coef	*ActCost* SE Coef	*ActCost* *p*-Value	*EndLate* Coef	*EndLate* SE Coef	*EndLate* *p*-Value
A	Constant		73,941	167.0	0.000*	24.74	0.801	0.000*
	Timing	Late	272	106.0	0.010	-0.08	0.525	0.873
	Awareness	0.8	1,793	149.0	0.000*	0.80	0.742	0.283
		0.9	1,539	149.0	0.000*	0.74	0.742	0.318
		Alternate	1,604	149.0	0.000*	0.97	0.742	0.194
B	Constant		74,810	279.0	0.000*	25.98	0.849	0.000*
	Timing	Late	495	184.0	0.007	0.87	0.563	0.121
	Awareness	0.8	2,585	261.0	0.000*	-0.54	0.796	0.497
		0.9	2,886	261.0	0.000*	-0.81	0.796	0.310
		Alternate	2,333	261.0	0.000*	-0.14	0.796	0.862
C	Constant		73,983	277.0	0.000*	25.75	0.840	0.000*
	Timing	Late	595	182.0	0.001	-0.26	0.546	0.633
	Awareness	0.8	4,987	257.0	0.000*	-0.76	0.773	0.324
		0.9	3,274	257.0	0.000*	-0.60	0.773	0.435
		Alternate	3,054	257.0	0.000*	-0.60	0.773	0.435
D	Constant		75,771	317.0	0.000*	25.95	0.863	0.000*
	Timing	Late	661	208.0	0.002	0.52	0.568	0.363
	Awareness	0.8	5,438	294.0	0.000*	-1.95	0.804	0.015
		0.9	4,734	294.0	0.000*	-0.92	0.804	0.254
		Alternate	3,703	294.0	0.000*	-0.60	0.804	0.460
E	Constant		75,694	280.0	0.000*	25.29	0.773	0.000*
	Timing	Late	582	184.0	0.002	0.27	0.506	0.598
	Awareness	0.8	5,509	260.0	0.000*	-0.38	0.715	0.596
		0.9	4,519	260.0	0.000*	-0.21	0.715	0.771
		Alternate	4,134	260.0	0.000*	-0.29	0.715	0.688
F	Constant		75,847	313.0	0.000*	27.11	0.769	0.000*
	Timing	Late	684	215.0	0.002	0.71	0.527	0.178
	Awareness	0.8	6,249	305.0	0.000*	-0.91	0.746	0.223
		0.9	4,565	305.0	0.000*	0.15	0.746	0.844
		Alternate	3,480	305.0	0.000*	-0.99	0.746	0.186

* $p < 0.001$

response variables *ActCost* and *EndLate*. Full results consisting of ANOVA and regression coefficient tables for *ActCost*, *AveLate*, and *EndLate* are provided in Appendix C. Figure 29 displays a full interaction plot for the factors of interest. The plot illustrates the consistency of the relationships between factors, with the lone exception being the relationship between *Location* and *Start*, where interactions appear to exist. However, by performing the statistical tests separately for the different network locations, and only for disruptions beginning in Period 5 or later, any meaningful impact on the interpretations of the statistical tests was eliminated. Furthermore, statistical tests for interactions found no meaningful interaction between factor levels.

From the table, the efficacy and behavior of the SCRF formulation in terms of meeting demand can be observed. The main factors of interest in this study are *Awareness*

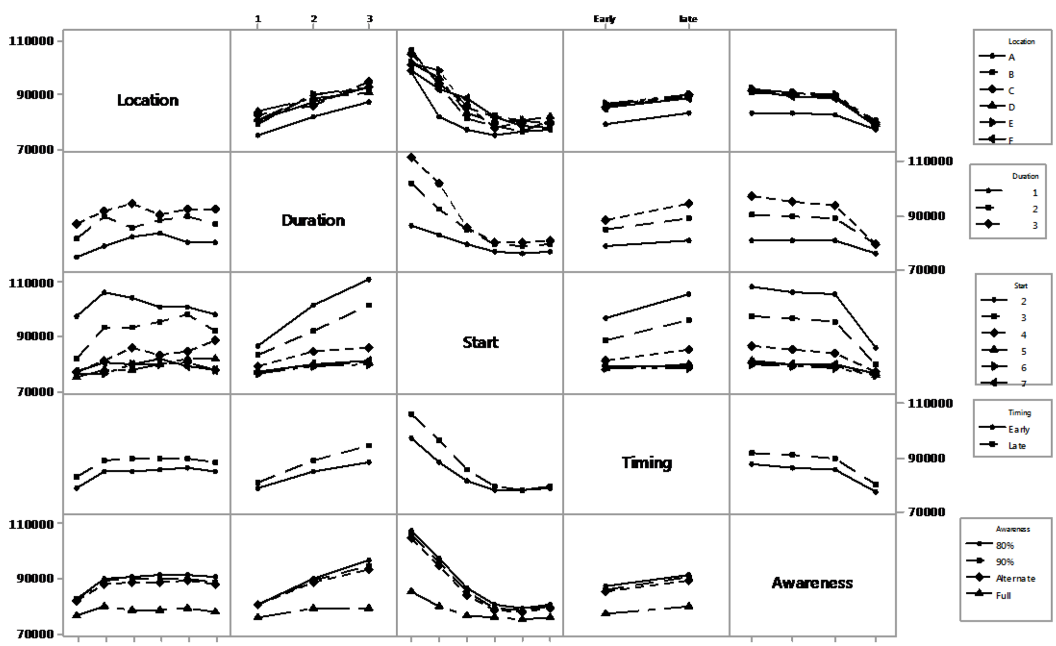


Figure 29: Serial Network, Interaction Plot *ActCost* versus Factors of Interest

and *Timing*, and the statistical tests compare the reference level of each factor (*Awareness* = *Full*, *Timing* = *Early*) with the other levels of the factor. For instance, the statistical test associated with a response to a disruption being delayed by one period (*Timing* = *Late*) can be interpreted with the *p*-value from the row associated with *Late* for the response variable of interest. Each of the three levels of *Awareness* (*Alternate*, *80*%, and *90%*) were significantly higher in terms of the cost of recovery (*ActCost*) than the reference group *Full* for each location. The factor *Timing* was also significant for *ActCost*, with *Late* being associated with higher costs compared to the reference group *Early* in every case. In terms of *EndLate*, comparisons for levels of *Awareness* show no distinction between the reference group *Full* and *Alternate* at any location. Differences between *Full* and levels *80%* and *90%* were also not significant at any location. Additionally, tests associated with *Timing* revealed no significant difference in responses of *EndLate* at any location.

These results show that in cases where redundant capacity is abundant, the formulation is effective at identifying least-cost plans that meet customer demand even when the optimal redundant capacity choices are removed from consideration or when the formulation of the plan is delayed by one planning period. Although not presented here, results of similar statistical tests that included all levels of *Start* yielded the same conclusions. Their omission from these findings are due to the exacerbating effect that low levels of available pre-disruption capacity (*PreDisCap*) have on network performance.

Assembly Network

Overview

The underlying interest in examining the behavior of assembly networks versus that of the serial networks is to determine if the ability of the SCRF formulation to effectively allocate capacity and inventory throughout the network is dependent on the structure of the network. Accordingly, the analysis and assessment procedures for the assembly network mirrored those of the serial network. It is therefore necessary to validate that certain assumptions regarding the characteristics of the network structures are also consistent. To assess whether or not the capacity within the network and the performance of the network under simulated variability were consistent with that of the serial network, the response variables *PreDisCap*, *AveLate*, and *EndLate* were examined.

In the same manner as was performed for the serial networks, Figure 30 illustrates the

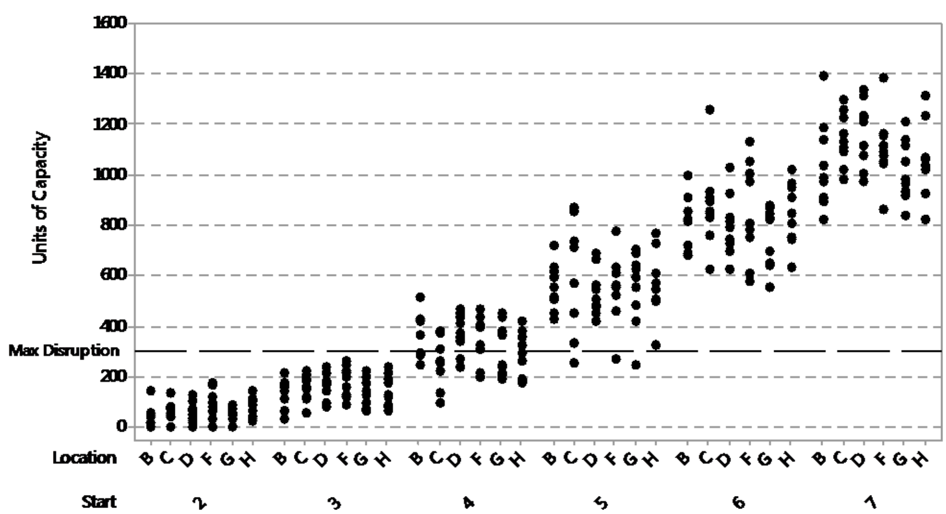


Figure 30: Assembly Network, Predisruption Capacity by Disruption Start & Location

pre-disruption capacity by *Location* and *Start* for the assembly networks. As with the serial network, it can be seen that there is generally a sufficient amount of pre-disruption capacity in the network to fully buffer a disruption prior to its occurrence for Period 5 or later. Disruptions lasting three periods generally do not have sufficient capacity if they occur in Period 4 or before. Additionally, *Start* and *PreDisCap* are correlated in much of the same manner for assembly networks as for serial networks. Table 20 illustrates similarities between the network types by comparing the response variables *AveLate* and *ExpLate* versus *Start* and *Duration*. The patterns, in which little distinction can be observed between the values for Period 5 and later, suggest that the performance of the assembly network also stabilizes during this time. Earlier disruptions, as well as those with longer durations, again have higher overall levels of average and expected late demand, and the differences are exacerbated by increasing levels of *Duration*.

Figure 31 shows that, in the same manner as serial networks, the factors *Start* and *Duration* drive the total amount of capacity deployed. Significantly higher levels of capacity are used to manage disruptions occurring early in the planning horizon, with disruptions beginning prior to Period 4 requiring increasing amounts of redundant capacity. The figures

Table 20: Assembly Network, *AveLate* and *ExpLate* by *Start* and *Duration*

	Duration					
	1		2		3	
Start	*AveLate*	*ExpLate*	*AveLate*	*ExpLate*	*AveLate*	*ExpLate*
2	51.50	7.66	82.15	12.21	120.92	18.02
3	27.06	3.94	54.36	8.68	65.37	9.95
4	17.60	1.58	20.32	1.95	24.39	2.64
5	13.56	0.20	13.31	0.16	14.19	0.24
6	12.98	0.03	13.34	0.08	13.02	0.06
7	13.47	0.06	13.04	0.01	13.11	0.12

show that the maximum capacity deployment ratio for a disruption occurring in Period 2 was between 5.0 and 6.0 for both serial and assembly networks and that ratios between 1.0 and 2.0 were common for disruptions starting in Period 5 or later. Complete results for global capacity deployed by network location for the assembly networks can be found in Appendix D.

The behavior of the network in terms of capacity and inventory distribution relative to the disruption was also examined. In the serial networks, capacity tended to be deployed to upstream resources prior to the onset of a disruption and to downstream resources afterward. Inventory also tended to build up on or upstream of the disrupted location prior to its onset, and then flow to downstream resources once the disruption began. This behavior is exhibited by the assembly networks, where disruptions occurring early in the planning horizon tended to have redundant capacity deployed to non-disrupted resources. It is also

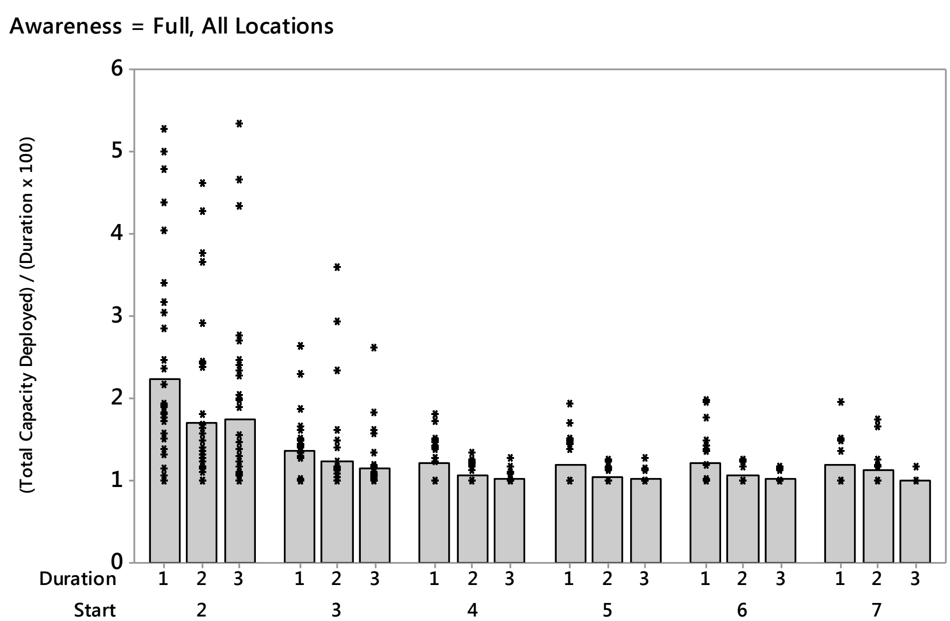


Figure 31: Assembly Network, Global Capacity Deployed as a Ratio of Capacity Loss

consistent that the allocation of redundant capacity throughout the network is a function of both the timing and location of the disruption. Figure 32 illustrates how the majority of redundant capacity is deployed on the disrupted node at the onset of a disruption, and that redundant capacity deployed prior to a disruption tends to occur upstream from the disruption, while capacity deployed after a disruption tends to occur downstream. In regards to inventory distribution within the network (Figure 33), inventory accumulates upstream of the disrupted resource prior to the disruption. It can also be seen from Figure 33, and those shown in Appendix D, that inventory will accumulate on other branches of the network. As shown in the figure for Resource C of the assembly network, inventory accumulation on upstream Resources B and A is accompanied by accumulation on Resources F and E from the

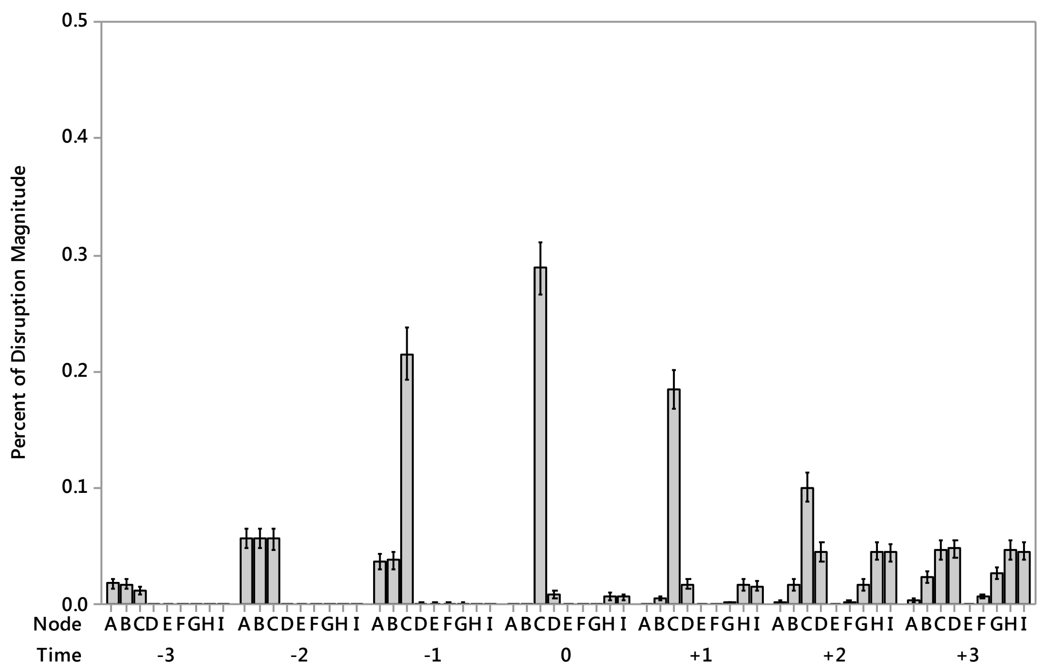


Figure 32: Assembly Network, Capacity Deployed Relative to Disruption Start for Location C

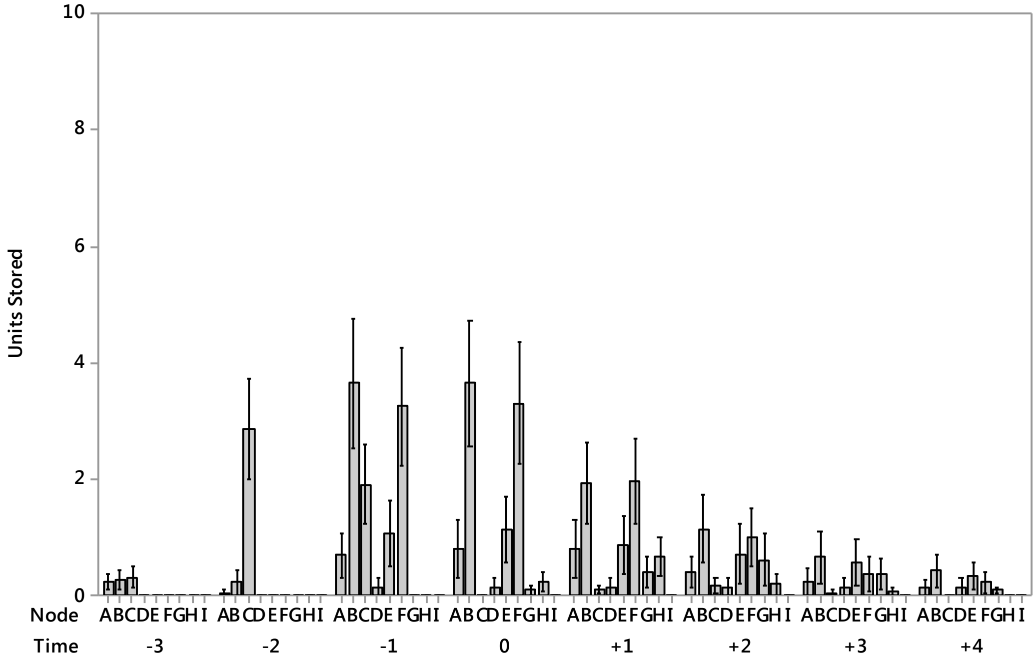


Figure 33: Assembly Network, Inventory Storage Relative to Disruption Start for Location C

adjacent branch of the network. This phenomenon is also observed on figures shown in the appendices. This behavior highlights the interdependent relationship between supply chain resources and suggests that, during disruptions, an upstream resource is not necessarily one that is directly connected to the disruption by way of an upstream arc.

Network Performance

The basic statistics for the performance of assembly networks provided in Table 21 show that network performance during disruptions at each node are generally consistent in terms of values of *ActCost* and *AveLate* (full tables shown in Appendix D). Differences in *ActCost* versus *Location* are less pronounced when *Awareness* is *Full* than at other levels (Figure 34). Differences between network locations are slightly more pronounced when

Table 21: Assembly Network Summary Statistics

Location	*ActCost*		*AveLate*		*EndLate*	
	Mean	SD	Mean	SD	Mean	SD
B	127,991	24,671	34.2	43.5	35.3	29.6
C	127,180	21,513	32.6	38.7	34.7	29.3
D	126,432	21,138	31.4	39.3	31.6	23.3
F	123,914	18,617	26.3	33.1	29.8	21.8
G	129,535	22,571	36.1	41.7	36.0	27.4
H	129,586	21,248	34.0	39.6	32.0	25.5
Overall	127,440	21,784	32.4	39.6	35.3	29.6

comparing levels of *Timing*, although the magnitude of differences in *Early* and *Late* appear to be consistent (Figure 35). As with serial networks, effects attributable to *Timing* appear to vary significantly at the different levels, with a greater disparity noticeable when disruptions begin prior to Period 5 (Figure 36).

Comparing *AveLate* and *EndLate* versus *Location* and *Awareness* in Figure 37 and Figure 40 reveals less variation between network locations when the *Awareness* level is *Full* than for other levels of *Awareness*. Differences in *AveLate* and *EndLate* versus *Location* and *Timing* reveal high levels of variability across both factors as shown in Figure 38 and Figure 41. Similar to comparisons for serial networks, *Duration* and *Timing* appear to significantly influence *AveLate* and *EndLate* when values of *Timing* are less than five (Figure 39 and Figure 42).

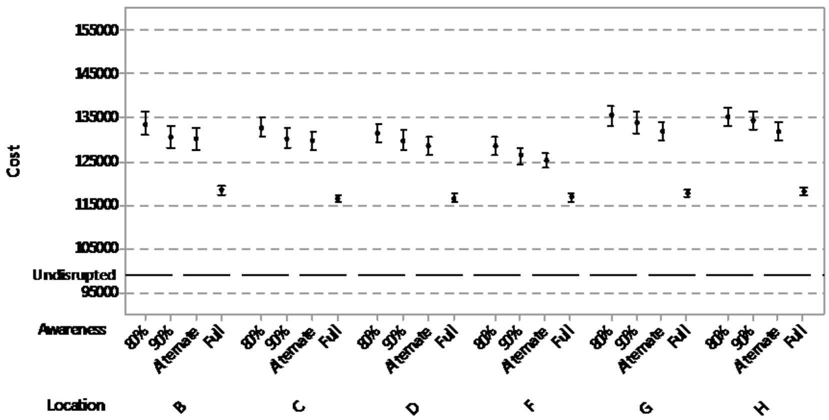


Figure 34: Assembly Network, *ActCost* by *Location* and *Awareness*

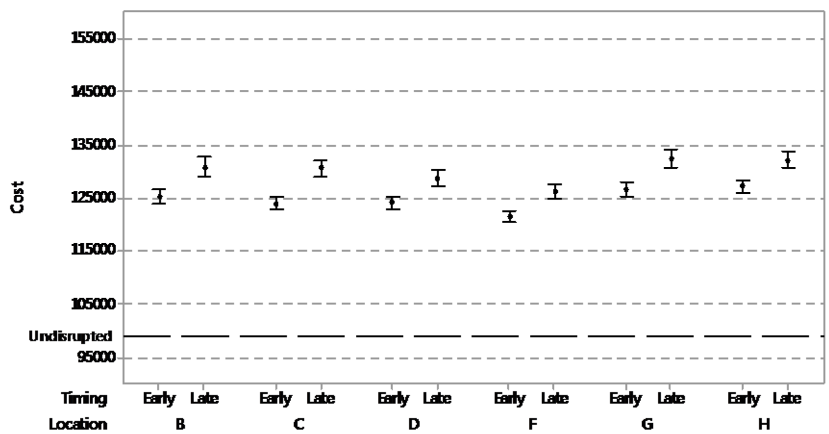


Figure 35: Assembly Network, *ActCost* by *Location* and *Timing*

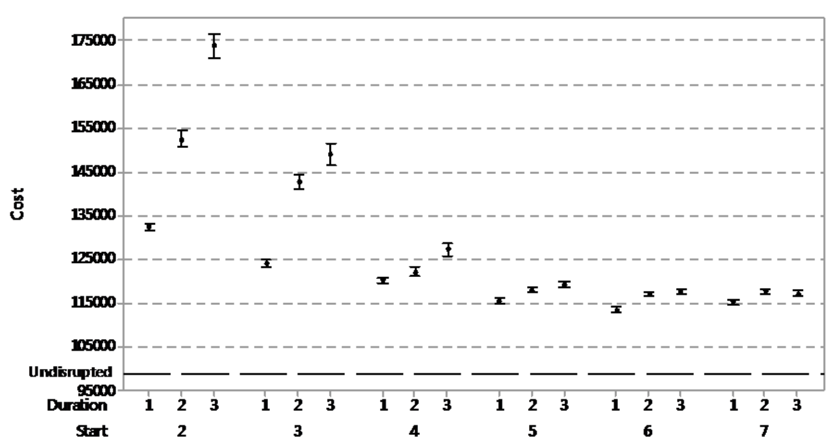


Figure 36: Assembly Network, *ActCost* by *Start* and *Duration*

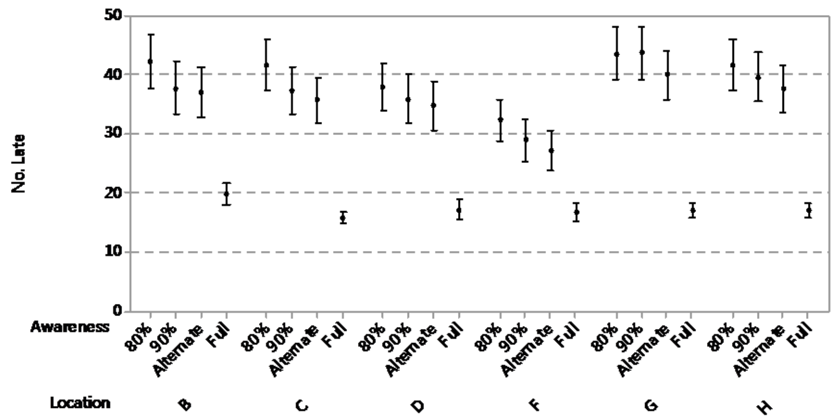


Figure 37: Assembly Network, *AveLate* by *Location* and *Awareness*

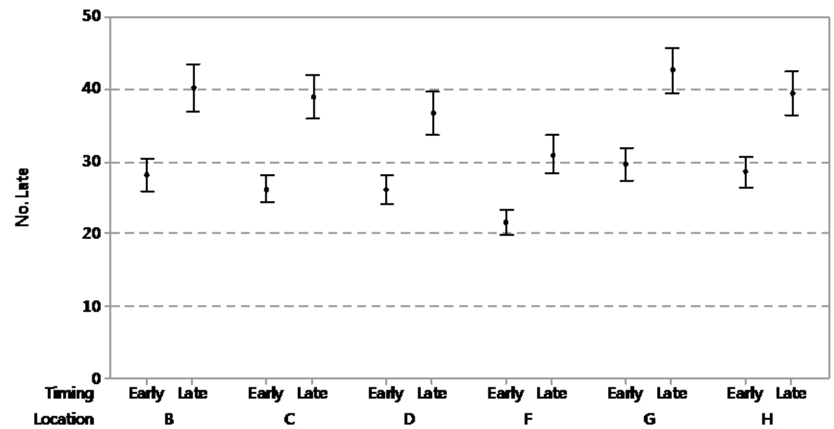


Figure 38: Assembly Network, *AveLate* by *Location* and *Timing*

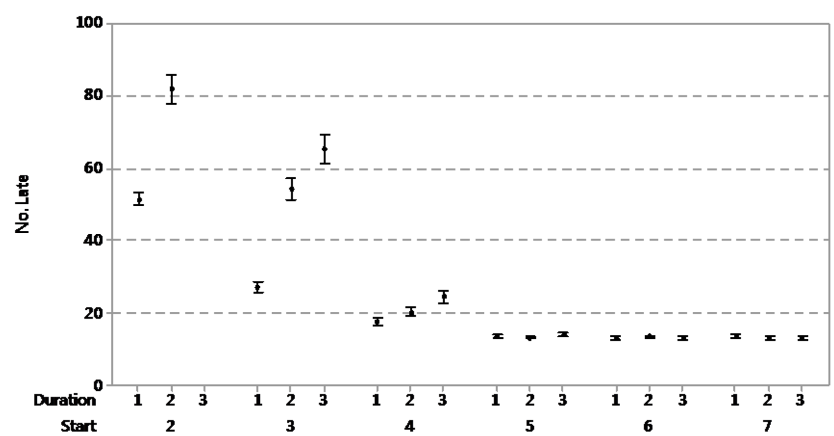


Figure 39: Assembly Network, *AveLate* by *Start* and *Duration*

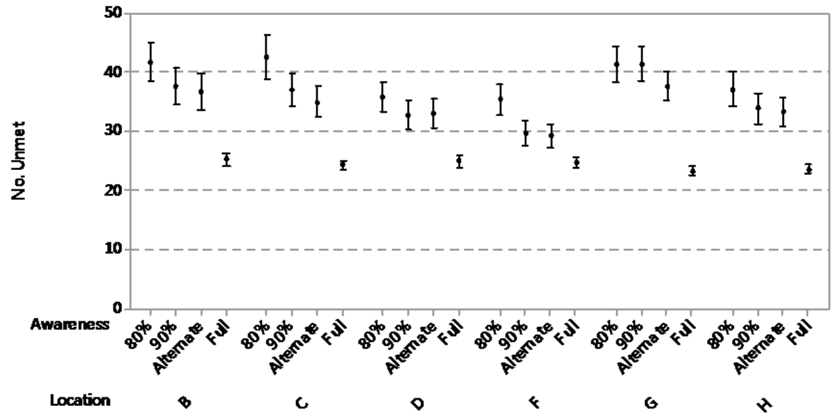


Figure 40: Assembly Network, *EndLate* by *Location* and *Awareness*

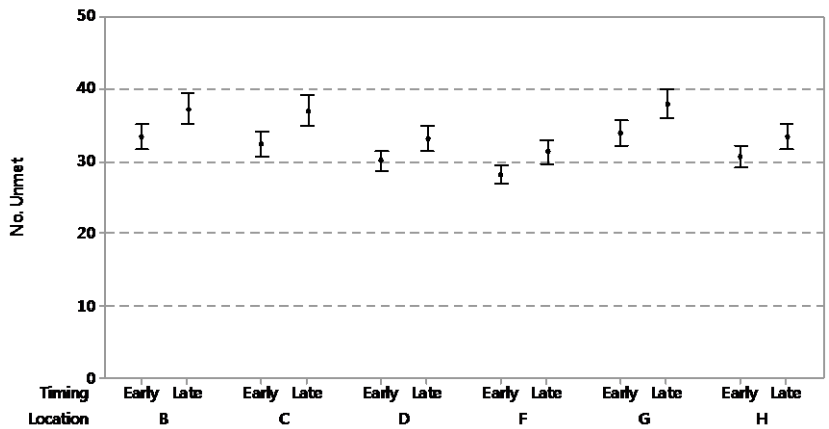


Figure 41: Assembly Network, *EndLate* by *Location* and *Timing*

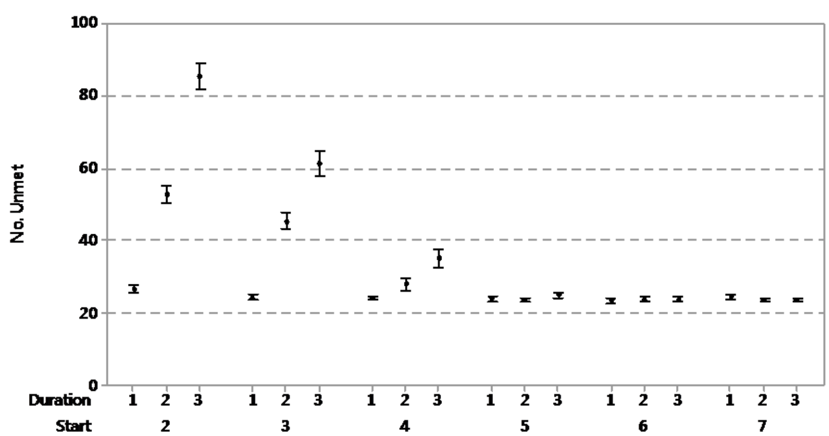


Figure 42: Assembly Network, *EndLate* by *Start* and *Duration*

Statistical Analysis

Following the analysis for the serial networks, statistical comparisons were made for individual locations of the assembly networks to examine *ActCost*, *AveLate*, and *EndLate*. Only configurations with disruptions beginning in Period 5 or later were examined. Table 22 presents a summary of regression coefficients from the analysis for *ActCost* and *EndLate*, and complete ANOVA tables are provided in Appendix D. Similar to the assembly networks, no meaningful interactions between factors were observed (Figure 43). The patterns observed were largely similar to those observed for the serial networks. The purpose of the statistical analysis in this experiment is to determine the efficacy of the SCRF formulation in deploying available sources of redundant capacity and to see if the relationships between serial networks and assembly networks are the same.

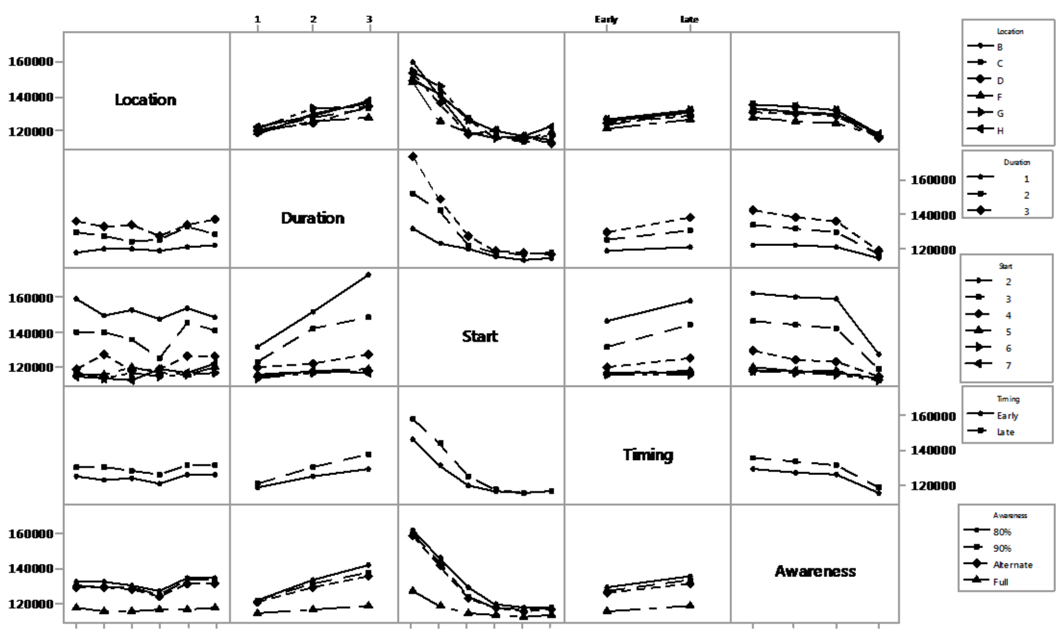


Figure 43: Assembly Network, Interaction Plot *ActCost* versus Factors of Interest

Table 22: Assembly Network, Selected Regression Coefficients by Location for *ActCost* and *AveLate*

			ActCost			*EndLate*		
Location	Factor	Level	Coef	SE Coef	*p*-Value	Coef	SE Coef	*p*-Value
B	Constant		113,160	307.0	0.000*	23.13	0.745	*0.000
	Timing	Late	467	199.0	0.019	-0.36	0.496	0.464
	Awareness	0.8	3,245	282.0	0.000	0.18	0.703	0.797
		0.9	3,110	282.0	0.000	0.63	0.703	0.370
		Alternate	2,441	282.0	0.000	0.41	0.703	0.562
C	Constant		110,410	280.0	0.000	24.82	0.819	0.000
	Timing	Late	414	186.0	0.026	0.18	0.521	0.729
	Awareness	0.8	4,133	263.0	0.000	0.05	0.736	0.945
		0.9	2,287	263.0	0.000	-0.59	0.736	0.425
		Alternate	2,329	263.0	0.000	-0.47	0.736	0.521
D	Constant		114,367	332.0	0.000	23.30	0.783	0.000
	Timing	Late	325	217.0	0.136	-0.61	0.518	0.237
	Awareness	0.8	5,574	307.0	0.000	1.41	0.733	0.054
		0.9	3,784	307.0	0.000	-1.05	0.733	0.152
		Alternate	3,324	307.0	0.000	0.35	0.733	0.636
F	Constant		114,586	340.0	0.000	23.92	0.896	0.000
	Timing	Late	418	222.0	0.060	-0.14	0.590	0.817
	Awareness	0.8	3,588	314.0	0.000	1.76	0.834	0.035
		0.9	2,499	314.0	0.000	-0.63	0.834	0.447
		Alternate	2,507	314.0	0.000	0.03	0.834	0.973
G	Constant		111,263	385.0	0.000	23.79	0.829	0.000
	Timing	Late	812	254.0	0.001	0.32	0.550	0.556
	Awareness	0.8	6,319	359.0	0.000	0.88	0.778	0.258
		0.9	4,701	359.0	0.000	1.58	0.778	0.042
		Alternate	4,005	359.0	0.000	0.82	0.778	0.295
H	Constant		115,291	469.0	0.000	24.57	0.867	0.000
	Timing	Late	1,049	312.0	0.001	0.28	0.545	0.607
	Awareness	0.8	6,727	442.0	0.000	0.28	0.770	0.714
		0.9	6,753	442.0	0.000	-0.71	0.770	0.355
		Alternate	4,202	442.0	0.000	1.25	0.770	0.105

* $p < 0.001$

CEDA Evaluation

Overview

The objective of the analysis relating to the evaluation of the CEDA algorithm centers on validating the premise that successive iterations of the algorithm produce demonstrable results when exposed to variability using the network simulation model developed for the research. Because the purpose of the algorithm is to deploy capacity more efficiently to meet demand, the basis for the evaluation is average backorder (*AveLate*) and the total number of backorders remaining at the end of the planning horizon (*EndLate*). As expected, successive iterations of the algorithm produced lower responses for both *AveLate* and *EndLate* for each of the 10 networks as a result of the new capacity being deployed throughout the network. The final iteration of the algorithm for each network was labeled as Iteration 0, with prior iterations decreasing incrementally (e.g., one iteration prior to the final iteration is labeled Iteration -1). Iteration 0 is the local optimal solution for the currently selected set of resources and capacity levels.

Network Performance

Figure 44 and Figure 45 present graphical response summaries for individual iterations of the CEDA algorithm. The figures show that successive iterations of the algorithm produce lower responses for both *AveLate* and *EndLate*. Figure 46 presents a summary of the optimal solutions for each iteration of the algorithm (*OptCost*) and illustrates that each successive iteration resulted in a lower value for the objective function. It can also be seen from the figures that comparatively higher responses for each variable are associated with networks requiring more iterations of the algorithm.

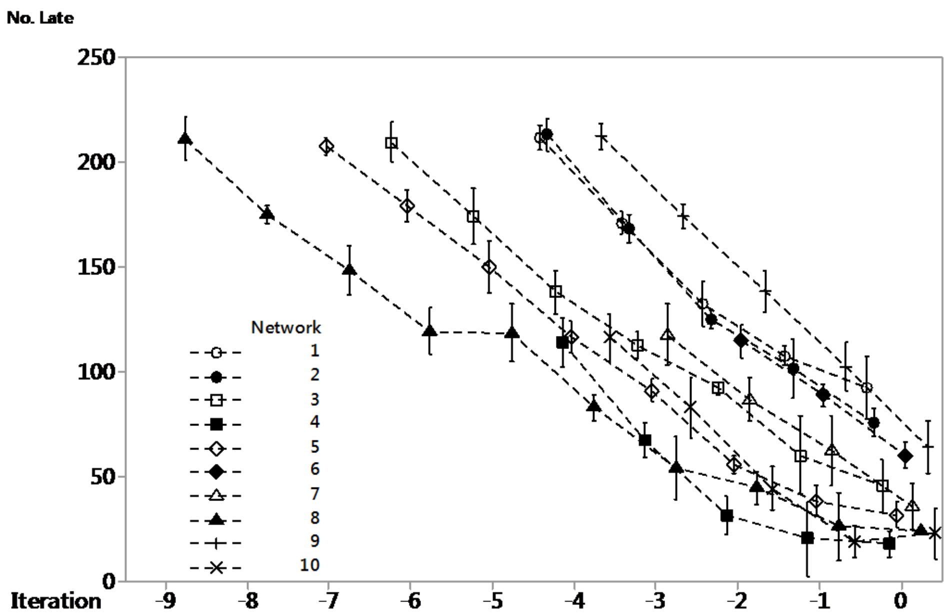


Figure 44: CEDA Evaluation, Average Late by Network & Iteration Step

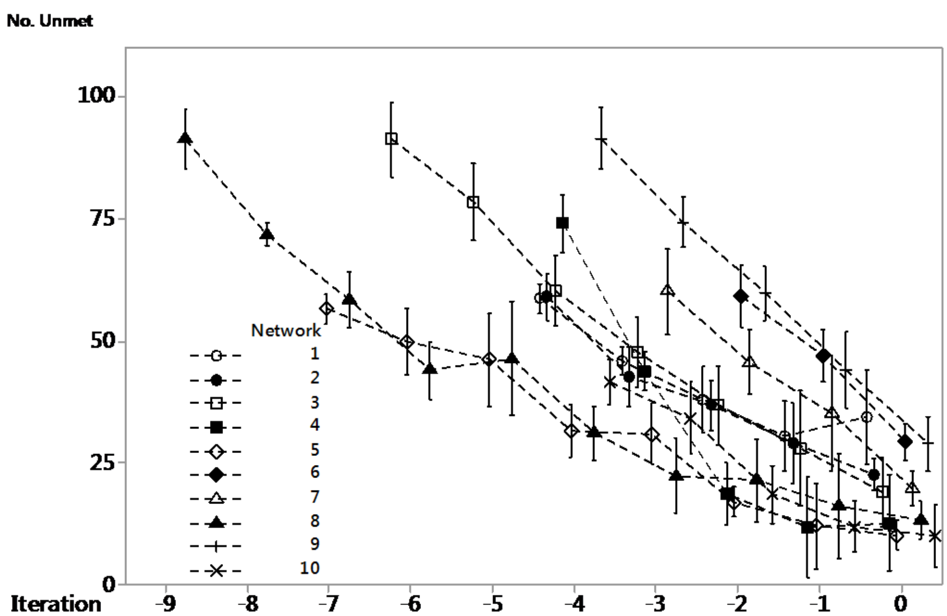


Figure 45: CEDA Evaluation, Ending Backorder by Network & Iteration Step

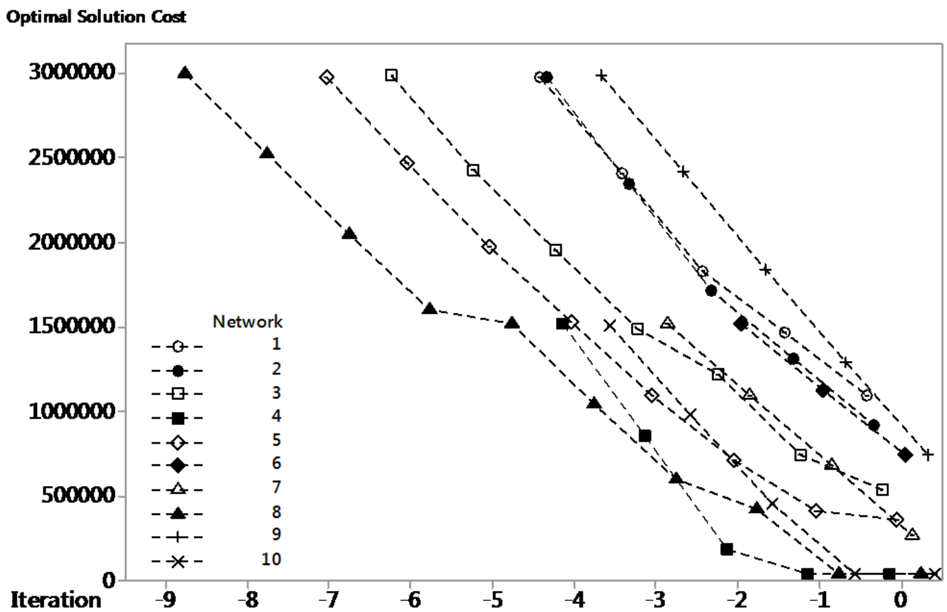


Figure 46: CEDA Evaluation, *OptCost* by Network & Iteration Step

Statistical Analysis

Due to the varied number of iterations produced between the individual networks, statistical comparisons for the variables of interest were limited to the final three iterations of the algorithm for each network. Comparisons for *AveLate* and *EndLate* were performed according to the statistical model presented in Chapter III in order to determine whether or not the differences between successive iterations were significant. Comparisons were made using Tukey pairwise comparisons ($\alpha = 0.05$). Analyses for responses of *OptCost* were not included in the statistical comparisons because of their deterministic nature. For the comparisons, Iteration 0 was treated as the reference group. Table 23 presents a summary of the comparisons for the statistical models, and a complete summary is available in Appendix E.

Table 23: CEDA Algorithm, Selected Regression Coefficients for *AveLate* and *EndLate*

		AveLate			*EndLate*		
Factor	Level	Coef	SE Coef	p-Value	Coef	SE Coef	p-Value
Constant		28.93	1.53	0.000*	97.59	3.20	0.000*
Iteration	-3	18.66	1.47	0.000*	65.52	3.07	0.000*
	-2	9.85	1.25	0.000*	35.92	2.69	0.000*
	-1	4.39	1.17	0.000*	14.21	2.46	0.000*

* $p < 0.001$

The results show that each subsequent iteration of the algorithm is significantly different than the reference group Iteration 0 for both *AveLate* and *EndLate*. Furthermore, Figure 47 and Figure 48 illustrates that Tukey comparisons found significant differences between each pairwise comparison made.

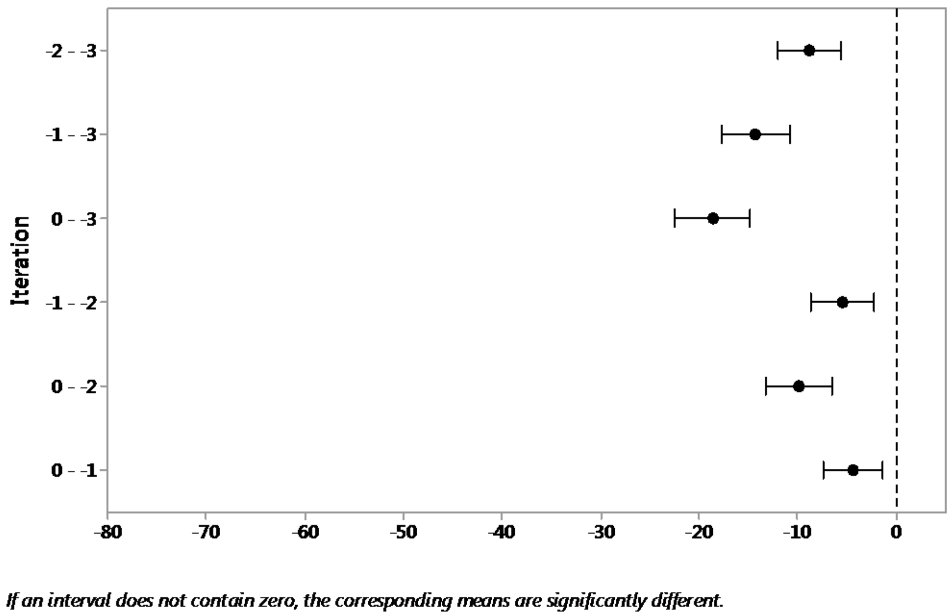


Figure 47: CEDA Evaluation, Pairwise Comparisons for *AveLate*

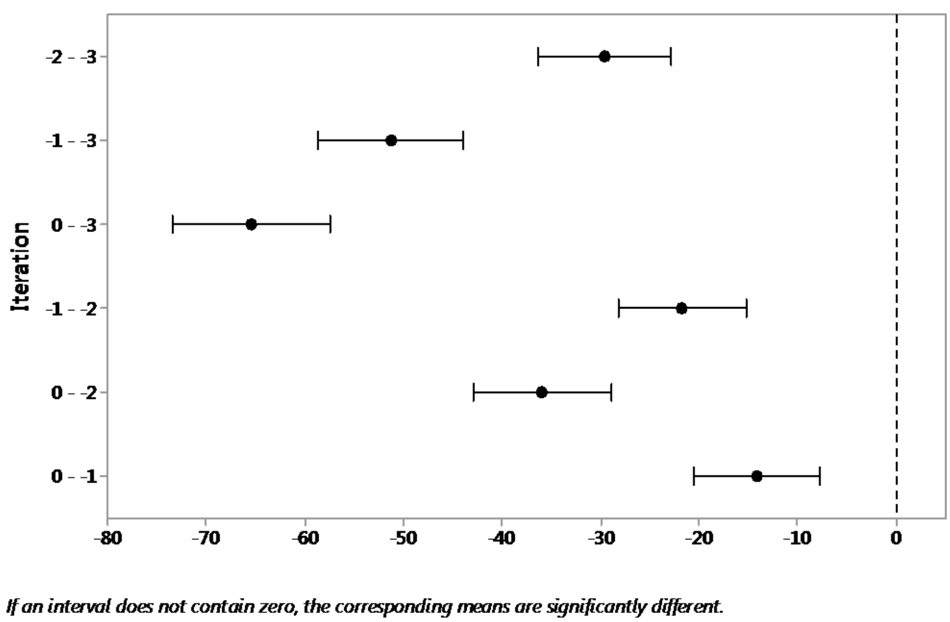


Figure 48: CEDA Evaluation, Pairwise Comparisons for *EndLate*

CHAPTER V

CASE STUDY EXAMPLE

Introduction

This chapter illustrates Supply Chain Recovery Formulation (SCRF) modeling techniques by way of a case study from the consumer goods packaging industry. This case study involves a manufacturer that recently has become aware of a sharp, long-term increase in the demand for a certain product that will happen in short order. The product in question, like many others, is manufactured on a dedicated production line. Under normal conditions demand spikes are buffered by borrowing capacity from an alternate line. The manufacturer anticipates that the new demand level for the product in question will surpass the available capacity for the product's primary and alternate lines, and their long-run solution is to replace the older alternate production line with one that is able to handle the higher volume on its own.

The new production line will physically replace the current alternate line, and once the new equipment is installed and operating, it will then become the primary line. The original primary line will absorb all work currently being done on the alternate line and eventually become a back-up resource for the new line. The decision to replace the older alternate line has been on the company's agenda for several years due to steadily increasing demand for the product, but the company is faced with the need to make the change on a much shorter notice than planned. As highlighted in Chapter I, a disruption recovery process begins once a disruption is discovered, which from the manufacturer's perspective is now.

The objectives of the manufacturer are to prevent or minimize negative impacts on customer deliveries by formulating capacity and inventory plans to sustain normal operations until the new production line is installed and operating at full capacity.

The subsequent sections of this chapter provide an overview of the operational parameters of the manufacturer, the modeling approach using the SCRF formulation, and the results of an analysis to determine the capacity and inventory plans. For this study, all operational parameters, costs, and customer demand have been adjusted and smoothed in a manner that preserves the relationships in the supply chain, yet conceals information that may be considered sensitive.

Case Study

Overview

The production system in this case study is a supply chain, comprised of six resources and one finished goods inventory location, where a single product is shipped to multiple customers. Long-term capacity planning for the 3-shift operation is performed on a monthly basis. The planning unit for equipment is hours, and inventory planning units are packages of finished goods. The current primary line is more or less dedicated to the product in question, and this will also be true when the new line is installed. A 10-month planning horizon is used in this case study to sufficiently accommodate the lead time for the new equipment, the time for installation, and the anticipated ramp-up period.

The primary objective for this case is determining production and inventory levels for the operation given the constraints surrounding equipment availability. The planning

department uses product forecasts, which drive capacity and inventory levels in any given month. The manufacturer assumes that all operations personnel are able to be flexibly deployed throughout the facility, so limits associated with human resources are not of concern. However, these aspects and the modeling of the warehouse location are included in the formulation of this case for demonstration purposes.

The resources for the supply chain include operations personnel (OP), material handlers (MH), three production lines (A, B, and C), and the warehouse (WH). The current primary line is Resource A, the current alternate line is Resource B, and the new production line is Resource C. A single operator is able to support the operation of any production line, but either two or three material handlers are used based on the production line. The operation supplies inventory to the single warehouse location that is used to fill all customer orders. Following conventions established in previous chapters, each resource has an associated inventory location, although only the warehouse can store its output from one period to the next. Scaling factors between various inventory locations and resources are employed to aggregate flows from both equipment and human resources and also to convert planning units from hours to packages.

Included in the model are sources of redundant capacity, which in this case represents the ability of the manufacturer to either delay launching the equipment replacement initiative or to accelerate its completion time. In the supply chain, delaying the start of the replacement (Resource DL) is associated with Production Line B. Accelerating the installation of the new equipment (Resource CR) is analogous to the project management practice of crashing a project, and its additional capacity is associated with Production Line C. Each of these decisions will compress the equipment replacement timeline, resulting in a fixed charge of

$10,000 to expedite contractor services.

Table 24 presents costs, production rates, and nominal capacities associated with the individual resources. Nominal hours available during any given month are 720, and it is to be noted that Resource B historically has had 168 hours of available capacity to support production if the capacity of Resource A is insufficient to meet demand for the product. The individual unit costs represent the relative contribution to overall costs for a finished package. The total package cost is then used to determine the inventory holding charge for packages from the different lines. For this study, periodic inventory holding charges are assumed to be 1% of the package cost based on the primary production line. Cost structures for redundant capacity resources are the same as their associated primary resource. The ability to hold inventory from one period to the next in the warehouse is assumed to be unlimited.

Table 25 presents forecast demand and several perspectives on equipment capacity in the demand planning unit of packages. The capacity types include a baseline capacity for Resources A and B, the expected capacity for each of the production lines resulting from the

Table 24: Capacity and Forecast Demand in Demand Unit (in Packages)

	Production Lines				Operators		Material Handlers		
Line	Nominal Capacity	Hourly Rate	Hourly Burden	Package Cost	No. OP	Package Cost	No. MH	Package Cost	Total Package Cost
A	720	83.52	165	1.976	1	0.599	3	1.437	4.012
B	168	65.77	161	2.448	1	0.760	3	1.824	5.032
C	720	118.80	150	1.263	1	0.421	2	0.673	2.357

Table 25: Capacity and Forecast Demand (in Packages)

Description	Planning Period									
	1	2	3	4	5	6	7	8	9	10
Demand	60,000	62,000	64,000	70,000	72,000	72,000	74,000	74,000	74,000	74,000
Baseline (A & B)	71,184	71,184	71,184	71,184	71,184	71,184	71,184	71,184	71,184	71,184
Resource A	60,134	60,134	60,134	60,134	60,134	60,134	14,031	14,031	14,031	14,031
Resource B	11,050	11,050	7,893	-	-	-	-	-	-	-
Resource C	-	-	-	-	-	-	21,384	42,768	85,536	85,536
Total	71,184	71,184	68,027	60,134	60,134	60,134	35,415	56,799	99,567	99,567
Redundant, DL	-	-	3,157	4,736	-	-	-	-	-	-
Redundant, CR	-	-	-	-	-	5,702	19,008	42,768	-	-

equipment replacement initiative, the total capacity available during replacement, and the capacity available from the two sources of redundant capacity. The reduction in capacity for Resource B in Period 3 signals the beginning of the equipment replacement, and the gradual increase in capacity of Resource C in Period 7 indicates the expected ramp-up of its capacity through Period 9. It is clear that the baseline capacity from the two current production Resources A and B is insufficient to meet the expected increase in demand, and combining the available capacity from the three lines results in shortfalls over several periods. It can also be seen that even when adding the capacity from the two redundant sources, shortfalls in certain periods are unavoidable. This suggests that inventory holding will be required in order to avoid missed shipments.

The planning activities of the manufacturer do not explicitly account for costs associated with lost sales or unmet demand resulting from inventory shortfall, but rather they choose to hold sufficient safety stock for buffering process and demand variability and approach a 100% on-time delivery capability. It is assumed that the manufacturer will only

use safety stock to buffer variations in supply and demand, and is therefore not explicitly factored into the formulation for this case study. Also, it is common practice within the industry to pursue a rationing strategy during supply shortages, meaning the manufacturer intentionally does not achieve 100% on-time deliveries. Because the costs of late and unmet demand were not available, these values were calculated as described in Chapter III so as to defer late or unmet demand to future periods.

Modeling

A graphic depiction of the 10-period supply chain modeled according to the SCRF formulation is shown in Figure 49. For visual clarity, nodes and arcs associated with unmet or backordered demands are omitted. The network begins with Resources OP and MH supplying flow to the individual Resources A, B, and C through their respective inventory

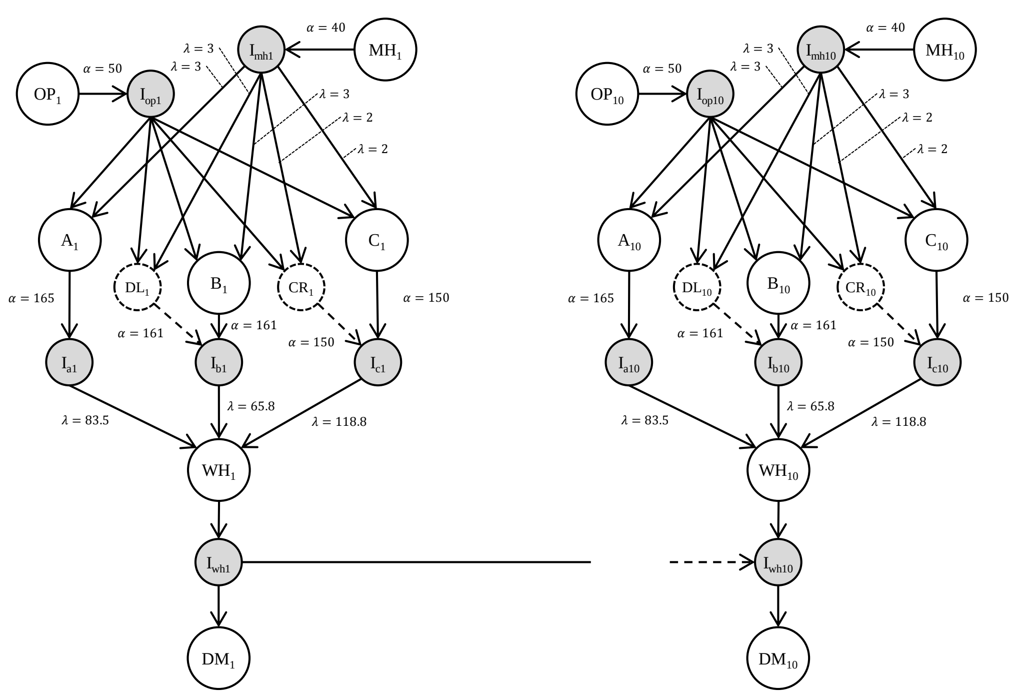


Figure 49: Graphic Depiction of the Case Study Supply Chain Network

locations. Each production resource draws flow in proportion to a scaling factor (λ) representing the number of operators or material handlers required to operate the equipment. Only scaling factors that are not equal to 1 are shown on the arcs where they are applied in the network diagram. Resource WH draws flow from inventory locations associated with each of the production lines according to the scaling factor representing the individual production rates. It is at this point that the flows are scaled in a manner to convert from the equipment planning unit of hours into the demand planning unit of packages. Redundant capacity sources DL and CR also supply flow through the inventory locations associated with Resources B and C respectively. Customer demand is supplied through the inventory location associated with WH, and at this point in the network, inventory can be stored from one period to the next. Costs associated with flows between a production line (α) and its corresponding inventory location are shown on the network diagram. The complete formulation for this problem is shown in Appendix D.

Analysis

The analysis for the case study involved solving the Linear Programming (LP) formulation of the model without allocating from any redundant resources to determine if a production and inventory plan that met all demand was possible, and it also involved solving the Mixed Integer Program (MIP) formulation to determine an optimal plan. After these initial solutions were obtained, it was found that a significant amount of late shipments would result from any plan not incorporating the sources of redundant capacity. Therefore, the Capacity Evaluation and Deployment Algorithm (CEDA) procedures were followed to determine how a plan without redundant capacity could be improved incrementally. The

algorithm terminated after thirteen iterations, finally arriving at the least cost solution found using the MIP formulation. This section provides a summary of the final solution and key intermediate steps using the CEDA algorithm, with tables depicting the capacity and inventory levels associated with the each resource. A narrative interpreting the key steps of the CEDA algorithm from a managerial perspective is also provided.

Table 26 displays the results of the MIP optimal solution. The results for production lines are shown in hours used, and inventory and demand results are shown in packages. The optimal solution calls for each of the redundant sources in this situation to be used, meaning that choosing to delay the decommissioning of Production Line C and paying extra to expedite the completion of the replacement line are both appropriate. For the optimal plan there is no demand left unmet, but late shipments are unavoidable. A total of 2,304 packages from Period 7 are expected to be shipped late to the customer. Using this optimal plan, the

Table 26: Optimal Plan from MIP Solution

Description	Planning Period									
	1	2	3	4	5	6	7	8	9	10
Line A	720	720	720	720	720	720	168	-	-	-
Line B	168	168	120	-	-	-	-	-	-	-
Line C	-	-	-	-	-	-	180	267	608	608
DL	-	-	48	72	-	-	-	-	-	-
CR	-	-	-	-	-	48	160	360	-	-
Inventory	13,069	24,138	33,206	29,966	19,994	15,861	-	-	-	-
Demand	60,000	62,000	64,000	70,000	72,000	72,000	74,000	74,000	74,000	74,000
Filled	60,000	62,000	64,000	70,000	72,000	72,000	71,696	74,000	74,000	74,000
Late	-	-	-	-	-	-	2,304	-	-	-
Unmet	-	-	-	-	-	-	-	-	-	-

manufacturer's operations and planning managers will realize that a solution that will fully eliminate late orders does not exist, and they can begin to plan accordingly. The manufacturer will at this time begin the process of determining the best course of action relating to the potential late shipments. This may include deciding whether or not to fill the orders from safety stock if available, alert customers to the potential of late shipments, or begin working on strategies to circumvent the effects of the late orders by securing delivery concessions from customers. The managers would also likely be interested in knowing the best-case scenario if they choose to forego utilizing available sources of redundant capacity. Determining the value of these scenarios is the intent of the CEDA algorithm.

Formulating the problem as an LP and applying the procedures of the CEDA algorithm with no capacity allocated to the redundant resources produces the solution shown in Table 27. Without the compressed installation timeline, more than 40,000 packages are expected to be late between Periods 7 and 8. Table 28 presents the results for the CEDA algorithm, which indicate that the greatest impact can be obtained by accelerating the completion of the replacement line through Resource CR for a savings of $473,956 to the objective function. From a managerial perspective, this answers the question of which source of redundant capacity should be applied first. Because there are no grouped resources to consider in this problem the interpretation is straightforward, and 95.7 hours of capacity

Table 27: Case Study, Optimal Plan from Iteration 1 of the CEDA Algorithm

Description	Planning Period									
	1	2	3	4	5	6	7	8	9	10
Line A	720	720	720	720	720	720	168	168	144	135
Line B	168	168	120	-	-	-	-	-	-	-
Line C	-	-	-	-	-	-	180	360	720	720
DL	-	-	-	-	-	-	-	-	-	-
CR	-	-	-	-	-	-	-	-	-	-
Inventory	13,069	24,138	30,052	22,080	12,108	2,136	-	-	-	-
Demand	60,000	62,000	64,000	70,000	72,000	72,000	74,000	74,000	74,000	74,000
Filled	60,000	62,000	64,000	70,000	72,000	72,000	38,506	58,268	74,000	74,000
Late	-	-	-	-	-	-	35,494	15,732	-	-
Unmet	-	-	-	-	-	-	-	-	-	-

Table 28: CEDA Algorithm, Iteration 1 Summary

R_i	Final Value	b_{R_i}	SP_{R_i}	AI_{R_i}	γ_{R_i}	Υ_{R_i}	$f(C)$
DL	0.0	0.0	-2,545.4	72.0	10,000	1	-173,269
CR	0.0	0.0	-5,059.1	95.7	10,000	1	-473,956
Plan Cost w/o Fixed Costs: 4,124,484				Optimal w/Fixed Costs: 4,124,484			

should be allocated to Resource CR by way of the Right-Hand Side (RHS) value in the formulation.

A natural question from this first iteration is how much overall capacity should be deployed to Resource CR before it is decided that delaying the decommissioning of resource B should also be pursued. The next 3 iterations of the CEDA algorithm continued to select Resource CR as the best alternative, and after the fourth iteration was complete, a total of 207.4 hours were allocated to Resource CR.

Table 29 presents the optimal plan of Iteration 4, and Table 30 presents the results of the CEDA algorithm indicating that Resource DL should be selected. From the table it can be seen that allocating 72 hours to DL is the most economical choice at this time. An additional 48 hours is applied to Resource DL after Iteration 5, bringing its total contribution to its maximum available capacity of 120 hours.

The remaining iterations incrementally apply a greater amount of capacity to Resource CR until its maximum available capacity is reached and the algorithm is terminated, with the optimal plan shown in Table 31 and the CEDA results presented in Table 32. Comparing the available capacity levels with the capacity and inventory plan from the optimal solution of the MIP formulation, it can be seen that the final iteration duplicates the MIP formulation and requires the use of all capacity sources available.

Discussion

The purpose of this case study was to apply the modeling techniques developed for the SCRF formulation as intended to a practical situation. This situation illustrates several of the key benefits of the SCRF formulation, in particular the use of assembly structures and scaling factors within the network. Past research has highlighted that disruptions are difficult to study because they are generally rare and organizations may to be hesitant to try unfamiliar techniques during stressful situations. In all likelihood, this barrier would be increasingly

Table 29: Case Study, Optimal Plan from Iteration 4 of CEDA

Description	Planning Period									
	1	2	3	4	5	6	7	8	9	10
Line A	720	720	720	720	720	720	168	168	144	-
Line B	168	168	120	-	-	-	-	-	-	-
Line C	-	-	-	-	-	-	180	360	720	608
DL	-	-	-	-	-	-	-	-	-	-
CR	-	-	-	-	-	47	160	-	-	-
Inventory	13,069	24,138	30,052	22,080	12,108	7,898	-	-	-	-
Demand	60,000	62,000	64,000	70,000	72,000	72,000	74,000	74,000	74,000	74,000
Filled	60,000	62,000	64,000	70,000	72,000	72,000	63,732	58,268	74,000	74,000
Late	-	-	-	-	-	-	10,268	15,732	-	-
Unmet	-	-	-	-	-	-	-	-	-	-

Table 30: CEDA Algorithm, Iteration 4 Summary

R_i	Final Value	b_{R_i}	SP_{R_i}	AI_{R_i}	γ_{R_i}	Υ_{R_i}	$f(C)$
DL	0.0	0.0	-2,366.8	-2,216.8	10,000	1	-160,411
CR	207.4	207.4	-4,556.0	-4,446.0	10,000	0	-2,898
Plan Cost w/o Fixed Costs: 3,097,044				Optimal w/Fixed Costs: 3,107,044			

Table 31: Case Study, Optimal Plan from Iteration 11 of the CEDA Algorithm

Description	Planning Period									
	1	2	3	4	5	6	7	8	9	10
Line A	720	720	720	720	720	720	168	-	-	-
Line B	168	168	120	-	-	-	-	-	-	-
Line C	-	-	-	-	-	-	180	360	608	608
DL	-	-	48	72	-	-	-	-	-	-
CR	-	-	-	-	-	48	160	267	-	-
Inventory	13,069	24,138	33,206	29,966	19,994	15,861	-	-	-	-
Demand	60,000	62,000	64,000	70,000	72,000	72,000	74,000	74,000	74,000	74,000
Filled	60,000	62,000	64,000	70,000	72,000	72,000	71,696	74,000	74,000	74,000
Late	-	-	-	-	-	-	2,304	-	-	-
Unmet	-	-	-	-	-	-	-	-	-	-

Table 32: CEDA Algorithm, Iteration 13 Summary

R_i	Final Value	b_{R_i}	SP_{R_i}	AI_{R_i}	γ_{R_i}	Υ_{R_i}	$f(C)$
DL	120.0	120.0	0.0	Inf.	10,000	0	0
CR	475.2	475.2	0.0	Inf.	10,000	0	0
Plan Cost w/o Fixed Costs: 2,393,631				Optimal w/Fixed Costs: 2,413,631			

true as the complexity of the supply chain or problem is amplified. This case study illustrates the flexible nature of the SCRF formulation through the efficient modeling of the assembly structures and differing planning units of the supply chain. Furthermore, its usefulness as a general planning tool can also be drawn from this case study. A proposition of this research is that the readily apparent efficiency and usefulness of this model will result in its acceptance both in the literature and by supply chain managers as a useful disruption mitigation tool.

CHAPTER VI

CONCLUSIONS AND DISCUSSION

Introduction

Two underlying objectives served as a basis for this research document. The first objective was to develop a mathematical modeling approach for supply chains that allows for flexible integration of redundant capacity sources for the purpose of recovering from a disruption. The second underlying objective was to leverage the structure of the formulation in order to provide practical sensitivity information for the deployment of that capacity. Prior chapters have illustrated the importance of these objectives and described the experimental methodology used in analyzing the model. This final chapter places the results of the experiments into context by addressing the research questions from Chapter 1, discussing the limitations of the research, highlighting the resulting implications for industry and contemporary literature, and briefly exploring how this study might serve as a catalyst for future research.

Research Questions and Hypothesis Tests

This section highlights the key findings from this study that pertain to the research questions from Chapter I. Each question is addressed individually.

> Q1: Can a comprehensive understanding of a supply chain's redundant capacity improve its ability to recover from a disruption?

The results of the experiments show that a reduced understanding of the supply chain's redundant capacity can negatively impact the ability to recover from a disruption as measured from a cost perspective. The increase in cost may be attributed to a rise in late or unmet demand as well as increases in both fixed and incremental costs. The results also suggest that the Supply Chain Recovery Formulation (SCRF) is able to effectively distribute any available redundant capacity in order to resist the effects of the disruption. These effects were measured by the average number of units late in a given period (*AveLate*) and by the total amount of unmet demand at the end of the planning period (*EndLate*). In cases where increases in the overall costs (*ActCost*) were forced by restricting the availability of the optimal redundant capacity configuration (*Awareness* = *Alternate*), no significant increases in *AveLate* or *EndLate* were observed for either the serial or assembly network structures at any network location. Additionally, in many instances no significant increases in *AveLate* were observed where overall capacity levels were further restricted in a probabilistic manner (*Awareness* = {*90%, 80%*}). Conversely, increases in *ActCost* were statistically significant in every case where redundant capacity was restricted.

These results provide additional credence for recommendations found in previous Supply Chain Resilience literature that suggest that a thorough understanding of available capacity in a supply chain is an important component of resilience. In earlier research, this idea was described using the concept of Structural Knowledge. Every instance where capacity awareness was reduced was met with increased costs. This was particularly true in cases where there was little time to prepare for the disruption, but this was also observed in cases where disruptions began in later planning periods and redundant capacity was abundant.

Q2: Can the timing of a manager's decision to begin utilizing a supply chain's redundant capacity affect its ability to recover from a disruption?

The experiment shows that a delay in reacting to a disruption by one period had a significant impact on the ability of the network to recover from a cost perspective. Significant increases of *ActCost* (α = 0.10) were observed for both network types when formulating a least-cost plan under a 1-period delay (*Timing* = *Late*) for all locations except Location D of the assembly network (p = 0.14). Conversely, with the exception of Location F of the serial network, no significant differences were observed for *AveLate* (α = 0.05) for any location in either network. No significant increases in *EndLate* (α = 0.05) were observed for any location within either of the networks.

For each network configuration, individual disruptions were examined under circumstances where the disruption was discovered or acted upon one period later than necessary. When taking in to consideration the experimental design of the study, the results of these analyses reinforce the importance of early detection for disruptive events that was highlighted in previous research, and they illustrate that the SCRF formulation is efficient in deploying capacity to mitigate the effects of a disruption on a marginal basis. The results also highlight the magnifying effect that limited capacity availability prior to a disruption's onset (*PreDisCap*) has on both cost and delivery. Because increases in costs associated with the delay were not accompanied by increases in either late or unmet demand, it can be concluded that on a marginal basis, the formulation was able to determine solutions to meet demand with the available resources.

Q3: Can a solution procedure for the generalized linear programming model for a

supply chain provide reliable insights into capacity acquisition decisions?

Q4: Can sensitivity information from the model's solution procedure provide reliable insight into locations within the supply chain that would benefit from additional resources or redundant capacity?

Research questions Q3 and Q4 are addressed through the experimental evaluation of the Capacity Evaluation and Deployment Algorithm (CEDA) described in Chapter V. The experimental evaluation found statistically significant reductions ($p < 0.001$) in late and unmet demand for successive iterations of the CEDA algorithm. The procedures of the CEDA algorithm also found effective capacity deployment strategies for the disruption situation described in the case study. In this instance, the algorithm selected and maximized the incremental value of the resource before selecting the next source to add and then continued to distribute capacity to the two resources until terminating at the globally optimal solution for the problem.

Q5: Do the findings differ when applied to an assembly network versus a serial network?

The findings of the research questions do not differ when comparing the structures of the networks. For both networks, increased costs were found when the networks were subjected to a reduction in knowledge of the supply chain's redundant capacity or a delay in formulating a least-cost capacity and inventory plan. For both networks, the least-costs plans formulated under these conditions did not produce meaningful increases in late or unmet demand in either case. Furthermore, the ability of the CEDA algorithm to identify improved

solutions for managing a recovery was not influenced by the presence of an assembly structure.

In addition to the comparable findings for network performance, similarities also existed between the networks in terms of the patterns observed for the distribution of capacity and inventory. Capacity deployed prior to a disruption tended to be deployed to upstream nodes for both networks, and this upstream distribution of capacity appeared to span across the branches of the assembly network. Furthermore, the pattern of capacity deployed to downstream nodes was also consistent between networks in that it tended to be deployed after the onset of a disruption. This pattern also held true for inventory distribution throughout the networks. Inventory tended to accumulate upstream from the disruption before it struck and then flowed downstream throughout the disruption. Patterns of inventory accumulation were also observed to be consistent for the branches of the assembly network.

Implications for Practice

The findings of this study illustrate several important issues that supply chain managers often face during disruptions, and they provide general guidance for supply chain managers that may be useful in allocating capacity during a disruption. The findings also demonstrate that the modeling formulation developed can be an effective decision-making tool for deploying the capacity of a system once the disruption or potential disruption is discovered. This research joins several other studies in acknowledging that redundant capacity is often not readily available to a supply chain manager or planner without first tolerating a time delay. A time delay, coupled with the potential of fixed charges and relative differences in incremental costs, contributes to the criticality of managerial decision-making

early in the recovery process. This research demonstrates that the SCRF formulation is efficient in making the best use of the redundant capacity available, even when applied later in time than might otherwise be ideal.

This research also shows that the physical distribution of capacity and inventory throughout a system during a disruption is a function of many factors including the disruption recovery stage and the location of a disruption in the network. During the preparation phase discussed in Chapters I and II, a supply chain may remain in a steady state of operation until the actual onset of the disruption. Once managers become aware of an active or pending disruption the recovery process begins. In many cases, additional capacity should be deployed to locations upstream before the disruption strikes. Once a disruption's effects begin to impact the system, such as an actual loss of capacity, redundant capacity tends to be deployed on and downstream from the disruption location. In this manner, it can generally be concluded that the emphasis for managerial oversight of the disruption should evolve as the disruption unfolds. The management of resources most important to the disruption, what may best be described as pinch points, changes throughout the disruption recovery process. The realization that a disruption's pinch points and bottlenecks may move about the supply chain is key to an effective recovery.

The movement of bottlenecks throughout the disruption recovery process has implications for the management of inventory. Because the accumulation of additional inventory in a system follows the deployment of capacity, accumulating upstream prior to a disruption and then flowing downstream, it can be concluded that the management of inventory is an equally important component of recovery. Although the efficiency of capacity is easily measured on a period-by-period basis through efficiency metrics, measuring

the efficiency of inventory levels is less straightforward. This is especially true in light of production systems that reward utilization of capacity and tend to punish inventory accumulation. In the context of disruption recovery, the usage of downstream capacity is inextricably linked to upstream inventory storage.

Another important aspect of capacity and inventory distribution for managers can be found in the relationship between the ability to fully replace the capacity of a given location and the need to deploy capacity at upstream or downstream network locations. In practice, an ideal response to a disruption would be to fully replace lost capacity with an alternate source, with little or no increase in incremental costs. It is reasonable to assume that most organizations do not have the ability to fully replace lost capacity though backup resources, even for operations deemed as critical. Instead, redundant capacity may come from sources with lower productivity rates or less overall availability. The results of this study show that in these cases, capacity replacement occurs over time, which in-turn requires additional capacity on upstream or downstream resources. The explicit implication for managers is that redundant capacity for critical nodes of the network may have lower productivity rates, but that upstream and downstream resources themselves become a critical node when formulating an optimal recovery plan. This reinforces the findings of prior studies, which also emphasize the responsiveness of capacity and inventory usage at other network locations to manage a disruption (Hu, Li, & Holloway, 2013).

Limitations

Although the findings of this study provide insights into the general behavior of supply chains modeled according to the SCRF formulation, there are a few key limitations

that must be noted. In exploring these limitations, it is important to acknowledge that the guiding principles in developing the SCRF formulation were to develop a model that features a straightforward mathematical formulation and would always provide a feasible capacity and inventory plan.

The most significant limitation is that the formulation and supply chain structures tested were simplified to address the specific research questions proposed. Although the structure of the problem encompasses many aspects of a supply chain that may be of concern to managers, such as the ability to store inventory and fill backorder demand, its accommodations are not able to fill every possible need that may exist. For instance, there is currently no explicit provision in the formulation to establish a proportion of backorders to lost-sales for a given period, which is featured in other supply chain modeling formulations. Although no such provision currently exists, the SCRF formulation was developed with a sharp awareness of the need for additional structures to ensure that future expansion of the model through side constraints would be possible.

Other limitations include the fact that the undisrupted supply chain structures tested were operating at 100% utilization and had no additional capacity available without incurring a fixed charge. Also, additional levels of safety stock were not treated as factors in the experiment. Both of these elements represent a form of redundant capacity that is available to managers. Although forcing all additional capacity to be from redundant sources that incur a fixed charge is unlikely to change the behavior of the system as a whole, this assumption was central to the objective of the research. The assumption that any additional capacity must be deployed from redundant sources also eases the interpretation of how capacity and inventory are distributed throughout a network. The remaining limitations of the modeling

approach proposed in this study are best understood by examining them in relation to the research areas of Supply Chain Resilience and recovery models.

Although the modeling formulation was drawn from widely accepted factors of resilience, aligns with elements of supply chain modeling literature, and has been applied to a disrupted supply chain through a case study, its usefulness in the disruption recovery process is theoretical until validated through its practical application. Recovery models have been readily available in the literature for several years, yet there is no indication in the literature as to whether or not any have been successfully integrated into organizational disruption management processes. As noted in Chapters I and II, questions surrounding the post-disruption activates of firms are primary drivers of this research. If the utilization of a recovery strategy is indeed a factor in well-managed disruptions, as suggested by Macdonald and Corsi (2013), the formulation proposed in this research could be a valuable addition to a recovery effort.

Another limitation of the SCRF formulation is that although it can be easily solved by readily-available software, constructing and interpreting all but the most simple supply chain configurations without automation may be difficult without formal training in Linear Programming (LP) techniques or specialized software. Conventional thinking also suggests that disruptive events in practice are infrequent and that managers might be reluctant to learn or to integrate complex planning methods into their formal or ad-hoc processes in stressful situations. The straight forward approach to the underlying formulation of the supply chain modeling presented in this research may serve to help it gain acceptance by supply chain managers and the academic community.

Although a global optimal solution can easily be obtained by solving the Mixed Integer Program (MIP) formulation directly, the sensitivity procedures described in the CEDA algorithm do not guarantee that a globally optimal solution will be achieved. This is due to the incremental nature of the algorithm accompanied by the presence of fixed charges and also due the need for managers to select the appropriate resource group for evaluation. The significance of this limitation would largely depend on the configuration, size, and complexity of the supply chain in question. In practice, the groups of redundant capacity being modeled would be at the discretion of the managers, and for supply chains with only a few sources of redundant capacity it would be relatively easy to examine all possible combinations of resource groups. However, for large and complex supply chains with many sources of redundant capacity the process of exhaustive evaluation would be impractical. Furthermore, it is reasonable to assume that managers would select resource groups based on their own knowledge of the supply chain, the circumstances surrounding the disruption, and according to a preference. While the ability to perform straightforward analyses according to their own preferences is an advantage, more research is needed to identify methods that will ensure the selection of proper resource groups. Regardless of the limitations, the true usefulness of the sensitivity procedures in this research centers on the ability to perform analysis on a group of resources and to identify thresholds where adding capacity on individual resources would not improve recovery.

Future Research

This research highlights new potential areas for future study and mirrors areas for future research cited in previous research. These areas include further validation of the methods through applications in actual supply chains, expansion of sensitivity analysis

procedures using the SCRF formulation, and exploration of additional cost structures to better understand the behavioral response of the model to changes in cost structures.

Applying this formulation to a wide range of actual supply chain structures through further case studies using historical data from disruptions or through guided interaction with supply chain managers during a disruption are perhaps the most important areas for future study. Practical benefits of the SCRF formulation are predicated on its adoption as a planning tool, which is in-turn dependent upon its usefulness to managers during disruptions. The formulation parameters are able to be generalized to a wide variety of conditions, and managers would benefit from guidance on rules or procedures for efficiently applying the SCRF formulation in their individual situations. Working closely with managers would also benefit researchers by helping to identify areas of the modeling approach that might hinder its adoption, and by developing best-practices for training managers on the formulation's theory and implementation.

Working closely with managers to further realize this formulation into real-life situations also addresses the need for further study regarding the ability of the model to provide useful information through sensitivity analysis. Applying this formulation to actual supply chain configurations would help to ensure that the variable and constraint structures are sufficient to achieve their intended purpose and would also serve to help researchers understand what other types of sensitivity information might be useful. In light of sophisticated mathematical techniques that are available to researchers, the greatest strength of linear programming is perhaps that its techniques are better understood by supply chain managers who presumably have had prior exposure to it in a business curriculum.

Lastly, studies geared toward a better understanding of how the model's cost structure impacts the behavior of the model in terms of how capacity is deployed should also be conducted. Other recovery models found in the literature suffer the same problem as this formulation, as the cost structure is a primary driver of capacity allocation. In many cases, accurate estimates of costs associated with lost sales and backorders are unavailable, and Schmitt (2011) points out that a fixed cost parameter alone is insufficient to model the complexities of stock-outs and lost sales. Providing managers with an approach for modeling based on the model's behavior rather than a specific cost structure may be of use to managers. Additionally, research geared toward understanding manager preferences regarding the relative importance of operational costs and broader recovery objectives would also be useful. The benefit of using operational costs is that this information is usually readily available, and understanding manager preferences could be useful in aligning the behavior of recovery models with these preferences.

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APPENDICES

Appendix A

Capacity Evaluation & Deployment Algorithm Pseudocode

Capacity Evaluation & Deployment Algorithm Pseudocode

***** Initialize CEDA**
DO For Each Redundant Capacity Source R_i
Determine initial Allotted Capacity for each Redundant Capacity Source
SET b_{R_i} = Allotted Capacity
Loop
***** Begin Iterative Analysis**
Solve for Min Z
***** Remove Slack from RHS**
DO FOR EACH Redundant Capacity Source in the formulation:
    SET b_{R_i} = LHS value of solved model
ENDDO
***** Evaluate Individual Redundant Resources**
DO FOR EACH Redundant Capacity Source in the formulation:
SET $\mathrm{b}_{R_i} = \mathrm{b}_{R_i} + \varepsilon$
Solve
SET $\mathrm{b}_{R_i} = \mathrm{b}_{R_i} - \varepsilon$
SET $\mathrm{SP}_{R_i} =$ Shadow Price for the Redundant Capacity Source
SET $\mathrm{AI}_{R_i} =$ Allowable increase for the Redundant Capacity Source $+\,\varepsilon$
IF $\mathrm{b}_{R_i} = 0$ THEN $\mathrm{Y}_{R_i} = 1$ ELSE $= 0$
SET C = Increase for resource, $(\mathrm{C} \le \mathrm{AI}_{R_i})$
SET Resource Shadow Price function: $f(\mathrm{C}) = \mathrm{SP}_{R_i}\mathrm{C} - \gamma_{R_i}\mathrm{Y}_{R_i}$
ENDDO
***** Evaluate Grouped Redundant Resources**
DO FOR EACH Redundant Capacity Group being evaluated:
SET $\mathrm{b}_G = \sum_{All\ R_i\ in\ Group} \mathrm{b}_{R_i}$
SET $\mathrm{R}_G = \sum_{All\ R_i\ in\ Group} \lambda_{I_i R_i} X_{R_{it} I_{it}}$
SET Constraint $R_G \le \mathrm{b}_G$
Remove constraints for individual Redundant Capacity Sources in the Group
SET $\mathrm{b}_G = \mathrm{b}_G + \varepsilon$
Solve
SET $\mathrm{b}_G = \mathrm{b}_G - \varepsilon$
SET $\mathrm{SP}_{R_G} =$ Shadow Price for current constraint
SET $\mathrm{AI}_{R_G} =$ Allowable increase for current constraint $+\,\varepsilon$
DO FOR EACH R_i in the Group
IF $\sum_{t=1}^{N} \mathrm{b}_{R_{it}} = 0$ THEN $\mathrm{Y}_{R_i} = 1$ ELSE $\mathrm{Y}_{R_i} = 0$
ENDDO
SET C = Increase for Group, $(\mathrm{C} \le \mathrm{AI}_G)$
SET Group Shadow Price Function: $f(\mathrm{C}) = \mathrm{SP}_G C - \sum_{All\ R_i\ in\ Group} \gamma_{R_{it}} \mathrm{Y}_{R_i}$
ENDDO
Replace individual constraints for each Redundant Capacity Source in the Group
Remove Redundant Capacity Group constraint
***** Determine Change in Capacity Allotment and Adjust RHS**

Make decision on which R_i or R_G to increase and the magnitude of increase.
IF Increasing capacity for a Redundant Capacity Source R_i
Set $\mathrm{C} = \mathrm{Increase}_{R_i}$ where $\mathrm{Increase}_{R_i} \leq \mathrm{AI}_{R_i}$
$\mathrm{b}_i = \mathrm{b}_i + \mathrm{C}$
ELSEIF Increasing capacity for a Redundant Capacity Group R_G
Set $\mathrm{C} = \mathrm{Increase}_{R_G}$ where $\mathrm{Increase}_{R_G} \leq \mathrm{AI}_{R_G}$
DO FOR EACH Redundant Capacity Source R_i in the group
$$\mathrm{b}_{R_i\prime} = \mathrm{b}_{R_i\prime} + \left({\lambda_{I_i R_i}} \Big/ {\sum_{All\ R_i\ in\ Group} \lambda_{I_i R_i}} \times \mathrm{C} \right)$$
ENDDO
ELSE No increase on any group, terminate algorithm.
ENDIF
***** Solve for new optimal solution**
Solve for $\mathrm{Min\,Z}$
Return to **Begin Iterative Analysis**

Appendix B
Capacity Evaluation & Deployment Algorithm Example

CEDA Example, Iteration 1

Variables

Name	Final Value	Reduced Costs	Objective Value	Allowable Increase	Allowable Decrease
SO->U1	0.0	100.3	5300.0	99999.0	100.3
SO->U2	20.0	0.0	5200.0	15.0	85.0
SO->U3	10.0	0.0	5100.0	85.0	105.0
SO->U4	0.0	15.0	5000.0	99999.0	15.0
A1->Ia1	100.0	0.0	0.0	5189.8	99999.0
A2->Ia2	80.0	0.0	0.0	6.0	0.3
A3->Ia3	90.0	0.0	0.0	0.3	0.3
A4->Ia4	100.0	0.0	0.0	0.3	99999.0
B1->Ib1	100.0	0.0	0.0	5181.8	99999.0
B2->Ib2	80.0	0.0	0.0	5190.0	99999.0
B3->Ib3	90.0	0.0	0.0	5090.0	99999.0
B4->Ib4	100.0	0.0	0.0	4974.8	99999.0
a12->Ia2	0.0	6.0	4.0	99999.0	6.0
a13->Ia3	0.0	6.0	4.0	99999.0	6.0
a14->Ia4	0.0	5.8	4.0	99999.0	5.8
a21->Ia1	0.0	0.0	4.0	5181.8	99999.0
a22->Ia2	0.0	5189.8	6.0	99999.0	5189.8
a23->Ia3	0.0	5189.8	6.0	99999.0	5189.8
a24->Ia4	0.0	5189.5	6.0	99999.0	5189.5
b11->Ib1	0.0	5190.0	6.0	99999.0	5190.0
b12->Ib2	0.0	0.0	10.0	100.0	99999.0
b13->Ib3	0.0	100.0	10.0	99999.0	100.0
b14->Ib4	0.0	215.3	10.0	99999.0	215.3
b21->Ib1	0.0	5190.0	12.0	99999.0	5190.0
b22->Ib2	0.0	0.0	12.0	100.0	99999.0
b23->Ib3	0.0	100.0	12.0	99999.0	100.0
b24->Ib4	0.0	215.3	12.0	99999.0	215.3
Ia1->Ia2	0.0	5190.0	11.0	99999.0	5190.0
Ia2->Ia3	0.0	0.3	11.0	99999.0	0.3
Ia3->Ia4	0.0	0.0	11.0	5.8	0.3
Ib1->Ib2	0.0	0.0	11.0	5181.8	15.3
Ib2->Ib3	0.0	100.3	13.0	99999.0	100.3
Ib3->Ib4	0.0	115.3	13.0	99999.0	115.3
Ib2->U1	0.0	210.3	13.0	99999.0	210.3
Ib3->U1	0.0	125.3	13.0	99999.0	125.3
Ib3->U2	0.0	105.0	0.0	99999.0	105.0
Ib4->U1	0.0	15.3	0.0	99999.0	15.3
Ib4->U2	0.0	0.0	0.0	15.3	15.0
Ib4->U3	0.0	85.0	0.0	99999.0	85.0
Ia0->Ia1	0.0	0.0	0.0	99999.0	99999.0
Ib0->Ib1	0.0	0.0	0.0	99999.0	99999.0
DM1->SI	100.0	0.0	0.0	15.3	99999.0
U1->SI	0.0	0.0	0.0	99999.0	15.3
DM2->SI	80.0	0.0	0.0	100.0	15.3
U2->SI	20.0	0.0	0.0	15.3	100.0
DM3->SI	90.0	0.0	0.0	105.0	100.0
U3->SI	10.0	0.0	0.0	100.0	105.0
DM4->SI	100.0	0.0	0.0	15.0	99999.0
U4->SI	0.0	0.0	0.0	99999.0	15.0
Ia1->B1	100.0	0.0	0.0	5181.8	99999.0
Ia1->b11	0.0	0.0	0.0	99999.0	5190.0
Ia1->b21	0.0	0.0	0.3	99999.0	5190.0
Ia2->B2	80.0	0.0	0.3	5190.0	99999.0
Ia2->b12	0.0	0.0	0.3	100.0	99999.0
Ia2->b22	0.0	0.0	0.3	100.0	99999.0
Ia3->B3	90.0	0.0	0.3	5090.0	99999.0
Ia3->b13	0.0	0.0	0.3	99999.0	100.0
Ia3->b23	0.0	0.0	210.0	99999.0	100.0
Ia4->B4	100.0	0.0	225.0	4974.8	99999.0
Ia4->b14	0.0	0.0	205.0	99999.0	215.3
Ia4->b24	0.0	0.0	230.0	99999.0	215.3
Ib1->DM1	100.0	0.0	215.0	15.3	99999.0
Ib2->DM2	80.0	0.0	200.0	100.0	15.3
Ib3->DM3	90.0	0.0	0.0	105.0	100.0
Ib4->DM4	100.0	0.0	0.0	15.0	99999.0

Constraints

Name	Final Value	Shadow Price	RHS Value	Allowable Increase	Allowable Decrease
a1	0.0	0.0	0.0	99999.0	0.0
a2	0.0	-5181.8	0.0	0.0	0.0
b1	0.0	-5185.0	0.0	10.0	0.0
b2	0.0	-5183.0	0.0	10.0	0.0
Capacity A1	100.0	-5189.8	100.0	0.0	0.0
Capacity A2	80.0	0.0	90.0	99999.0	10.0
Capacity A3	90.0	0.0	100.0	99999.0	10.0
Capacity A4	100.0	-0.3	100.0	0.0	5.0
Capacity B1	100.0	0.0	100.0	99999.0	0.0
Capacity B2	80.0	-5190.0	80.0	10.0	80.0
Capacity B3	90.0	-5090.0	90.0	10.0	90.0
Capacity B4	100.0	-4974.8	100.0	5.0	0.0
Capacity a12	0.0	0.0	5.0	99999.0	5.0
Capacity a13	0.0	0.0	5.0	99999.0	5.0
Capacity a14	0.0	0.0	5.0	99999.0	5.0
Capacity a21	0.0	0.0	15.0	99999.0	15.0
Capacity a22	0.0	0.0	15.0	99999.0	15.0
Capacity a23	0.0	0.0	15.0	99999.0	15.0
Capacity a24	0.0	0.0	15.0	99999.0	15.0
Capacity b11	0.0	0.0	10.0	99999.0	10.0
Capacity b12	0.0	0.0	10.0	99999.0	10.0
Capacity b13	0.0	0.0	10.0	99999.0	10.0
Capacity b14	0.0	0.0	10.0	99999.0	10.0
Capacity b21	0.0	0.0	15.0	99999.0	15.0
Capacity b22	0.0	0.0	15.0	99999.0	15.0
Capacity b23	0.0	0.0	15.0	99999.0	15.0
Capacity b24	0.0	0.0	15.0	99999.0	15.0
Transfer Ia1 Ia2	0.0	0.0	5.0	99999.0	5.0
Transfer Ia2 Ia3	0.0	0.0	5.0	99999.0	5.0
Transfer Ia3 Ia4	0.0	0.0	5.0	99999.0	5.0
Transfer Ib1 Ib2	0.0	0.0	5.0	99999.0	5.0
Transfer Ib2 Ib3	0.0	0.0	5.0	99999.0	5.0
Transfer Ib3 Ib4	0.0	0.0	5.0	99999.0	5.0
Initial Inv Ia	0.0	-5193.8	0.0	0.0	0.0
Initial Inv Ib	0.0	-5199.8	0.0	5.0	0.0
Demand 1	100.0	5199.8	100.0	0.0	5.0
Demand 2	100.0	5200.0	100.0	99999.0	20.0
Demand 3	100.0	5100.0	100.0	99999.0	10.0
Demand 4	100.0	4985.0	100.0	0.0	20.0
Balance Ia1	0.0	5193.8	0.0	0.0	0.0
Balance Ia2	0.0	4.0	0.0	10.0	80.0
Balance Ia3	0.0	4.0	0.0	10.0	90.0
Balance Ia4	0.0	4.3	0.0	5.0	0.0
Balance Ib1	0.0	5199.8	0.0	0.0	5.0
Balance Ib2	0.0	5200.0	0.0	80.0	20.0
Balance Ib3	0.0	5100.0	0.0	90.0	10.0
Balance Ib4	0.0	4985.0	0.0	0.0	20.0
Balance DM1	0.0	5199.8	0.0	0.0	5.0
Balance DM2	0.0	5200.0	0.0	80.0	20.0
Balance DM3	0.0	5100.0	0.0	90.0	10.0
Balance DM4	0.0	4985.0	0.0	0.0	20.0
Balance U1	0.0	5199.8	0.0	0.0	5.0
Balance U2	0.0	5200.0	0.0	99999.0	20.0
Balance U3	0.0	5100.0	0.0	99999.0	10.0
Balance U4	0.0	4985.0	0.0	0.0	20.0
Balance B1	0.0	5193.8	0.0	0.0	0.0
Balance B2	0.0	4.0	0.0	10.0	80.0
Balance B3	0.0	4.0	0.0	10.0	90.0
Balance B4	0.0	4.3	0.0	5.0	0.0
Balance b11	0.0	5193.8	0.0	0.0	0.0
Balance b12	0.0	4.0	0.0	10.0	0.0
Balance b13	0.0	4.0	0.0	10.0	0.0
Balance b14	0.0	4.3	0.0	5.0	0.0
Balance b21	0.0	5193.8	0.0	0.0	0.0
Balance b22	0.0	4.0	0.0	10.0	0.0
Balance b23	0.0	4.0	0.0	10.0	0.0
Balance b24	0.0	4.3	0.0	5.0	0.0

CEDA Example, Iteration 2

Variables

Name	Final Value	Reduced Costs	Objective Value	Allowable Increase	Allowable Decrease
SO->U1	0	100.25	5300	99999	100.25
SO->U2	10	0	5200	15.0000001	85.0000001
SO->U3	10	0	5100	85.0000001	105.0000001
SO->U4	0	15	5000	99999	15
A1->Ia1	100	0	0	99.7500001	99999
A2->Ia2	90	0	0	100.0000001	99999
A3->Ia3	90	0	0	115.0000001	0.2500001
A4->Ia4	100	0	0	0.2500001	115.0000001
B1->Ib1	100	0	0	5090	99999
B2->Ib2	80	0	0	5090	99999
B3->Ib3	90	0	0	5090	99999
B4->Ib4	100	0	0	4975	99999
a12->Ia2	0	0	4	94.0000001	99999
a13->Ia3	0	100	4	99999	100
a14->Ia4	0	100	4	99999	100
a21->Ia1	0	0.25	4	99999	0.25
a22->Ia2	0	0	6	0.2500001	99999
a23->Ia3	0	100	6	99999	100
a24->Ia4	0	100	6	99999	100
b11->Ib1	0	0	6	0	99999
b12->Ib2	0	0	10	99999	0
b13->Ib3	0	0	10	99999	0
b14->Ib4	0	115	10	99999	115
b21->Ib1	0	0	12	0	0
b22->Ib2	10	0	12	0	0
b23->Ib3	0	0	12	0	92.0000001
b24->Ib4	0	115	12	99999	115
Ia1->Ia2	0	0	11	99999	0
Ia2->Ia3	0	100.25	11	99999	100.25
Ia3->Ia4	0	0.25	11	99999	0.25
Ib1->Ib2	0	0	11	0	0.2500001
Ib2->Ib3	0	100.25	13	99999	100.25
Ib3->Ib4	0	115.25	13	99999	115.25
Ib2->U1	0	210.25	13	99999	210.25
Ib3->U1	0	125.25	13	99999	125.25
Ib3->U2	0	105	0	99999	105
Ib4->U1	0	15.25	0	99999	15.25
Ib4->U2	0	0	0	15.2500001	15.0000001
Ib4->U3	0	85	0	99999	85
Ia0->Ia1	0	0	0	99999	99999
Ib0->Ib1	0	0	0	99999	99999
DM1->SI	100	0	0	15.2500001	99999
U1->SI	0	0	0	99999	15.2500001
DM2->SI	90	0	0	92.0000001	15.2500001
U2->SI	10	0	0	15.2500001	92.0000001
DM3->SI	90	0	0	105.0000001	92.0000001
U3->SI	10	0	0	92.0000001	105.0000001
DM4->SI	100	0	0	15.0000001	99999
U4->SI	0	0	0	99999	15.0000001
Ia1->B1	100	0	0	5090	99999
Ia1->b11	0	0	0	0	99999
Ia1->b21	0	0	0.25	0	0
Ia2->B2	80	0	0.25	5090	99999
Ia2->b12	0	0	0.25	99999	0
Ia2->b22	10	0	0.25	0	0
Ia3->B3	90	0	0.25	5090	99999
Ia3->b13	0	0	0.25	99999	0
Ia3->b23	0	0	210	0	92.0000001
Ia4->B4	100	0	225	4975	99999
Ia4->b14	0	0	205	99999	115.0000001
Ia4->b24	0	0	230	99999	115.0000001
Ib1->DM1	100	0	215	15.2500001	99999
Ib2->DM2	90	0	200	92.0000001	15.2500001
Ib3->DM3	90	0	0	105.0000001	92.0000001
Ib4->DM4	100	0	0	15.0000001	99999

Constraints

Name	Final Value	Shadow Price	RHS Value	Allowable Increase	Allowable Decrease
a1	0.0	-94.0	0.0	0.0	0.0
a2	0.0	-92.0	0.0	0.0	0.0
b1	0.0	-5085.0	0.0	0.0	0.0
b2	10.0	-5083.0	10.0	10.0	0.0
Capacity A1	100.0	-99.8	100.0	0.0	0.0
Capacity A2	90.0	-100.0	90.0	0.0	10.0
Capacity A3	90.0	0.0	100.0	99999.0	10.0
Capacity A4	100.0	0.0	100.0	99999.0	0.0
Capacity B1	100.0	-5090.0	100.0	0.0	0.0
Capacity B2	80.0	-5090.0	80.0	10.0	0.0
Capacity B3	90.0	-5090.0	90.0	10.0	90.0
Capacity B4	100.0	-4975.0	100.0	0.0	0.0
Capacity a12	0.0	0.0	5.0	99999.0	5.0
Capacity a13	0.0	0.0	5.0	99999.0	5.0
Capacity a14	0.0	0.0	5.0	99999.0	5.0
Capacity a21	0.0	0.0	15.0	99999.0	15.0
Capacity a22	0.0	0.0	15.0	99999.0	15.0
Capacity a23	0.0	0.0	15.0	99999.0	15.0
Capacity a24	0.0	0.0	15.0	99999.0	15.0
Capacity b11	0.0	0.0	10.0	99999.0	10.0
Capacity b12	0.0	0.0	10.0	99999.0	10.0
Capacity b13	0.0	0.0	10.0	99999.0	10.0
Capacity b14	0.0	0.0	10.0	99999.0	10.0
Capacity b21	0.0	0.0	15.0	99999.0	15.0
Capacity b22	10.0	0.0	15.0	99999.0	5.0
Capacity b23	0.0	0.0	15.0	99999.0	15.0
Capacity b24	0.0	0.0	15.0	99999.0	15.0
Transfer Ia1 Ia2	0.0	0.0	5.0	99999.0	5.0
Transfer Ia2 Ia3	0.0	0.0	5.0	99999.0	5.0
Transfer Ia3 Ia4	0.0	0.0	5.0	99999.0	5.0
Transfer Ib1 Ib2	0.0	0.0	5.0	99999.0	5.0
Transfer Ib2 Ib3	0.0	0.0	5.0	99999.0	5.0
Transfer Ib3 Ib4	0.0	0.0	5.0	99999.0	5.0
Initial Inv Ia	0.0	-103.8	0.0	0.0	0.0
Initial Inv Ib	0.0	-5199.8	0.0	5.0	0.0
Demand 1	100.0	5199.8	100.0	0.0	5.0
Demand 2	100.0	5200.0	100.0	99999.0	10.0
Demand 3	100.0	5100.0	100.0	99999.0	10.0
Demand 4	100.0	4985.0	100.0	0.0	10.0
Balance Ia1	0.0	103.8	0.0	0.0	0.0
Balance Ia2	0.0	104.0	0.0	10.0	0.0
Balance Ia3	0.0	4.0	0.0	10.0	90.0
Balance Ia4	0.0	4.0	0.0	0.0	100.0
Balance Ib1	0.0	5199.8	0.0	0.0	5.0
Balance Ib2	0.0	5200.0	0.0	90.0	10.0
Balance Ib3	0.0	5100.0	0.0	90.0	10.0
Balance Ib4	0.0	4985.0	0.0	0.0	10.0
Balance DM1	0.0	5199.8	0.0	0.0	5.0
Balance DM2	0.0	5200.0	0.0	90.0	10.0
Balance DM3	0.0	5100.0	0.0	90.0	10.0
Balance DM4	0.0	4985.0	0.0	0.0	10.0
Balance U1	0.0	5199.8	0.0	0.0	5.0
Balance U2	0.0	5200.0	0.0	99999.0	10.0
Balance U3	0.0	5100.0	0.0	99999.0	10.0
Balance U4	0.0	4985.0	0.0	0.0	10.0
Balance B1	0.0	103.8	0.0	0.0	0.0
Balance B2	0.0	104.0	0.0	10.0	0.0
Balance B3	0.0	4.0	0.0	10.0	90.0
Balance B4	0.0	4.0	0.0	0.0	100.0
Balance b11	0.0	103.8	0.0	0.0	0.0
Balance b12	0.0	104.0	0.0	10.0	0.0
Balance b13	0.0	4.0	0.0	10.0	0.0
Balance b14	0.0	4.0	0.0	0.0	0.0
Balance b21	0.0	103.8	0.0	0.0	0.0
Balance b22	0.0	104.0	0.0	10.0	0.0
Balance b23	0.0	4.0	0.0	10.0	0.0
Balance b24	0.0	4.0	0.0	0.0	0.0

CEDA Example, Iteration 3

Variables

Name	Final Value	Reduced Costs	Objective Value	Allowable Increase	Allowable Decrease
SO->U1	0	100.25	5300	99999	100.25
SO->U2	10	0	5200	15.0000001	4975
SO->U3	0	105	5100	99999	105
SO->U4	0	15	5000	99999	15
A1->Ia1	100	0	0	204.7500001	99999
A2->Ia2	90	0	0	205.0000001	99999
A3->Ia3	100	0	0	10.0000001	0.2500001
A4->Ia4	100	0	0	0.2500001	10.0000001
B1->Ib1	100	0	0	4985	99999
B2->Ib2	80	0	0	4985	99999
B3->Ib3	90	0	0	4985	99999
B4->Ib4	100	0	0	4975	99999
a12->Ia2	0	0	4	199.0000001	99999
a13->Ia3	0	205	4	99999	205
a14->Ia4	0	205	4	99999	205
a21->Ia1	0	0.25	4	99999	0.25
a22->Ia2	0	0	6	0.2500001	99999
a23->Ia3	0	205	6	99999	205
a24->Ia4	0	205	6	99999	205
b11->Ib1	0	0	6	0	99999
b12->Ib2	0	0	10	99999	0
b13->Ib3	0	0	10	99999	0
b14->Ib4	0	10	10	99999	10
b21->Ib1	0	0	12	0	0
b22->Ib2	10	0	12	0	0
b23->Ib3	10	0	12	0	197.0000001
b24->Ib4	0	10	12	99999	10
Ia1->Ia2	0	0	11	99999	0
Ia2->Ia3	0	205.25	11	99999	205.25
Ia3->Ia4	0	0.25	11	99999	0.25
Ib1->Ib2	0	0	11	0	0.2500001
Ib2->Ib3	0	205.25	13	99999	205.25
Ib3->Ib4	0	10.25	13	99999	10.25
Ib2->U1	0	210.25	13	99999	210.25
Ib3->U1	0	20.25	13	99999	20.25
Ib3->U2	0	0	0	10.0000001	105.0000001
Ib4->U1	0	15.25	0	99999	15.25
Ib4->U2	0	0	0	15.2500001	10.0000001
Ib4->U3	0	190	0	99999	190
Ia0->Ia1	0	0	0	99999	99999
Ib0->Ib1	0	0	0	99999	99999
DM1->SI	100	0	0	15.2500001	99999
U1->SI	0	0	0	99999	15.2500001
DM2->SI	90	0	0	197.0000001	15.2500001
U2->SI	10	0	0	15.2500001	197.0000001
DM3->SI	100	0	0	105.0000001	99999
U3->SI	0	0	0	99999	105.0000001
DM4->SI	100	0	0	15.0000001	99999
U4->SI	0	0	0	99999	15.0000001
Ia1->B1	100	0	0	4985	99999
Ia1->b11	0	0	0	0	99999
Ia1->b21	0	0	0.25	0	0
Ia2->B2	80	0	0.25	4985	99999
Ia2->b12	0	0	0.25	99999	0
Ia2->b22	10	0	0.25	0	0
Ia3->B3	90	0	0.25	4985	99999
Ia3->b13	0	0	0.25	99999	0
Ia3->b23	10	0	210	0	197.0000001
Ia4->B4	100	0	225	4975	99999
Ia4->b14	0	0	205	99999	10.0000001
Ia4->b24	0	0	230	99999	10.0000001
Ib1->DM1	100	0	215	15.2500001	99999
Ib2->DM2	90	0	200	197.0000001	15.2500001
Ib3->DM3	100	0	0	105.0000001	99999
Ib4->DM4	100	0	0	15.0000001	99999

Constraints

Name	Final Value	Shadow Price	RHS Value	Allowable Increase	Allowable Decrease
a1	0.0	-199.0	0.0	0.0	0.0
a2	0.0	-197.0	0.0	0.0	0.0
b1	0.0	-4980.0	0.0	0.0	0.0
b2	20.0	-4978.0	20.0	0.0	0.0
Capacity A1	100.0	-204.8	100.0	0.0	0.0
Capacity A2	90.0	-205.0	90.0	0.0	0.0
Capacity A3	100.0	0.0	100.0	99999.0	0.0
Capacity A4	100.0	0.0	100.0	99999.0	0.0
Capacity B1	100.0	-4985.0	100.0	0.0	0.0
Capacity B2	80.0	-4985.0	80.0	0.0	0.0
Capacity B3	90.0	-4985.0	90.0	0.0	0.0
Capacity B4	100.0	-4975.0	100.0	0.0	0.0
Capacity a12	0.0	0.0	5.0	99999.0	5.0
Capacity a13	0.0	0.0	5.0	99999.0	5.0
Capacity a14	0.0	0.0	5.0	99999.0	5.0
Capacity a21	0.0	0.0	15.0	99999.0	15.0
Capacity a22	0.0	0.0	15.0	99999.0	15.0
Capacity a23	0.0	0.0	15.0	99999.0	15.0
Capacity a24	0.0	0.0	15.0	99999.0	15.0
Capacity b11	0.0	0.0	10.0	99999.0	10.0
Capacity b12	0.0	0.0	10.0	99999.0	10.0
Capacity b13	0.0	0.0	10.0	99999.0	10.0
Capacity b14	0.0	0.0	10.0	99999.0	10.0
Capacity b21	0.0	0.0	15.0	99999.0	15.0
Capacity b22	10.0	0.0	15.0	99999.0	5.0
Capacity b23	10.0	0.0	15.0	99999.0	5.0
Capacity b24	0.0	0.0	15.0	99999.0	15.0
Transfer Ia1 Ia2	0.0	0.0	5.0	99999.0	5.0
Transfer Ia2 Ia3	0.0	0.0	5.0	99999.0	5.0
Transfer Ia3 Ia4	0.0	0.0	5.0	99999.0	5.0
Transfer Ib1 Ib2	0.0	0.0	5.0	99999.0	5.0
Transfer Ib2 Ib3	0.0	0.0	5.0	99999.0	5.0
Transfer Ib3 Ib4	0.0	0.0	5.0	99999.0	5.0
Initial Inv Ia	0.0	-208.8	0.0	0.0	0.0
Initial Inv Ib	0.0	-5199.8	0.0	5.0	0.0
Demand 1	100.0	5199.8	100.0	0.0	5.0
Demand 2	100.0	5200.0	100.0	99999.0	10.0
Demand 3	100.0	4995.0	100.0	0.0	10.0
Demand 4	100.0	4985.0	100.0	0.0	10.0
Balance Ia1	0.0	208.8	0.0	0.0	0.0
Balance Ia2	0.0	209.0	0.0	0.0	0.0
Balance Ia3	0.0	4.0	0.0	0.0	100.0
Balance Ia4	0.0	4.0	0.0	0.0	100.0
Balance Ib1	0.0	5199.8	0.0	0.0	5.0
Balance Ib2	0.0	5200.0	0.0	90.0	10.0
Balance Ib3	0.0	4995.0	0.0	0.0	10.0
Balance Ib4	0.0	4985.0	0.0	0.0	10.0
Balance DM1	0.0	5199.8	0.0	0.0	5.0
Balance DM2	0.0	5200.0	0.0	90.0	10.0
Balance DM3	0.0	4995.0	0.0	0.0	10.0
Balance DM4	0.0	4985.0	0.0	0.0	10.0
Balance U1	0.0	5199.8	0.0	0.0	5.0
Balance U2	0.0	5200.0	0.0	99999.0	10.0
Balance U3	0.0	4995.0	0.0	0.0	10.0
Balance U4	0.0	4985.0	0.0	0.0	10.0
Balance B1	0.0	208.8	0.0	0.0	0.0
Balance B2	0.0	209.0	0.0	0.0	0.0
Balance B3	0.0	4.0	0.0	0.0	90.0
Balance B4	0.0	4.0	0.0	0.0	100.0
Balance b11	0.0	208.8	0.0	0.0	0.0
Balance b12	0.0	209.0	0.0	0.0	0.0
Balance b13	0.0	4.0	0.0	0.0	0.0
Balance b14	0.0	4.0	0.0	0.0	0.0
Balance b21	0.0	208.8	0.0	0.0	0.0
Balance b22	0.0	209.0	0.0	0.0	0.0
Balance b23	0.0	4.0	0.0	0.0	10.0
Balance b24	0.0	4.0	0.0	0.0	0.0

CEDA Example, Iteration 4

Variables

Name	Final Value	Reduced Costs	Objective Value	Allowable Increase	Allowable Decrease
SO->U1	0	100.25	5300	99999	100.25
SO->U2	5	0	5200	15.0000001	4975
SO->U3	0	105	5100	99999	105
SO->U4	0	15	5000	99999	15
A1->Ia1	100	0	0	204.7500001	99999
A2->Ia2	90	0	0	205.0000001	99999
A3->Ia3	100	0	0	6.0000001	0.2500001
A4->Ia4	100	0	0	0.2500001	10.0000001
B1->Ib1	100	0	0	4985	99999
B2->Ib2	80	0	0	4985	99999
B3->Ib3	90	0	0	4985	99999
B4->Ib4	100	0	0	4975	99999
a12->Ia2	5	0	4	199.0000001	99999
a13->Ia3	0	6	4	99999	6
a14->Ia4	0	6	4	99999	6
a21->Ia1	0	0.25	4	99999	0.25
a22->Ia2	0	0	6	0.2500001	99999
a23->Ia3	0	205	6	99999	205
a24->Ia4	0	205	6	99999	205
b11->Ib1	0	0	6	0	99999
b12->Ib2	0	0	10	99999	0
b13->Ib3	0	0	10	99999	0
b14->Ib4	0	10	10	99999	10
b21->Ib1	0	0	12	0	0
b22->Ib2	15	0	12	0	0
b23->Ib3	10	0	12	0	197.0000001
b24->Ib4	0	10	12	99999	10
Ia1->Ia2	0	0	11	99999	0
Ia2->Ia3	0	205.25	11	99999	205.25
Ia3->Ia4	0	0.25	11	99999	0.25
Ib1->Ib2	0	0	11	0	0.2500001
Ib2->Ib3	0	205.25	13	99999	205.25
Ib3->Ib4	0	10.25	13	99999	10.25
Ib2->U1	0	210.25	13	99999	210.25
Ib3->U1	0	20.25	13	99999	20.25
Ib3->U2	0	0	0	10.0000001	105.0000001
Ib4->U1	0	15.25	0	99999	15.25
Ib4->U2	0	0	0	15.2500001	10.0000001
Ib4->U3	0	190	0	99999	190
Ia0->Ia1	0	0	0	99999	99999
Ib0->Ib1	0	0	0	99999	99999
DM1->SI	100	0	0	15.2500001	99999
U1->SI	0	0	0	99999	15.2500001
DM2->SI	95	0	0	197.0000001	15.2500001
U2->SI	5	0	0	15.2500001	197.0000001
DM3->SI	100	0	0	105.0000001	99999
U3->SI	0	0	0	99999	105.0000001
DM4->SI	100	0	0	15.0000001	99999
U4->SI	0	0	0	99999	15.0000001
Ia1->B1	100	0	0	4985	99999
Ia1->b11	0	0	0	0	99999
Ia1->b21	0	0	0.25	0	0
Ia2->B2	80	0	0.25	4985	99999
Ia2->b12	0	0	0.25	99999	0
Ia2->b22	15	0	0.25	0	0
Ia3->B3	90	0	0.25	4985	99999
Ia3->b13	0	0	0.25	99999	0
Ia3->b23	10	0	210	0	197.0000001
Ia4->B4	100	0	225	4975	99999
Ia4->b14	0	0	205	99999	10.0000001
Ia4->b24	0	0	230	99999	10.0000001
Ib1->DM1	100	0	215	15.2500001	99999
Ib2->DM2	95	0	200	197.0000001	15.2500001
Ib3->DM3	100	0	0	105.0000001	99999
Ib4->DM4	100	0	0	15.0000001	99999

Constraints

Name	Final Value	Shadow Price	RHS Value	Allowable Increase	Allowable Decrease
a1	5.0	0.0	5.0	99999.0	0.0
a2	0.0	-197.0	0.0	0.0	0.0
b1	0.0	-4980.0	0.0	0.0	0.0
b2	25.0	-4978.0	25.0	0.0	0.0
Capacity A1	100.0	-204.8	100.0	0.0	0.0
Capacity A2	90.0	-205.0	90.0	0.0	0.0
Capacity A3	100.0	0.0	100.0	99999.0	0.0
Capacity A4	100.0	0.0	100.0	99999.0	0.0
Capacity B1	100.0	-4985.0	100.0	0.0	0.0
Capacity B2	80.0	-4985.0	80.0	0.0	0.0
Capacity B3	90.0	-4985.0	90.0	0.0	0.0
Capacity B4	100.0	-4975.0	100.0	0.0	0.0
Capacity a12	5.0	-199.0	5.0	0.0	0.0
Capacity a13	0.0	0.0	5.0	99999.0	5.0
Capacity a14	0.0	0.0	5.0	99999.0	5.0
Capacity a21	0.0	0.0	15.0	99999.0	15.0
Capacity a22	0.0	0.0	15.0	99999.0	15.0
Capacity a23	0.0	0.0	15.0	99999.0	15.0
Capacity a24	0.0	0.0	15.0	99999.0	15.0
Capacity b11	0.0	0.0	10.0	99999.0	10.0
Capacity b12	0.0	0.0	10.0	99999.0	10.0
Capacity b13	0.0	0.0	10.0	99999.0	10.0
Capacity b14	0.0	0.0	10.0	99999.0	10.0
Capacity b21	0.0	0.0	15.0	99999.0	15.0
Capacity b22	15.0	0.0	15.0	99999.0	0.0
Capacity b23	10.0	0.0	15.0	99999.0	5.0
Capacity b24	0.0	0.0	15.0	99999.0	15.0
Transfer Ia1 Ia2	0.0	0.0	5.0	99999.0	5.0
Transfer Ia2 Ia3	0.0	0.0	5.0	99999.0	5.0
Transfer Ia3 Ia4	0.0	0.0	5.0	99999.0	5.0
Transfer Ib1 Ib2	0.0	0.0	5.0	99999.0	5.0
Transfer Ib2 Ib3	0.0	0.0	5.0	99999.0	5.0
Transfer Ib3 Ib4	0.0	0.0	5.0	99999.0	5.0
Initial Inv Ia	0.0	-208.8	0.0	0.0	0.0
Initial Inv Ib	0.0	-5199.8	0.0	5.0	0.0
Demand 1	100.0	5199.8	100.0	0.0	5.0
Demand 2	100.0	5200.0	100.0	99999.0	5.0
Demand 3	100.0	4995.0	100.0	0.0	5.0
Demand 4	100.0	4985.0	100.0	0.0	5.0
Balance Ia1	0.0	208.8	0.0	0.0	0.0
Balance Ia2	0.0	209.0	0.0	0.0	0.0
Balance Ia3	0.0	4.0	0.0	0.0	100.0
Balance Ia4	0.0	4.0	0.0	0.0	100.0
Balance Ib1	0.0	5199.8	0.0	0.0	5.0
Balance Ib2	0.0	5200.0	0.0	95.0	5.0
Balance Ib3	0.0	4995.0	0.0	0.0	5.0
Balance Ib4	0.0	4985.0	0.0	0.0	5.0
Balance DM1	0.0	5199.8	0.0	0.0	5.0
Balance DM2	0.0	5200.0	0.0	95.0	5.0
Balance DM3	0.0	4995.0	0.0	0.0	5.0
Balance DM4	0.0	4985.0	0.0	0.0	5.0
Balance U1	0.0	5199.8	0.0	0.0	5.0
Balance U2	0.0	5200.0	0.0	99999.0	5.0
Balance U3	0.0	4995.0	0.0	0.0	5.0
Balance U4	0.0	4985.0	0.0	0.0	5.0
Balance B1	0.0	208.8	0.0	0.0	0.0
Balance B2	0.0	209.0	0.0	0.0	0.0
Balance B3	0.0	4.0	0.0	0.0	90.0
Balance B4	0.0	4.0	0.0	0.0	100.0
Balance b11	0.0	208.8	0.0	0.0	0.0
Balance b12	0.0	209.0	0.0	0.0	0.0
Balance b13	0.0	4.0	0.0	0.0	0.0
Balance b14	0.0	4.0	0.0	0.0	0.0
Balance b21	0.0	208.8	0.0	0.0	0.0
Balance b22	0.0	209.0	0.0	0.0	0.0
Balance b23	0.0	4.0	0.0	0.0	10.0
Balance b24	0.0	4.0	0.0	0.0	0.0

CEDA Example, Iteration 5

Variables

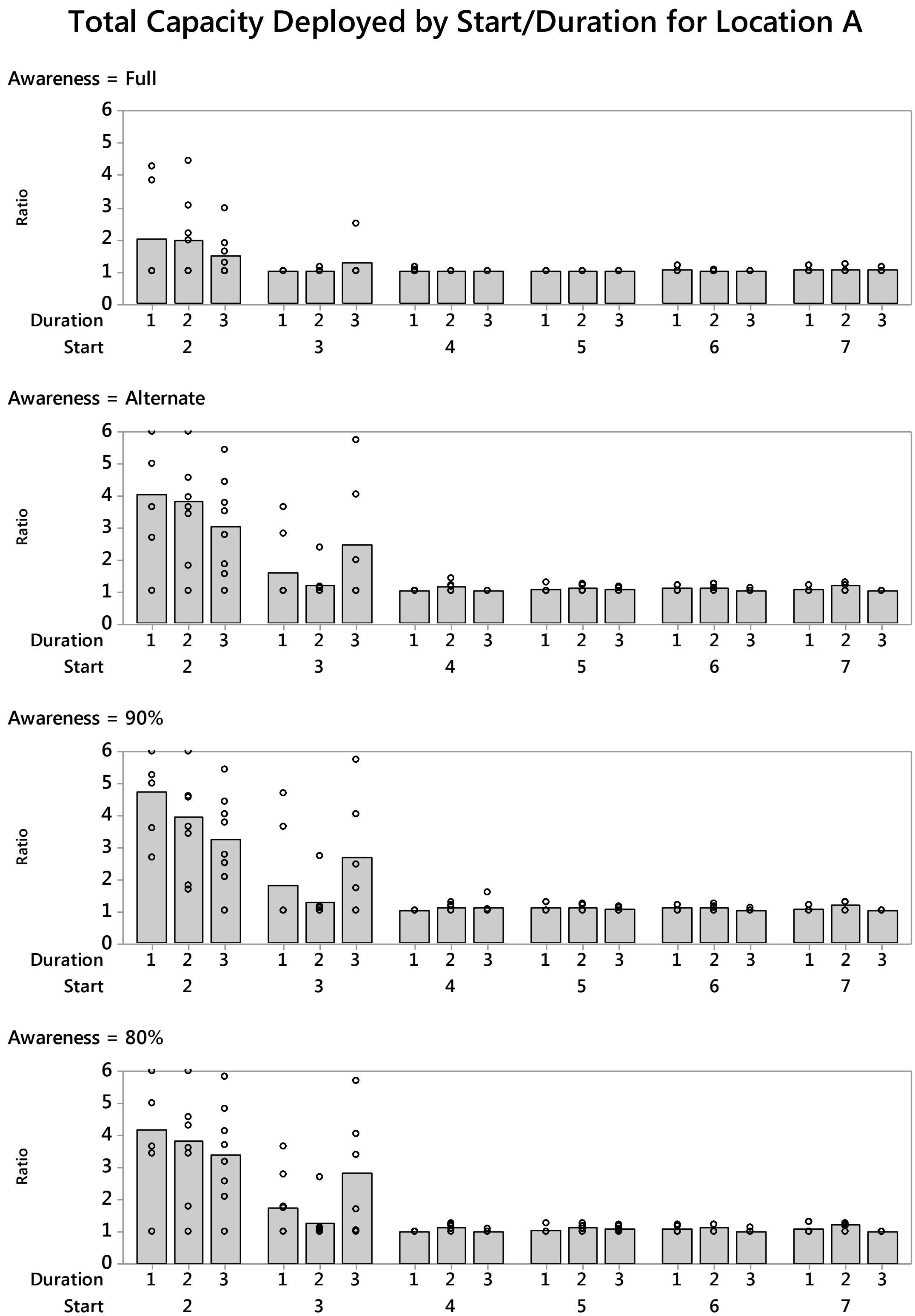
Name	Final Value	Reduced Costs	Objective Value	Allowable Increase	Allowable Decrease
SO->U1	0	5275	5300	99999	5275
SO->U2	0	5174.75	5200	99999	5174.75
SO->U3	0	5083	5100	99999	5083
SO->U4	0	4990	5000	99999	4990
A1->Ia1	100	0	0	8.0000001	99999
A2->Ia2	90	0	0	8.0000001	99999
A3->Ia3	100	0	0	6.0000001	0.2500001
A4->Ia4	100	0	0	0.2500001	193.0000001
B1->Ib1	100	0	0	7.0000001	99999
B2->Ib2	80	0	0	7.2500001	99999
B3->Ib3	90	0	0	7.0000001	99999
B4->Ib4	100	0	0	7.0000001	193.0000001
a12->Ia2	5	0	4	2.0000001	99999
a13->Ia3	0	6	4	99999	6
a14->Ia4	0	6	4	99999	6
a21->Ia1	5	0	4	196.7500001	0.2500001
a22->Ia2	0	0	6	0.2500001	2.0000001
a23->Ia3	0	8	6	99999	8
a24->Ia4	0	8	6	99999	8
b11->Ib1	0	0.25	6	99999	0.25
b12->Ib2	0	0	10	0.2500001	99999
b13->Ib3	0	0.25	10	99999	0.25
b14->Ib4	0	7.25	10	99999	7.25
b21->Ib1	5	0	12	196.7500001	0.2500001
b22->Ib2	15	0	12	0.2500001	99999
b23->Ib3	10	0	12	0.2500001	7.0000001
b24->Ib4	0	7	12	99999	7
Ia1->Ia2	0	0.25	11	99999	0.25
Ia2->Ia3	0	8.25	11	99999	8.25
Ia3->Ia4	0	0.25	11	99999	0.25
Ib1->Ib2	5	0	11	196.7500001	0.2500001
Ib2->Ib3	0	8.5	13	99999	8.5
Ib3->Ib4	0	7.25	13	99999	7.25
Ib2->U1	0	210.25	13	99999	210.25
Ib3->U1	0	217	13	99999	217
Ib3->U2	0	196.75	0	99999	196.75
Ib4->U1	0	215	0	99999	215
Ib4->U2	0	199.75	0	99999	199.75
Ib4->U3	0	193	0	99999	193
Ia0->Ia1	0	0	0	99999	99999
Ib0->Ib1	0	0	0	99999	99999
DM1->SI	100	0	0	210.2500001	99999
U1->SI	0	0	0	99999	210.2500001
DM2->SI	100	0	0	196.7500001	99999
U2->SI	0	0	0	99999	196.7500001
DM3->SI	100	0	0	193.0000001	99999
U3->SI	0	0	0	99999	193.0000001
DM4->SI	100	0	0	4990	99999
U4->SI	0	0	0	99999	4990
Ia1->B1	100	0	0	7.0000001	99999
Ia1->b11	0	0	0	99999	0.2500001
Ia1->b21	5	0	0.25	196.7500001	0.2500001
Ia2->B2	80	0	0.25	7.2500001	99999
Ia2->b12	0	0	0.25	0.2500001	99999
Ia2->b22	15	0	0.25	0.2500001	99999
Ia3->B3	90	0	0.25	7.0000001	99999
Ia3->b13	0	0	0.25	99999	0.2500001
Ia3->b23	10	0	210	0.2500001	7.0000001
Ia4->B4	100	0	225	7.0000001	193.0000001
Ia4->b14	0	0	205	99999	7.2500001
Ia4->b24	0	0	230	99999	7.0000001
Ib1->DM1	100	0	215	210.2500001	99999
Ib2->DM2	100	0	200	196.7500001	99999
Ib3->DM3	100	0	0	193.0000001	99999
Ib4->DM4	100	0	0	4990	99999

Constraints

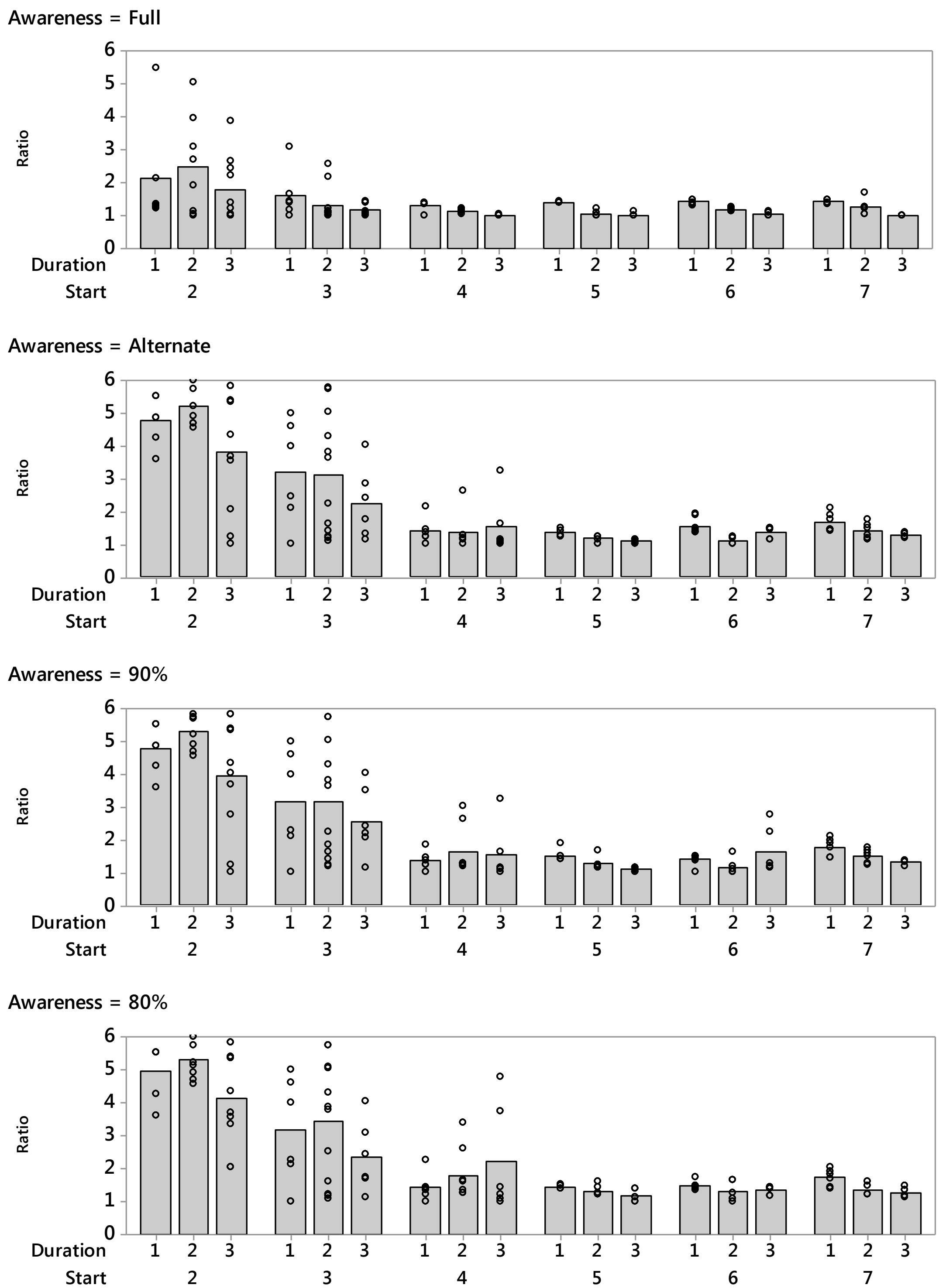
Name	Final Value	Shadow Price	RHS Value	Allowable Increase	Allowable Decrease
a1	5.0	0.0	5.0	99999.0	0.0
a2	5.0	0.0	5.0	99999.0	0.0
b1	0.0	-2.3	0.0	5.0	0.0
b2	30.0	0.0	30.0	99999.0	0.0
Capacity A1	100.0	-8.0	100.0	5.0	0.0
Capacity A2	90.0	-8.0	90.0	0.0	0.0
Capacity A3	100.0	0.0	100.0	99999.0	0.0
Capacity A4	100.0	0.0	100.0	99999.0	0.0
Capacity B1	100.0	-7.0	100.0	5.0	0.0
Capacity B2	80.0	-7.3	80.0	5.0	0.0
Capacity B3	90.0	-7.0	90.0	10.0	0.0
Capacity B4	100.0	0.0	100.0	99999.0	0.0
Capacity a12	5.0	-2.0	5.0	0.0	0.0
Capacity a13	0.0	0.0	5.0	99999.0	5.0
Capacity a14	0.0	0.0	5.0	99999.0	5.0
Capacity a21	5.0	0.0	15.0	99999.0	10.0
Capacity a22	0.0	0.0	15.0	99999.0	15.0
Capacity a23	0.0	0.0	15.0	99999.0	15.0
Capacity a24	0.0	0.0	15.0	99999.0	15.0
Capacity b11	0.0	0.0	10.0	99999.0	10.0
Capacity b12	0.0	0.0	10.0	99999.0	10.0
Capacity b13	0.0	0.0	10.0	99999.0	10.0
Capacity b14	0.0	0.0	10.0	99999.0	10.0
Capacity b21	5.0	0.0	15.0	99999.0	10.0
Capacity b22	15.0	-0.3	15.0	5.0	0.0
Capacity b23	10.0	0.0	15.0	99999.0	5.0
Capacity b24	0.0	0.0	15.0	99999.0	15.0
Transfer Ia1 Ia2	0.0	0.0	5.0	99999.0	5.0
Transfer Ia2 Ia3	0.0	0.0	5.0	99999.0	5.0
Transfer Ia3 Ia4	0.0	0.0	5.0	99999.0	5.0
Transfer Ib1 Ib2	5.0	0.0	5.0	99999.0	0.0
Transfer Ib2 Ib3	0.0	0.0	5.0	99999.0	5.0
Transfer Ib3 Ib4	0.0	0.0	5.0	99999.0	5.0
Initial Inv Ia	0.0	-12.0	0.0	5.0	0.0
Initial Inv Ib	0.0	-25.0	0.0	5.0	0.0
Demand 1	100.0	25.0	100.0	0.0	5.0
Demand 2	100.0	25.3	100.0	0.0	5.0
Demand 3	100.0	17.0	100.0	0.0	10.0
Demand 4	100.0	10.0	100.0	0.0	100.0
Balance Ia1	0.0	12.0	0.0	0.0	5.0
Balance Ia2	0.0	12.0	0.0	0.0	0.0
Balance Ia3	0.0	4.0	0.0	0.0	100.0
Balance Ia4	0.0	4.0	0.0	0.0	100.0
Balance Ib1	0.0	25.0	0.0	0.0	5.0
Balance Ib2	0.0	25.3	0.0	0.0	5.0
Balance Ib3	0.0	17.0	0.0	0.0	10.0
Balance Ib4	0.0	10.0	0.0	0.0	100.0
Balance DM1	0.0	25.0	0.0	0.0	5.0
Balance DM2	0.0	25.3	0.0	0.0	5.0
Balance DM3	0.0	17.0	0.0	0.0	10.0
Balance DM4	0.0	10.0	0.0	0.0	100.0
Balance U1	0.0	25.0	0.0	0.0	5.0
Balance U2	0.0	25.3	0.0	0.0	5.0
Balance U3	0.0	17.0	0.0	0.0	10.0
Balance U4	0.0	10.0	0.0	0.0	100.0
Balance B1	0.0	12.0	0.0	0.0	5.0
Balance B2	0.0	12.0	0.0	0.0	0.0
Balance B3	0.0	4.0	0.0	0.0	90.0
Balance B4	0.0	4.0	0.0	0.0	100.0
Balance b11	0.0	12.0	0.0	0.0	0.0
Balance b12	0.0	12.0	0.0	0.0	0.0
Balance b13	0.0	4.0	0.0	0.0	0.0
Balance b14	0.0	4.0	0.0	0.0	0.0
Balance b21	0.0	12.0	0.0	0.0	5.0
Balance b22	0.0	12.0	0.0	0.0	0.0
Balance b23	0.0	4.0	0.0	0.0	10.0
Balance b24	0.0	4.0	0.0	0.0	0.0

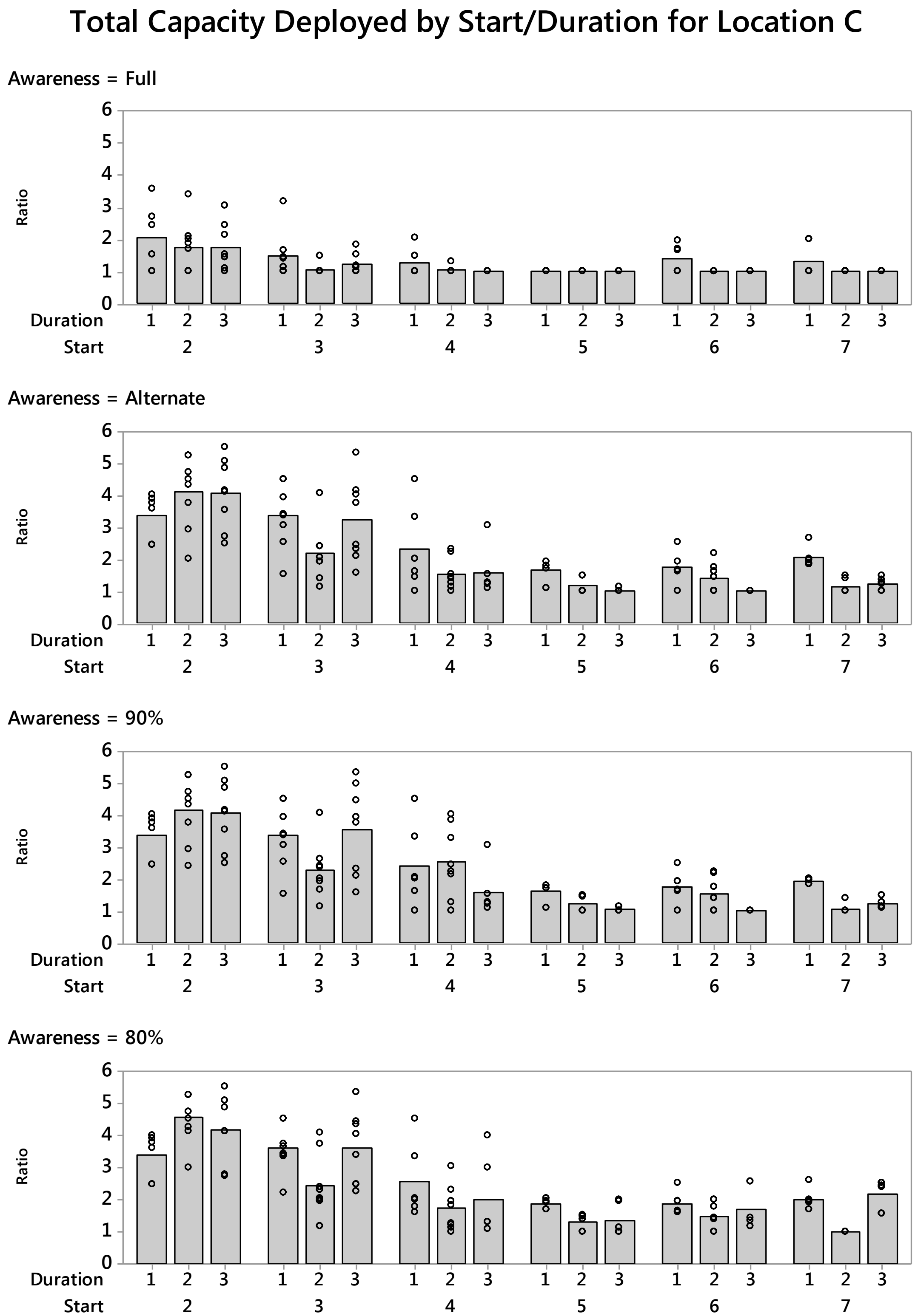
Appendix C

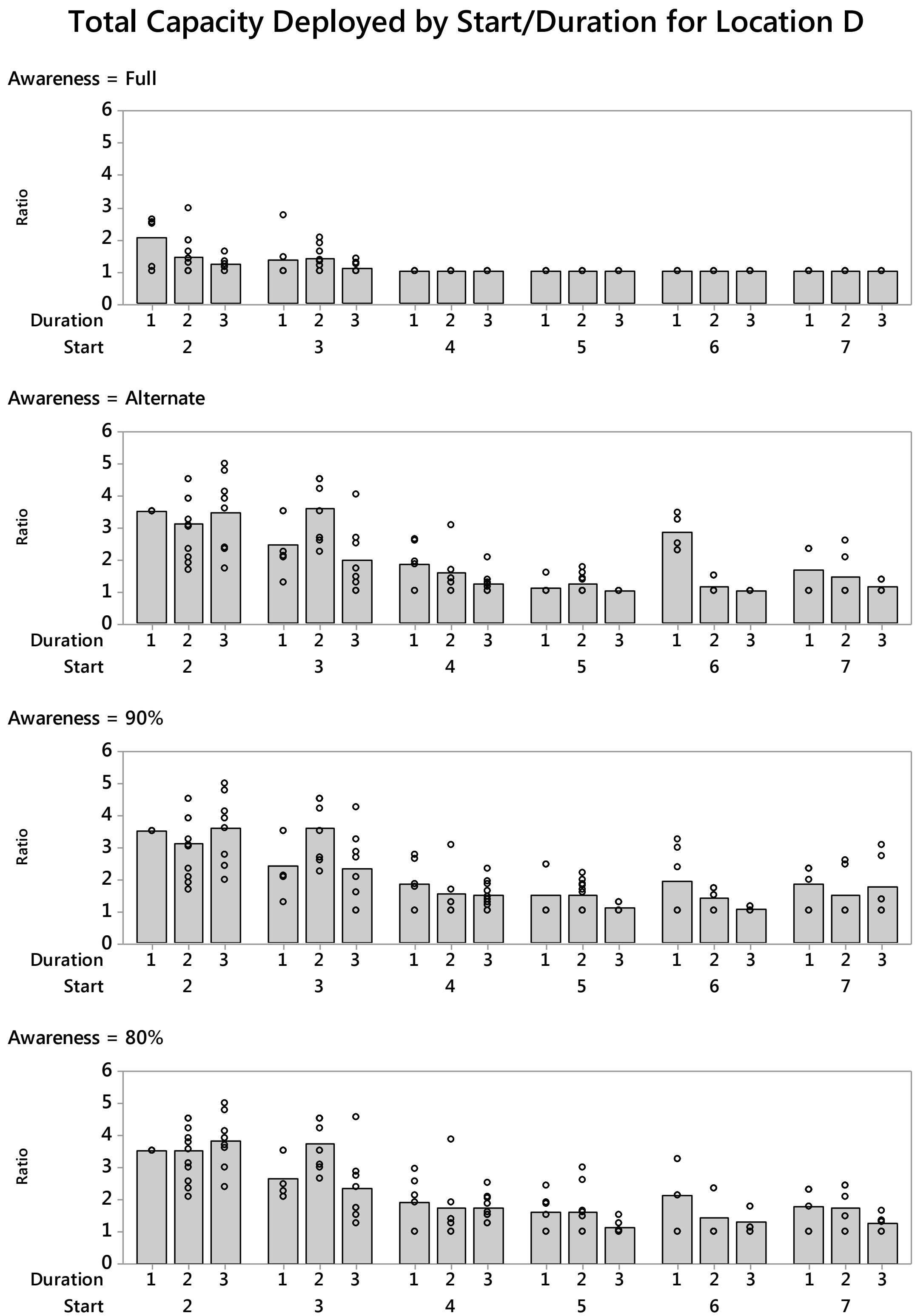
Serial Network Summary Charts


Total Capacity Deployed by Start/Duration for Location A
Awareness = Full
Awareness = Alternate
Awareness = 90%
Awareness = 80%
Ratio
0
1
2
3
4
5
6
Duration
1
2
3
Start
2
3
4
5
6
7

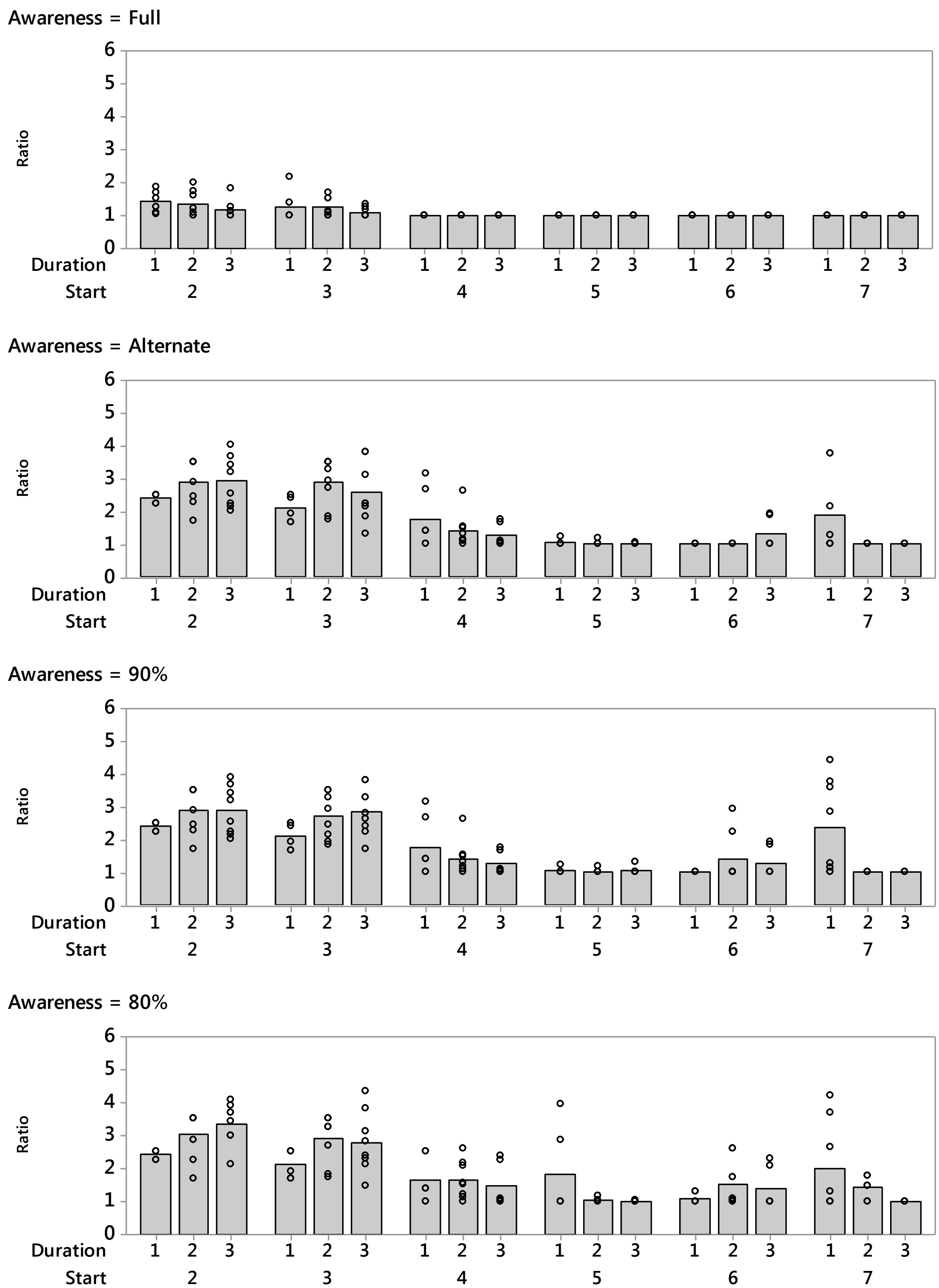
Total Capacity Deployed by Start/Duration for Location B



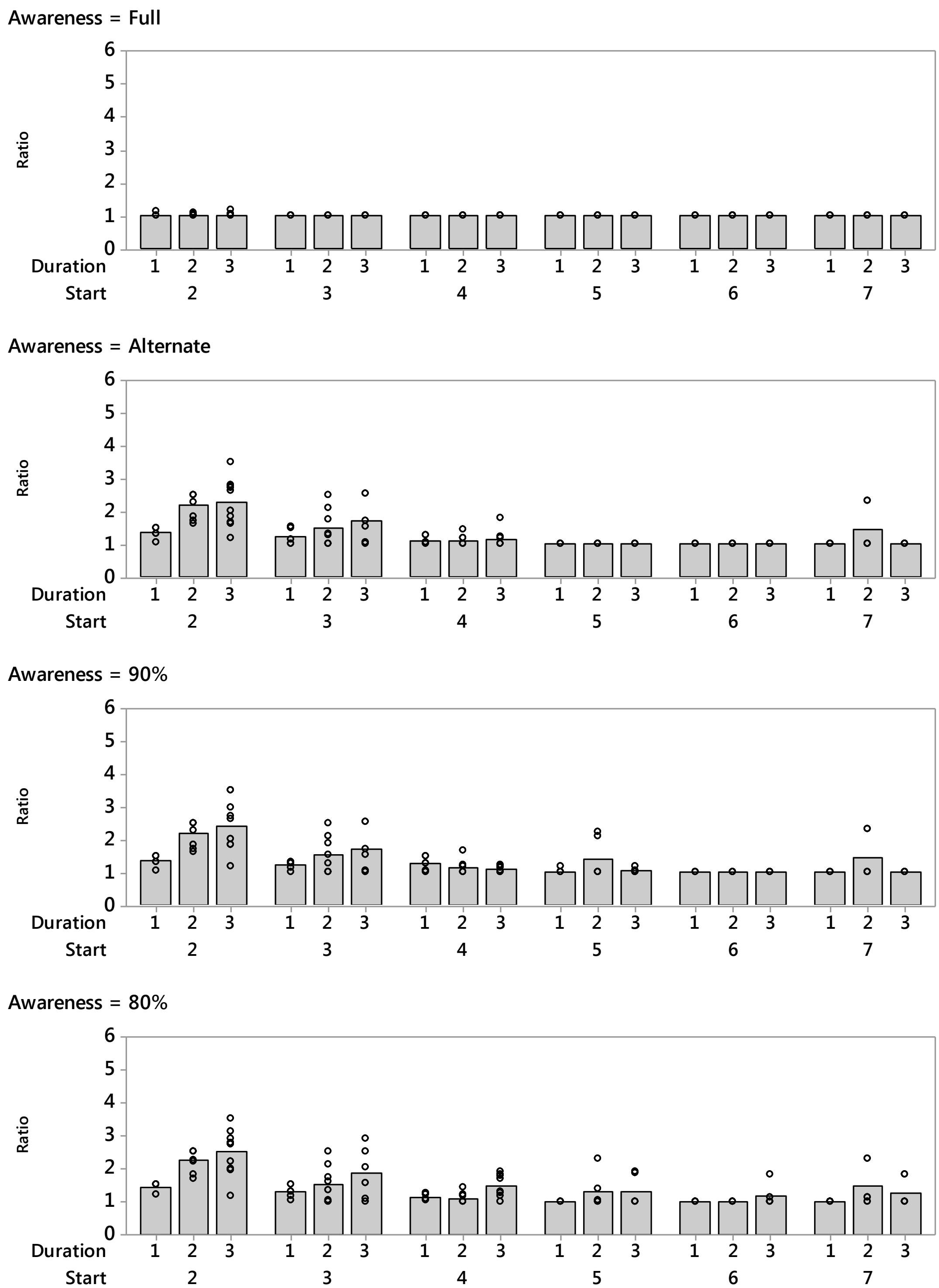

Total Capacity Deployed by Start/Duration for Location C
Awareness = Full
Awareness = Alternate
Awareness = 90%
Awareness = 80%
Ratio
Duration
Start
0
1
2
3
4
5
6
7


Total Capacity Deployed by Start/Duration for Location D
Awareness = Full
Awareness = Alternate
Awareness = 90%
Awareness = 80%
Ratio
0
1
2
3
4
5
6
Duration
1 2 3
Start
2 3 4 5 6 7

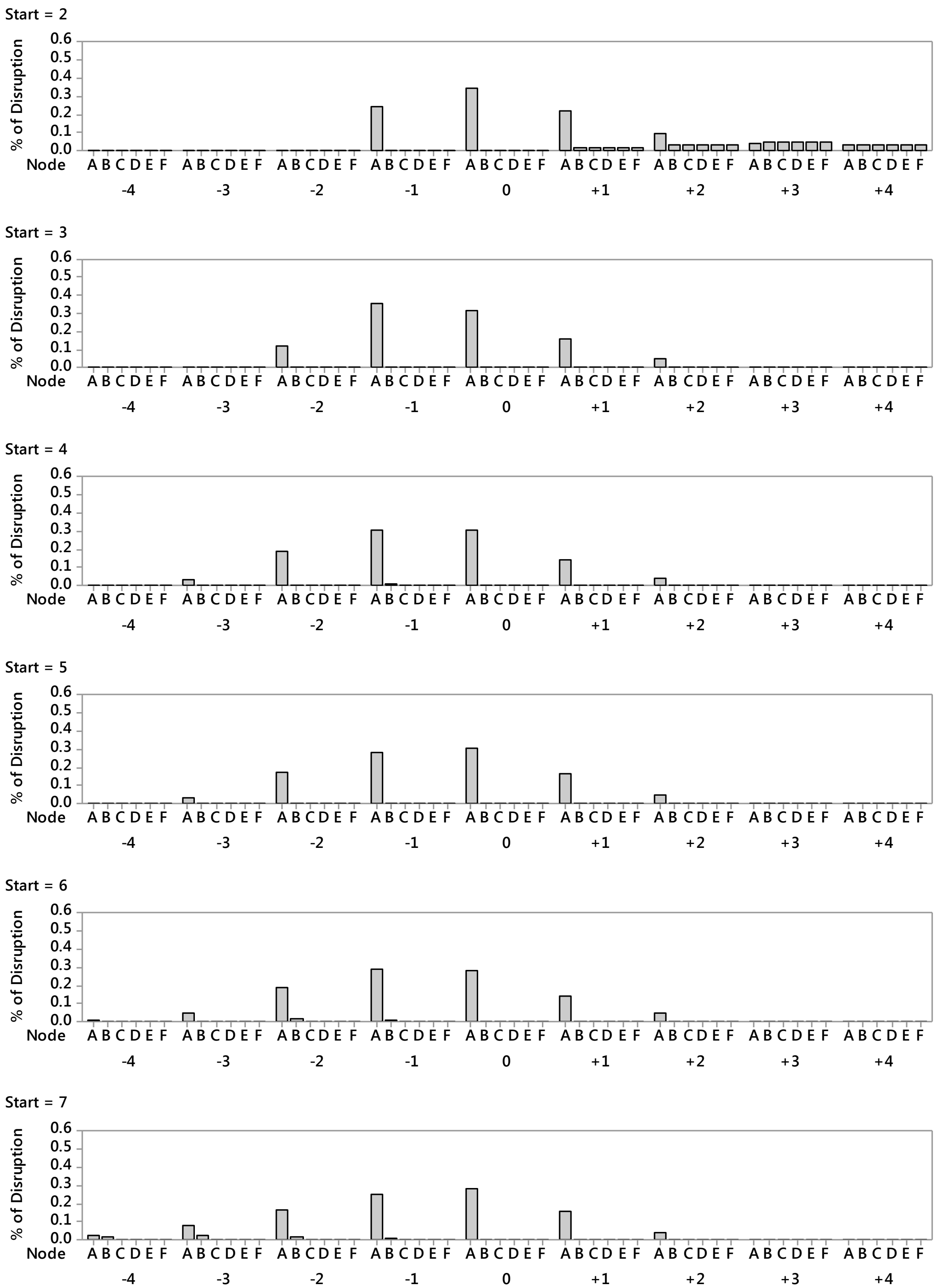
Total Capacity Deployed by Start/Duration for Location E



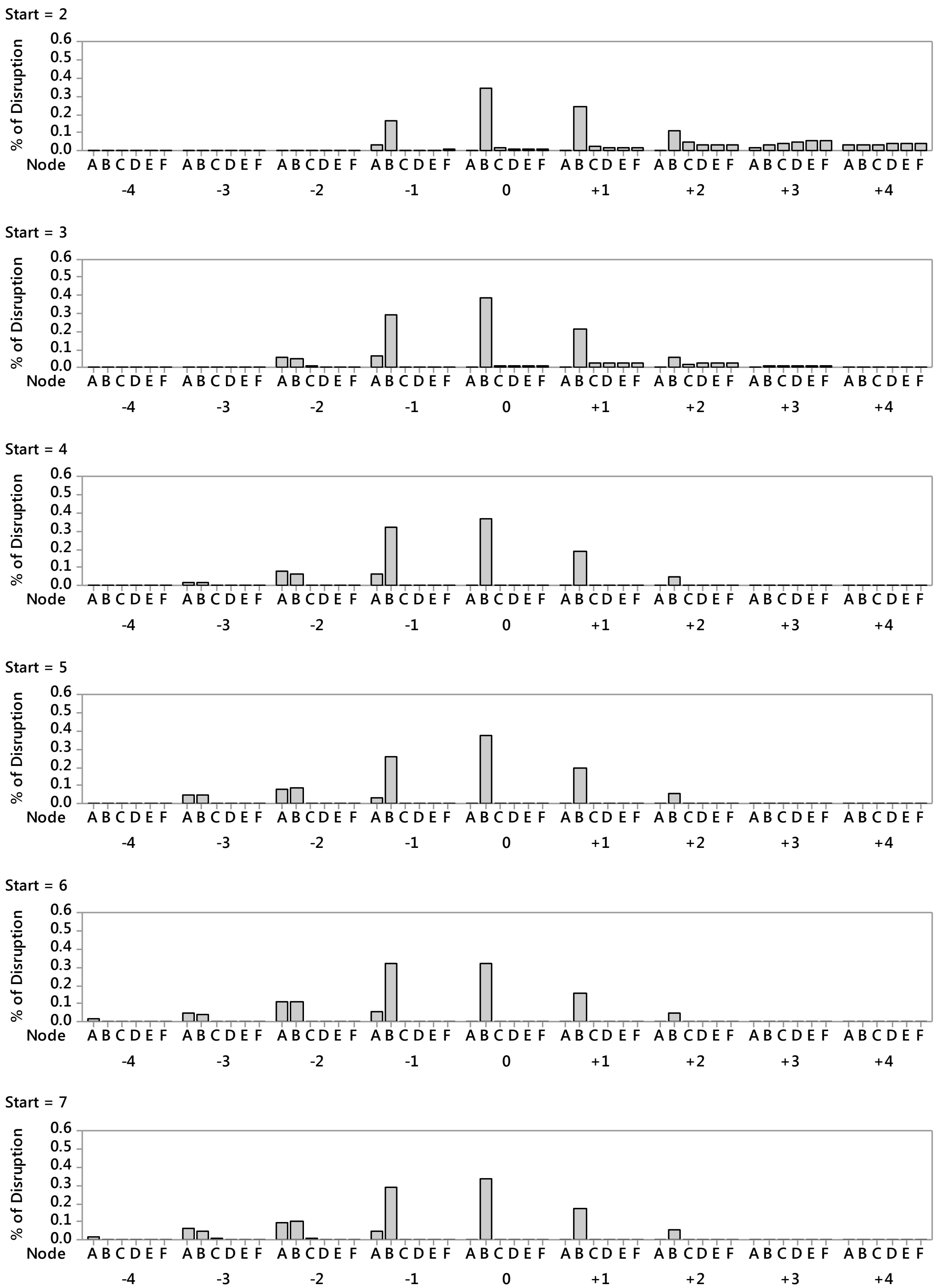
Total Capacity Deployed by Start/Duration for Location F



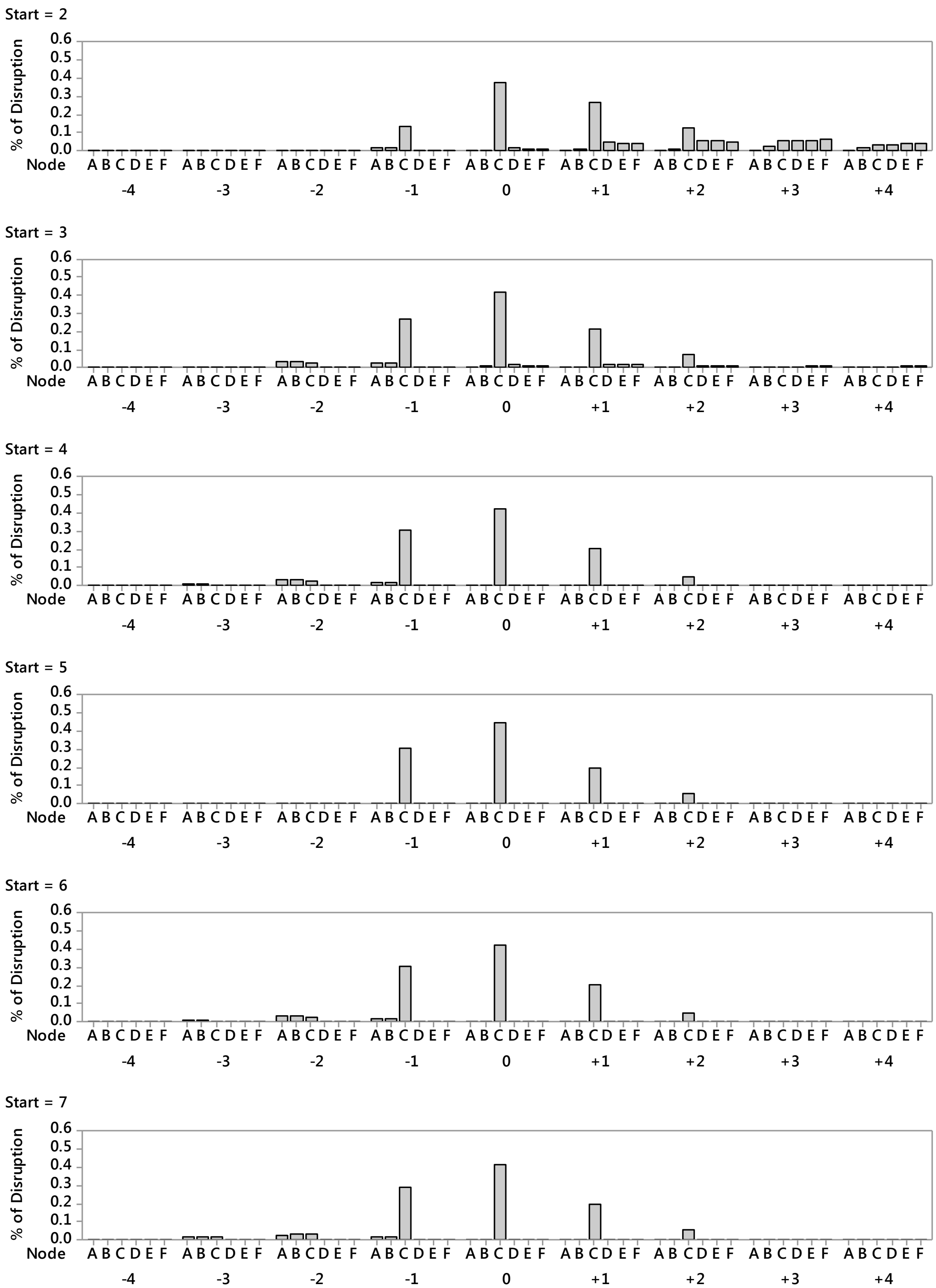
Capacity Deployed by Loaction Relative to Disruption Start, Node A Disrupted

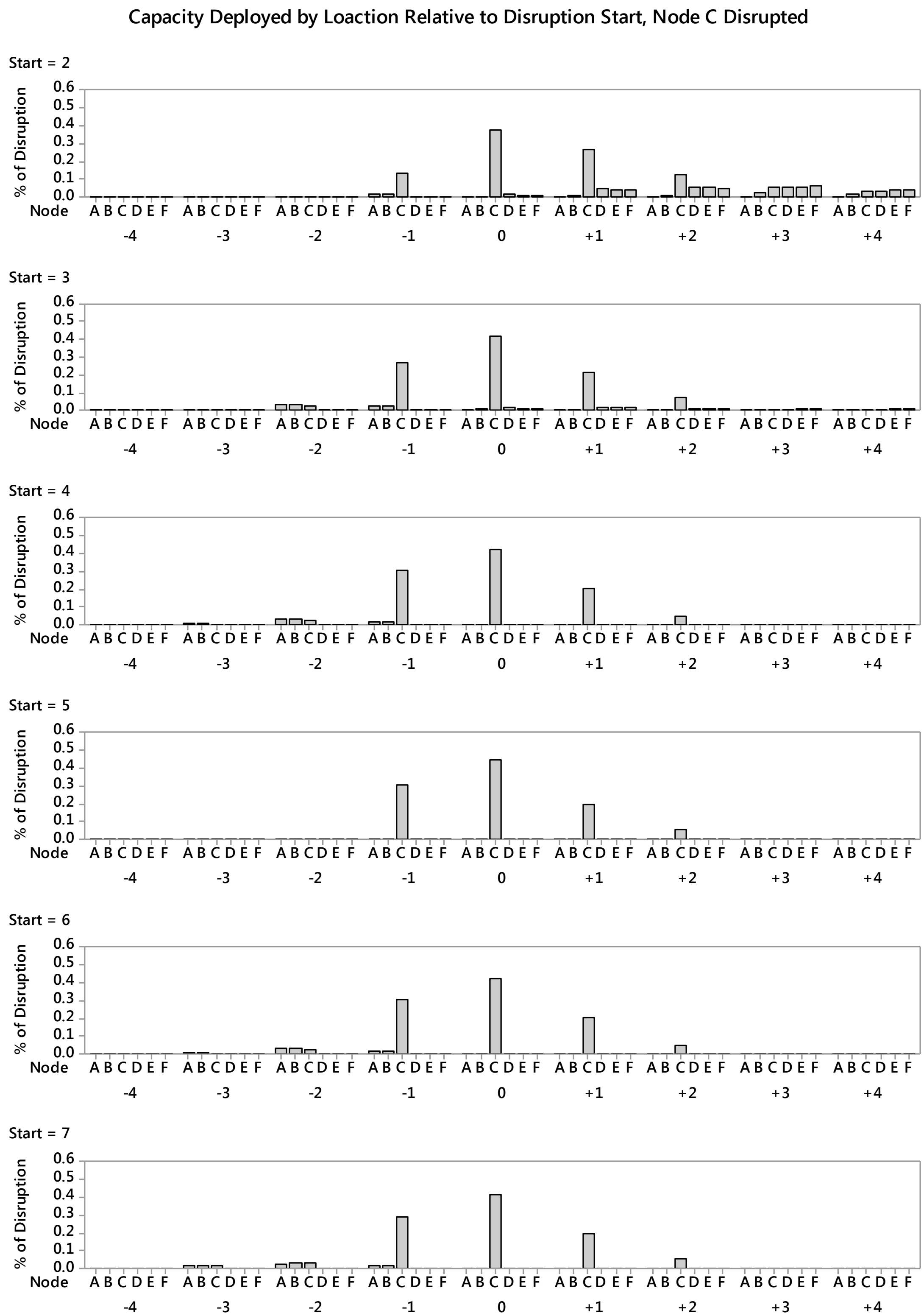


Capacity Deployed by Loaction Relative to Disruption Start, Node B Disrupted

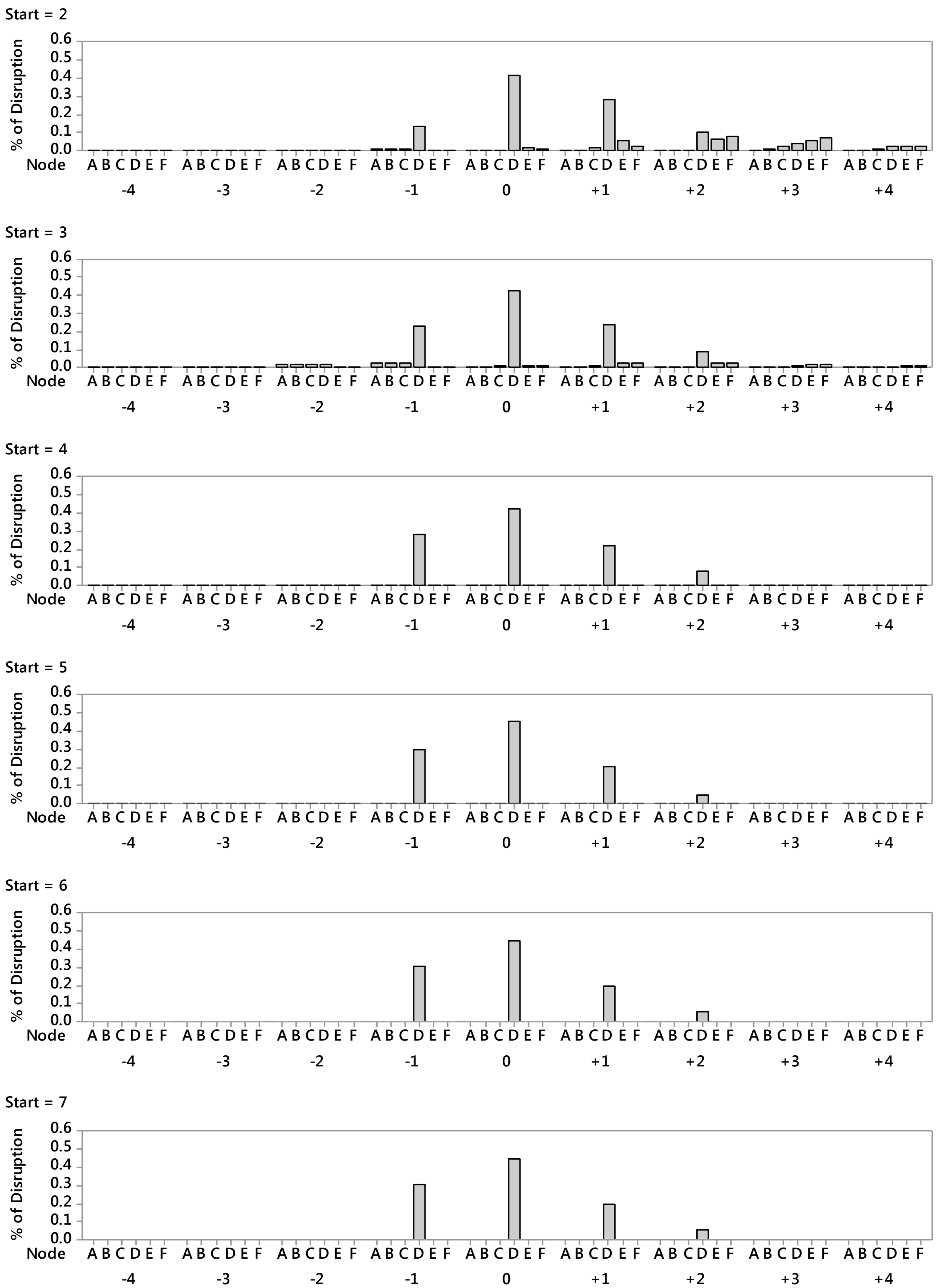


Capacity Deployed by Loaction Relative to Disruption Start, Node C Disrupted

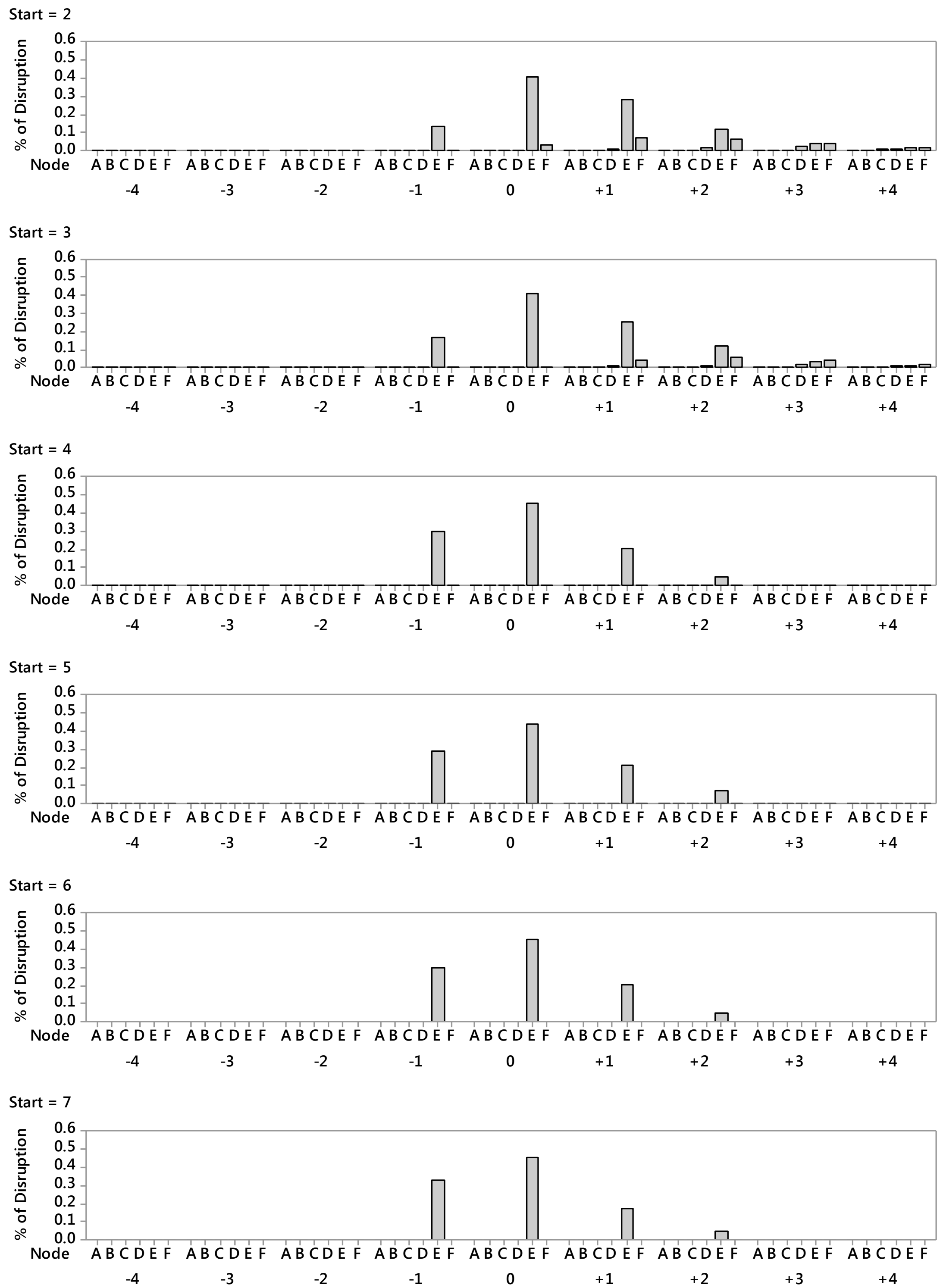



Capacity Deployed by Loaction Relative to Disruption Start, Node C Disrupted
Start = 2
Start = 3
Start = 4
Start = 5
Start = 6
Start = 7
% of Disruption
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Node
A B C D E F
-4
-3
-2
-1
0
+1
+2
+3
+4

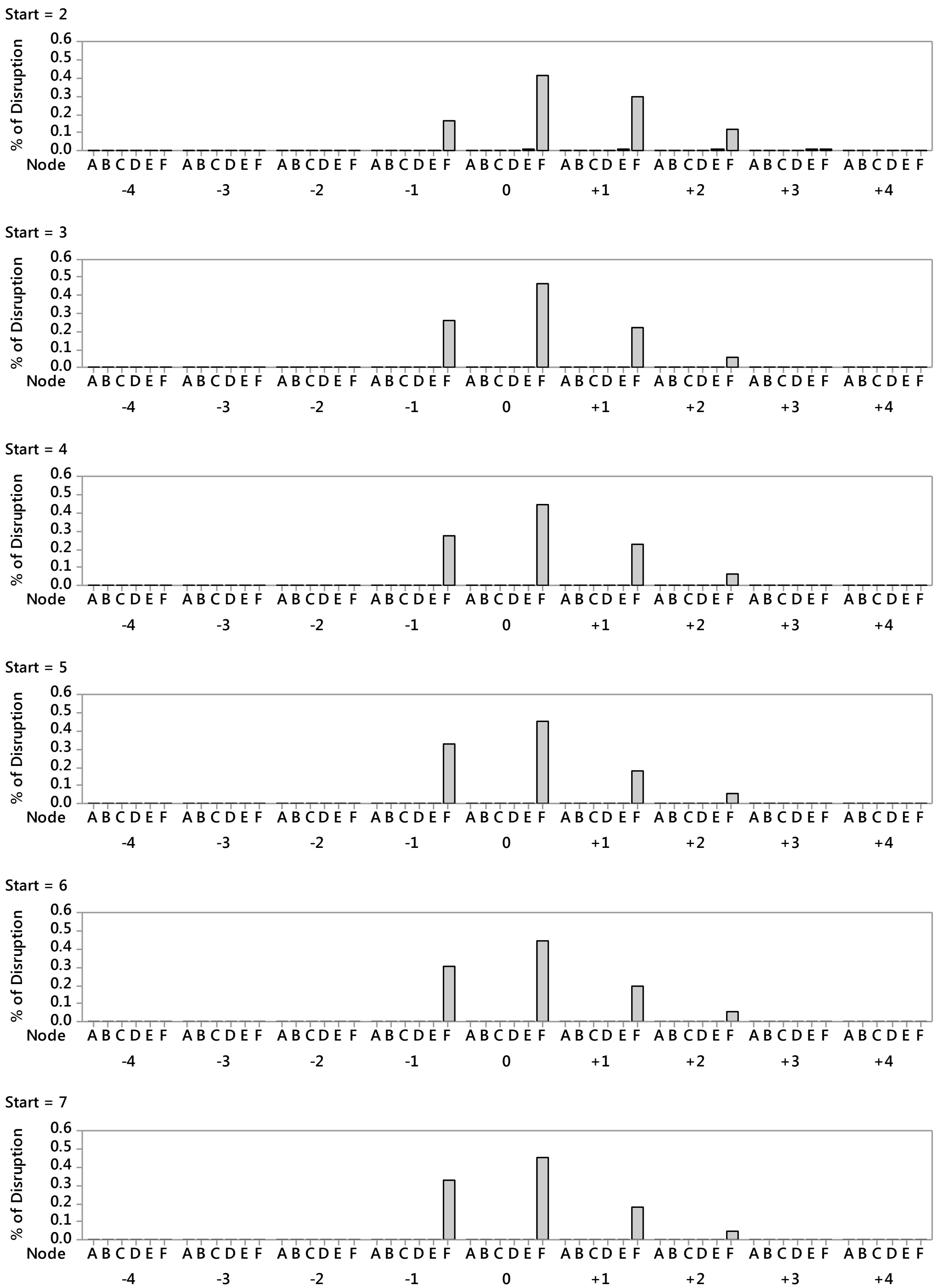
Capacity Deployed by Loaction Relative to Disruption Start, Node D Disrupted



Capacity Deployed by Loaction Relative to Disruption Start, Node E Disrupted

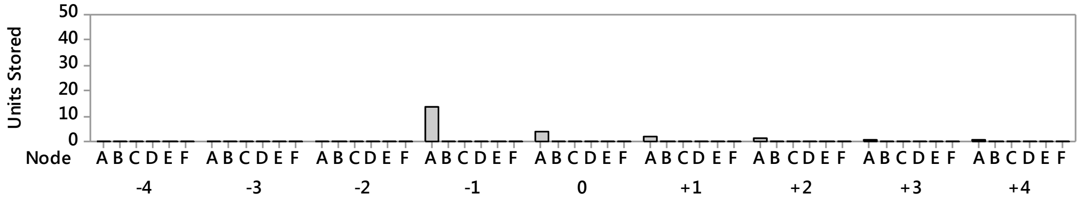


Capacity Deployed by Loaction Relative to Disruption Start, Node F Disrupted

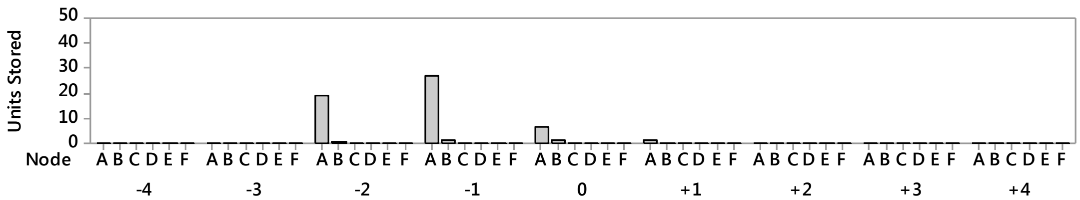


Inventory Stored by Location Relative to Disruption Start, Node A Distrupted

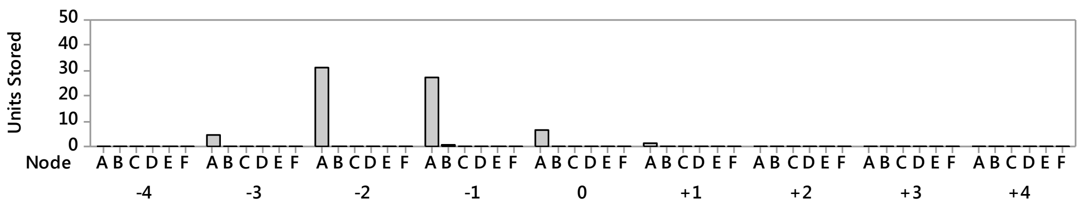
Start = 2



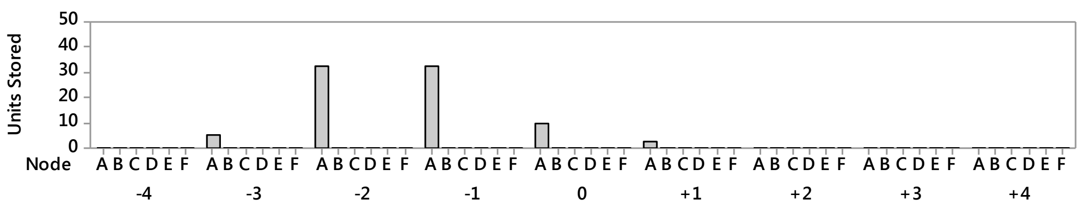
Start = 3



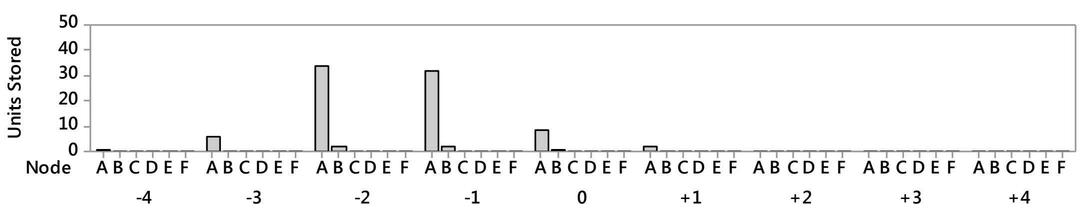
Start = 4



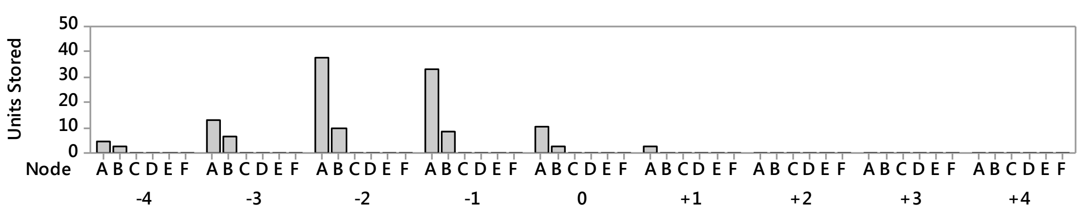
Start = 5



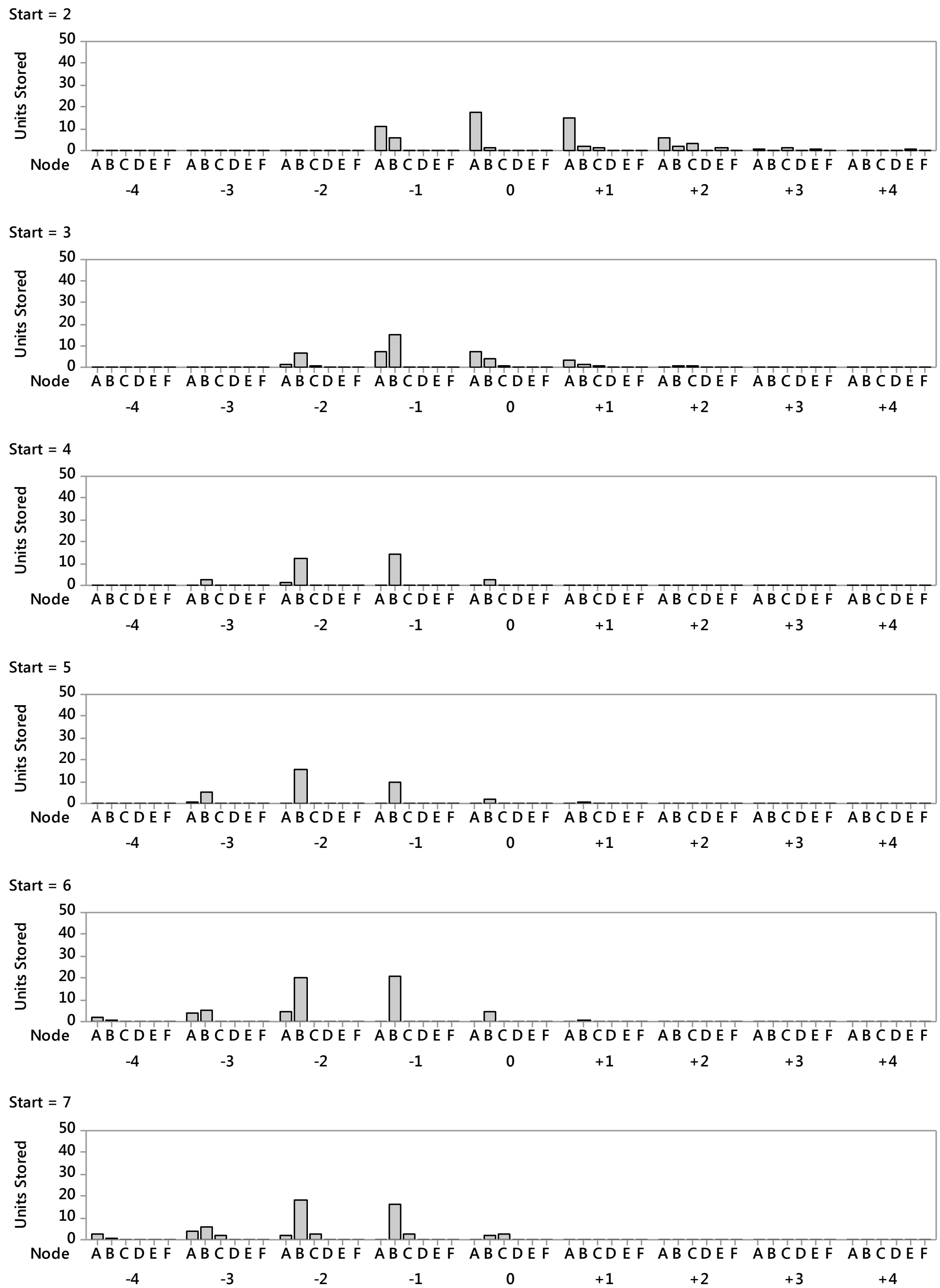
Start = 6



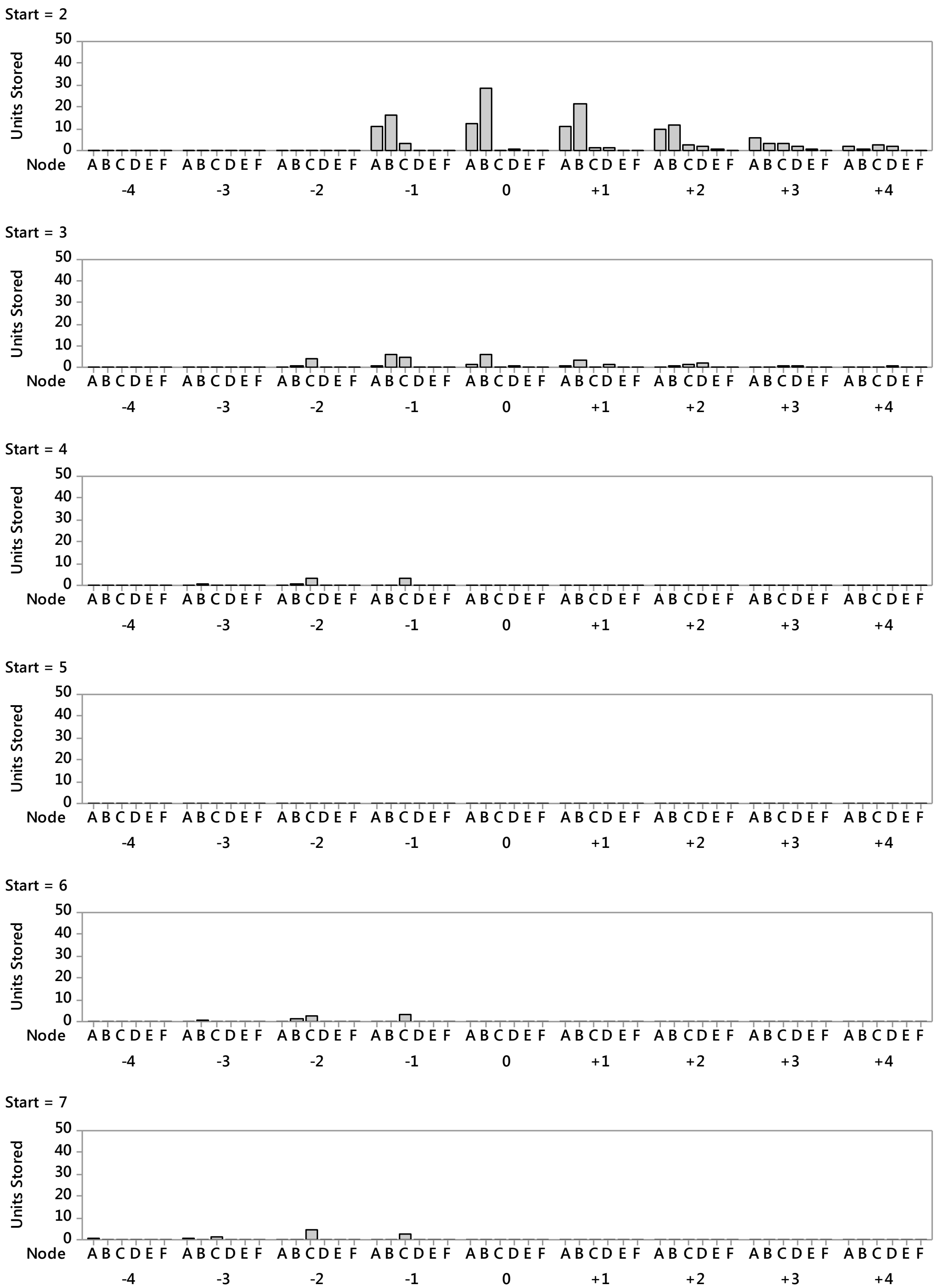
Start = 7



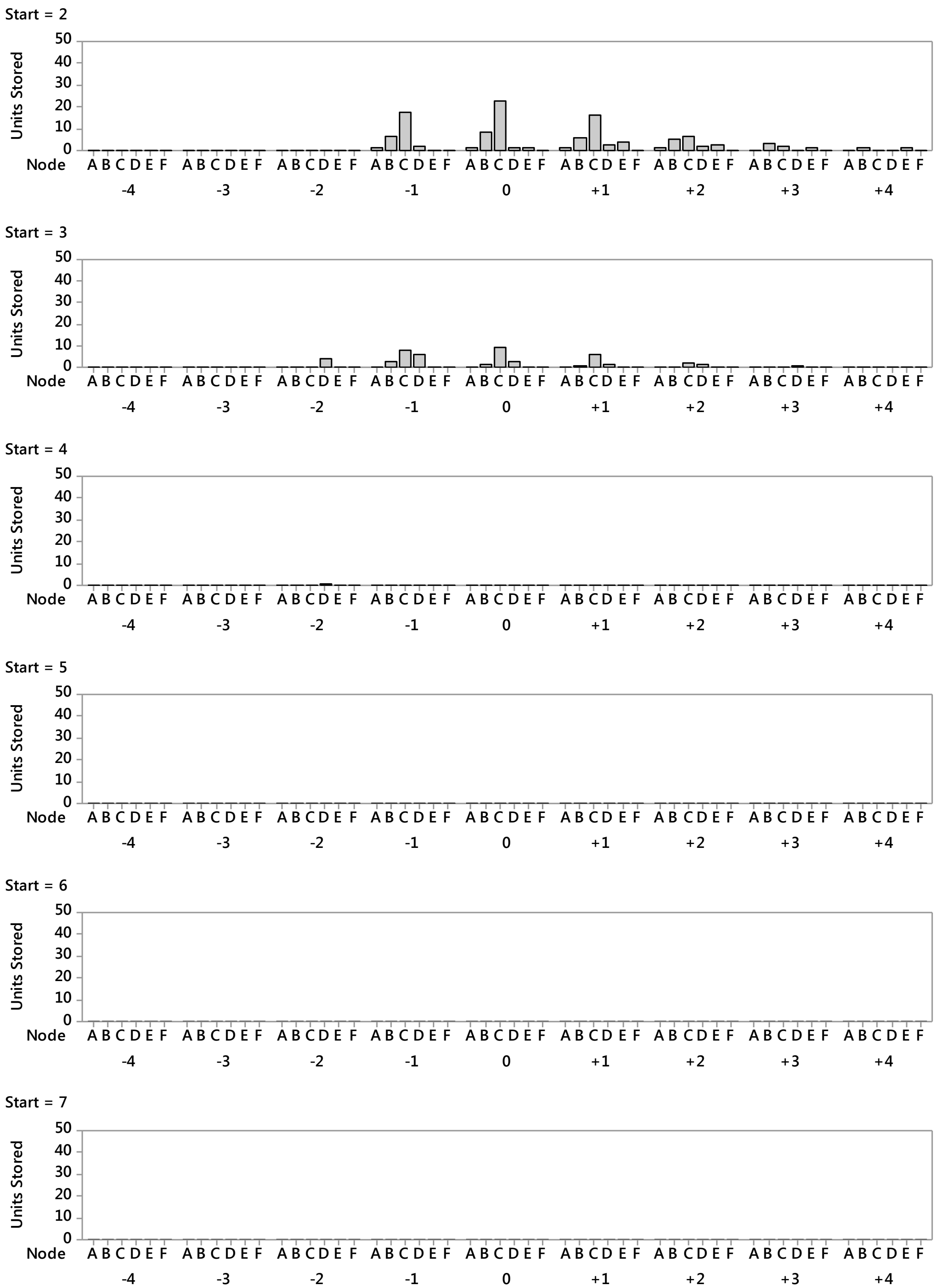
Inventory Stored by Location Relative to Disruption Start, Node B Distrupted



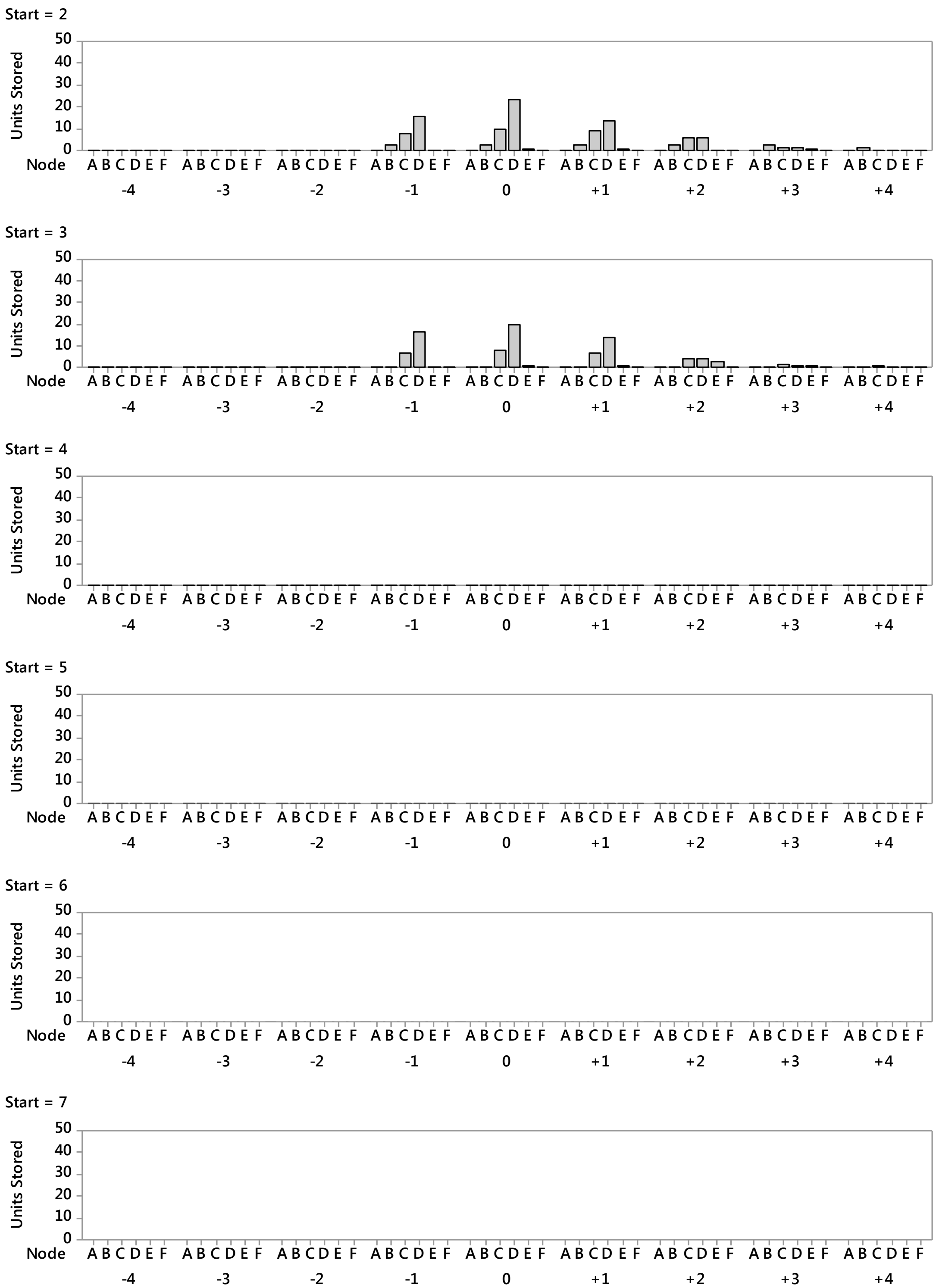
Inventory Stored by Location Relative to Disruption Start, Node C Distrupted



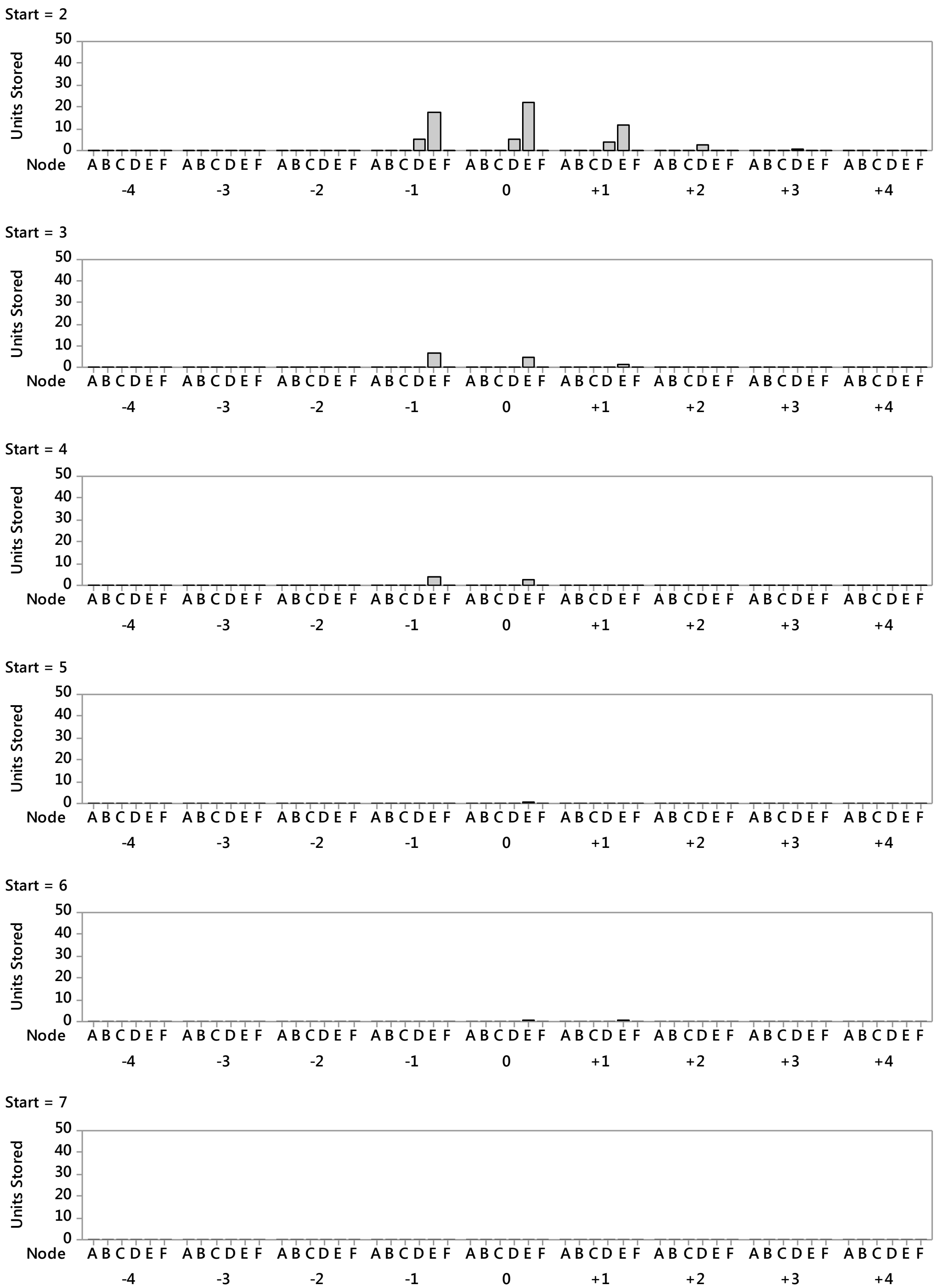
Inventory Stored by Location Relative to Disruption Start, Node D Distrupted



Inventory Stored by Location Relative to Disruption Start, Node E Distrupted



Inventory Stored by Location Relative to Disruption Start, Node F Distrupted



Serial Network Descriptive Statistics Summary

Serial Network Summary Statistics for *ActCost*

Location	Timing	Awareness	N	Mean	SD	Min	Max
A	Early	0.8	248	80,433	12,893	62,343	129,338
		0.9	248	80,389	12,524	63,250	130,065
		Full	248	75,074	6,197	62,018	90,642
		Alternate	248	79,843	12,021	62,240	128,152
	Late	0.8	248	85,236	17,762	62,884	149,950
		0.9	248	84,789	17,427	63,185	150,468
		Full	248	77,899	9,940	61,757	109,138
		Alternate	248	83,968	16,902	63,521	148,600
B	Early	0.8	248	87,794	15,853	66,533	147,898
		0.9	248	86,916	15,664	65,065	148,337
		Full	248	77,995	7,143	64,510	105,633
		Alternate	248	86,305	15,116	66,241	145,614
	Late	0.8	248	92,575	19,777	66,551	154,919
		0.9	248	91,841	19,093	65,764	153,722
		Full	248	81,686	10,894	65,893	113,026
		Alternate	248	90,667	18,714	65,632	152,804
C	Early	0.8	248	88,923	14,592	64,657	140,126
		0.9	248	87,635	14,593	64,833	142,107
		Full	248	77,385	5,911	63,029	96,072
		Alternate	248	86,425	13,531	65,122	139,333
	Late	0.8	248	93,536	18,338	68,438	147,446
		0.9	248	92,662	18,390	66,882	148,092
		Full	248	80,711	9,260	63,611	109,171
		Alternate	248	91,298	17,811	66,614	146,528
D	Early	0.8	256	89,566	12,802	67,947	132,314
		0.9	256	88,061	12,593	68,386	133,371
		Full	256	77,645	5,892	63,398	90,776
		Alternate	256	86,838	12,338	68,670	130,971
	Late	0.8	256	94,410	16,453	68,962	143,919
		0.9	256	92,690	16,775	68,813	145,789
		Full	256	80,329	7,525	67,605	100,381
		Alternate	256	91,364	16,314	67,914	143,817

Serial Network Summary Statistics for *ActCost* Continued . . .

Location	Timing	Awareness	N	Mean	SD	Min	Max
E	Early	0.8	248	90,016	14,240	65,556	124,939
		0.9	248	88,377	12,945	67,116	120,825
		Full	248	77,776	5,786	62,875	90,300
		Alternate	248	88,116	12,735	66,894	121,904
	Late	0.8	248	93,649	18,107	65,820	136,181
		0.9	248	92,080	16,861	69,224	133,679
		Full	248	80,947	8,453	63,432	102,953
		Alternate	248	91,816	17,062	65,972	134,369
F	Early	0.8	248	88,780	13,327	66,700	125,468
		0.9	248	87,115	12,491	68,039	133,556
		Full	248	76,983	5,993	63,179	90,371
		Alternate	248	86,185	11,951	67,781	125,532
	Late	0.8	248	92,718	16,252	65,945	133,532
		0.9	248	91,176	16,080	68,165	135,235
		Full	248	79,234	7,342	63,446	99,581
		Alternate	248	90,394	15,825	68,050	133,454

Serial Network Summary Statistics for *AveLate*

Location	Timing	Awareness	N	Mean	SD	Min	Max
A	Early	0.8	248	23.5	19.0	1.6	104.8
		0.9	248	22.7	18.0	2.9	97.5
		Full	248	16.2	5.6	3.4	33.0
		Alternate	248	22.3	17.5	4.2	98.3
	Late	0.8	248	32.6	34.0	3.8	156.2
		0.9	248	32.1	32.8	5.6	155.6
		Full	248	20.6	13.6	4.6	74.6
		Alternate	248	30.9	32.4	3.0	157.4
B	Early	0.8	248	32.3	29.8	4.3	143.6
		0.9	248	31.7	31.0	4.8	141.3
		Full	248	18.0	9.3	4.7	70.1
		Alternate	248	30.1	28.4	3.1	136.3
	Late	0.8	248	44.5	41.2	3.6	162.4
		0.9	248	42.9	41.3	5.8	169.1
		Full	248	23.7	19.6	3.3	124.5
		Alternate	248	40.1	38.7	2.2	167.3
C	Early	0.8	248	33.0	28.9	3.5	131.6
		0.9	248	31.0	27.4	3.8	135.4
		Full	248	16.9	6.3	2.2	38.5
		Alternate	248	28.9	25.8	2.8	122.8
	Late	0.8	248	43.4	40.6	2.3	159.4
		0.9	248	43.6	40.2	4.7	161.7
		Full	248	22.6	15.0	5.5	88.5
		Alternate	248	40.7	39.2	4.1	166.5
D	Early	0.8	256	33.4	27.5	4.3	127.4
		0.9	256	30.3	24.2	4.9	118.0
		Full	256	16.2	5.9	2.5	36.8
		Alternate	256	29.7	24.5	3.9	120.7
	Late	0.8	256	47.2	40.9	4.6	159.8
		0.9	256	43.5	39.7	2.3	169.2
		Full	256	21.2	11.0	3.5	68.7
		Alternate	256	41.1	39.0	5.2	167.2

Serial Network Summary Statistics for *AveLate* Continued . . .

Location	Timing	Awareness	N	Mean	SD	Min	Max
E	Early	0.8	248	36.4	30.5	5.2	123.4
		0.9	248	35.2	32.4	2.5	153.6
		Full	248	16.6	5.8	3.2	35.4
		Alternate	248	32.9	25.9	5.6	111.8
	Late	0.8	248	47.3	43.9	3.4	161.4
		0.9	248	46.6	44.5	3.2	181.6
		Full	248	22.1	11.2	4.1	70.6
		Alternate	248	43.8	40.1	5.0	148.1
F	Early	0.8	248	31.7	26.4	5.3	127.0
		0.9	248	31.4	23.0	6.1	138.2
		Full	248	17.0	5.8	5.2	34.3
		Alternate	248	29.4	22.0	2.5	133.4
	Late	0.8	248	44.7	36.2	4.9	154.9
		0.9	248	41.3	34.9	4.5	160.5
		Full	248	19.3	7.8	3.7	47.2
		Alternate	248	40.0	35.3	4.1	160.2

Serial Network Summary Statistics for *EndLate*

Location	Timing	Awareness	N	Mean	SD	Min	Max
A	Early	0.8	248	25.9	8.38	4.0	63.0
		0.9	248	25.4	7.63	7.0	50.0
		Full	248	24.6	8.06	5.0	47.0
		Alternate	248	25.9	8.09	7.0	51.0
	Late	0.8	248	25.9	8.28	6.0	50.0
		0.9	248	25.3	8.19	6.0	53.0
		Full	248	25.2	8.86	7.0	54.0
		Alternate	248	26.3	7.60	5.0	46.0
B	Early	0.8	248	25.0	8.07	1.0	46.0
		0.9	248	25.7	10.20	3.0	69.0
		Full	248	25.9	7.69	9.0	49.0
		Alternate	248	25.0	8.49	0.0	61.0
	Late	0.8	248	26.1	8.40	6.0	55.0
		0.9	248	26.6	10.00	6.0	73.0
		Full	248	24.9	7.80	5.0	46.0
		Alternate	248	25.6	8.35	6.0	54.0
C	Early	0.8	248	25.8	8.43	7.0	51.0
		0.9	248	24.5	8.19	9.0	50.0
		Full	248	25.2	8.88	4.0	60.0
		Alternate	248	24.5	8.06	4.0	52.0
	Late	0.8	248	24.4	8.98	5.0	59.0
		0.9	248	25.4	8.08	5.0	48.0
		Full	248	25.1	7.80	6.0	53.0
		Alternate	248	24.6	7.69	5.0	49.0
D	Early	0.8	256	24.2	7.97	7.0	50.0
		0.9	256	24.6	8.19	6.0	49.0
		Full	256	24.8	8.05	5.0	53.0
		Alternate	256	24.8	8.27	5.0	53.0
	Late	0.8	256	24.6	7.46	7.0	43.0
		0.9	256	24.8	8.74	4.0	57.0
		Full	256	25.3	8.78	5.0	56.0
		Alternate	256	24.8	8.00	4.0	58.0

Serial Network Summary Statistics for *EndLate* Continued . . .

Location	Timing	Awareness	N	Mean	SD	Min	Max
E	Early	0.8	248	24.7	7.42	3.0	47.0
		0.9	248	27.5	19.82	4.0	140.0
		Full	248	24.8	8.47	7.0	52.0
		Alternate	248	25.9	8.47	6.0	57.0
	Late	0.8	248	24.5	7.42	7.0	54.0
		0.9	248	28.5	20.12	6.0	138.0
		Full	248	25.6	7.39	7.0	47.0
		Alternate	248	25.5	8.31	8.0	51.0
F	Early	0.8	248	23.8	7.63	5.0	50.0
		0.9	248	25.9	8.71	6.0	49.0
		Full	248	26.1	8.31	7.0	52.0
		Alternate	248	24.5	7.94	6.0	49.0
	Late	0.8	248	25.5	7.83	9.0	57.0
		0.9	248	24.7	8.08	7.0	59.0
		Full	248	25.7	7.98	5.0	51.0
		Alternate	248	25.1	7.98	6.0	48.0

Serial Network ANOVA Summary

Network: Serial
Variable: ActCost
Location A

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAct	1	18664540179	18664540179	7210.57	0.000
Duration	2	229488535	114744268	44.33	0.000
Start	2	6794098	3397049	1.31	0.270
Timing	1	17169439	17169439	6.63	0.010
Awareness	3	479207372	159735791	61.71	0.000
Error	918	2376238865	2588495		
Lack-of-Fit	222	1194092308	5378794	3.17	0.000
Pure Error	696	1182146558	1698486		
Total	927	27858098307			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
1608.88	91.47%	91.39%	91.28%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	73941	167	442.05	0.000	
NormAct	0.9038	0.0106	84.92	0.000	1.24
Duration					
2	787	137	5.73	0.000	1.53
3	1308	139	9.39	0.000	1.49
Start					
6	-109	132	-0.82	0.412	1.42
7	-216	134	-1.62	0.106	1.45
Timing					
Late	272	106	2.58	0.010	1.00
Awareness					
80%	1793	149	12.00	0.000	1.50
90%	1539	149	10.31	0.000	1.50
Alternate	1604	149	10.74	0.000	1.50

Network: Serial
Variable: ActCost
Location B

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAct	1	16364344515	16364344515	2151.60	0.000
Duration	2	1395563316	697781658	91.75	0.000
Start	2	62629411	31314706	4.12	0.017
Timing	1	54797468	54797468	7.20	0.007
Awareness	3	1171206853	390402284	51.33	0.000
Error	886	6738604786	7605649		
Lack-of-Fit	214	5442929864	25434252	13.19	0.000
Pure Error	672	1295674923	1928088		
Total	895	30759437245			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2757.83	78.09%	77.87%	77.61%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	74810	279	267.73	0.000	
NormAct	0.9194	0.0198	46.39	0.000	1.23
Duration					
2	1300	226	5.75	0.000	1.31
3	3080	228	13.51	0.000	1.33
Start					
6	-239	226	-1.06	0.291	1.38
7	-686	240	-2.86	0.004	1.48
Timing					
Late	495	184	2.68	0.007	1.00
Awareness					
80%	2585	261	9.92	0.000	1.50
90%	2886	261	11.07	0.000	1.50
Alternate	2333	261	8.95	0.000	1.50

Network: Serial
Variable: ActCost
Location C

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAct	1	21240571401	21240571401	2770.57	0.000
Duration	2	1230792537	615396268	80.27	0.000
Start	2	70100879	35050439	4.57	0.011
Timing	1	82021938	82021938	10.70	0.001
Awareness	3	2994894152	998298051	130.22	0.000
Error	918	7037839226	7666492		
Lack-of-Fit	222	5805123885	26149207	14.76	0.000
Pure Error	696	1232715341	1771143		
Total	927	34564433313			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2768.84	79.64%	79.44%	79.20%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	73983	277	266.73	0.000	
NormAct	0.9040	0.0172	52.64	0.000	1.08
Duration					
2	971	227	4.27	0.000	1.47
3	2869	231	12.41	0.000	1.38
Start					
6	676	223	3.02	0.003	1.42
7	373	233	1.60	0.110	1.41
Timing					
Late	595	182	3.27	0.001	1.00
Awareness					
80%	4987	257	19.40	0.000	1.50
90%	3274	257	12.73	0.000	1.50
Alternate	3054	257	11.88	0.000	1.50

Network: Serial
Variable: ActCost
Location D

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAct	1	16407739709	16407739709	1634.76	0.000
Duration	2	595037217	297518609	29.64	0.000
Start	2	354549180	177274590	17.66	0.000
Timing	1	101463584	101463584	10.11	0.002
Awareness	3	4075184319	1358394773	135.34	0.000
Error	918	9213774246	10036791		
Lack-of-Fit	222	7932394026	35731505	19.41	0.000
Pure Error	696	1281380220	1841064		
Total	927	31683213637			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
3168.09	70.92%	70.63%	70.32%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	75771	317	239.07	0.000	
NormAct	0.9892	0.0245	40.43	0.000	1.09
Duration					
2	1773	254	6.98	0.000	1.41
3	1686	264	6.38	0.000	1.38
Start					
6	-1468	258	-5.68	0.000	1.32
7	-317	261	-1.21	0.225	1.35
Timing					
Late	661	208	3.18	0.002	1.00
Awareness					
80%	5438	294	18.49	0.000	1.50
90%	4734	294	16.09	0.000	1.50
Alternate	3703	294	12.59	0.000	1.50

Network: Serial
Variable: ActCost
Location E

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAct	1	26022292736	26022292736	3203.53	0.000
Duration	2	241067011	120533506	14.84	0.000
Start	2	53229342	26614671	3.28	0.038
Timing	1	81211071	81211071	10.00	0.002
Awareness	3	4253155733	1417718578	174.53	0.000
Error	950	7716866471	8123017		
Lack-of-Fit	230	6458029048	28078387	16.06	0.000
Pure Error	720	1258837424	1748385		
Total	959	40936548277			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2850.09	81.15%	80.97%	80.73%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	75694	280	270.67	0.000	
NormAct	1.0790	0.0191	56.60	0.000	1.07
Duration					
2	1100	227	4.85	0.000	1.35
3	1052	230	4.57	0.000	1.39
Start					
6	255	228	1.12	0.263	1.36
7	-324	229	-1.42	0.157	1.37
Timing					
Late	582	184	3.16	0.002	1.00
Awareness					
80%	5509	260	21.18	0.000	1.50
90%	4519	260	17.37	0.000	1.50
Alternate	4134	260	15.89	0.000	1.50

Network: Serial
Variable: ActCost
Location F

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAct	1	30162936075	30162936075	2800.92	0.000
Duration	2	148177778	74088889	6.88	0.001
Start	2	936351706	468175853	43.47	0.000
Timing	1	108578536	108578536	10.08	0.002
Awareness	3	4853761451	1617920484	150.24	0.000
Error	918	9885885509	10768938		
Lack-of-Fit	222	8672161372	39063790	22.40	0.000
Pure Error	696	1213724137	1743857		
Total	927	51472058476			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
3281.61	80.79%	80.61%	80.36%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	75847	313	242.22	0.000	
NormAct	1.0789	0.0204	52.92	0.000	1.12
Duration					
2	996	269	3.71	0.000	1.33
3	467	269	1.74	0.082	1.33
Start					
6	-2492	268	-9.29	0.000	1.33
7	-1020	264	-3.86	0.000	1.36
Timing					
Late	684	215	3.18	0.002	1.00
Awareness					
80%	6249	305	20.51	0.000	1.50
90%	4565	305	14.98	0.000	1.50
Alternate	3480	305	11.42	0.000	1.50

Network: Serial
Variable: AveLate
Location A

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	106.5	106.461	3.54	0.060
Duration	2	6.6	3.288	0.11	0.896
Start	2	28.1	14.047	0.47	0.627
Timing	1	43.6	43.622	1.45	0.229
Awareness	3	70.4	23.454	0.78	0.506
Error	918	27620.8	30.088		
Lack-of-Fit	222	5626.9	25.346	0.80	0.975
Pure Error	696	21993.9	31.600		
Total	927	27886.3			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
5.48525	0.95%	0.00%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	16.116	0.550	29.32	0.000	
NormAveLate	0.1280	0.0680	1.88	0.060	1.06
Duration					
2	0.208	0.445	0.47	0.640	1.38
3	0.115	0.455	0.25	0.801	1.37
Start					
6	0.365	0.446	0.82	0.414	1.39
7	-0.006	0.446	-0.01	0.990	1.39
Timing					
Late	-0.434	0.360	-1.20	0.229	1.00
Awareness					
80%	0.663	0.509	1.30	0.193	1.50
90%	0.509	0.509	1.00	0.317	1.50
Alternate	0.679	0.509	1.33	0.183	1.50

Network: Serial
Variable: AveLate
Location B

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	0.9	0.860	0.02	0.875
Duration	2	34.2	17.120	0.49	0.610
Start	2	59.5	29.770	0.86	0.423
Timing	1	109.1	109.061	3.15	0.076
Awareness	3	9.6	3.185	0.09	0.964
Error	886	30647.7	34.591		
Lack-of-Fit	214	9052.5	42.301	1.32	0.005
Pure Error	672	21595.2	32.136		
Total	895	30859.7			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
5.88142	0.69%	0.00%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	16.243	0.593	27.39	0.000	
NormAveLate	0.0140	0.0890	0.16	0.875	1.16
Duration					
2	-0.217	0.487	-0.44	0.657	1.34
3	0.273	0.499	0.55	0.584	1.41
Start					
6	0.510	0.479	1.06	0.287	1.36
7	-0.071	0.502	-0.14	0.888	1.42
Timing					
Late	0.698	0.393	1.78	0.076	1.00
Awareness					
80%	-0.267	0.556	-0.48	0.631	1.50
90%	-0.109	0.556	-0.20	0.844	1.50
Alternate	-0.219	0.556	-0.39	0.694	1.50

Network: Serial
Variable: AveLate
Location C

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	28.7	28.6869	0.85	0.357
Duration	2	27.0	13.4999	0.40	0.670
Start	2	10.5	5.2667	0.16	0.855
Timing	1	0.0	0.0228	0.00	0.979
Awareness	3	24.8	8.2778	0.25	0.865
Error	918	30965.3	33.7313		
Lack-of-Fit	222	8581.6	38.6558	1.20	0.042
Pure Error	696	22383.7	32.1605		
Total	927	31045.1			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
5.80786	0.26%	0.00%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	16.269	0.587	27.73	0.000	
NormAveLate	0.0708	0.0768	0.92	0.357	1.31
Duration					
2	0.181	0.464	0.39	0.696	1.39
3	0.444	0.498	0.89	0.373	1.46
Start					
6	-0.091	0.489	-0.19	0.853	1.55
7	-0.270	0.488	-0.55	0.580	1.40
Timing					
Late	-0.010	0.381	-0.03	0.979	1.00
Awareness					
80%	-0.066	0.539	-0.12	0.903	1.50
90%	-0.419	0.539	-0.78	0.438	1.50
Alternate	-0.249	0.539	-0.46	0.644	1.50

Network: Serial
Variable: AveLate
Location D

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	38.3	38.25	0.84	0.360
Duration	2	89.6	44.79	0.98	0.375
Start	2	254.5	127.26	2.79	0.062
Timing	1	63.0	63.00	1.38	0.240
Awareness	3	32.1	10.70	0.23	0.872
Error	918	41874.1	45.61		
Lack-of-Fit	222	18562.6	83.62	2.50	0.000
Pure Error	696	23311.5	33.49		
Total	927	42355.0			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
6.75385	1.14%	0.17%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	16.783	0.673	24.93	0.000	
NormAveLate	0.0747	0.0816	0.92	0.360	1.19
Duration					
2	0.657	0.542	1.21	0.226	1.41
3	-0.017	0.576	-0.03	0.977	1.44
Start					
6	-0.667	0.556	-1.20	0.231	1.35
7	-1.272	0.540	-2.36	0.019	1.27
Timing					
Late	0.521	0.443	1.18	0.240	1.00
Awareness					
80%	0.069	0.627	0.11	0.912	1.50
90%	-0.300	0.627	-0.48	0.633	1.50
Alternate	-0.363	0.627	-0.58	0.562	1.50

Network: Serial
Variable: AveLate
Location E

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	63.3	63.29	1.85	0.175
Duration	2	91.5	45.73	1.33	0.264
Start	2	37.6	18.81	0.55	0.578
Timing	1	31.4	31.36	0.91	0.339
Awareness	3	154.5	51.51	1.50	0.212
Error	950	32571.3	34.29		
Lack-of-Fit	230	11555.8	50.24	1.72	0.000
Pure Error	720	21015.5	29.19		
Total	959	32983.5			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
5.85539	1.25%	0.31%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	16.132	0.578	27.91	0.000	
NormAveLate	0.1076	0.0792	1.36	0.175	1.11
Duration					
2	0.366	0.466	0.79	0.432	1.35
3	0.767	0.469	1.63	0.103	1.37
Start					
6	0.133	0.465	0.29	0.774	1.35
7	-0.358	0.479	-0.75	0.455	1.43
Timing					
Late	0.361	0.378	0.96	0.339	1.00
Awareness					
80%	0.770	0.535	1.44	0.150	1.50
90%	-0.257	0.535	-0.48	0.630	1.50
Alternate	-0.138	0.535	-0.26	0.796	1.50

Network: Serial
Variable: AveLate
Location F

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	278.4	278.36	6.96	0.008
Duration	2	140.4	70.22	1.76	0.173
Start	2	992.3	496.14	12.41	0.000
Timing	1	438.6	438.62	10.97	0.001
Awareness	3	754.2	251.40	6.29	0.000
Error	918	36713.2	39.99		
Lack-of-Fit	222	15817.7	71.25	2.37	0.000
Pure Error	696	20895.5	30.02		
Total	927	39762.6			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
6.32397	7.67%	6.76%	5.60%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	18.172	0.605	30.02	0.000	
NormAveLate	0.1927	0.0730	2.64	0.008	1.25
Duration					
2	0.120	0.503	0.24	0.812	1.26
3	-0.820	0.523	-1.57	0.117	1.36
Start					
6	-2.386	0.526	-4.54	0.000	1.37
7	-2.201	0.536	-4.10	0.000	1.51
Timing					
Late	1.375	0.415	3.31	0.001	1.00
Awareness					
80%	2.184	0.587	3.72	0.000	1.50
90%	1.533	0.587	2.61	0.009	1.50
Alternate	0.247	0.587	0.42	0.674	1.50

Network: Serial
Variable: EndLate
Location A

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	312.5	312.514	4.89	0.027
Duration	2	62.5	31.264	0.49	0.613
Start	2	47.3	23.673	0.37	0.691
Timing	1	1.6	1.639	0.03	0.873
Awareness	3	127.6	42.521	0.67	0.574
Error	918	58685.2	63.927		
Lack-of-Fit	222	12899.9	58.108	0.88	0.866
Pure Error	696	45785.3	65.783		
Total	927	59303.9			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
7.99545	1.04%	0.07%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	24.737	0.801	30.87	0.000	
NormAveLate	0.2193	0.0992	2.21	0.027	1.06
Duration					
2	0.544	0.649	0.84	0.402	1.38
3	0.582	0.663	0.88	0.380	1.37
Start					
6	0.301	0.651	0.46	0.644	1.39
7	-0.245	0.651	-0.38	0.706	1.39
Timing					
Late	-0.084	0.525	-0.16	0.873	1.00
Awareness					
80%	0.797	0.742	1.07	0.283	1.50
90%	0.741	0.742	1.00	0.318	1.50
Alternate	0.966	0.742	1.30	0.194	1.50

Network: Serial
Variable: EndLate
Location B

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	4.4	4.414	0.06	0.803
Duration	2	91.6	45.789	0.65	0.524
Start	2	13.2	6.585	0.09	0.911
Timing	1	170.6	170.626	2.41	0.121
Awareness	3	92.1	30.715	0.43	0.729
Error	886	62805.9	70.887		
Lack-of-Fit	214	14895.2	69.604	0.98	0.578
Pure Error	672	47910.8	71.296		
Total	895	63183.5			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
8.41944	0.60%	0.00%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	25.975	0.849	30.60	0.000	
NormAveLate	-0.032	0.127	-0.25	0.803	1.16
Duration					
2	-0.571	0.697	-0.82	0.413	1.34
3	-0.780	0.714	-1.09	0.275	1.41
Start					
6	0.061	0.685	0.09	0.929	1.36
7	-0.232	0.719	-0.32	0.747	1.42
Timing					
Late	0.873	0.563	1.55	0.121	1.00
Awareness					
80%	-0.540	0.796	-0.68	0.497	1.50
90%	-0.808	0.796	-1.02	0.310	1.50
Alternate	-0.138	0.796	-0.17	0.862	1.50

Network: Serial

Variable: EndLate
Location C

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	45.3	45.29	0.65	0.419
Duration	2	57.0	28.51	0.41	0.663
Start	2	67.7	33.85	0.49	0.613
Timing	1	15.8	15.78	0.23	0.633
Awareness	3	79.0	26.32	0.38	0.767
Error	918	63551.4	69.23		
Lack-of-Fit	222	16093.1	72.49	1.06	0.280
Pure Error	696	47458.3	68.19		
Total	927	63870.6			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
8.32034	0.50%	0.00%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	25.754	0.840	30.64	0.000	
NormAveLate	0.089	0.110	0.81	0.419	1.31
Duration					
2	0.572	0.665	0.86	0.389	1.39
3	0.133	0.714	0.19	0.852	1.46
Start					
6	-0.692	0.701	-0.99	0.324	1.55
7	-0.345	0.699	-0.49	0.622	1.40
Timing					
Late	-0.261	0.546	-0.48	0.633	1.00
Awareness					
80%	-0.763	0.773	-0.99	0.324	1.50
90%	-0.603	0.773	-0.78	0.435	1.50
Alternate	-0.603	0.773	-0.78	0.435	1.50

Network: Serial
Variable: EndLate
Location D

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	7.1	7.058	0.09	0.759
Duration	2	2.5	1.265	0.02	0.983
Start	2	179.0	89.476	1.19	0.304
Timing	1	62.1	62.069	0.83	0.363
Awareness	3	465.6	155.198	2.07	0.103
Error	918	68820.9	74.968		
Lack-of-Fit	222	19013.9	85.648	1.20	0.045
Pure Error	696	49807.0	71.562		
Total	927	69527.9			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
8.65842	1.02%	0.05%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	25.947	0.863	30.07	0.000	
NormAveLate	-0.032	0.105	-0.31	0.759	1.19
Duration					
2	-0.065	0.695	-0.09	0.925	1.41
3	0.068	0.738	0.09	0.926	1.44
Start					
6	0.336	0.713	0.47	0.637	1.35
7	-0.764	0.692	-1.10	0.270	1.27
Timing					
Late	0.517	0.568	0.91	0.363	1.00
Awareness					
80%	-1.953	0.804	-2.43	0.015	1.50
90%	-0.918	0.804	-1.14	0.254	1.50
Alternate	-0.595	0.804	-0.74	0.460	1.50

Network: Serial
Variable: EndLate
Location E

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	313.5	313.496	5.11	0.024
Duration	2	47.4	23.676	0.39	0.680
Start	2	42.8	21.404	0.35	0.706
Timing	1	17.1	17.067	0.28	0.598
Awareness	3	18.8	6.274	0.10	0.959
Error	950	58293.4	61.362		
Lack-of-Fit	230	13988.9	60.821	0.99	0.536
Pure Error	720	44304.5	61.534		
Total	959	58785.8			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
7.83336	0.84%	0.00%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	25.288	0.773	32.70	0.000	
NormAveLate	0.239	0.106	2.26	0.024	1.11
Duration					
2	0.069	0.623	0.11	0.912	1.35
3	0.509	0.628	0.81	0.418	1.37
Start					
6	0.423	0.623	0.68	0.497	1.35
7	-0.065	0.641	-0.10	0.919	1.43
Timing					
Late	0.267	0.506	0.53	0.598	1.00
Awareness					
80%	-0.379	0.715	-0.53	0.596	1.50
90%	-0.208	0.715	-0.29	0.771	1.50
Alternate	-0.288	0.715	-0.40	0.688	1.50

Network: Serial
Variable: EndLate
Location F

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	278.7	278.72	4.32	0.038
Duration	2	245.4	122.70	1.90	0.150
Start	2	100.2	50.11	0.78	0.460
Timing	1	117.3	117.35	1.82	0.178
Awareness	3	245.3	81.77	1.27	0.285
Error	918	59254.6	64.55		
Lack-of-Fit	222	15148.1	68.23	1.08	0.242
Pure Error	696	44106.5	63.37		
Total	927	60293.3			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
8.03414	1.72%	0.76%	0.00%

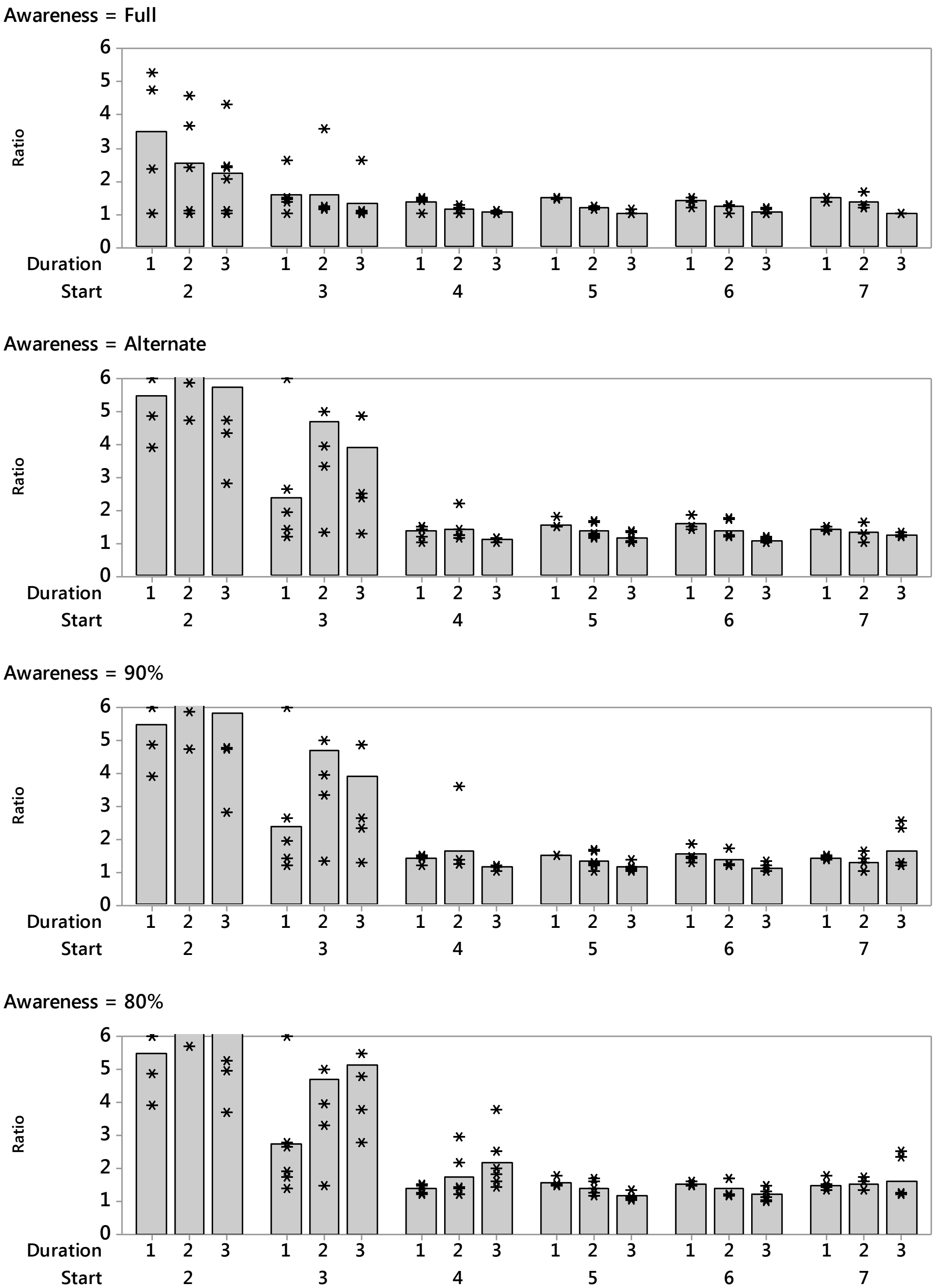
Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	27.110	0.769	35.25	0.000	
NormAveLate	0.1928	0.0928	2.08	0.038	1.25
Duration					
2	-0.850	0.639	-1.33	0.184	1.26
3	-1.239	0.665	-1.86	0.063	1.36
Start					
6	-0.832	0.668	-1.25	0.213	1.37
7	-0.435	0.681	-0.64	0.523	1.51
Timing					
Late	0.711	0.527	1.35	0.178	1.00
Awareness					
80%	-0.909	0.746	-1.22	0.223	1.50
90%	0.147	0.746	0.20	0.844	1.50
Alternate	-0.987	0.746	-1.32	0.186	1.50

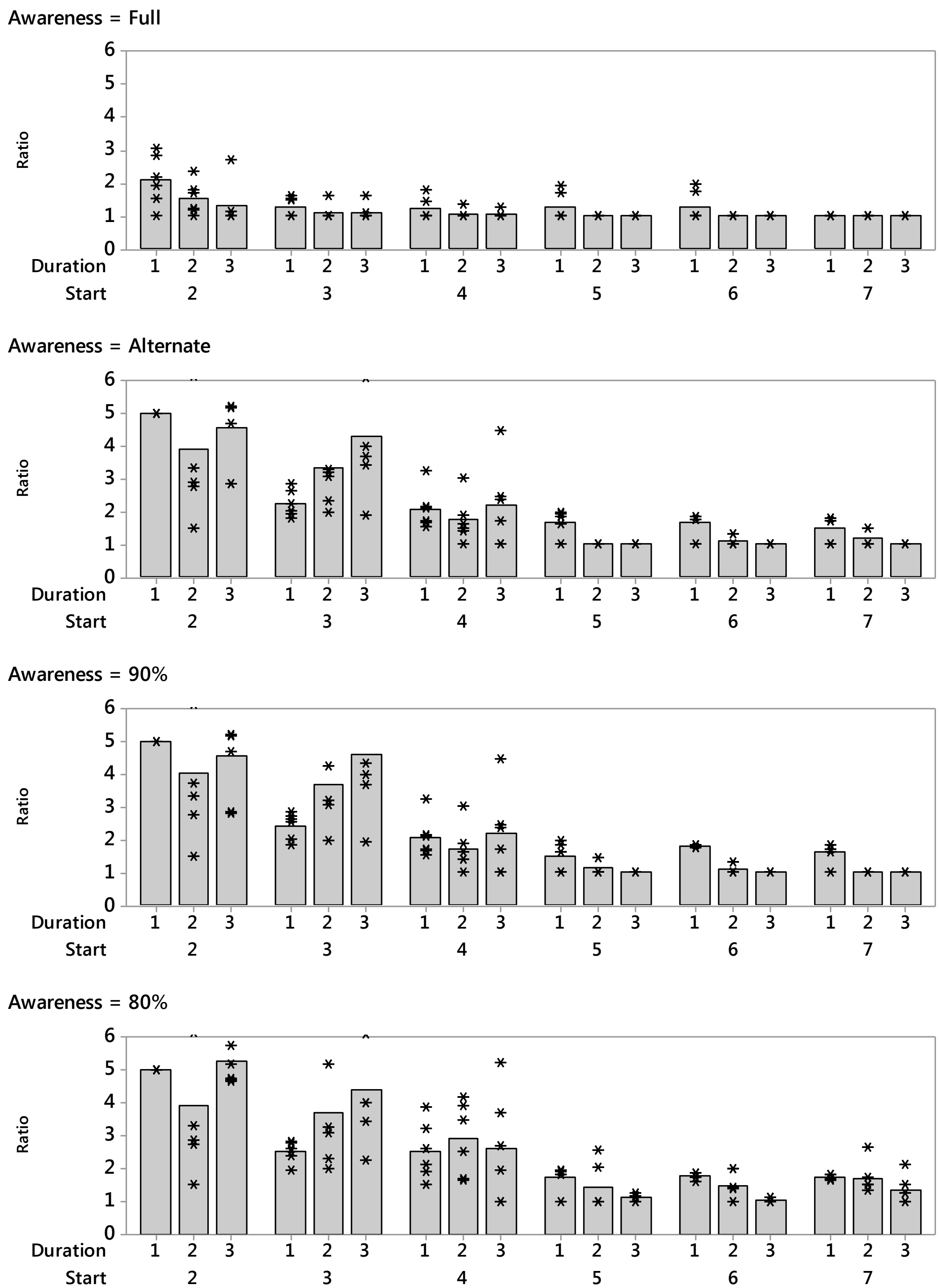
Appendix D

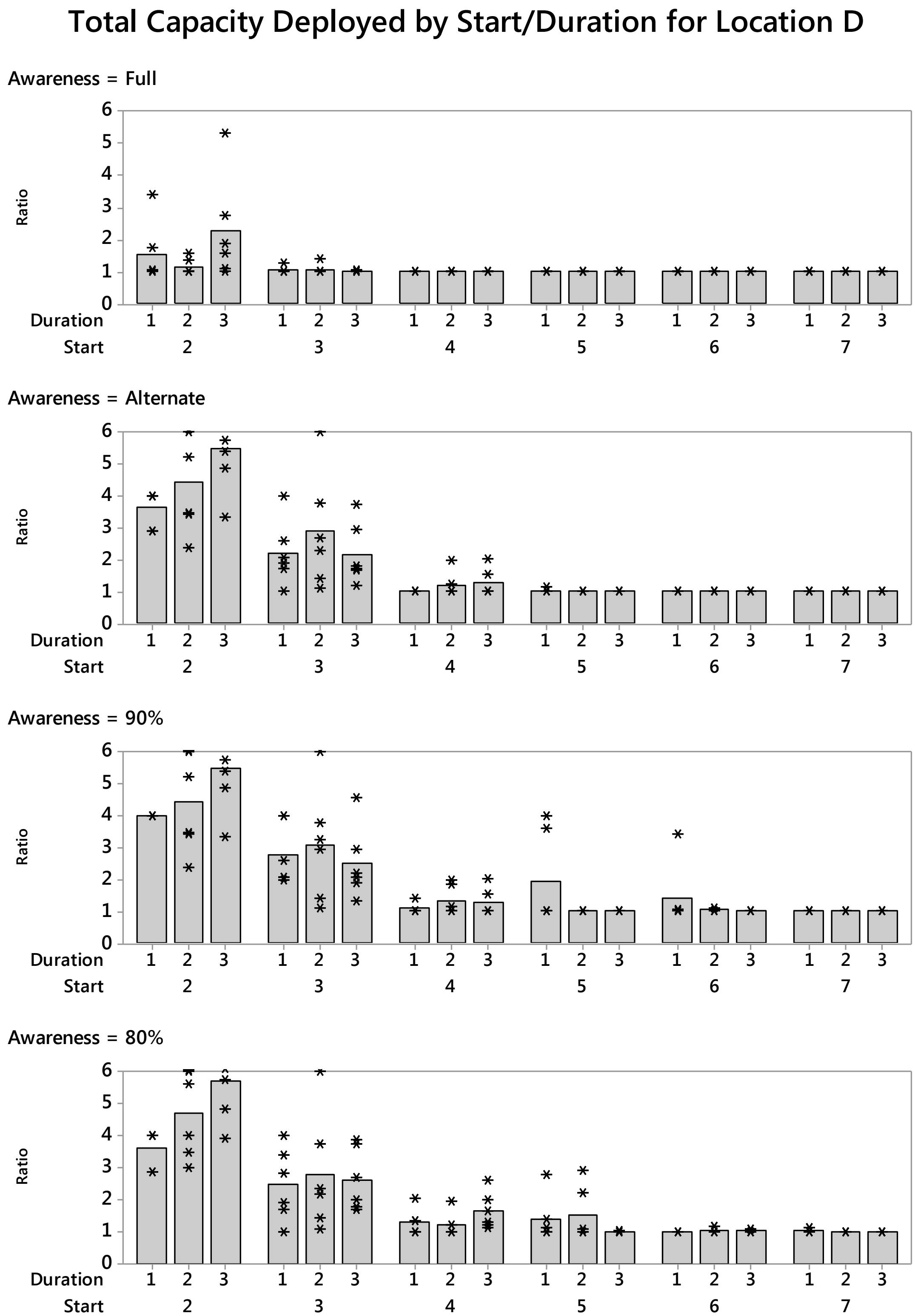
Assembly Network Summary Charts

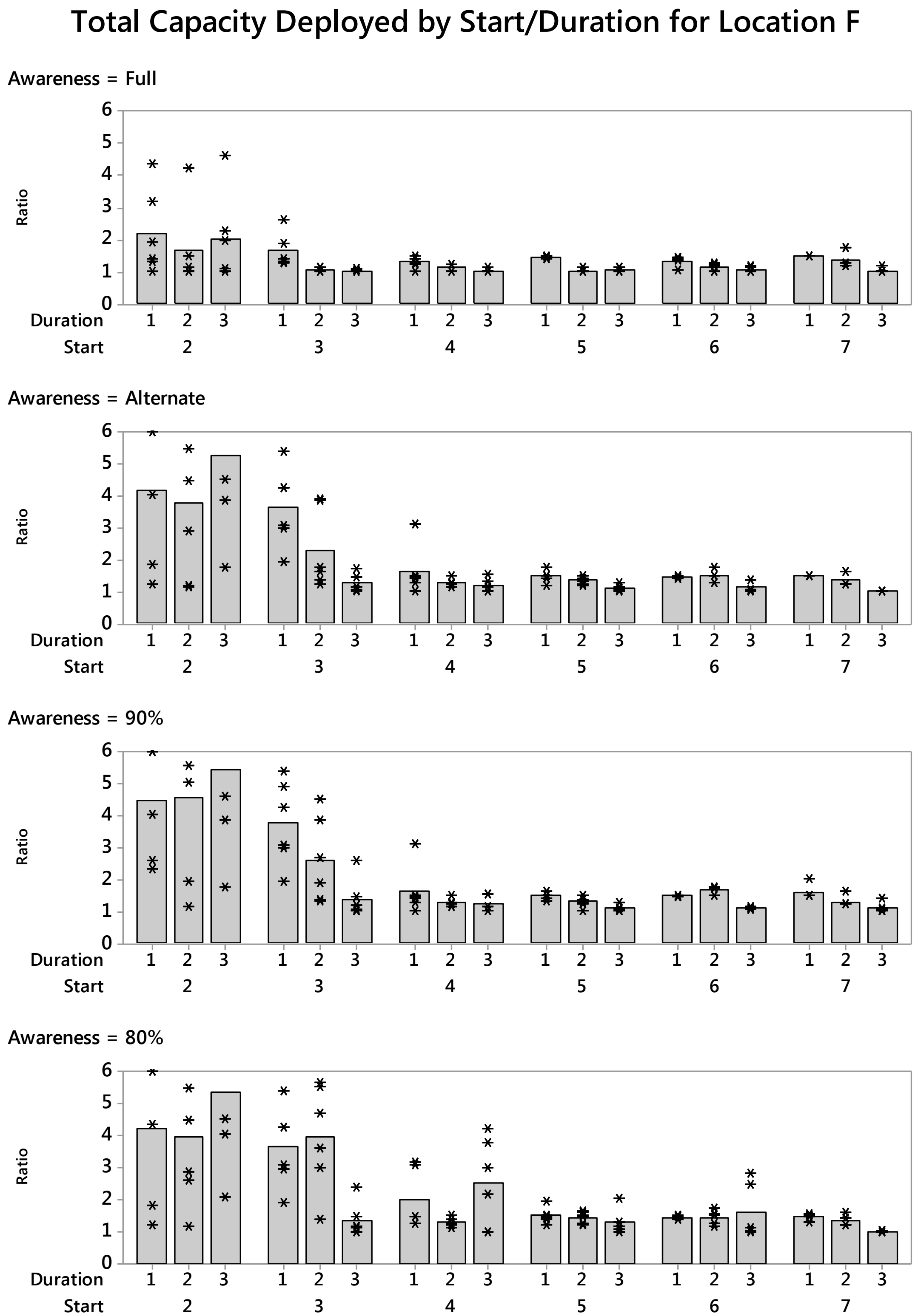
Total Capacity Deployed by Start/Duration for Location B

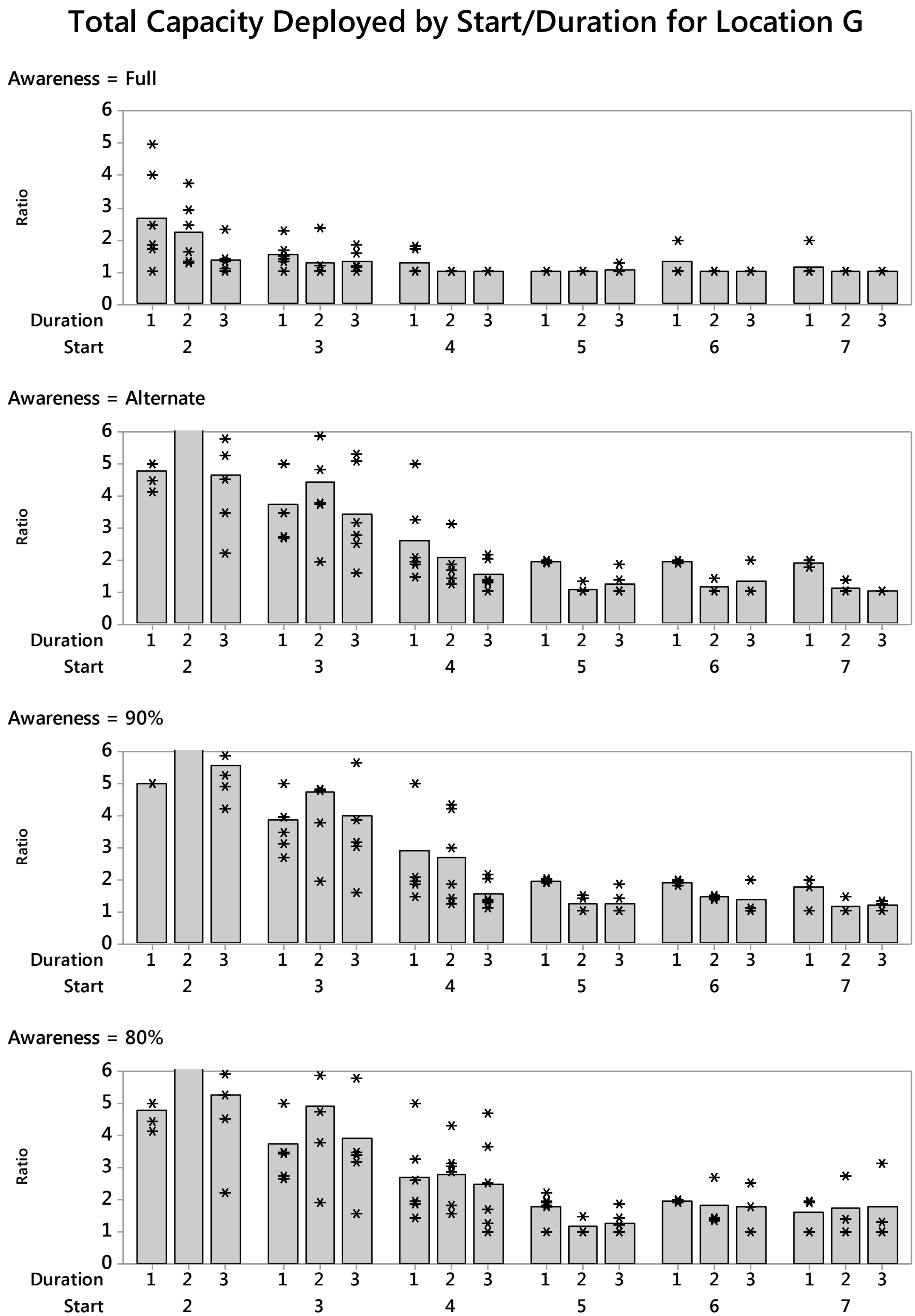


Total Capacity Deployed by Start/Duration for Location C

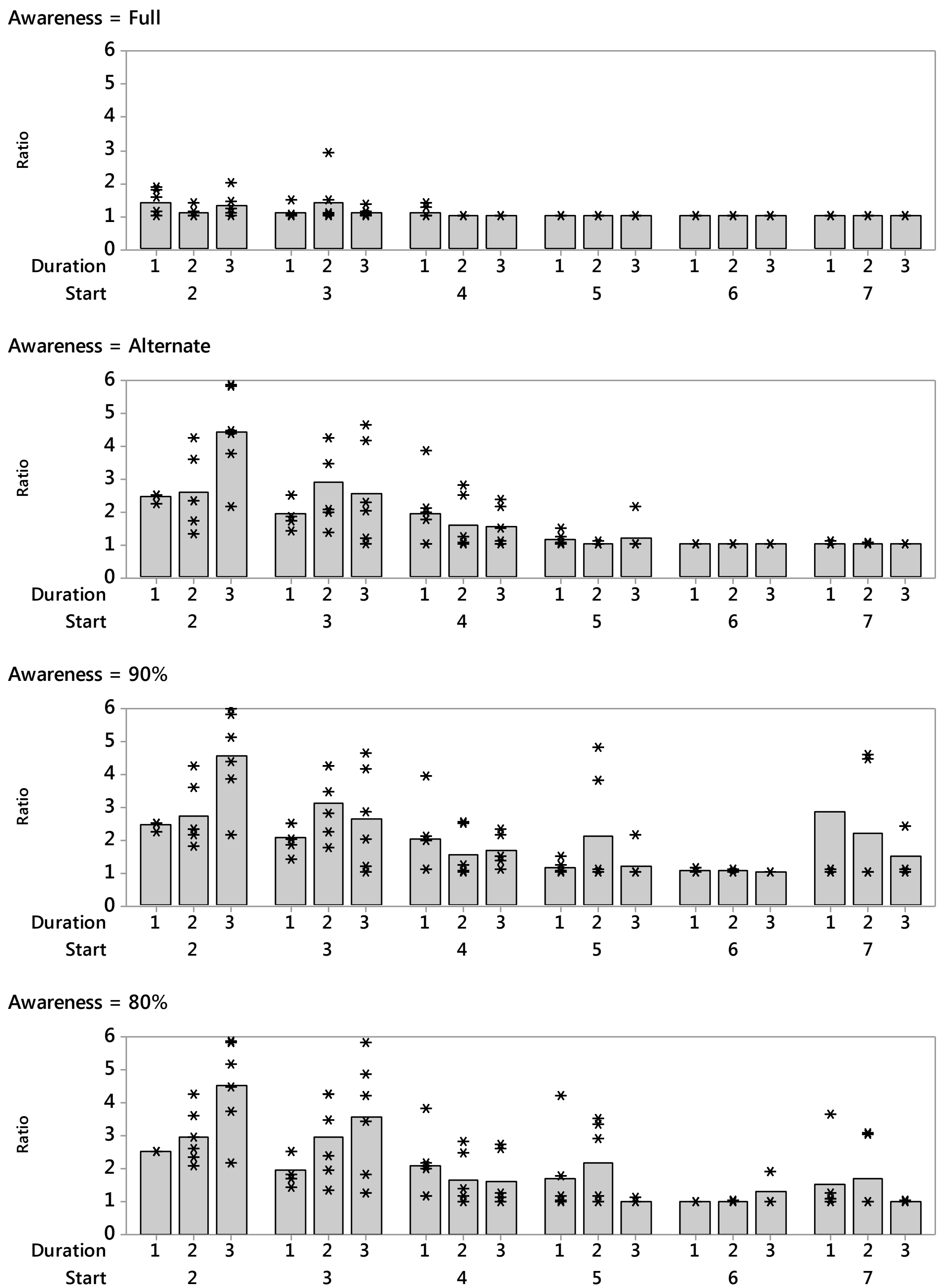



Total Capacity Deployed by Start/Duration for Location D
Awareness = Full
Awareness = Alternate
Awareness = 90%
Awareness = 80%
Ratio
Duration
Start
0
1
2
3
4
5
6
7

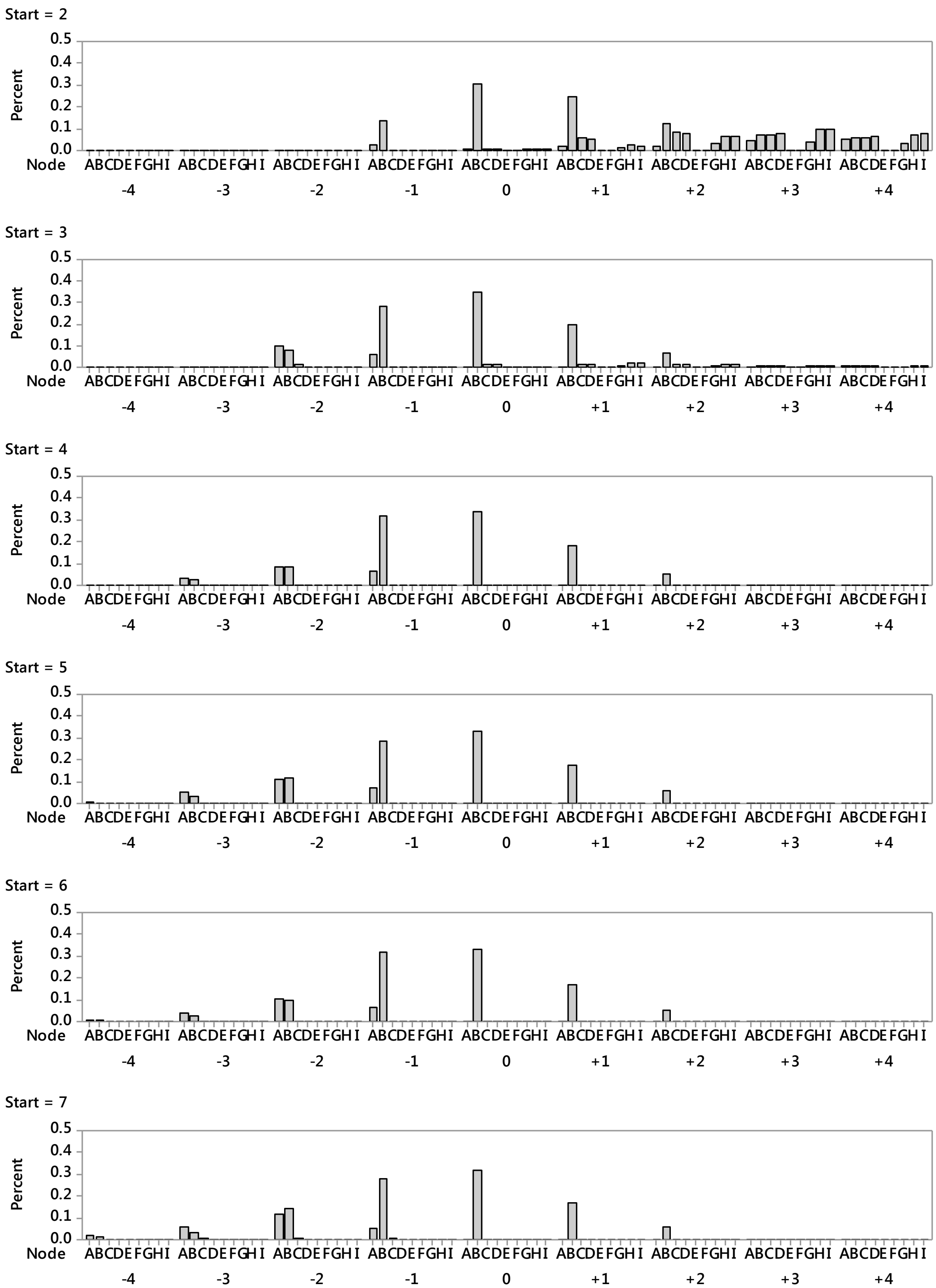

Total Capacity Deployed by Start/Duration for Location F
Awareness = Full
Awareness = Alternate
Awareness = 90%
Awareness = 80%
Ratio
Duration
Start
0
1
2
3
4
5
6
7


Total Capacity Deployed by Start/Duration for Location G
Awareness = Full
Awareness = Alternate
Awareness = 90%
Awareness = 80%
Ratio
0
1
2
3
4
5
6
Duration
1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3
Start
2 3 4 5 6 7

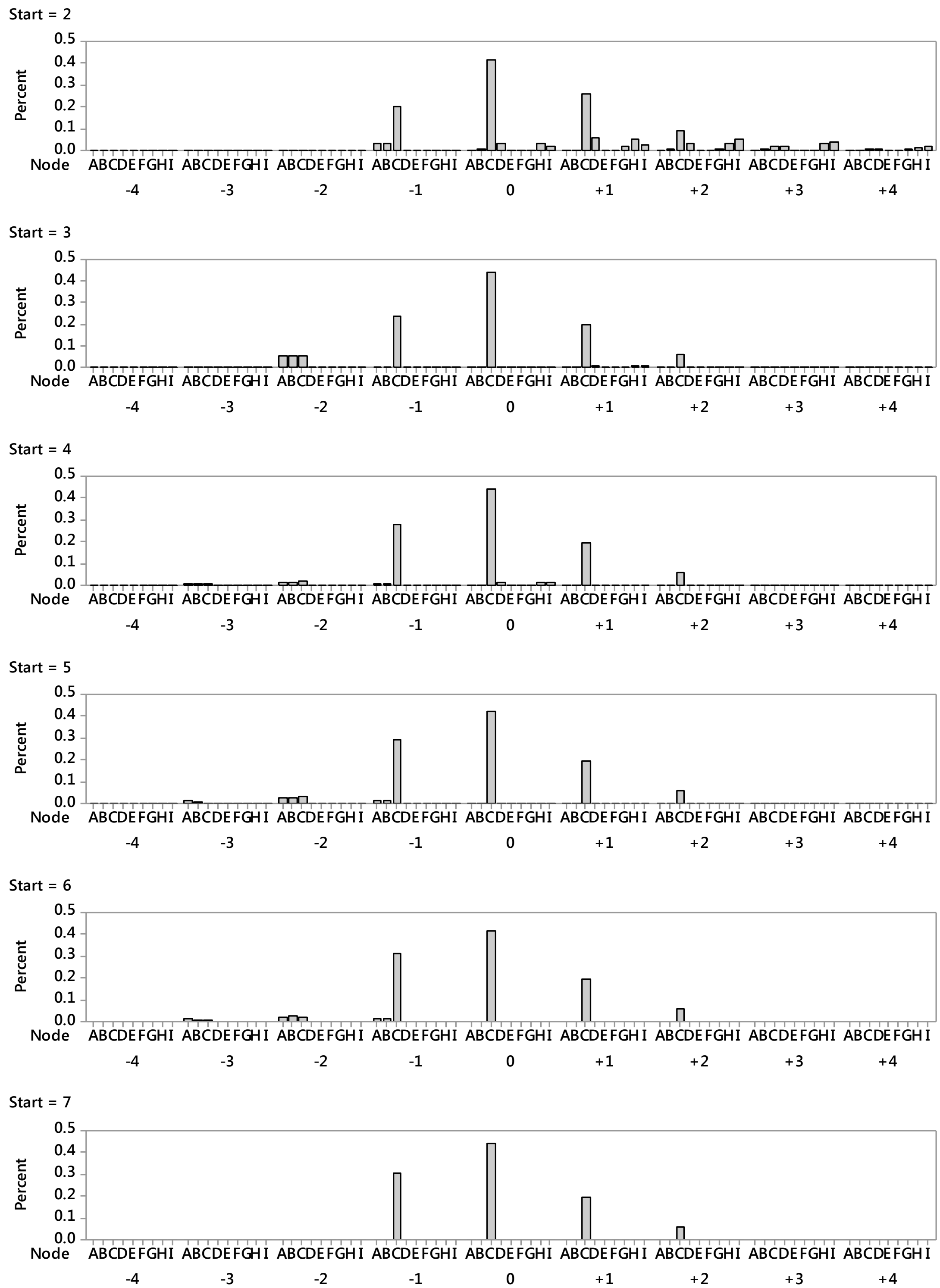
Total Capacity Deployed by Start/Duration for Location H



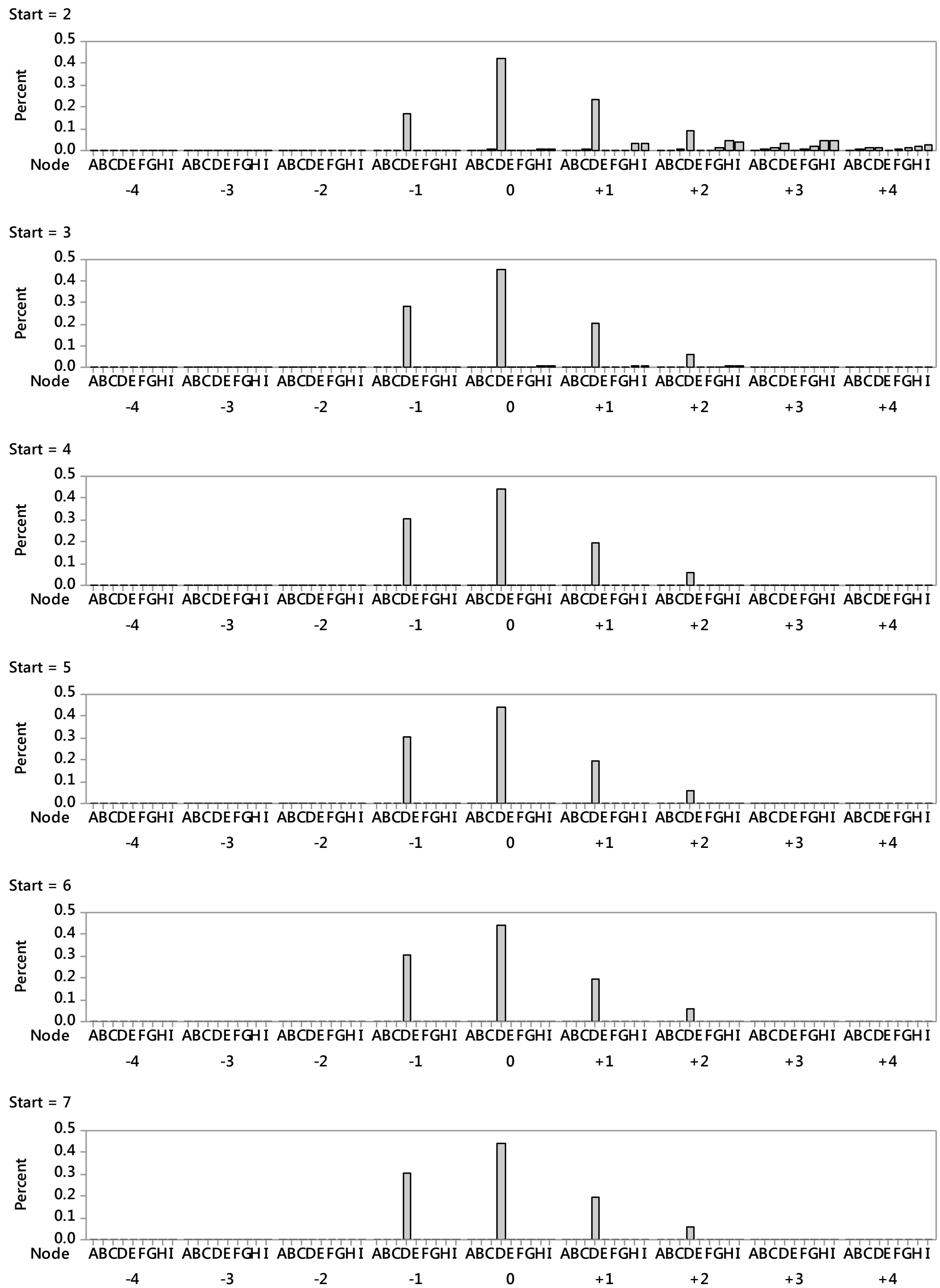
% Capacity Deployed Relative to Disruption Start, Location B

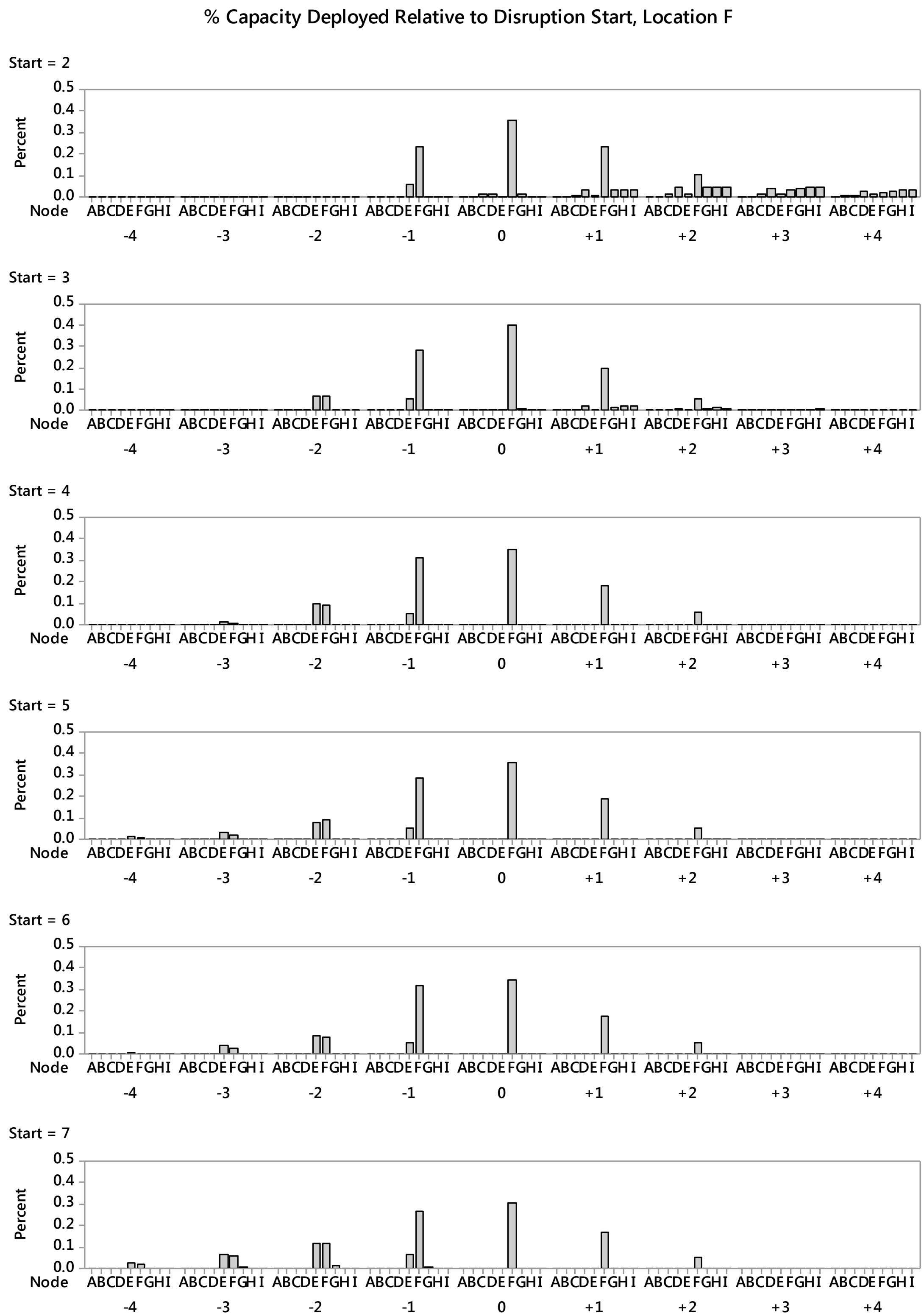


% Capacity Deployed Relative to Disruption Start, Location C

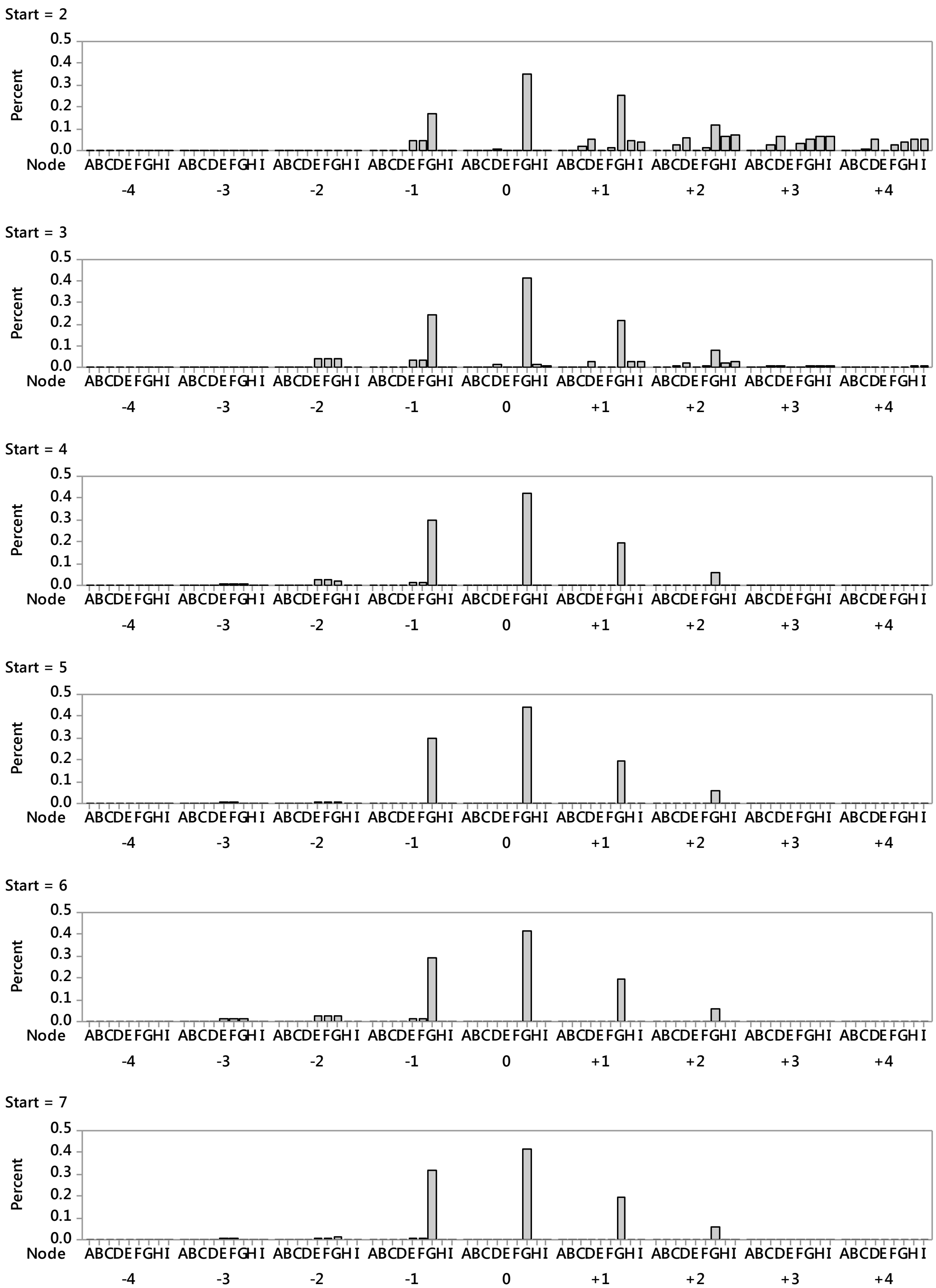


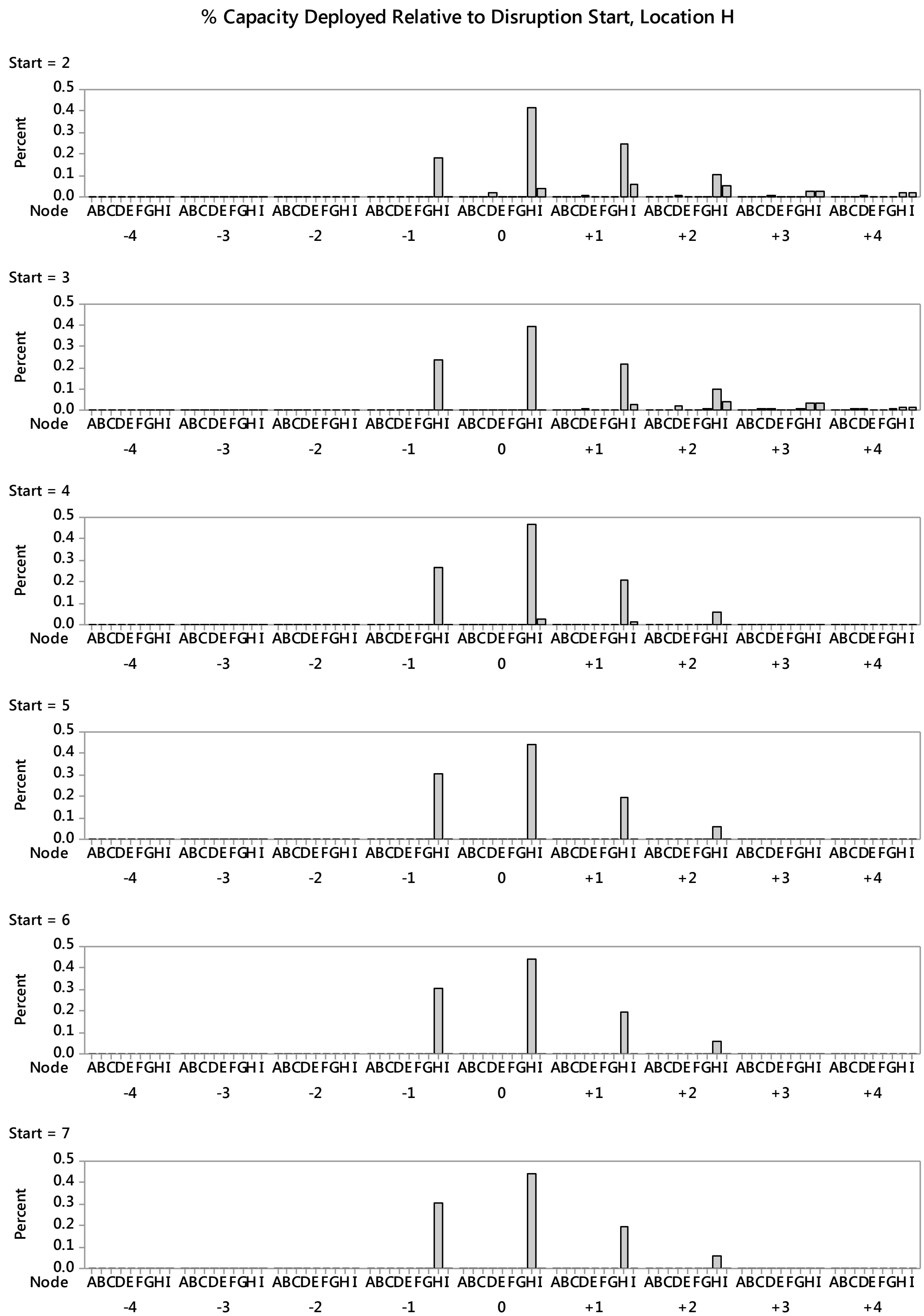
% Capacity Deployed Relative to Disruption Start, Location D



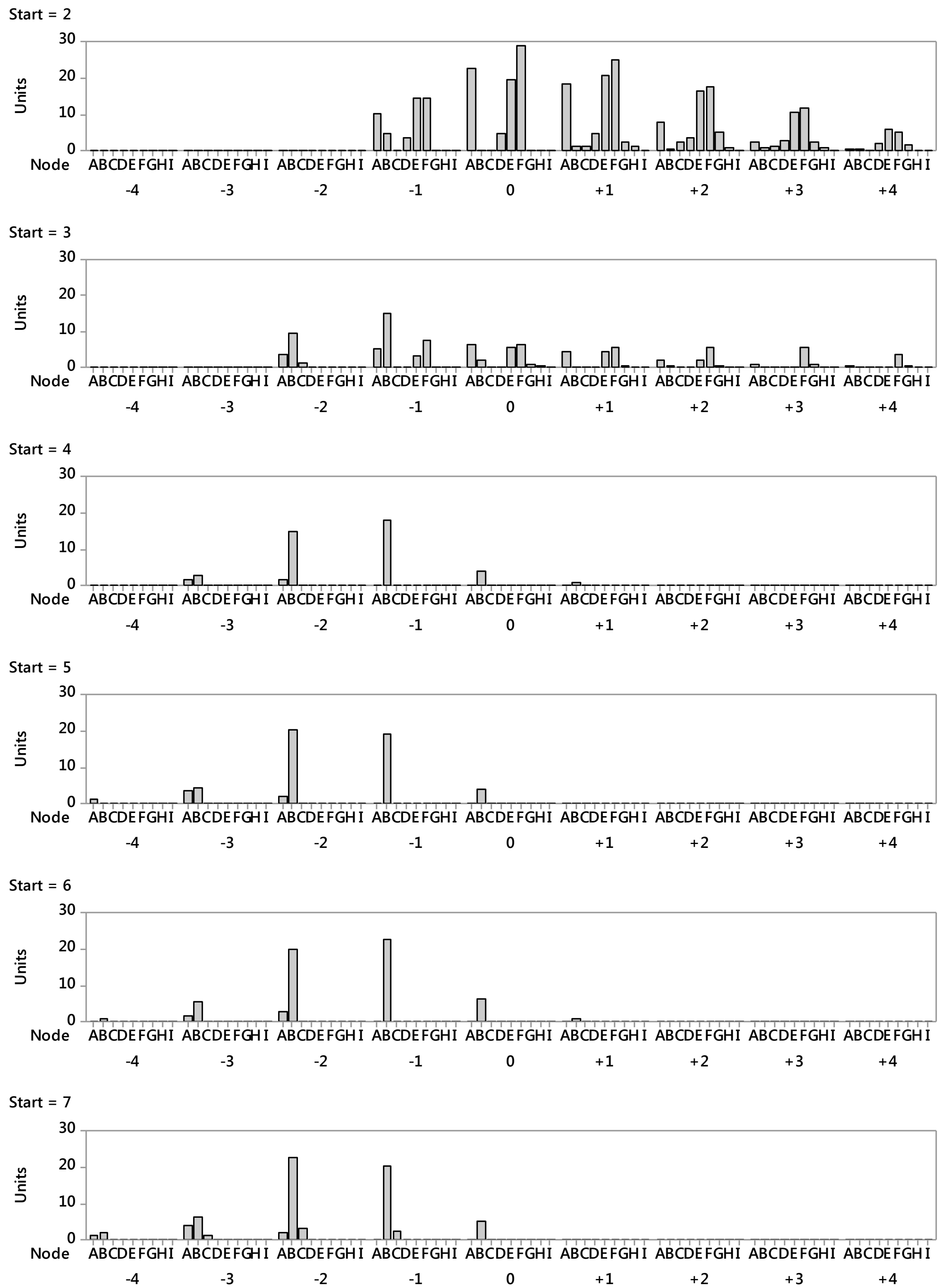

% Capacity Deployed Relative to Disruption Start, Location F
Start = 2
Start = 3
Start = 4
Start = 5
Start = 6
Start = 7
Percent
Node
ABCDEFGHI
-4
-3
-2
-1
0
+1
+2
+3
+4
0.0
0.1
0.2
0.3
0.4
0.5

% Capacity Deployed Relative to Disruption Start, Location G

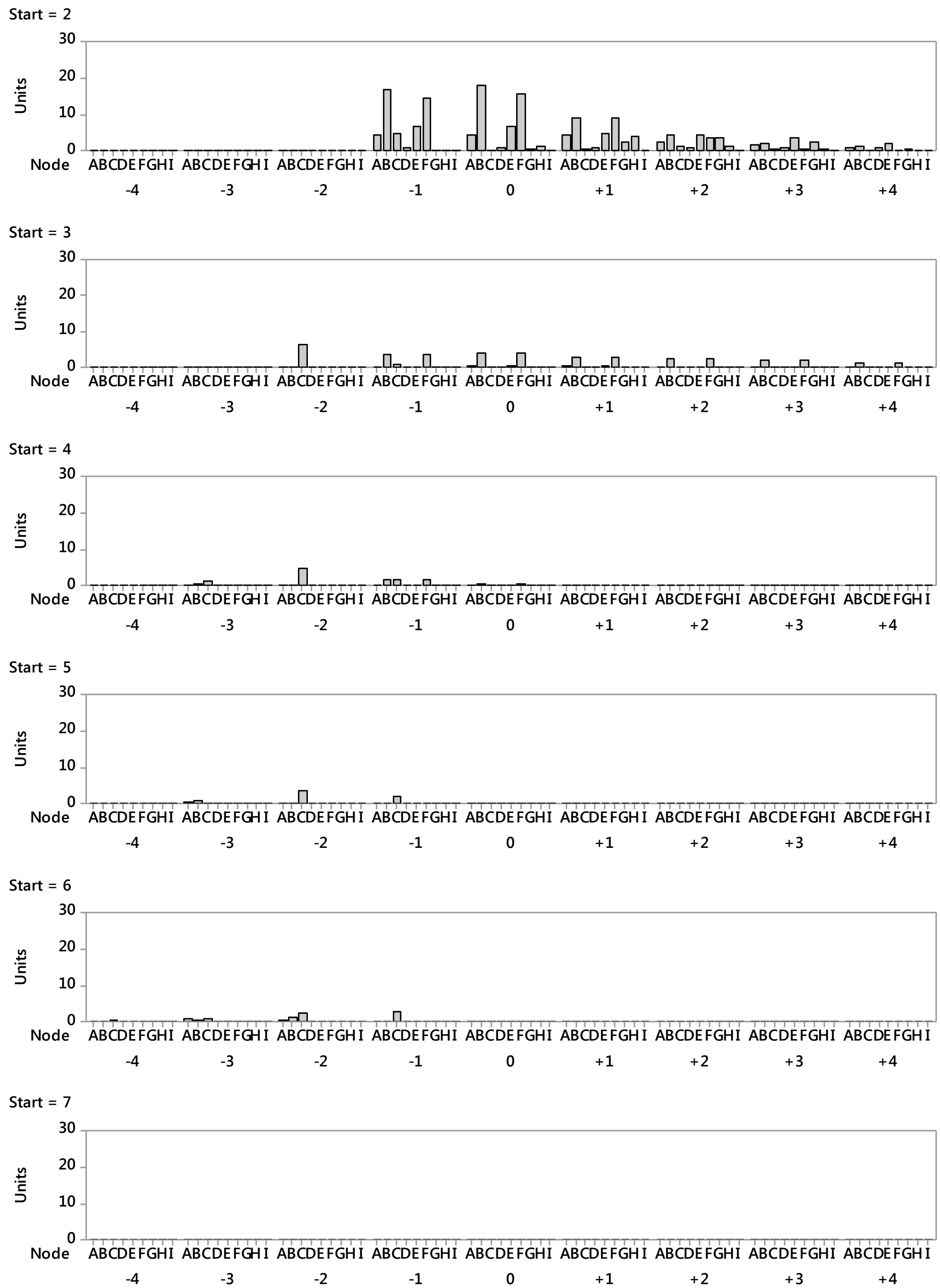


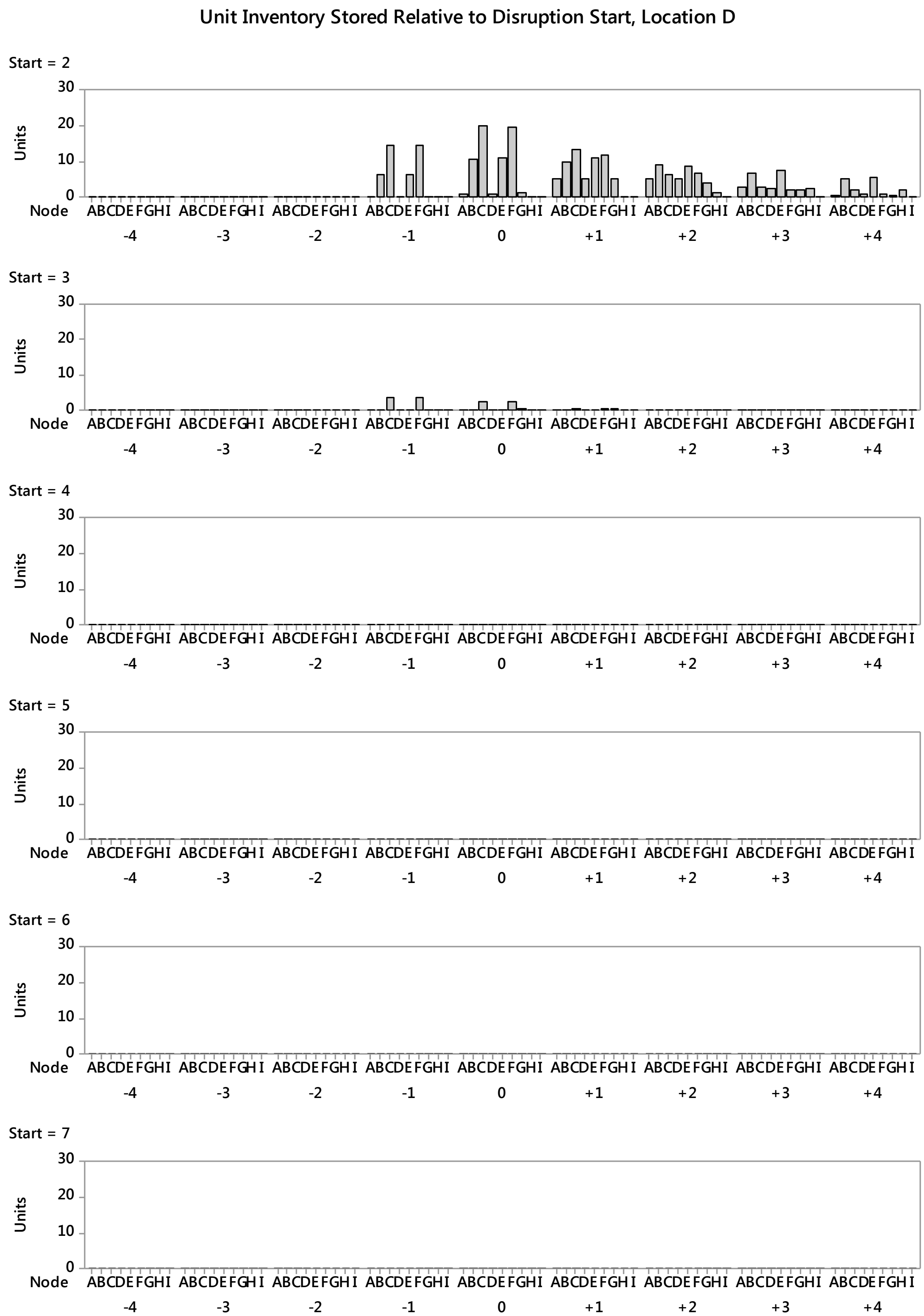

% Capacity Deployed Relative to Disruption Start, Location H
Start = 2
Start = 3
Start = 4
Start = 5
Start = 6
Start = 7
Percent
0.0
0.1
0.2
0.3
0.4
0.5
Node
ABCDEFGHI
-4
-3
-2
-1
0
+1
+2
+3
+4

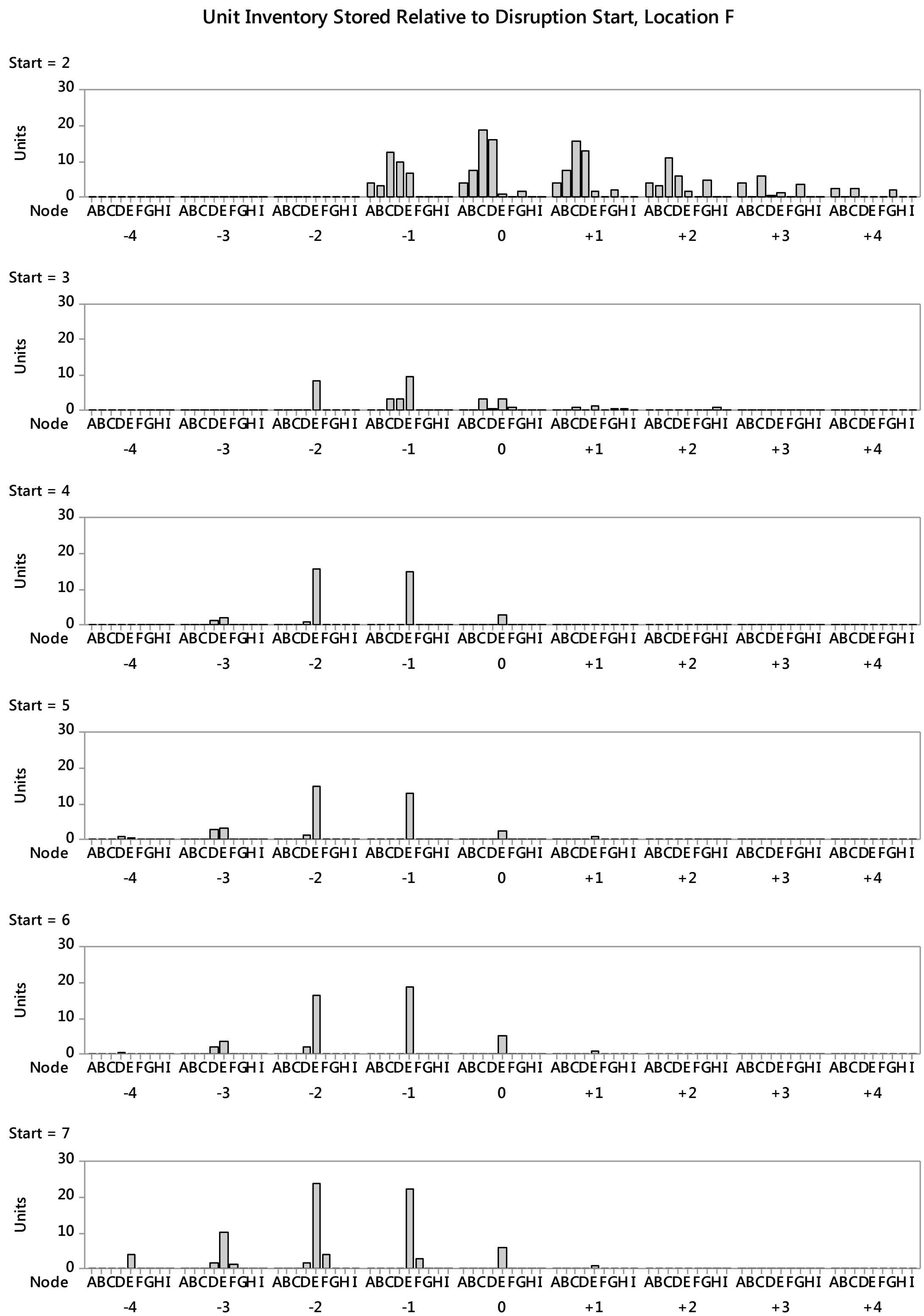
Unit Inventory Stored Relative to Disruption Start, Location B



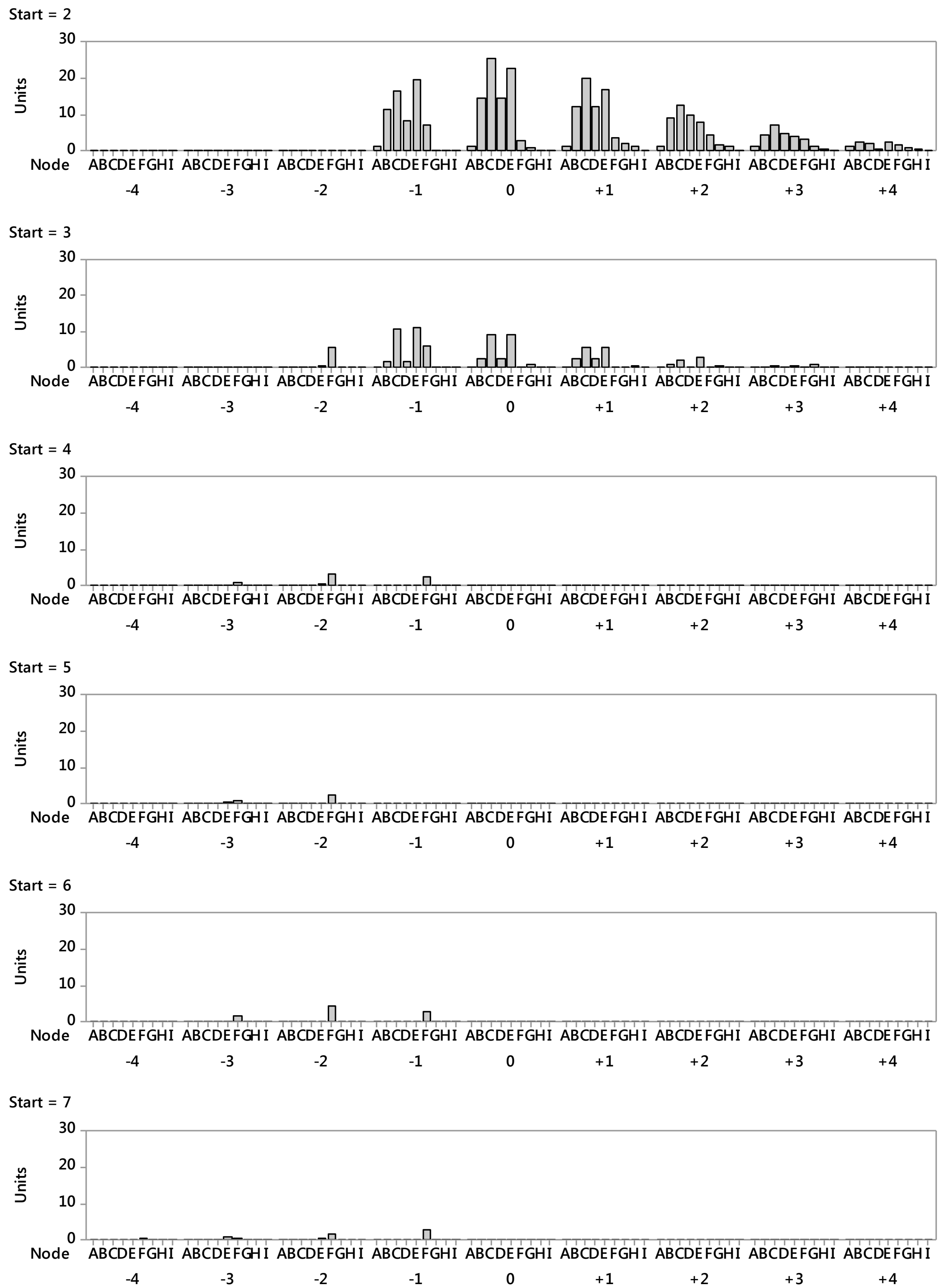
Unit Inventory Stored Relative to Disruption Start, Location C



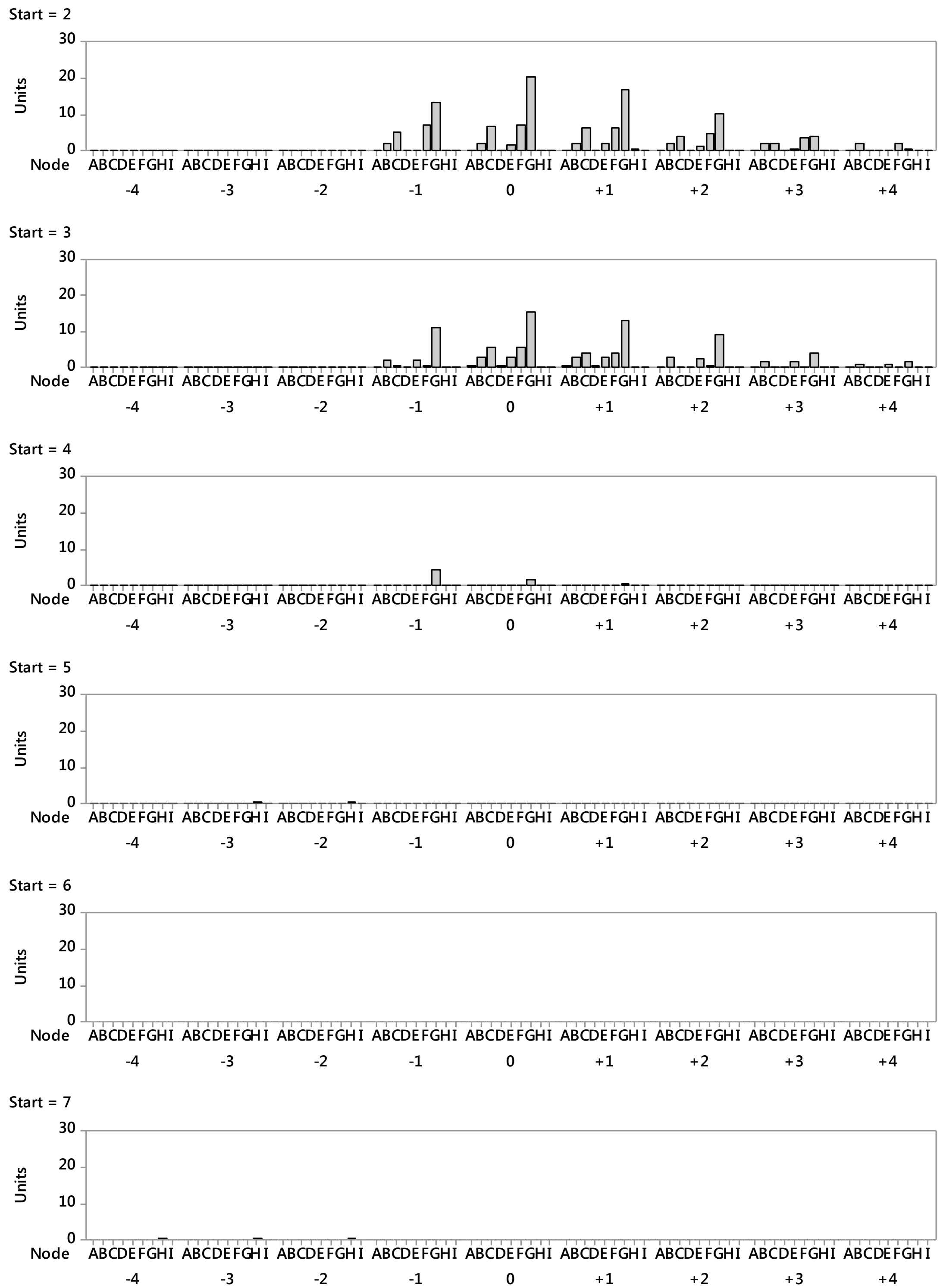

Unit Inventory Stored Relative to Disruption Start, Location D
Start = 2
Start = 3
Start = 4
Start = 5
Start = 6
Start = 7
Units
0
10
20
30
Node
A B C D E F G H I
-4
-3
-2
-1
0
+1
+2
+3
+4


Unit Inventory Stored Relative to Disruption Start, Location F
Start = 2
Start = 3
Start = 4
Start = 5
Start = 6
Start = 7
Units
30
20
10
0
Node
ABCDEFGHI
-4
-3
-2
-1
0
+1
+2
+3
+4

Unit Inventory Stored Relative to Disruption Start, Location G



Unit Inventory Stored Relative to Disruption Start, Location H



Assembly Network Descriptive Statistics Summary

Serial Network Summary Statistics for *ActCost*

Location	Timing	Awareness	N	Mean	SD	Min	Max
B	Early	0.8	216	130,122	24,800	97,047	212,336
		0.9	216	127,583	23,272	93,939	209,683
		Full	216	127,288	22,805	94,985	211,423
		Alternate	216	115,887	9,171	95,729	157,353
	Late	0.8	216	136,863	30,869	96,111	219,302
		0.9	216	133,372	28,468	97,422	216,822
		Full	216	132,448	28,492	96,089	215,105
		Alternate	216	120,368	14,642	96,220	169,200
C	Early	0.8	216	129,118	19,121	98,979	182,794
		0.9	216	126,206	17,644	99,293	183,346
		Full	216	125,436	16,859	96,600	181,589
		Alternate	216	114,788	7,191	96,061	140,970
	Late	0.8	216	136,211	26,683	99,103	207,125
		0.9	216	134,161	27,427	97,808	207,850
		Full	216	133,728	26,407	99,884	206,063
		Alternate	216	117,793	10,881	94,801	157,595
D	Early	0.8	216	128,473	19,804	102,038	207,697
		0.9	216	127,282	19,126	99,895	197,929
		Full	216	125,863	18,460	101,803	196,404
		Alternate	216	114,887	8,090	100,664	159,335
	Late	0.8	216	134,052	25,403	100,687	218,257
		0.9	216	132,266	25,374	100,042	217,818
		Full	216	130,740	25,058	103,075	217,157
		Alternate	216	117,898	13,574	99,138	195,486
F	Early	0.8	216	125,045	17,991	104,384	199,104
		0.9	216	123,614	17,695	103,626	207,413
		Full	216	122,412	15,637	102,319	195,406
		Alternate	216	114,955	6,738	102,768	145,821
	Late	0.8	216	131,359	23,712	104,340	216,527
		0.9	216	128,486	22,410	103,320	214,710
		Full	216	127,405	21,269	104,900	213,875
		Alternate	216	118,035	11,517	101,933	174,152

Serial Network Summary Statistics for *ActCost* Continued . . .

Location	Timing	Awareness	N	Mean	SD	Min	Max
G	Early	0.8	216	132,074	21,190	106,959	192,075
		0.9	216	130,710	21,487	105,100	193,465
		Full	216	128,363	19,426	103,780	191,024
		Alternate	216	115,303	6,669	97,422	130,923
	Late	0.8	216	138,663	27,064	104,744	210,502
		0.9	216	136,828	27,436	104,596	211,175
		Full	216	134,884	25,717	103,591	210,727
		Alternate	216	119,453	11,499	96,940	151,825
H	Early	0.8	216	132,415	20,792	106,264	204,406
		0.9	216	130,953	18,738	105,351	200,705
		Full	216	128,578	17,921	105,793	190,942
		Alternate	216	116,286	7,822	98,184	143,357
	Late	0.8	216	137,538	25,999	108,276	211,480
		0.9	216	137,139	24,453	106,446	210,580
		Full	216	134,401	24,911	107,815	208,993
		Alternate	216	119,376	11,358	102,804	162,710

Serial Network Summary Statistics for *AveLate*

Location	Timing	Awareness	N	Mean	SD	Min	Max
B	Early	0.8	216	35.4	40.4	4.3	176.1
		0.9	216	31.1	37.4	1.0	174.9
		Full	216	30.9	37.0	2.4	176.1
		Alternate	216	15.4	9.1	2.4	62.7
	Late	0.8	216	49.2	56.9	1.1	219.6
		0.9	216	44.5	54.8	3.4	218.7
		Full	216	43.2	54.8	2.9	217.7
		Alternate	216	24.0	24.5	3.0	119.3
C	Early	0.8	216	34.2	36.1	4.6	170.3
		0.9	216	29.2	29.5	3.0	131.4
		Full	216	27.6	27.9	3.1	127.9
		Alternate	216	13.7	5.1	2.4	30.4
	Late	0.8	216	49.3	52.4	3.0	211.6
		0.9	216	45.3	50.9	0.7	181.6
		Full	216	43.7	48.5	2.7	171.0
		Alternate	216	17.6	13.4	0.7	91.9
D	Early	0.8	216	31.3	34.9	3.9	157.9
		0.9	216	29.4	33.6	2.7	147.7
		Full	216	29.0	32.7	4.0	155.0
		Alternate	216	15.0	12.0	3.3	96.0
	Late	0.8	216	44.7	49.7	5.1	196.9
		0.9	216	42.5	49.9	1.7	203.6
		Full	216	40.4	50.2	3.7	203.1
		Alternate	216	19.2	23.1	2.9	168.9
F	Early	0.8	216	25.8	29.0	2.0	162.0
		0.9	216	23.4	28.3	1.3	167.0
		Full	216	22.6	26.5	2.1	154.9
		Alternate	216	14.5	7.2	1.1	58.1
	Late	0.8	216	38.9	44.7	1.4	211.3
		0.9	216	34.3	43.0	0.6	210.4
		Full	216	31.7	41.0	3.3	211.3
		Alternate	216	18.9	20.8	2.9	146.3

Serial Network Summary Statistics for *AveLate* Continued . . .

Location	Timing	Awareness	N	Mean	SD	Min	Max
G	Early	0.8	216	35.4	37.6	2.9	144.4
		0.9	216	36.5	37.9	3.4	137.9
		Full	216	32.7	34.9	3.7	137.3
		Alternate	216	13.8	6.3	3.0	41.7
	Late	0.8	216	51.9	53.7	1.9	194.0
		0.9	216	50.9	53.3	4.4	195.0
		Full	216	47.3	49.9	4.3	194.1
		Alternate	216	20.4	16.8	3.7	86.4
H	Early	0.8	216	36.0	37.4	2.3	168.1
		0.9	216	32.3	34.7	2.3	158.9
		Full	216	31.5	32.8	2.9	151.1
		Alternate	216	14.4	6.9	1.7	43.1
	Late	0.8	216	47.3	51.6	3.4	205.0
		0.9	216	46.9	49.8	1.9	209.3
		Full	216	43.9	48.7	3.3	203.6
		Alternate	216	19.4	16.5	3.1	96.1

Serial Network Summary Statistics for *EndLate*

Location	Timing	Awareness	N	Mean	SD	Min	Max
B	Early	0.8	216	40.2	32.3	9.0	152.0
		0.9	216	34.8	29.1	3.0	160.0
		Full	216	23.9	7.7	7.0	49.0
		Alternate	216	34.9	27.9	6.0	148.0
	Late	0.8	216	43.3	37.4	7.0	160.0
		0.9	216	40.6	35.0	6.0	160.0
		Full	216	26.4	11.9	7.0	72.0
		Alternate	216	38.5	34.6	4.0	154.0
C	Early	0.8	216	41.1	38.0	9.0	198.0
		0.9	216	33.4	24.6	6.0	121.0
		Full	216	24.3	8.1	6.0	49.0
		Alternate	216	31.3	22.2	7.0	118.0
	Late	0.8	216	44.2	40.6	7.0	193.0
		0.9	216	40.8	34.8	2.0	160.0
		Full	216	24.4	7.9	2.0	55.0
		Alternate	216	38.5	31.0	6.0	142.0
D	Early	0.8	216	33.8	23.2	3.0	123.0
		0.9	216	30.1	21.7	5.0	114.0
		Full	216	25.1	9.9	8.0	77.0
		Alternate	216	31.2	22.3	8.0	141.0
	Late	0.8	216	37.8	27.8	9.0	128.0
		0.9	216	35.2	28.3	7.0	143.0
		Full	216	24.7	13.8	5.0	110.0
		Alternate	216	34.7	29.1	8.0	142.0
F	Early	0.8	216	32.7	25.0	3.0	150.0
		0.9	216	27.7	18.6	7.0	141.0
		Full	216	24.2	7.0	2.0	41.0
		Alternate	216	28.2	18.9	5.0	134.0
	Late	0.8	216	38.0	30.4	6.0	157.0
		0.9	216	31.7	25.8	0.0	158.0
		Full	216	25.4	12.4	5.0	107.0
		Alternate	216	30.4	23.6	9.0	154.0

Serial Network Summary Statistics for *EndLate* Continued . . .

Location	Timing	Awareness	N	Mean	SD	Min	Max
G	Early	0.8	216	37.8	30.4	3.0	125.0
		0.9	216	38.8	28.1	7.0	123.0
		Full	216	23.6	8.2	6.0	50.0
		Alternate	216	35.5	24.2	8.0	119.0
	Late	0.8	216	44.9	35.6	6.0	142.0
		0.9	216	44.2	32.4	10.0	149.0
		Full	216	23.0	6.8	8.0	40.0
		Alternate	216	40.0	28.4	8.0	139.0
H	Early	0.8	216	36.4	31.7	3.0	156.0
		0.9	216	30.9	23.0	0.0	118.0
		Full	216	22.9	7.7	6.0	44.0
		Alternate	216	32.5	23.2	7.0	123.0
	Late	0.8	216	37.9	33.5	7.0	173.0
		0.9	216	36.8	29.6	0.0	149.0
		Full	216	24.3	8.9	0.0	62.0
		Alternate	216	34.4	27.7	5.0	146.0

Assembly Network ANOVA Summary

Network: Assembly
Variable: ActCost
Location B

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAct	1	25810670247	25810670247	3014.51	0.000
Duration	2	1018738641	509369321	59.49	0.000
Start	2	344150053	172075027	20.10	0.000
Timing	1	47141668	47141668	5.51	0.019
Awareness	3	1472827786	490942595	57.34	0.000
Error	854	7312061958	8562133		
Lack-of-Fit	206	4543209203	22054414	5.16	0.000
Pure Error	648	2768852754	4272921		
Total	863	43453792596			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2926.11	83.17%	83.00%	82.77%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	113160	307	368.08	0.000	
NormAct	1.0461	0.0191	54.90	0.000	1.24
Duration					
2	386	257	1.50	0.134	1.49
3	2543	259	9.83	0.000	1.50
Start					
6	-1571	250	-6.28	0.000	1.40
7	-548	244	-2.25	0.025	1.33
Timing					
Late	467	199	2.35	0.019	1.00
Awareness					
0.8	3245	282	11.53	0.000	1.50
0.9	3110	282	11.04	0.000	1.50
Alternate	2441	282	8.67	0.000	1.50

Network: Assembly
Variable: ActCost
Location C

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAct	1	27552757578	27552757578	3691.37	0.000
Duration	2	1098272853	549136427	73.57	0.000
Start	2	140698937	70349469	9.43	0.000
Timing	1	37061326	37061326	4.97	0.026
Awareness	3	1857557670	619185890	82.96	0.000
Error	854	6374349763	7464110		
Lack-of-Fit	206	3279485104	15919831	3.33	0.000
Pure Error	648	3094864659	4776026		
Total	863	39450086331			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2732.05	83.84%	83.67%	83.47%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	110410	280	394.57	0.000	
NormAct	0.9729	0.0160	60.76	0.000	1.08
Duration					
2	2374	229	10.35	0.000	1.35
3	2418	228	10.62	0.000	1.33
Start					
6	803	234	3.44	0.001	1.41
7	-110	232	-0.48	0.635	1.38
Timing					
Late	414	186	2.23	0.026	1.00
Awareness					
0.8	4133	263	15.72	0.000	1.50
0.9	2287	263	8.70	0.000	1.50
Alternate	2329	263	8.86	0.000	1.50

Network: Assembly
Variable: ActCost
Location D

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAct	1	15407568920	15407568920	1510.09	0.000
Duration	2	50851134	25425567	2.49	0.083
Start	2	1217172403	608586201	59.65	0.000
Timing	1	22766561	22766561	2.23	0.136
Awareness	3	3505263254	1168421085	114.52	0.000
Error	854	8713448373	10203101		
Lack-of-Fit	206	5820521720	28254960	6.33	0.000
Pure Error	648	2892926652	4464393		
Total	863	35174161114			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
3194.23	75.23%	74.97%	74.64%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	114367	332	344.27	0.000	
NormAct	0.9156	0.0236	38.86	0.000	1.20
Duration					
2	567	270	2.10	0.036	1.37
3	99	266	0.37	0.710	1.34
Start					
6	-633	272	-2.32	0.020	1.40
7	-2937	286	-10.27	0.000	1.54
Timing					
Late	325	217	1.49	0.136	1.00
Awareness					
0.8	5574	307	18.13	0.000	1.50
0.9	3784	307	12.31	0.000	1.50
Alternate	3324	307	10.81	0.000	1.50

Network: Assembly
Variable: ActCost
Location F

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAct	1	25824999162	25824999162	2428.17	0.000
Duration	2	296242840	148121420	13.93	0.000
Start	2	349583139	174791570	16.43	0.000
Timing	1	37801267	37801267	3.55	0.060
Awareness	3	1498795284	499598428	46.97	0.000
Error	854	9082786924	10635582		
Lack-of-Fit	206	6266095509	30417939	7.00	0.000
Pure Error	648	2816691414	4346746		
Total	863	43534758181			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
3261.22	79.14%	78.92%	78.62%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	114586	340	336.79	0.000	
NormAct	1.1447	0.0232	49.28	0.000	1.34
Duration					
2	-132	294	-0.45	0.654	1.56
3	1172	282	4.16	0.000	1.43
Start					
6	223	275	0.81	0.418	1.36
7	-1321	280	-4.72	0.000	1.41
Timing					
Late	418	222	1.89	0.060	1.00
Awareness					
0.8	3588	314	11.43	0.000	1.50
0.9	2499	314	7.96	0.000	1.50
Alternate	2507	314	7.99	0.000	1.50

Network: Assembly
Variable: ActCost
Location G

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAct	1	24774969593	24774969593	1778.17	0.000
Duration	2	1182506247	591253124	42.44	0.000
Start	2	168096479	84048239	6.03	0.003
Timing	1	142254110	142254110	10.21	0.001
Awareness	3	4672500608	1557500203	111.79	0.000
Error	854	11898683915	13932885		
Lack-of-Fit	206	8938258345	43389604	9.50	0.000
Pure Error	648	2960425570	4568558		
Total	863	45696773064			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
3732.68	73.96%	73.69%	73.34%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	111263	385	288.87	0.000	
NormAct	0.9408	0.0223	42.17	0.000	1.12
Duration					
2	1873	320	5.85	0.000	1.41
3	2819	311	9.06	0.000	1.33
Start					
6	-1066	313	-3.41	0.001	1.35
7	-735	316	-2.32	0.020	1.38
Timing					
Late	812	254	3.20	0.001	1.00
Awareness					
0.8	6319	359	17.59	0.000	1.50
0.9	4701	359	13.09	0.000	1.50
Alternate	4005	359	11.15	0.000	1.50

Network: Assembly
Variable: ActCost
Location H

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAct	1	12193611705	12193611705	578.48	0.000
Duration	2	54948419	27474209	1.30	0.272
Start	2	653492800	326746400	15.50	0.000
Timing	1	237590752	237590752	11.27	0.001
Awareness	3	6554959596	2184986532	103.66	0.000
Error	854	18001075997	21078543		
Lack-of-Fit	206	14881520437	72240390	15.01	0.000
Pure Error	648	3119555560	4814129		
Total	863	42647349646			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
4591.14	57.79%	57.35%	56.81%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	115291	469	246.03	0.000	
NormAct	0.7709	0.0321	24.05	0.000	1.26
Duration					
2	604	386	1.56	0.119	1.36
3	140	389	0.36	0.719	1.38
Start					
6	-1906	390	-4.89	0.000	1.38
7	86	390	0.22	0.826	1.39
Timing					
Late	1049	312	3.36	0.001	1.00
Awareness					
0.8	6727	442	15.23	0.000	1.50
0.9	6753	442	15.29	0.000	1.50
Alternate	4202	442	9.51	0.000	1.50

Network: Assembly
Variable: AveLate
Location B

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	214.4	214.436	10.16	0.001
Duration	2	66.6	33.278	1.58	0.207
Start	2	3.2	1.620	0.08	0.926
Timing	1	8.6	8.591	0.41	0.524
Awareness	3	3.7	1.237	0.06	0.981
Error	854	18029.2	21.111		
Lack-of-Fit	206	4521.3	21.948	1.05	0.317
Pure Error	648	13507.8	20.845		
Total	863	18311.9			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
4.59472	1.54%	0.51%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	12.899	0.471	27.41	0.000	
NormAveLate	0.0920	0.0289	3.19	0.001	1.07
Duration					
2	0.646	0.385	1.68	0.094	1.35
3	0.128	0.383	0.33	0.739	1.33
Start					
6	-0.116	0.383	-0.30	0.762	1.33
7	-0.142	0.388	-0.37	0.715	1.37
Timing					
Late	-0.200	0.313	-0.64	0.524	1.00
Awareness					
0.8	0.030	0.444	0.07	0.946	1.51
0.9	0.162	0.444	0.36	0.716	1.51
Alternate	0.007	0.444	0.02	0.988	1.51

Network: Assembly
Variable: AveLate
Location C

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	298.1	298.088	12.65	0.000
Duration	2	29.7	14.867	0.63	0.532
Start	2	87.1	43.554	1.85	0.158
Timing	1	4.8	4.826	0.20	0.651
Awareness	3	68.8	22.926	0.97	0.405
Error	854	20117.6	23.557		
Lack-of-Fit	206	5506.0	26.728	1.19	0.061
Pure Error	648	14611.6	22.549		
Total	863	20686.2			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
4.85355	2.75%	1.72%	0.43%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	13.535	0.520	26.04	0.000	
NormAveLate	0.2316	0.0651	3.56	0.000	1.28
Duration					
2	0.180	0.421	0.43	0.670	1.44
3	0.488	0.442	1.10	0.271	1.59
Start					
6	-0.599	0.421	-1.42	0.155	1.44
7	-0.753	0.409	-1.84	0.066	1.36
Timing					
Late	0.149	0.330	0.45	0.651	1.00
Awareness					
0.8	0.447	0.467	0.96	0.339	1.50
0.9	-0.170	0.467	-0.36	0.716	1.50
Alternate	-0.300	0.467	-0.64	0.521	1.50

Network: Assembly
Variable: AveLate
Location D

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	36.7	36.6783	1.56	0.212
Duration	2	28.1	14.0744	0.60	0.549
Start	2	36.3	18.1316	0.77	0.462
Timing	1	0.1	0.0967	0.00	0.949
Awareness	3	263.0	87.6727	3.73	0.011
Error	854	20046.5	23.4736		
Lack-of-Fit	206	4536.1	22.0198	0.92	0.762
Pure Error	648	15510.4	23.9358		
Total	863	20423.2			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
4.84496	1.84%	0.81%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	12.673	0.498	25.44	0.000	
NormAveLate	0.0825	0.0660	1.25	0.212	1.19
Duration					
2	0.188	0.410	0.46	0.647	1.37
3	0.441	0.405	1.09	0.276	1.34
Start					
6	0.222	0.420	0.53	0.597	1.44
7	0.504	0.406	1.24	0.214	1.35
Timing					
Late	-0.021	0.330	-0.06	0.949	1.00
Awareness					
0.8	1.132	0.466	2.43	0.015	1.50
0.9	-0.345	0.466	-0.74	0.460	1.50
Alternate	0.444	0.466	0.95	0.341	1.50

Network: Assembly
Variable: AveLate
Location F

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	128.5	128.520	5.07	0.025
Duration	2	115.5	57.769	2.28	0.103
Start	2	49.3	24.629	0.97	0.379
Timing	1	6.9	6.862	0.27	0.603
Awareness	3	84.3	28.103	1.11	0.345
Error	854	21653.4	25.355		
Lack-of-Fit	206	7486.0	36.340	1.66	0.000
Pure Error	648	14167.4	21.863		
Total	863	22096.7			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
5.03540	2.01%	0.97%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	13.873	0.520	26.65	0.000	
NormAveLate	0.1661	0.0738	2.25	0.025	1.15
Duration					
2	-0.512	0.420	-1.22	0.223	1.33
3	0.413	0.434	0.95	0.342	1.42
Start					
6	-0.597	0.431	-1.38	0.167	1.41
7	-0.358	0.422	-0.85	0.397	1.35
Timing					
Late	-0.178	0.343	-0.52	0.603	1.00
Awareness					
0.8	0.424	0.485	0.87	0.382	1.50
0.9	-0.444	0.485	-0.92	0.360	1.50
Alternate	-0.142	0.485	-0.29	0.769	1.50

Network: Assembly
Variable: AveLate
Location G

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	249.3	249.26	8.98	0.003
Duration	2	57.0	28.52	1.03	0.359
Start	2	150.6	75.31	2.71	0.067
Timing	1	91.9	91.95	3.31	0.069
Awareness	3	135.3	45.09	1.62	0.182
Error	854	23711.7	27.77		
Lack-of-Fit	206	7889.3	38.30	1.57	0.000
Pure Error	648	15822.4	24.42		
Total	863	24606.3			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
5.26930	3.64%	2.62%	1.30%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	12.634	0.541	23.36	0.000	
NormAveLate	0.2328	0.0777	3.00	0.003	1.43
Duration					
2	0.199	0.440	0.45	0.652	1.34
3	0.680	0.482	1.41	0.159	1.61
Start					
6	-1.021	0.444	-2.30	0.022	1.36
7	-0.609	0.456	-1.34	0.182	1.44
Timing					
Late	0.652	0.359	1.82	0.069	1.00
Awareness					
0.8	0.597	0.507	1.18	0.239	1.50
0.9	1.044	0.507	2.06	0.040	1.50
Alternate	0.869	0.507	1.71	0.087	1.50

Network: Assembly
Variable: AveLate
Location H

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	14.9	14.89	0.53	0.468
Duration	2	401.5	200.77	7.10	0.001
Start	2	300.7	150.35	5.32	0.005
Timing	1	92.9	92.88	3.28	0.070
Awareness	3	432.4	144.12	5.10	0.002
Error	854	24148.8	28.28		
Lack-of-Fit	206	9714.3	47.16	2.12	0.000
Pure Error	648	14434.5	22.28		
Total	863	25386.5			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
5.31764	4.88%	3.87%	2.64%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	14.510	0.576	25.18	0.000	
NormAveLate	-0.0700	0.0964	-0.73	0.468	1.75
Duration					
2	-0.876	0.458	-1.91	0.056	1.42
3	-1.836	0.488	-3.76	0.000	1.62
Start					
6	-1.365	0.521	-2.62	0.009	1.84
7	-1.261	0.443	-2.85	0.005	1.33
Timing					
Late	0.656	0.362	1.81	0.070	1.00
Awareness					
0.8	1.017	0.512	1.99	0.047	1.50
0.9	-0.548	0.512	-1.07	0.285	1.50
Alternate	1.151	0.512	2.25	0.025	1.50

Network: Assembly
Variable: EndLate
Location B

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	668.1	668.128	12.64	0.000
Duration	2	49.7	24.850	0.47	0.625
Start	2	0.3	0.162	0.00	0.997
Timing	1	28.4	28.367	0.54	0.464
Awareness	3	48.1	16.040	0.30	0.823
Error	854	45135.6	52.852		
Lack-of-Fit	206	11623.6	56.425	1.09	0.213
Pure Error	648	33512.0	51.716		
Total	863	45921.3			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
7.26994	1.71%	0.68%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	23.130	0.745	31.07	0.000	
NormAveLate	0.1623	0.0457	3.56	0.000	1.07
Duration					
2	0.552	0.609	0.91	0.365	1.35
3	0.093	0.606	0.15	0.877	1.33
Start					
6	0.030	0.606	0.05	0.960	1.33
7	-0.017	0.615	-0.03	0.978	1.37
Timing					
Late	-0.363	0.496	-0.73	0.464	1.00
Awareness					
0.8	0.181	0.703	0.26	0.797	1.51
0.9	0.630	0.703	0.90	0.370	1.51
Alternate	0.408	0.703	0.58	0.562	1.51

Network: Assembly
Variable: EndLate
Location C

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	466.5	466.485	7.97	0.005
Duration	2	83.7	41.868	0.72	0.489
Start	2	255.6	127.784	2.18	0.113
Timing	1	7.0	7.042	0.12	0.729
Awareness	3	68.4	22.798	0.39	0.761
Error	854	49993.5	58.540		
Lack-of-Fit	206	13973.5	67.833	1.22	0.035
Pure Error	648	36020.0	55.586		
Total	863	51066.3			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
7.65117	2.10%	1.07%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	24.824	0.819	30.29	0.000	
NormAveLate	0.290	0.103	2.82	0.005	1.28
Duration					
2	-0.045	0.664	-0.07	0.946	1.44
3	0.668	0.697	0.96	0.338	1.59
Start					
6	-1.134	0.663	-1.71	0.088	1.44
7	-1.232	0.645	-1.91	0.056	1.36
Timing					
Late	0.181	0.521	0.35	0.729	1.00
Awareness					
0.8	0.051	0.736	0.07	0.945	1.50
0.9	-0.588	0.736	-0.80	0.425	1.50
Alternate	-0.472	0.736	-0.64	0.521	1.50

Network: Assembly
Variable: EndLate
Location D

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	58.3	58.29	1.01	0.316
Duration	2	79.6	39.79	0.69	0.504
Start	2	174.0	86.98	1.50	0.224
Timing	1	81.3	81.28	1.40	0.237
Awareness	3	668.2	222.73	3.84	0.010
Error	854	49508.4	57.97		
Lack-of-Fit	206	12841.1	62.34	1.10	0.189
Pure Error	648	36667.3	56.59		
Total	863	50579.7			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
7.61396	2.12%	1.09%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	23.303	0.783	29.77	0.000	
NormAveLate	0.104	0.104	1.00	0.316	1.19
Duration					
2	0.084	0.644	0.13	0.896	1.37
3	0.682	0.636	1.07	0.284	1.34
Start					
6	0.763	0.660	1.16	0.248	1.44
7	1.067	0.637	1.67	0.095	1.35
Timing					
Late	-0.613	0.518	-1.18	0.237	1.00
Awareness					
0.8	1.412	0.733	1.93	0.054	1.50
0.9	-1.051	0.733	-1.43	0.152	1.50
Alternate	0.347	0.733	0.47	0.636	1.50

Network: Assembly
Variable: EndLate
Location F

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	279.6	279.636	3.73	0.054
Duration	2	309.1	154.573	2.06	0.128
Start	2	17.0	8.488	0.11	0.893
Timing	1	4.0	4.029	0.05	0.817
Awareness	3	683.8	227.939	3.04	0.028
Error	854	64108.6	75.069		
Lack-of-Fit	206	30194.9	146.577	2.80	0.000
Pure Error	648	33913.8	52.336		
Total	863	65628.5			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
8.66422	2.32%	1.29%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	23.918	0.896	26.71	0.000	
NormAveLate	0.245	0.127	1.93	0.054	1.15
Duration					
2	-0.308	0.722	-0.43	0.669	1.33
3	1.145	0.746	1.54	0.125	1.42
Start					
6	-0.352	0.742	-0.47	0.635	1.41
7	-0.159	0.726	-0.22	0.827	1.35
Timing					
Late	-0.137	0.590	-0.23	0.817	1.00
Awareness					
0.8	1.759	0.834	2.11	0.035	1.50
0.9	-0.634	0.834	-0.76	0.447	1.50
Alternate	0.028	0.834	0.03	0.973	1.50

Network: Assembly
Variable: EndLate
Location G

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	317.9	317.88	4.87	0.028
Duration	2	34.7	17.34	0.27	0.767
Start	2	471.9	235.94	3.61	0.027
Timing	1	22.7	22.69	0.35	0.556
Awareness	3	271.9	90.62	1.39	0.245
Error	854	55762.8	65.30		
Lack-of-Fit	206	17157.3	83.29	1.40	0.001
Pure Error	648	38605.5	59.58		
Total	863	57063.0			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
8.08060	2.28%	1.25%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	23.792	0.829	28.69	0.000	
NormAveLate	0.263	0.119	2.21	0.028	1.43
Duration					
2	-0.114	0.675	-0.17	0.866	1.34
3	0.399	0.739	0.54	0.590	1.61
Start					
6	-1.801	0.681	-2.64	0.008	1.36
7	-1.111	0.700	-1.59	0.113	1.44
Timing					
Late	0.324	0.550	0.59	0.556	1.00
Awareness					
0.8	0.880	0.778	1.13	0.258	1.50
0.9	1.583	0.778	2.04	0.042	1.50
Alternate	0.815	0.778	1.05	0.295	1.50

Network: Assembly
Variable: EndLate
Location H

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
NormAveLate	1	9.4	9.388	0.15	0.702
Duration	2	609.8	304.881	4.76	0.009
Start	2	21.6	10.788	0.17	0.845
Timing	1	16.9	16.946	0.26	0.607
Awareness	3	428.3	142.754	2.23	0.084
Error	854	54739.3	64.097		
Lack-of-Fit	206	19665.0	95.461	1.76	0.000
Pure Error	648	35074.3	54.127		
Total	863	55865.7			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
8.00609	2.02%	0.98%	0.00%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	24.569	0.867	28.32	0.000	
NormAveLate	-0.056	0.145	-0.38	0.702	1.75
Duration					
2	-0.820	0.689	-1.19	0.235	1.42
3	-2.229	0.734	-3.03	0.002	1.62
Start					
6	-0.453	0.785	-0.58	0.564	1.84
7	-0.124	0.667	-0.19	0.852	1.33
Timing					
Late	0.280	0.545	0.51	0.607	1.00
Awareness					
0.8	0.282	0.770	0.37	0.714	1.50
0.9	-0.713	0.770	-0.93	0.355	1.50
Alternate	1.250	0.770	1.62	0.105	1.50

Appendix E
CEDA Network ANOVA Tables

Variable: AveLate

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
ExpLate	1	2307	2306.95	86.96	0.000
Network	9	9604	1067.08	40.23	0.000
Iteration	3	4561	1520.27	57.31	0.000
Error	142	3767	26.53		
Lack-of-Fit	25	1443	57.73	2.91	0.000
Pure Error	117	2324	19.86		
Total	155	41466			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
5.15051	90.92%	90.08%	89.07%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	28.93	1.53	18.95	0.000	
ExpLate	3.144	0.337	9.33	0.000	5.77
Network					
2	-4.44	1.82	-2.44	0.016	1.79
3	-10.31	1.93	-5.34	0.000	2.02
4	-20.57	1.90	-10.82	0.000	1.96
5	-19.65	1.82	-10.79	0.000	1.79
6	-11.82	3.30	-3.58	0.000	4.55
7	-14.97	2.65	-5.64	0.000	3.81
8	-18.85	1.82	-10.35	0.000	1.79
9	1.21	2.32	0.52	0.601	2.91
10	-18.53	1.82	-10.18	0.000	1.79
Iteration					
-3	18.66	1.47	12.73	0.000	2.24
-2	9.85	1.28	7.67	0.000	1.85
-1	4.39	1.17	3.74	0.000	1.55

Grouping Information Using the Tukey Method and 95% Confidence

Iteration	N	Mean	Grouping			
-3	36	41.9391	A			
-2	40	33.1354		B		
-1	40	27.6729			C	
0	40	23.2814				D

Means that do not share a letter are significantly different.

Tukey Simultaneous Tests for Differences of Means

Difference of Iteration Levels	Difference of Means	SE of Difference	Simultaneous 95% CI	T-Value	Adjusted P-Value
-2 - -3	-8.80	1.23	(-11.99, -5.61)	-7.18	0.000
-1 - -3	-14.27	1.35	(-17.77, -10.76)	-10.60	0.000
0 - -3	-18.66	1.47	(-22.47, -14.84)	-12.73	0.000
-1 - -2	-5.46	1.20	(-8.59, -2.34)	-4.55	0.000
0 - -2	-9.85	1.28	(-13.20, -6.51)	-7.67	0.000
0 - -1	-4.39	1.17	(-7.45, -1.34)	-3.74	0.002

Individual confidence level = 98.98%

Variable: EndLate
Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
ExpLate	1	1121	1121.1	9.61	0.002
Network	9	171425	19047.2	163.25	0.000
Iteration	3	57338	19112.5	163.81	0.000
Error	142	16568	116.7		
Lack-of-Fit	25	11514	460.6	10.66	0.000
Pure Error	117	5054	43.2		
Total	155	302892			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
10.8017	94.53%	94.03%	93.41%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	97.59	3.20	30.47	0.000	
ExpLate	2.191	0.707	3.10	0.002	5.77
Network					
2	-8.31	3.82	-2.18	0.031	1.79
3	-52.60	4.05	-12.99	0.000	2.02
4	-95.56	3.99	-23.96	0.000	1.96
5	-72.00	3.82	-18.85	0.000	1.79
6	-42.35	6.92	-6.12	0.000	4.55
7	-62.92	5.56	-11.31	0.000	3.81
8	-88.87	3.82	-23.27	0.000	1.79
9	-15.63	4.86	-3.22	0.002	2.91
10	-84.06	3.82	-22.01	0.000	1.79
Iteration					
-3	65.52	3.07	21.32	0.000	2.24
-2	35.92	2.69	13.33	0.000	1.85
-1	14.21	2.46	5.77	0.000	1.55

Grouping Information Using the Tukey Method and 95% Confidence

Iteration	N	Mean	Grouping			
-3	36	115.161	A			
-2	40	85.559		B		
-1	40	63.847			C	
0	40	49.637				D

Means that do not share a letter are significantly different.

Tukey Simultaneous Tests for Differences of Means

Difference of Iteration Levels	Difference of Means	SE of Difference	Simultaneous 95% CI	T-Value	Adjusted P-Value
-2 - -3	-29.60	2.57	(-36.29, -22.91)	-11.51	0.000
-1 - -3	-51.31	2.82	(-58.66, -43.97)	-18.18	0.000
0 - -3	-65.52	3.07	(-73.52, -57.52)	-21.32	0.000
-1 - -2	-21.71	2.52	(-28.27, -15.16)	-8.62	0.000
0 - -2	-35.92	2.69	(-42.93, -28.91)	-13.33	0.000
0 - -1	-14.21	2.46	(-20.62, -7.80)	-5.77	0.000

Individual confidence level = 98.98%

Appendix F

Case Study Formulation

Variable Identification

$\mathbf{Y}_{DL}$	Delay Installation Decision Variable	$X_{OP_t Iop_t}$	Operator Hours, period t	$X_{C_t Ic_t}$	Line C Hours, period t	D_{tSI}	Demand filled in period t
$\mathbf{Y}_{CR}$	Crash Project Decision Variable	$X_{MH_t Imh_t}$	Material Handler Hours, period t	$X_{DL_t Ib_t}$	Line B Hours from delay, period t	U_{tSI}	Combined Late/Unmet Demand in period t
$\mathbf{M}_{DL}$	Large number	$X_{A_t Ia_t}$	Line A Hours, period t	$X_{CR_t Ic_t}$	Line C Hours from delay, period t	$U_{tIwh_{t'}}$	Late Demand from period t, filled in period t'
$\mathbf{M}_{CR}$	Large Number	$X_{B_t Ib_t}$	Line B Hours, period t	$X_{WH_t Iwh_t}$	Packages produced in period t	U_{SOt}	Unmet Demand from Period t
$\boldsymbol{\alpha}$	Cost Parameter	$\boldsymbol{\lambda}$	Flow Scaling Factor				

Objective Function

$$\min z =$$

$$\mathbf{10{,}000Y}_{DL} + \mathbf{10{,}000Y}_{CR} + \sum_{t=1}^{10} 50X_{OP_t Iop_t} + 40X_{MH_t Imh_t} + 165X_{A_t Ia_t} + 161X_{B_t Ib_t} + 150X_{C_t Ic_t} + 161X_{DL_t Ib_t} + 150X_{CR_t Ic_t} + 0.04I_{Iwh_{t(t+1)}}$$

$$+ \sum_{t=1}^{10}(21{,}900U_{SOt} - 100t - 100) + \sum_{t=1}^{9}(100U_{tIwh_{10}} - 10t - 10) + \sum_{t=1}^{8}(90U_{tIwh_9} - 10t - 10) + \sum_{t=1}^{7}(80U_{tIwh_8} - 10t - 10)$$

$$+ \sum_{t=1}^{6}(70U_{tIwh_7} - 10t - 10) + \sum_{t=1}^{5}(60U_{tIwh_6} - 10t - 10) + \sum_{t=1}^{4}(50U_{tIwh_5} - 10t - 10)$$

$$+ \sum_{t=1}^{3}(40U_{tIwh_4} - 10t - 10) + \sum_{t=1}^{2}(30U_{tIwh_3} - 10t - 10) + \sum_{t=1}^{1}(20U_{tIwh_2} - 10t - 10)$$

s.t.

Redundant Capacity Decision Constraints

$$X_{DL_3Ib_3} + X_{DL_4Ib_4} - \mathrm{M}_{DL}\mathrm{Y}_{DL} \leq 0$$

$$X_{CR_6Ic_6} + X_{CR_7Ic_7} + X_{CR_8Ic_8} - \mathrm{M}_{CR}\mathrm{Y}_{CR} \leq 0$$

Binary Decision Variable Constraint

$$\mathrm{Y}_{DL} = Binary$$

$$\mathrm{Y}_{CR} = Binary$$

Demand Constraints

$$D_{1SI} + U_{1SI} = 60{,}000$$

$$D_{2SI} + U_{2SI} = 62{,}000$$

$$D_{3SI} + U_{3SI} = 64{,}000$$

$$D_{4SI} + U_{4SI} = 70{,}000$$

$$D_{5SI} + U_{5SI} = 72{,}000$$

$$D_{6SI} + U_{6SI} = 72{,}000$$

$$D_{7SI} + U_{7SI} = 74{,}000$$

$$D_{8SI} + U_{8SI} = 74{,}000$$

$$D_{9SI} + U_{9SI} = 74{,}000$$

$$D_{10SI} + U_{10SI} = 74{,}000$$

Capacity Constraints for Redundant Resources DL & CR

$$X_{DL_3Ib_3} \leq 48$$

$$X_{DL_4Ib_4} \leq 72$$

$$X_{CR_6Ic_6} \leq 48$$

$$X_{CR_7Ic_7} \leq 160$$

$$X_{CR_8Ic_8} \leq 360$$

Capacity Constraints for Lines A, B, and C

$X_{A_1 Ia_1} \leq 720$

$X_{A_2 Ia_2} \leq 720$

$X_{A_3 Ia_3} \leq 720$

$X_{A_4 Ia_4} \leq 720$

$X_{A_5 Ia_5} \leq 720$

$X_{A_6 Ia_6} \leq 720$

$X_{A_7 Ia_7} \leq 168$

$X_{A_8 Ia_8} \leq 168$

$X_{A_9 Ia_9} \leq 168$

$X_{A_{10} Ia_{10}} \leq 168$

$X_{B_1 Ib_1} \leq 168$

$X_{B_2 Ib_2} \leq 168$

$X_{B_3 Ib_3} \leq 120$

$X_{C_8 Ic_8} \leq 180$

$X_{C_9 Ic_9} \leq 360$

$X_{C_{10} Ic_{10}} \leq 720$

$X_{WH_t Iwh_t} \leq 100{,}000$ (*t* = 1, 2, 3, …, 10)

Inventory Capacity Constraints

$I_{Iwh_{t(t-1)}} \leq 50{,}000$ (*t* = 1, 2, 3, …, 10)

$I_{Iwh_0} = 0$

Production Balance Constraints

$I_{Imh_tA_t} - 3X_{A_tIa_t} = 0$ (*t* = 1, 2, 3, …, 10)

$I_{Iop_tA_t} - X_{A_tIa_t} = 0$ (*t* = 1, 2, 3, …, 10)

$I_{Imh_tB_t} - 3X_{B_tIb_t} = 0$ (*t* = 1, 2, 3, …, 10)

$I_{Iop_tB_t} - X_{B_tIb_t} = 0$ (*t* = 1, 2, 3, …, 10)

$I_{Imh_tC_t} - 2X_{C_tIc_t} = 0$ (*t* = 1, 2, 3, …, 10)

$I_{Iop_tC_t} - X_{C_tIc_t} = 0$ (*t* = 1, 2, 3, …, 10)

$I_{Imh_tDL_t} - 3X_{DL_tIb_t} = 0$ (*t* = 1, 2, 3, …, 10)

$I_{Iop_tDL_t} - X_{DL_tIb_t} = 0$ (*t* = 1, 2, 3, …, 10)

$I_{Imh_tCR_t} - 2X_{CR_tIc_t} = 0$ (*t* = 1, 2, 3, …, 10)

$I_{Iop_tCR_t} - X_{CR_tIc_t} = 0$ (*t* = 1, 2, 3, …, 10)

$86.1I_{Ia_tWH_t} + 65.7I_{Ib_tWH_t} + 121.7I_{Ic_tWH_t} - X_{WH_tIwh_t} = 0$ (*t* = 1, 2, 3, …, 10)

Demand Balance Constraints

$D_{Iwh_t} - D_{tSI} = 0$ (*t* = 1, 2, 3, …, 10)

Unmet/Late Demand Balance Constraints

$$U_{SO1} + U_{1Iwh_2} + U_{1Iwh_3} + U_{1Iwh_4} + U_{1Iwh_5} + U_{1Iwh_6} + U_{1Iwh_7} + U_{1Iwh_8} + U_{1Iwh_9} + U_{1Iwh_{10}} - U_{1SI} = 0$$

$$U_{SO2} + U_{2Iwh_3} + U_{2Iwh_4} + U_{2Iwh_5} + U_{2Iwh_6} + U_{2Iwh_7} + U_{2Iwh_8} + U_{2Iwh_9} + U_{2Iwh_{10}} - U_{2SI} = 0$$

$$U_{SO3} + U_{3Iwh_4} + U_{3Iwh_5} + U_{3Iwh_6} + U_{3Iwh_7} + U_{3Iwh_8} + U_{3Iwh_9} + U_{3Iwh_{10}} - U_{3SI} = 0$$

$$U_{SO4} + U_{4Iwh_5} + U_{4Iwh_6} + U_{4Iwh_7} + U_{4Iwh_8} + U_{4Iwh_9} + U_{4Iwh_{10}} - U_{4SI} = 0$$

$$U_{SO5} + U_{5Iwh_6} + U_{5Iwh_7} + U_{5Iwh_8} + U_{5Iwh_9} + U_{5Iwh_{10}} - U_{5SI} = 0$$

$$U_{SO6} + U_{6Iwh_7} + U_{6Iwh_8} + U_{6Iwh_9} + U_{6Iwh_{10}} - U_{6SI} = 0$$

$$U_{SO7} + U_{7Iwh_8} + U_{7Iwh_9} + U_{7Iwh_{10}} - U_{7SI} = 0$$

$$U_{SO8} + U_{8Iwh_9} + U_{8Iwh_{10}} - U_{8SI} = 0$$

$$U_{SO9} + U_{9Iwh_{10}} - U_{9SI} = 0$$

$$U_{SO10} - U_{10SI} = 0$$

Non-negativity constraints omitted for brevity