ABSTRACT

MARCH, SEAN MICHAEL. Describing Demand Difficulty in Spare Parts Supply Chains with Heterogeneous Intermittent Demand. (Under the direction of Brandon M. McConnell).

With the emerging field of study in the application of additive manufacturing (AM) technology, military and industrial organizations alike stand to benefit from incorporating AM into the spare parts supply chain (SPSC). This technology can significantly reduce costs, enhance customer satisfaction levels, and reduce the number of backorders and product lead times compared to traditional supply chains for spare parts. These SPSC's face challenges such as demand forecasting and inventory management while experiencing irregular and intermittent parts demand. This intermittent demand is classified into four separate classifications based on the average demand interval, coefficient of variation squared, and mean level of the demand. However, there is a lack of research that analyzes how spare parts of heterogeneous demand classification affect the AM-enabled SPSC network's performance. This research examines the resultant dispersion value from the demand parameters and compares them to the network's performance measure using homogeneous demand as a pilot study. We propose novel difficulty indices determined by the interaction of dispersion values from a heterogeneous demand network to describe demand difficulty within the SPSC, and assess these indices' ability to describe degrading network performance. Regression analysis identifies the prominent difficulty indices that effectively consolidate the demand parameters into one value describing demand difficulty in network performance. This research provides a tool for future work in analyzing the impact of heterogeneous demand of spare parts in an AM-enabled SPSC.

Describing Demand Difficulty in Spare Parts Supply Chains with Heterogeneous Intermittent Demand

by
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DEDICATION

For my children, Anderson, Pierson, and Everly. Thank you for all your support along the way and for bearing with me on those long days that we would spend at campus together in the grad office and attending meetings. You all are the driving factor for me to reach higher and work harder. I love you, and you make everything worth it.

For my wife, Ashley. I love you, and thank you for believing in me throughout this process and this chapter in our lives together.

BIOGRAPHY

Lieutenant Commander Sean March is a native of Raleigh, North Carolina. He attended Broughton High School in Raleigh and graduated in 2007 where he went on to study Operations Research and Computer Analysis at the United States Coast Guard Academy, in New London, Connecticut. After receiving his Bachelor's of Science Degree, and his commission as an Ensign in the U.S. Coast Guard in May of 2011, he went on to serve as an Apprentice Marine Inspector at Coast Guard Sector Los Angeles - Long Beach in California until June of 2014. From there he served as a Coast Guard Investigating Officer at Coast Guard Sector North Carolina, in Wilmington, North Carolina until July of 2017. Following his tour in Wilmington he was selected to serve as the Supervisor of Marine Safety Detachment Panama City, in Panama City Beach, Florida where he oversaw all unit operations until he was selected to attend Graduate School at North Carolina State University in August of 2020, in pursuit of his Master's of Science in Industrial and Systems Engineering. Following his time at North Carolina State University he will serve in the Coast Guard Manpower Requirements Determination Division located in Millington, Tennessee.

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INTRODUCTION

1.1 Spare Parts Supply Chain

Effectively managing spare parts logistics is critical in minimizing downtime and maximizing operational effectiveness and resiliency for service operations in military and industrial organizations whenever a component requires replacement, whether through scheduled maintenance or part failure (Xu et al. 2021). The difficulty in understanding the intricacies of a spare parts supply network lies in the irregular demand distribution and frequency where there are periods of no demand at all. The intermittent nature of spare parts demand distributions create challenges for both forecasting and inventory control, which have a significant impact on cost to the supply chain network (Syntetos et al. 2009).

Due to the forecasting challenges and the critical impact of not having equipment operational, organizations may carry large quantities of spare parts in stock so that they are immediately available when needed (McDermott et al. 2021). The consequences of not having readily available parts are significant within industry, exemplified by the estimated cost of $10,000 per hour of downtime in the aviation industry (Abbink 2015). In military applications the consequences from downtime of essential response vehicles or aircraft

not only lead to robust budget expenditures (US Government Accountability Office 2016) but also may result in loss of life, thus requiring inventory is maintained to meet constant operational readiness. The combination of these factors create high inventory carrying costs within the network, and the challenge lies within effectively managing these high costs while maintaining customer service level/operational requirements (McDermott et al. 2021). One solution in managing this challenge is the recent advancements in additive manufacturing technology to print spare parts on demand or to stock.

1.2 Additive Manufacturing

Additive manufacturing (AM) technology is the process of fabricating parts by adding and processing material layer by layer. It is commonly referred to as “3D Printing", and has several properties that have made it an attractive technology for use in manufacturing, supply chains, and business models (Rosen and Kim 2021). AM processes are able to produce complex and unique parts readily. Materials can be processed differently within different regions of the part creating unique performance characteristics, and in some applications it is possible to fabricate working mechanisms within the AM machine without the need for post-processing (Rosen and Kim 2021). Additionally, the reduced costs of AM machines and the improvement of these machines to produce comparable parts to traditionally manufactured counterparts has increased the use of this technology in public applications (McDermott et al. 2021).

AM technology emerged in the 1990s for use primarily in rapid prototyping of parts, which led to a significant decrease in product development time and cost (Rosen and Kim 2021). AM use in manufacturing final parts is more recent and over 500,000 AM machines were sold world-wide in 2017, with 14,000 of those being industry grade machines (Rosen and Kim 2021). Although not considered ‘mature’ technology yet compared to the rapid prototyping, there is an increasing use of AM production of final parts across industry and widespread interest in its application that continues to develop (Verboeket and Krikke 2019). An area that stands to benefit from the implementation of AM technology is its use in the spare parts supply chain network.

1.3 Additive Manufacturing in the Spare Parts Logistics Network

Past research shows that the implementation of AM technology into the spare parts supply chain can positively impact the network in several ways (Holmström et al. 2010; Liu et al. 2014; Khajavi et al. 2014; Eggenberger et al. 2017; Khajavi et al. 2018; Ghadge et al. 2018; Li et al. 2019; Song and Zhang 2020; de Brito et al. 2020; Westerweel et al. 2021; Xu et al. 2021; McDermott et al. 2021). AM utilization can produce lowered costs along with higher parts availability, which directly affects customer service level and operational readiness requirements (Li et al. 2019). The aerospace and medical industries have demonstrated implementation of AM in their spare parts supply chain due to each industry's respective production batch sizes, the complexity of parts, and the customization requirements that have made it economically attractive to implement AM (Khajavi et al. 2018). Further research into the aerospace spare parts supply chain showed that AM utilization reduced safety inventory, which decreased inventory holding costs across the entire supply chain. Additional economic benefits stem from the elimination of transportation costs given a network that justifies a distributed implementation of AM technology, where AM capability is at the service locations, as compared to a centralized AM network, where the AM capability resides at a distribution facility servicing multiple service locations (Liu et al. 2014).

Several factors determine the appropriate or most economical configuration of AM in the supply chain network, which are part demand classification, penalty costs of sojourn time, and the investment costs associated with the particular AM equipment (Li et al. 2019). Much of the research shows the most economical and service level advantage to mixing centralized and distributed configurations to reduce costs while maintaining a speed advantage by having higher proximity to the customer (Eggenberger et al. 2017). As AM technology develops further, so will its impact on the supply chain network.

1.4 Research Goal

The previous research conducted into this area has explored different methods and simulations focusing on the implementation of AM capabilities within the spare parts supply chain network and the impact on network performance measures such as sojourn time (back orders) and costs within the network (Li et al. 2019; Westerweel et al. 2021; McDermott et al. 2021). Much of this research utilizes real demand data and demonstrates the effectiveness

of AM within the network, however it must make simplifications that stray from what a real-world scenario would entail (Eggenberger et al. 2017). There a few papers such as Li et al. (2019) that examine products of different or heterogeneous demand classifications, which is a more applicable scenario.

This research extends McDermott (2020) and Doudnikoff (2021) specifically looking at expanding the varying AM utilization in the network, measuring performance when faced with heterogeneous demand, and evaluating a method in order to accurately measure network performance based on the heterogeneous demand inputs.

1.5 Research Paper Structure

This paper is organized as follows: Chapter 2 reviews the current literature concerning spare parts supply chains, AM technologies, demand classification, and heterogeneous demand in spare parts supply chain networks. Chapter 3 introduces the optimization model for evaluation of network performance and demand classification. Chapter 4 presents a pilot study looking at heterogeneous product demand. Chapter 5 validates the use of Index of Dispersion as a measure to be used in evaluating performance in a heterogeneous demand network and the creation of a difficulty index. Chapter 6 discusses conclusions of this research, limitations, and proposes future work and extensions.

CHAPTER

2

LITERATURE REVIEW

The previous research consists of several studies that examine the impact of AM on spare parts supply chain networks and evaluate the resulting performance metrics. This chapter highlights the critical concepts and methods covered in the literature involving AM utilization in supply chains, demand classification, demand forecasting, and index of dispersion as a possible measure of difficulty within the network.

2.1 Additive Manufacturing in Spare Parts Supply Chains

Over the past decade, researchers have explored how to optimally configure AM technology within the spare parts supply chain while understanding the trade-offs various configurations. Figure 2.1 summarizes the methods and models used in these papers and compares them to this research. While this builds upon a recent unique approach explored in McDermott (2020) and Doudnikoff (2021), this paper analyzes intermittent demand commonly found in the study of spare parts supply chains (Figure 2.1).

Type	Feature	This research	Doudnikoff (2021)	McDermott et al. (2021)	Xu et. al. (2021)	Westerweel et. al. (2021)	de Brito et. al. (2021)	Song & Zhang (2020)	Li et al. (2019)	Ghadge et al. (2018)	Khajavi et al. (2018)	Eggenberger et. al. (2017)	Khajavi et al. (2014)	Liu et al. (2014)	Holmstrom et al. (2010)
Network	Centralized	X	X	X	X	X			X		X	X	X	X	X
	Distributed	X	X	X	X				X	X	X	X	X	X	X
	Hub				X						X				
	Mixed								X						
Method	Conceptual											X			X
	Analytical							X						X	
	Simulation					X			X						
	Systems Dynamics									X					
	Markov Decision Process					X									
	Hybrid Simulation				X										
	Agent-Based Simulation				X										
	Discrete Event Simulation	X	X	X	X										
	Scenario Model (Monte Carlo)	X	X	X							X		X		
	Optimization (MILP)	X	X	X			X								
SPSC	General (hypothetical)	X	X	X				X						X	X
	Aircraft (real-world)				X					X	X		X		
	Maintenance (real-world)					X	X					X			
Metrics	Inventory Holdings		X	X		X	X			X				X	
	Cost	X	X	X	X	X	X	X	X		X		X		
	Lead Time to Fullfill Order				X										
	Backorders	X	X	X		X									
Demand	Case Study				X	X	X				X				
	Normal Distribution									X				X	
	Poisson Process							X	X						
	Discrete Uniform Distribution										X		X		
	Bernoulli Failure Distribution					X									
	Intermittent Demand	X	X	X											
	Heterogeneous Demand	X							X						

Figure 2.1: Previous research conducted that compare AM-enabled network configurations, related to this research. Note: MILP: Mixed Integer Linear Program; DCs: Distribution Centers.

2.1.1 AM Configuration

Originally proposed by Holmström et al. (2010), the two most commonly studied network configurations are centralized and distributed (McDermott et al. 2021; Xu et al. 2021; Westerweel et al. 2021; Li et al. 2019; Ghadge et al. 2018; Khajavi et al. 2018; Eggenberger et al. 2017; Liu et al. 2014; Holmström et al. 2010). There are significant trade-offs between these two designs.

In the centralized configuration, AM machines are located at distribution centers (DCs), consolidated further upstream in the supply network serving their corresponding service locations (SLs). The supply chain benefits from the reduced inventory holding costs due to the reduced need for safety stock on hand at the SLs (Holmström et al. 2010). The network can also benefit from the pooling effect by maximizing the capacity of the AM machines located upstream at the DCs as the demands from the SLs are aggregated (Ghadge et al. 2018). The disadvantages of the centralized setup are the transportation costs incurred from the DCs to the SLs and the associated lead time concerns since the parts are stored upstream (McDermott et al. 2021).

The distributed network places the AM capability at the SLs, eliminating inventory holding at the DCs and the subsequent transportation costs from the DCs to the SLs, providing a faster response time for part demand. This network configuration works best when the part demand is high enough to justify the initial investment and logistical costs to maintain the equipment at the SLs (Liu et al. 2014). A disadvantage in addition to the initial costs of this network setup is that the supply chain loses the ability to utilize the pooling effect from having the AM machines located at the DCs (Li et al. 2019).

An additional configuration discussed in the literature is the AM hub configuration which locates the AM capacity near an area of multiple downstream SLs (Xu et al. 2021; Khajavi et al. 2018). The hub setup has the advantages of the centralized network by having fewer machines with resulting lower labor/maintenance costs and the advantages of the distributed network by having lower transportation costs and reduced lead times to customers. Lastly, the mixed network studied by Li et al. (2019) showed that locating AM machines at both the DCs and SLs outperformed the strictly centralized or distributed networks when demand frequency and production rate were at specific levels (Li et al. 2019). However, further analysis of this network configuration is needed to highlight when this configuration is optimal.

2.1.2 AM Network Evaluation

There are several methods for evaluating network performance concerning the impact of AM. Holmström et al. (2010) take a conceptual approach to analyze aircraft spare parts in centralized and distributed network configurations. Eggenberger et al. (2017) conceptually evaluate four network scenarios for AM use in the automotive spare parts industry: centralized, mixed, distributed (decentralized), and outsourcing of AM. They develop a list of opportunities and challenges for real-world applications while also providing the economic prerequisites necessary for scenario feasbility (Eggenberger et al. 2017).

Liu et al. (2014) continues a conceptual analysis where they apply a standard framework, the supply chain operations reference (SCOR) model, to evaluate the performance of a hypothetical aircraft spare parts supply chain in the traditional manufacturing, AM centralized, and AM distributed scenarios. The primary measure in this research was safety stock levels maintained at each location in the different scenarios (Liu et al. 2014). Ghadge et al. (2018) take a similar approach to studying aircraft spare parts supply chains by evaluating traditional (conventional) and distributed AM network designs by their inventory management systems and aggregate inventory levels (Ghadge et al. 2018). Both studies show that implementing AM has a strong potential to reduce inventory risk within a spare parts supply chain.

Analyzing the cost trade-off between centralized and distributed configurations, Khajavi et al. (2014) use Monte-Carlo simulation to analyze total operating costs of a case study for the F-18 Super Hornet fighter jet spare parts supply chain, and Khajavi et al. (2018) extend this study to evaluate an additional hub configuration along with centralized and distributed configurations for current AM technologies. Additionally, they discuss potential impacts of AM hubs to make the spare parts supply chains of the future fully decentralized.

Li et al. (2019)'s analysis uses alternative performance metrics, where they used simulation to compare the total sojourn time and the total costs of the centralized and distributed (decentralized) supply chain configurations when adopting AM for demand to order. They also highlight the importance of the mixed configuration as the ideal setup given specific demand frequencies and AM production rates (Li et al. 2019). Song and Zhang (2020) expand on the make-to-order (MTO) analysis by looking at a make-to-stock (MTS) option examining the long-run average cost in the system. Their research also noted that the printing rate contributes to each part's average printing cost and that as the printing rate increases, both the optimal print set and the value of the AM increase to a limit (Song and Zhang 2020).

de Brito et al. (2020) employ a mixed-integer linear program (MILP) to optimize the total costs of production and distribution of spare parts for a real-world industrial case study of elevator maintenance services. The aim was to place AM machines throughout cities in Brazil optimally, minimizing total costs to the supply chain and exploring the trade-offs between printing or sourcing parts conventionally. Additionally, Westerweel et al. (2021) evaluate the trade-offs of costs, inventory holdings, and back-orders between expediting spare parts and AM printing at remote locations. They show that AM capabilities could be used in conjunction with the expediting option to manage spare parts shortages at remote locations, based on real-world Royal Netherlands Army (RNLA) operations in Mali (Westerweel et al. 2021). Both studies, however, pull from actual scenarios and look at specific sets/subsets of spare parts supply chains and lack analyzing the spare parts demand characteristics and associated supply chain configurations.

Further research by Xu et al. (2021) uses simulation to analyze AM capabilities in centralized, distributed, and hub configurations in the spare parts supply chain, evaluating performance based on average lead time to fulfill orders, the proportion of cannibalization of an order, and the average cost to fulfill an order. This study takes the analysis further by combining agent-based simulation with discrete-event simulation to test the configurations under a simulated cyber attack, emergency scenarios, and the introduction of advanced AM technologies (Xu et al. 2021). Results show that utilization of the hub configuration is less vulnerable in the face of cyber threats and emergencies.

McDermott (2020) takes a novel approach to combine the previous research to analyze the inventory holdings, costs, and backorders among centralized, distributed, and mixed AM network configurations. The model uses a MILP to identify the optimal (s, S) order up to inventory policy, then employs Monte-Carlo simulation to evaluate the inventory policy day to day over the specified time horizon, based on generated intermittent demand (McDermott et al. 2021). Their research is the first to link both the AM spare parts supply chain analysis with intermittent demand forecasting, revealing more real-world insights.

2.2 Demand Modeling

Most academic models rely on either a Poisson process (Li et al. 2019; Song and Zhang 2020) or Normal (Gaussian) distribution (Ghadge et al. 2018; Liu et al. 2014) to model demand within a spare parts supply chain in order to make assumptions and calculations more simplistic. However, as pointed out in McDermott (2020) and McDermott et al. (2021),

modeling the demand in this manner is an over-simplification and not indicative of the real-world demand distribution for a SPSC, and thus not ideal when exploring real-world problems and insights.

2.2.1 Demand Classification

The study of spare parts supply chains is a unique field due to spare parts encompassing many stock-keeping units (SKUs) with varying costs, customer service level requirements, and underlying demand patterns (McDermott et al. 2021). Each one of these characteristics requires different methods for forecasting demand and inventory management, and the selection of these methods is predominantly based on the underlying demand pattern (Boylan et al. 2008). This research follows McDermott et al. (2021) by categorizing spare parts by their associated demand patterns.

Proposed by Syntetos et al. (2005) and used in this research, spare parts demand classifications are commonly referred to as intermittent, meaning there are random demand values with large proportions of zero demands between demand occurrences over the demand horizon. Such demand becomes difficult to predict and may result in expensive obsolecent stock or unmet demand costs(Syntetos and Boylan 2005). Previous research shows that this type of demand can be categorized and split further into four classifications: Smooth, Erratic, Intermittent, and Lumpy. These classifications are derived from the demand's average demand interval (ADI) and squared coefficient of variation (CV^2). ADI is the average measure of time between non-zero demand occurrences, and CV^2 represents the relative demand variability of the non-zero demand occurrences (Syntetos et al. 2005). Figure 2.2 illustrates the four separate demand classifications and the associated ADI and CV^2 cut-off values for each of the classifications. This proposed demand categorization was designed to select the most appropriate estimation procedure and further determine the suitable forecasting technique, which we use in this research to forecast demand, similar to Tian et al. (2021) and McDermott et al. (2021).

In reality, a spare parts supply chain would face diverse demands ranging in all demand classifications. Liu et al. (2014) was the first to incorporate heterogeneous spare parts demand when implementing AM in the supply chain network. However, considered parts were MTS vice the realistic approach of MTO (Liu et al. 2014). Li et al. (2019) address this gap by investigating the AM effect on the spare parts supply chain with heterogeneous demands from multiple SLs in MTO (Li et al. 2019).

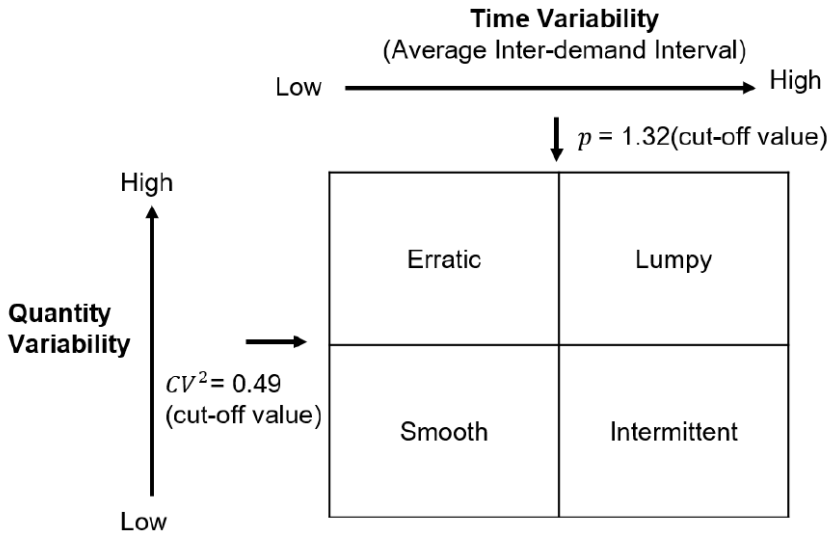

Figure 2.2: Intermittent Demand Classification by Syntetos et al. (2005). Adapted from McDermott (2020)

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2.2.2 Demand Forecasting

Due to the intermittent nature of spare parts in the supply chain, forecasting spare part demands is a complex and challenging endeavor for businesses and researchers alike. Experimentation with traditional forecasting methods such as simple exponential smoothing (SES) or simple moving average (SMA) has shown that they do not accurately predict intermittent demand and that more specialized methods must be used when examining spare parts demand (McDermott et al. 2021).

The first to address the forecasting issue with intermittent demand was Croston (1972), who developed the Croston Method, which was specifically designed to improve forecasting of intermittent time-series demand by factoring in demand size and the interval between demand occurrences. Syntetos and Boylan found a forecasting bias in Croston's Method, and they later proposed a modification, the Syntetos & Boylan Approximation (SBA), that removes the forecasting bias (Syntetos et al. 2005). They provide a framework for selecting the appropriate forecasting method (Croston's or SBA) given an intermittent demand classification (Figure 2.3). Further research by Kostenko and Hyndman analyzes these cut-off values , primarily concerning the delineation of methods to be used in smooth demand forecasting. However, Syntetos et al. (2006) show that their method still holds due to its

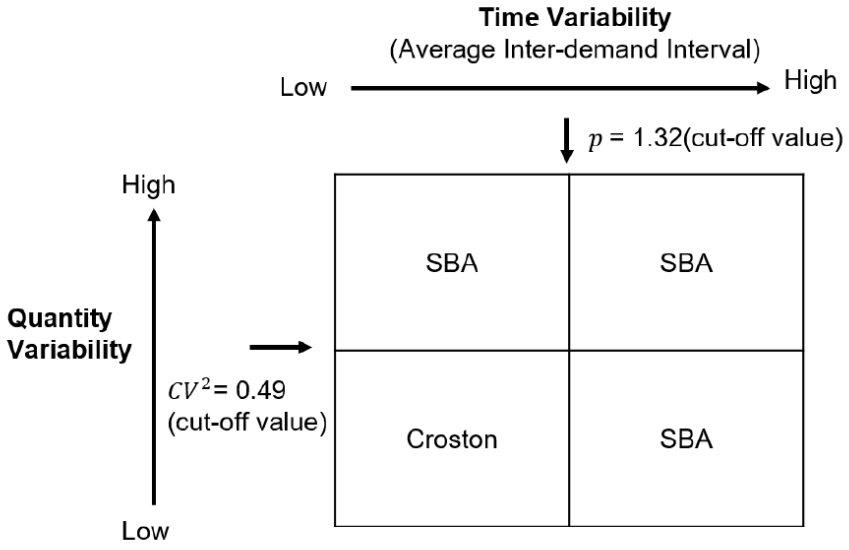

Figure 2.3: Forecasting method based on intermittent demand properties. Adapted from Syntetos et al. (2005)(McDermott 2020).

robustness across many possible underlying demand classifications.

An additional method for forecasting intermittent demand is the Markov-Bootstrap Method (Willemain and Smart 2001; Willemain et al. 2004, 2005) that forecasts the cumulative distribution of demand over a fixed lead time using a novel time-series bootstrap. They develop a modified bootstrap that was responsive to the challenging features of intermittent demand that includes auto-correlation, frequently repeated values, and relatively short series (Willemain et al. 2004). This method has the advantage of being easily modified to handle varying lead times by sampling from empirical distributions of lead times.

2.2.3 Model Overview

For this research, we used the model created in Doudnikoff (2021) that was adapted from McDermott et al. (2021). We designate the ADI, CV^2, and average demand values that determine the mean level of the non-zero demands, and generate the historical intermittent demand stream for a specified number of demand realizations over the time horizon. The simulated historical demand is used to forecast the future demand for the time horizon by applying the appropriate forecasting method, either Croston's or SBA, based on the ADI and

CV^2 of the demand (Doudnikoff 2021). To determine the (s,S) inventory policy, the "Markov Bootstrap Method" developed in Willemain and Smart (2001); Willemain et al. (2004, 2005) is used to determine the re-order point, s, and a network optimization model developed by McDermott et al. (2021) is used to determine the order up to point, S. The network performance is evaluated through Monte Carlo simulation, by generating a number of demand realizations over the time horizon and then comparing the performance to the calculated (s,S) inventory policy. We maintain the same model assumptions detailed in Doudnikoff (2021, p.21-23) and input parameters detailed in Doudnikoff (2021, p.32-33).

2.3 Index of Dispersion

One of the issues raised when studying the effects of heterogeneous demand on the AM-enabled spare parts supply chain configurations is the problem with dimensionality in isolating which parameters cause difficulty in the network when evaluating performance metrics. The input variables for a single (homogeneous) demand are the ADI, CV^2, and mean level demand (McDermott et al. 2021; Doudnikoff 2021). The ADI and CV^2 values are varied to mimic more realistic spare parts demand, and now in heterogeneous demand, there are twice as many input variables to consider for network evaluation. For additional products of heterogeneous demand, the number of input parameters to evaluate would continue to increase by a factor of two (keeping the mean level amongst all product demands constant), complicating the ability to identify which input parameters have a significant impact on the network. A solution to this problem that this research later validates as an applicable metric is to combine input parameters into one single measure: the index of dispersion.

Suppose $\{A(t), t \geq 0\}$ is defined as the counting process that tracks the number of arrivals (demand) by time t. In that case, the arrival process index of dispersion (for counts), $I(t)$, is the variance-to-mean ratio of the cumulative numbers of arrivals (demands) as given by Equation (2.1). If the network sees M_t arrivals according to a nonhomogeneous Poisson process (McConnell et al. 2021), $I(t) = 1, t > 0$:

$$I(t) = \frac{\text{Var}(A(t))}{\text{E}[A(t)]}, t > 0. \tag{2.1}$$

The index of dispersion is utilized in operations research and stochastic models for stationary point processes (Cox and Lewis 1966). In the literature, the index of dispersion is commonly found in the study of queuing theory, where it is considered one of the essential properties affecting performance measures (Liu et al. 2019). Whitt and You (2019) show

the advantage of approximating steady-state performance measures in queuing models by characterizing each arrival counting process by its index of dispersion for counts (IOD), effectively reducing the other parameters used to describe the process into a single measure. They note that IODs can be estimated from simulation output or large data sets (Whitt and You 2019). In Whitt and You (2022), they show how for renewal processes, the IOD can be approximated by asymptotic analysis. McConnell et al. (2021) use the IOD to assess whether a nonstationary queueing network model for determining uncertainty and risk will underestimate the risk to the decision-makers. Other studies use the IOD to quantify the level of uncertainty, and hence difficulty, in a stochastic arrival process in applications such as healthcare, call centers, or military spare part demand (Moore et al. 2018; McConnell et al. 2021).

2.4 Discussion

This research utilizes the model developed by Doudnikoff (2021) to effectively study the performance of AM network configurations under intermittent demand (McDermott 2020; McDermott et al. 2021). These performance metrics are then compared to the IOD values in a study of homogeneous demand and several interactions of IOD values in a study of heterogeneous demand. This research seeks to extend the real-world understanding using the Monte-Carlo simulation and model design from McDermott et al. (2021) and Doudnikoff (2021) by evaluating the AM network performance for products of heterogeneous demands and proposes a novel idea on how to describe and predict difficulty within the network for products of heterogeneous demands based on the IOD values for the underlying demand inputs.

CHAPTER

3

EMPIRICALLY ESTIMATING THE INDEX OF DISPERSION

To determine whether or not the IOD will be an adequate measure for explaining the difficulty throughout different AM configurations within our spare parts supply chain networks, we have to empirically estimate the value and analyze it against our performance metrics. The first step to empirically estimate the value of the dispersion index is to generate a set of random demand data based on the inputs of the number of observations, ADI, CV^2, and mean level of demand values. Since the intermittent demand is a stochastic process over time, based on stationary input values, theoretically the index of dispersion will eventually converge to a stationary value. This chapter presents analysis conducted to empirically estimate the theoretical IOD values for a specified range of input parameters within a specified tolerance. This analysis was conducted in Python (Van Rossum and Drake 2009) using the “tsintermittentPackage" (Kourentzes and Petropoulos 2016) to generate the set of intermittent demand given our demand parameters. Interested readers may consult the source code (March 2022).

3.1 Exploratory Analysis

The initial demand data is generated assuming that the non-zero demand arrivals follow a Bernoulli distribution and that the non-zero demands follow a negative binomial distribution (Petropoulos et al. 2014). The demand input parameters, ADI, CV^2, and mean level of demand, are required to randomly generate the intermittent demand (Kourentzes and Petropoulos 2016).

The first step in understanding the convergence of the IOD was to plot the calculated IOD value over a time horizon and analyze its behavior. Three initial trials are run for a randomly generated set of intermittent demand data with a 60 day time horizon with the following input parameters: 50 realizations, ADI $= 1.5$, $CV^2 = 2.5$, Mean Level Demand $= 3$. The convergence for the index of dispersion is analyzed by looking at the difference between the subsequent IOD values in our time horizon,

$$\Delta_{IOD}(t) = I(t) - I(t-1), \;\; t = 2, \ldots, T \tag{3.1}$$

From Figure 3.1 we see that the difference in the IOD value decreases and approaches zero as we move through the time horizon. Since the intermittent demand parameters are stationary, $\lim_{t\to\infty} \Delta_{IOD}(t) = 0$.

This process is repeated with the same input parameters except the number of realizations per trial is increased by a factor of 10, to identify the IOD convergence under increased demand sample paths. We notice that as the number of realizations per trial is increased by a factor of 10, $\Delta_{IOD}(t)$ approaches zero more quickly for our 60 day time horizon. Appendix B provides additional numerical results.

3.2 Analyzing Index of Dispersion Convergence for Varying Tolerance Levels

Understanding that the IOD value theoretically converges and how the number of realizations affects how quickly the empirically derived value approaches its stationary value, we need to establish an acceptable tolerance level for when it converges to be used in our further analysis of performance metrics within the different network designs. The process

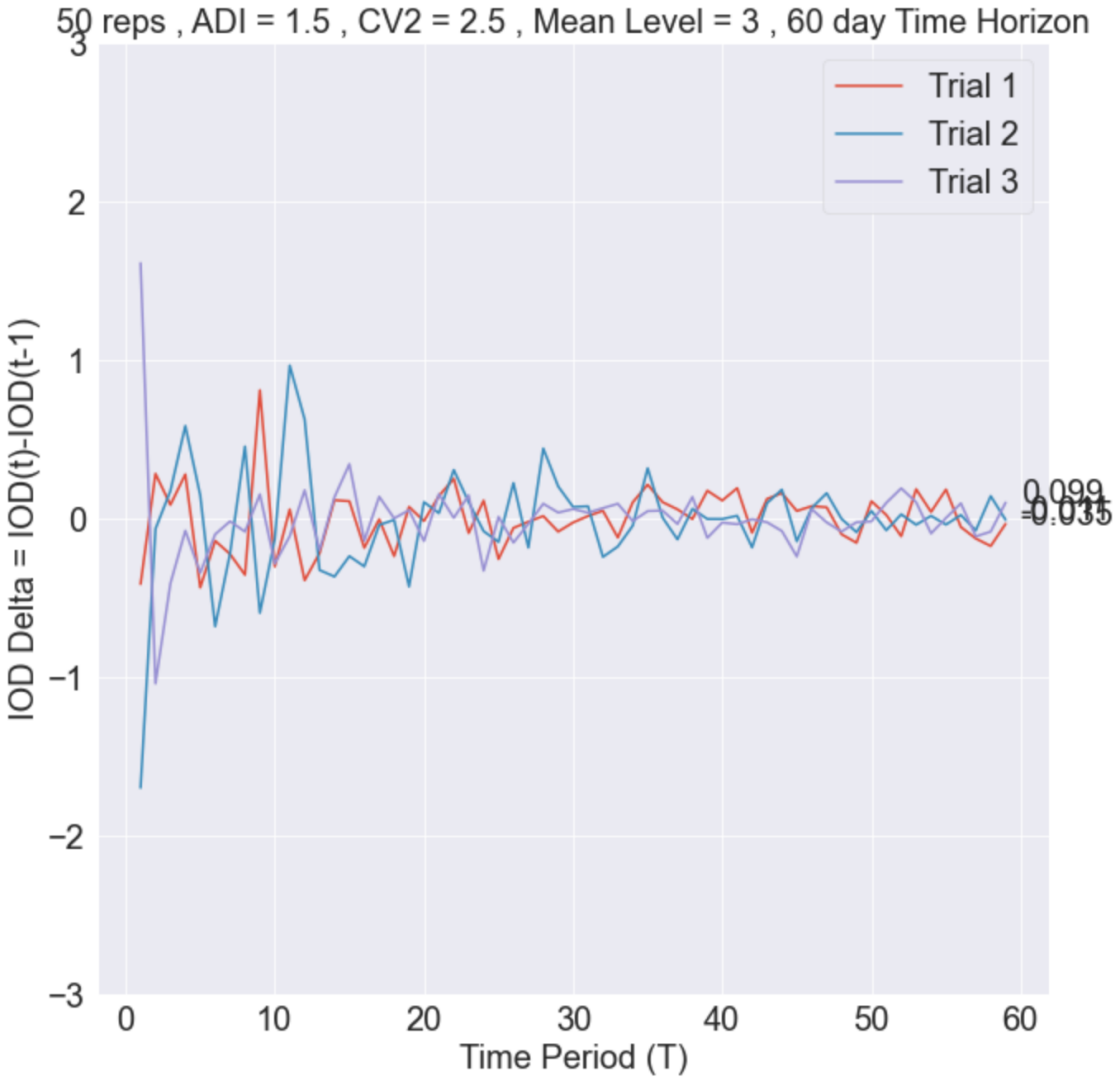

Figure 3.1: (color online) Change in IOD Value, $\Delta_{IOD}(t)$, over 60 day Time Horizon.

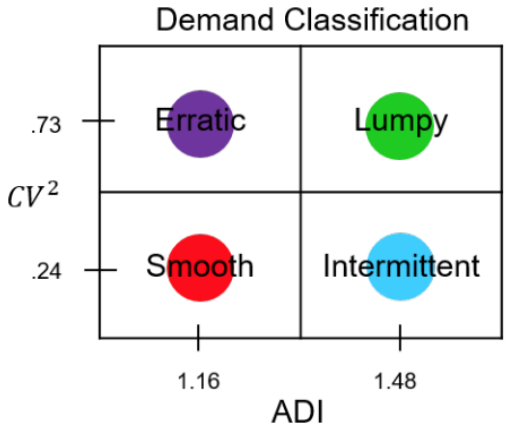

Figure 3.2: Demand Classifications with associated ADI and CV^2 Values. Adpated from McDermott (2020).

was to test tolerance values of 0.01, 0.001, and 0.0001 against randomly generated intermittent demand data using the average ADI, CV^2 values from McDermott et al.'s experimental study, shown in Figure 3.2. The results from the experimentation are described in Table 3.1.

This process is repeated for each tolerance level as the number of realizations is increased by a factor of 10. Appendix B includes these additional results. In general, as the number of realizations was increased by a factor of 10, the number of days to convergence within the specified tolerance decreased.

The results from our four demand classifications provide an understanding for the time it takes for the IOD value to converge at each tolerance level and each set of realizations. In the next section, this same analysis is expanded over a range of ADI, CV^2, mean level demand, and several realization values to provide a deeper understanding and allow a more detailed analysis to identify the ideal time (t^*) and ideal number of realizations (n^*) for IOD convergence.

3.3 Identifying Ideal Time Period (t^*) and Ideal Number of Realizations (n^*) for Dispersion Convergence

We iterate over a range of input parameters, shown in Table 3.2, to create a data set that can be studied containing the times for IOD convergence. The maximum and average

Table 3.1: The number of days that the dispersion for each demand classification converged by tolerance level.

Days to Convergence by Tolerance Level for 50 Realizations			
Demand Classification (Mean Level = 4.5)	**Tol = 0.01**	**Tol = 0.001**	**Tol = 0.0001**
Smooth (ADI = 1.16, $CV^2 = 0.24$)	70	200	585
Erratic (ADI = 1.16, $CV^2 = 0.73$)	61	145	96
Lumpy (ADI = 1.48, $CV^2 = 0.73$)	74	130	315
Intermittent (ADI = 1.48, $CV^2 = 0.24$)	64	269	1,716

Table 3.2: Input Parameters and Corresponding Range of Values to Identify IOD Convergence.

Input Parameter	**Range**
Realizations (n)	50; 500; 5,000
ADI	1 to 1.8; step size: 0.2
CV^2	0.25 to 0.95; step size: 0.1
Mean Level	3.0 to 4.0; step size: 0.5

convergence times are calculated from the demand scenarios generated for each tolerance level and set of realizations. Table 3.3 includes the results detailing the days to convergence for each set of realizations by tolerance level.

Since the purpose of the analysis is to identify the ideal time horizon (t^*) and ideal number of realizations (n^*) that we can use to reliably estimate the IOD such that we are confident $\Delta(t)$ is approximately zero, we are able to reduce the number of values in the input range and just look at the more difficult demand scenarios with higher ADI and CV^2 values contained within our original range for the increased number of realizations to save

Table 3.3: Time in Days for Convergence

Days to Convergence			
Tolerance Level	**Realizations**		
	50	**500**	**5,000**
0.01	Max: 99	Max: 73	Max: 70
	Average: 71.57	Average: 63.32	Average: 61.52
0.001	Max: 1,225	Max: 660	Max: 660
	Average: 401.08	Average: 230.42	Average: 208.17
0.0001	Max: 8,180	Max: 4,890	Max: 2,450
	Average: 3,297.67	Average: 1,820.67	Average: 1,041.17

computational time (ADI = 1.4 to 1.8 and $CV^2 = 0.55$ to 0.95). The key insight gleaned from this analysis is that as the number of realizations is increased by a factor of 10, the max convergence times for a tolerance of 0.0001 reduce from approximately 8,000 days to 2,500 days. The average and maximum times to convergence with tolerances of 0.01 and 0.001 also decrease as the number of realizations are increased.

In Figure 3.3 the combined data shows the convergence times for each of the tolerances delineated by color for the number of realizations. This shows that for a tolerance of 0.01 all the values are centered around 60 days for the time it takes the IOD to converge to a stationary value. Based on this plot we can make an evaluation as to what level of tolerance would be acceptable and what our ideal time (t^*) and ideal number of realizations (n^*) will suffice to calculate the IOD for a specified set of ADI, CV^2, and mean level values.

For our purposes of analyzing the difficulty of AM in the spare parts supply chain network by its resultant IOD value, an ideal time horizon time $t^* = 180$ days and an ideal number of realizations $n^* = 5{,}000$, is more than sufficient to be within a tolerance of 0.01 for the empirically estimated IOD value. Using 180 days as our time horizon, which exceeds our maximum values on this tolerance for all realizations, we are able to generate a library of IOD values across a range of ADI, CV^2, and mean level values. Figure 3.4 shows how the increase in the IOD value is primarily increased as the variability in the network, the CV^2 value, increases. Additional plots, showing a range of mean level values from 3.0 to 5.0 can be found in Appendix B.

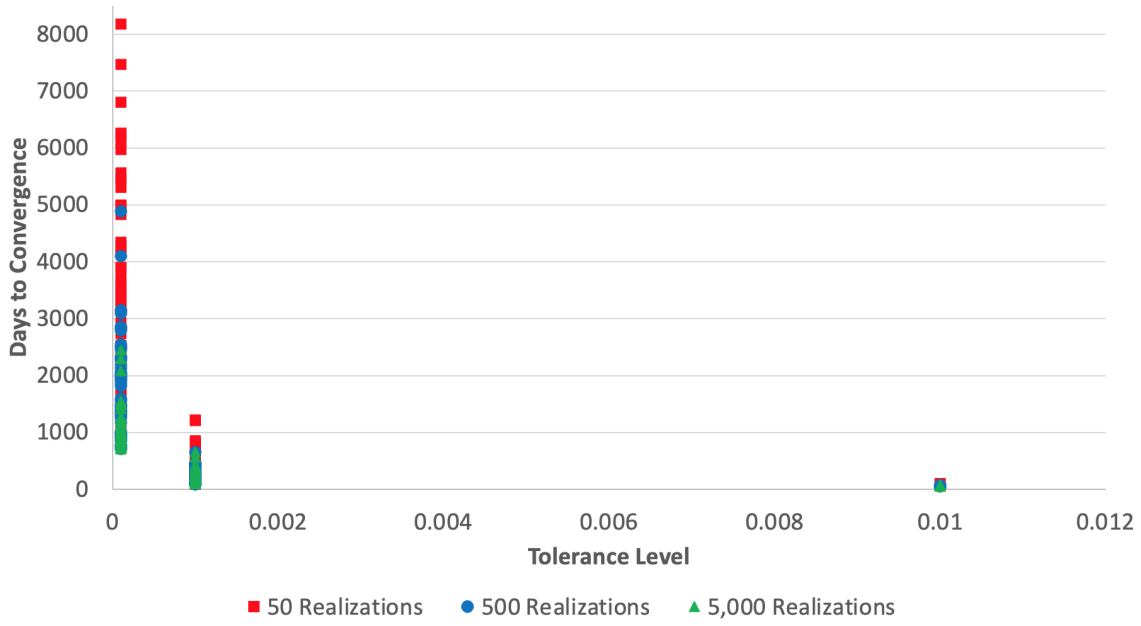

Figure 3.3: (color online) Scatterplot of Convergence Times by Tolerance Level. ADI = 1.4 to 1.8, $CV^2 = 0.55$ to 0.95, ML = 3 to 4.

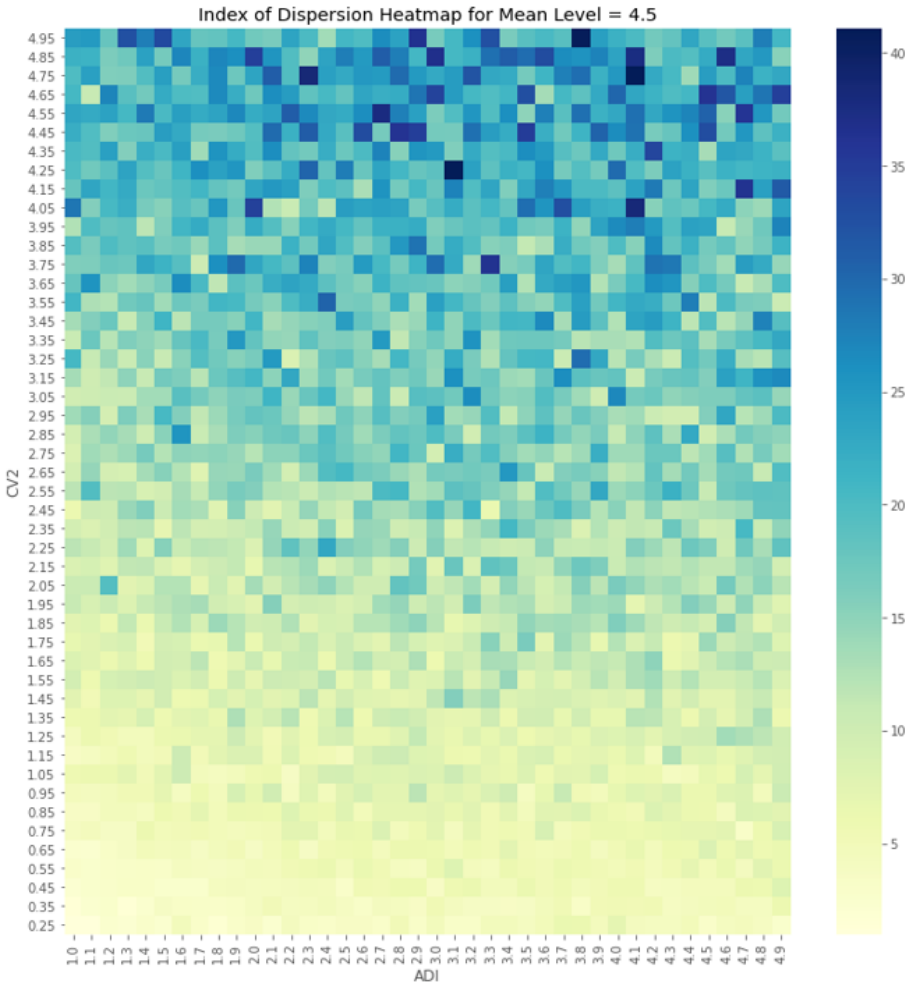

Figure 3.4: (color online) Heatmap of Dispersion Value by ADI and CV^2 Value for Mean Level = 4.5.

CHAPTER

4

PILOT STUDY - COMPARATIVE ANALYSIS OF HOMOGENEOUS DEMAND

4.1 Research Objective

Based on the previous work by McDermott (2020) and Doudnikoff (2021), we have an understanding of how the different AM network configurations perform when faced with multiple products of the same demand classification. The initial step in the exploration is to check whether the IOD would be an adequate measure to describe the difficulty for products of homogeneous demand, prior to looking at the IOD interaction value for products of heterogeneous demand. To the best of our knowledge, this is the first study to look at using this measure as a way to consolidate the variable input parameters (ADI, CV^2, and Mean Level) into a single measure to capture difficulty in the industrial application.

4.2 Design

The total average cost and total number of backorders are selected as the two performance metrics used to evaluate the efficacy of the IOD value as a measure of demand difficulty. These values are the average from the number of replications performed in a Monte Carlo simulation consistent with McDermott. The spare parts network design follows the simple 1-3-2 configuration, comprised of a traditional manufacturer, three distribution centers and two different service locations adapted from McDermott (2020) and shown in Figure 4.1. This network was chosen as the design due to the simplicity and for comparison with aligned research (Doudnikoff 2021; McDermott 2020; McDermott et al. 2021).

The design remains consistent with McDermott et al. (2021), where AM machine capabilities can only be placed at the DCs and SLs. In a 1-3-2 network design, this provides a possible 32 separate network configurations where AM capability can be implemented. For the purposes of evaluating the dispersion measure with the performance metrics of products with homogeneous demand classification, the analysis is focused on analyzing four different network configurations: No AM capability, Full AM capability, Centralized, and Distributed, as pictured in Figure 4.2. Additionally, in McDermott et al. (2021) the total demand generated for each demand classification was controlled by multiplying an average demand value by the ADI value resulting in an adjusted mean level for the demand generation. It allows for comparing similar total demand amounts between two separate demand classifications. This methodology was utilized for the analysis and the corresponding IOD values were calculated using the adjusted mean level value.

4.3 Method

For this analysis, two products of homogeneous demand classification were evaluated in each of the network configurations. The demand classifications for these products were selected based on previously studied demand parameters (Doudnikoff 2021; McDermott et al. 2021; McDermott 2020), previously shown in Figure 3.2. To generate additional data points two levels of average demand were utilized, 3 and 4.5, to test the system under increased demand consistent with the previous IOD Exploration Study completed in Chapter 3. The other parameters that are held constant in this analysis are described in Table 4.1.

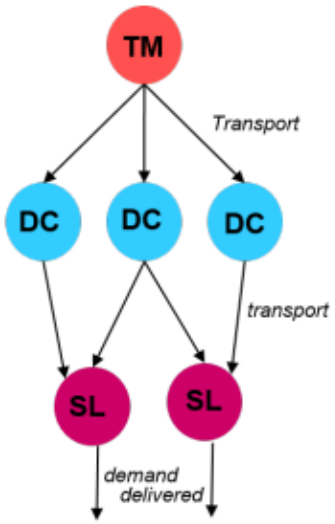

Figure 4.1: Network model representing the AM Spare Parts Logistics Network. Adapted from McDermott et al. (2021).

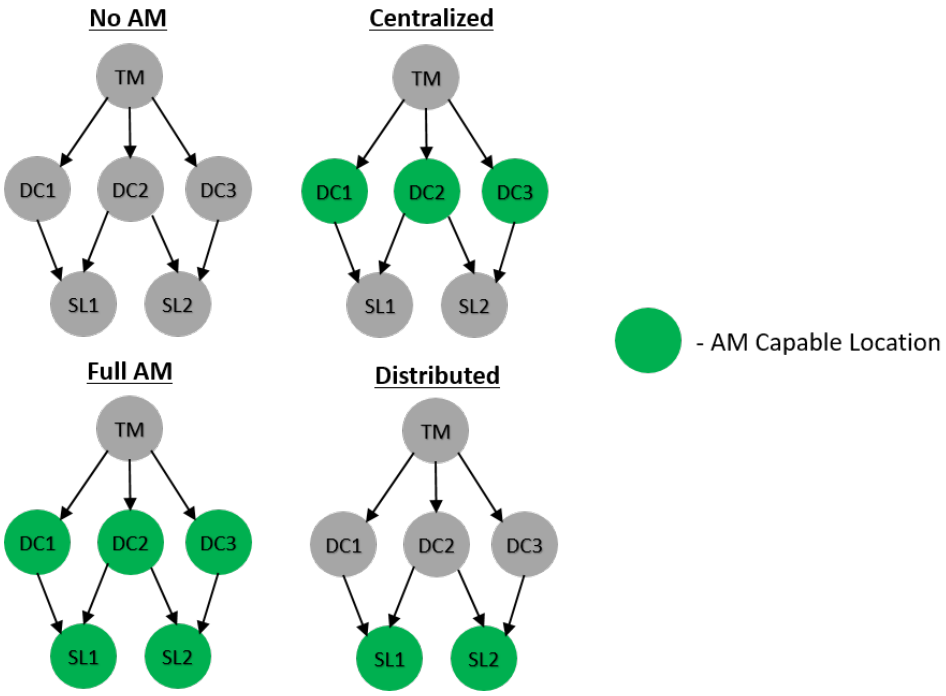

Figure 4.2: (Color online) Network Configurations: No AM, Full AM, Centralized, and Distributed. The green node represents AM Capability at that location.

Table 4.1: Model constants for initial IOD measure of homogeneous demand experiments.

Constants used in Homogeneous Demand Experiment		
Constant	**Value**	**Units of Measure**
Number of Realizations (replications)	50	n/a
Time Horizon (T)	60	days
Lead Time to DCs	7	days
Lead Time to SLs	2	days
Number of Products (G)	2	products
Cost of Transportation	25	$ per part
AM Fixed Cost	121	$ per machine per day
Inventory Carrying Cost	3	$ per part per day

Additionally, the AM capacities at each location were increased from 1 to 4 by a value of 1 to generate additional data points with the same dispersion values.

4.4 Findings

Knowing that the IOD is a measure of the variability of the number of demands (counts) divided by the expected demand (mean), and that the input parameter, CV^2, has the greater impact in driving this dispersion measure as shown in Chapter 3, we expect that as the variability within the system increases, the dispersion measure increases and the costs and backorders increase correspondingly. The details for each of these performance metrics measured by their empirically estimated dispersion value will be described in the next section.

4.4.1 Total Cost

In this analysis the total cost is considered for each network configuration under varying demand classifications. The total cost is composed of several components: AM and TM production costs, transportation costs, inventory carrying costs, and AM fixed costs. The AM fixed cost is the measure that corresponds to owning and operating an AM machine at the specific network node locations where AM capability exists (Doudnikoff 2021).

In Figure 4.3, the first noticeable distinction is between the four groupings ranging from approximately $50,000 to $67,000 and the four groupings ranging from approximately $80,000 to $100,000. The distinction in the total costs between the lower and upper two

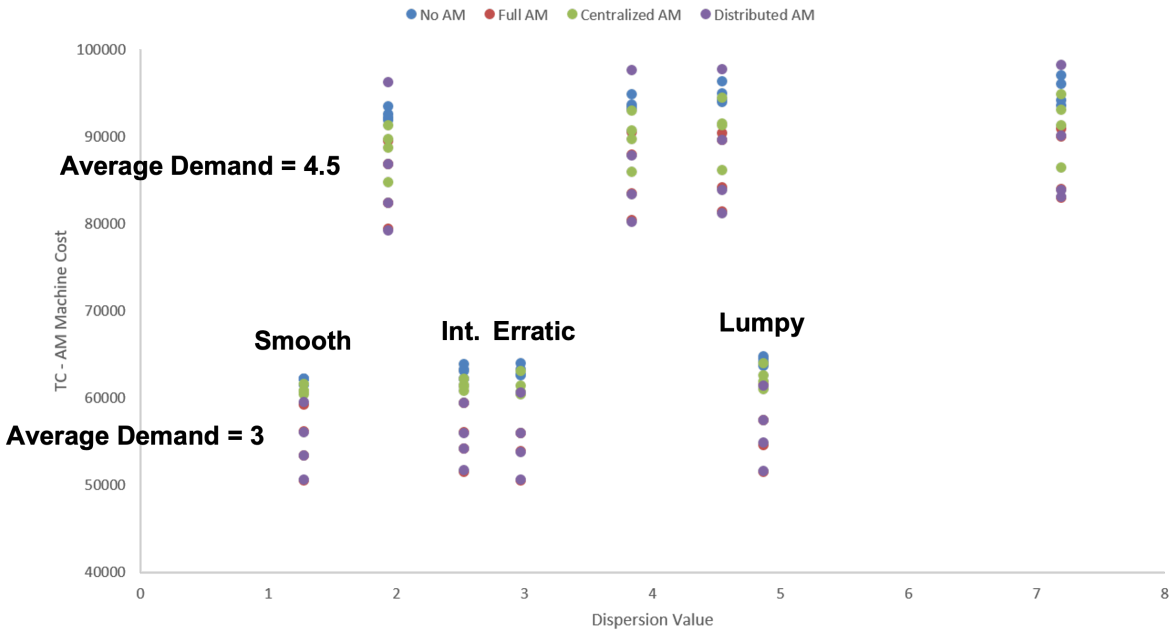

Figure 4.3: (color online) Total Cost by Dispersion Value (IOD) for each Network Configuration.

groups is due to the average demand values of 3 to 4.5, respectively, where the cost components are scaling due to the increased demand proportionally. Next, as we move from lower to increasing dispersion values in each cost group, we see that the dispersion increase is consistent with the increasing variability in the demand classifications. For both average demand level groups, the dispersion value increases corresponding to the Smooth Demand (ADI $= 1.16$, $CV^2 = 0.24$), Intermittent Demand (ADI $= 1.48$, $CV^2 = 0.24$), Erratic Demand (ADI $= 1.16$, $CV^2 = 0.73$), and Lumpy Demand (ADI $= 1.48$, $CV^2 = 0.73$) for both average demand levels. This insight is further pronounced in the dispersion value jump between the Erratic and Lumpy demand groups.

Isolating the No AM network configuration, we see marginal increases in the total cost to the network and dispersion value increases. The key finding here is that for the purposes of using the dispersion value to correspondingly measure difficulty in the AM enabled networks, total cost is not an ideal performance metric to evaluate. This is due to the varied sub-cost components that are incorporated in the total cost, such as the fixed AM cost that can vary in industrial applications from \$80,000 to \$1 million for metal AM machines (Doudnikoff 2021; Hay 2021; Greguric 2020).

Table 4.2: Correlation of Backorders and IOD Value by Network Configuration

Network Configuration	Correlation Value
No AM	0.849
Full AM	0.634
Centralized	0.694
Distributed	0.706

4.4.2 Backorders

When evaluating the backorders generated from each network configuration under the varying demand classifications, we see a positive relationship in the number of backorders and dispersion value. From Table 4.2, we see that there is a strong correlation between the value of the average total number of backorders and their corresponding dispersion values.

Plotting the results, we can visually confirm the correlation as seen in Figure 4.4. Taking the average value of the backorders from the network configurations at each dispersion value we see that the trend line has a positive slope with a value of approximately 0.60. This shows that the dispersion value would be an appropriate measure to describe the ADI, CV^2, and Mean Level values when evaluating difficulty in terms of backorders in the network, a commonly used performance metric (Doudnikoff 2021; McDermott et al. 2021; Westerweel et al. 2021).

Performing a regression analysis on the number of total backorders as a function of the dispersion value, d_i for product demand i, we test the following hypothesis that the dispersion value is a significant predictor of the number of backorders according to:

$$BO_{Total} = \beta_0 + \beta_1 d_i + \varepsilon_{BO_{Total}}. \tag{4.1}$$

With the error $\varepsilon_{BO_{Total}} \sim N(0, \sigma^2)$.
We test the null hypothesis:

$$H_0 : \beta_1 = 0,$$

against the alternative:

$$H_A : \beta_1 \neq 0,$$

For this study, the regression analysis used the same training and test sets for each of the network configurations, however, only one fold was used to calculate the test Mean Squared

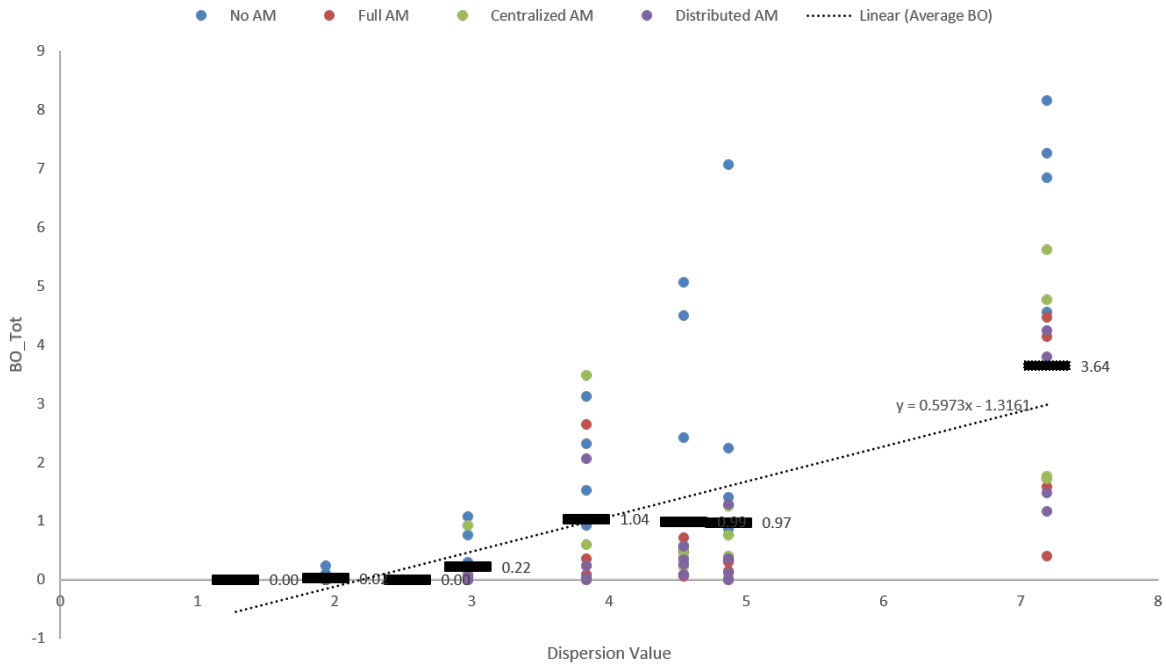

Figure 4.4: (color online) Average Total Number of Backorders by Dispersion Value (IOD) for each Network Configuration. Black rectangles represent the average of the total backorders at each dispersion value across the different network configurations.

Table 4.3: Linear Regression Analysis of the Backorders as a function of IOD Value , $\alpha = 0.05$

Linear Regression Analysis of the Backorders as a function of IOD Value, $\alpha = 0.05$			
Network Configuration	**R^2**	**MSE**	**p-value for β_1**
No AM	0.83	4.39	2.47E-10
Full AM	0.54	1.21	2.77E-05
Centralized AM	0.53	0.79	3.77E-05
Distributed AM	0.53	0.49	2.02E-05

Error (MSE). The regression analysis shows that the dispersion value is statistically significant as a predictor for the number of backorders. The full results and statistical measures are captured in Table 4.3. Of note, is the fact that in the No AM Network Configuration the R^2 value is 0.8304, showing that the IOD explains 83% of the variation in the network. This R^2 value drops for the other network configurations where AM capabilities exist, showing that the variability in the system is reduced and effectively absorbed by the implementation of AM capabilities in the network. The residual plots for each of the regression models is contained in Appendix C.

4.5 Summary

From the analysis, we showed that the total cost performance metric is not ideal for evaluating the difficulty of the AM enabled network by dispersion value. This is due to the varying cost components that are generalized in the model to be consistent with previous studies (Doudnikoff 2021; McDermott et al. 2021; McDermott 2020). Additionally, as described in Knofius et al. (2021), AM capabilities also include post-processing costs, quality checks, and high process variability that were not captured in the study.

Conversely, evaluating backorders as a measure of their corresponding dispersion value was shown to be a valid method when looking at the performance of the AM enabled network. Additionally, we showed that the variability within the network was reduced when AM capabilities were implemented as shown in the decrease in backorders consistent with the findings in McDermott et al. (2021). This was captured in analyzing the R^2 value for each of the regression functions for the different network configurations.

The AM capacity at each location was varied between 1 to 4 in this analysis at each AM capable location. However, for the purposes of evaluating IOD as a way to measure difficulty

we will only consider the No AM network configuration when looking at the networks under heterogeneous demand.

CHAPTER

5

INDEX OF DISPERSION AS A DIFFICULTY MEASURE FOR HETEROGENEOUS DEMAND

In Chapter 4 we showed that the implementation of AM into the different networks (Full AM, Centralized, and Distributed) resulted in a decrease in the variability of the networks' backorders, and determined in the No AM network that the IOD accounted for the majority of the variability in the network when facing two products of homogeneous demand classification. Our research goal is to examine products of heterogeneous demand, and determine whether an interaction of the IOD values is an adequate measure to compare performance of the network based on the number of average backorders.

As discussed in Chapter 2, very few studies examine AM-enabled SPSC performance with heterogeneous demand (Li et al. 2019). Knowing that differing demand input parameters for each of the demand classifications for products of heterogeneous demand result in different dispersion values, the research objective is to determine whether or not the interaction of IOD values is an adequate measure to evaluate difficulty in the network under

heterogeneous demand. For this experiment we only focused on the total backorders of the No AM network, since we showed in Chapter 4 that the resultant dispersion makes up the majority of the variability in the network. This is with the understanding that the No AM network will show the greatest effect of the dispersion value measured against the performance metric, in this case backorders, for the network. For this study, we utilized the same logistics network pictured in Figure 4.2.

5.1 Experimental Design

For the design of the experiment we expand upon the demand input parameters to look at the following points detailed in Figure 5.1. For the project scope, we were only considering heterogeneous demand of two products in the network. These points were selected based on the work of McDermott (2020), where they compared network configuration performances based on lowest average number of backorders.

The blue highlighted points from Figure 5.1 represent the previously studied demand parameters. For these four demand points, the average demand was varied from 3 to 4.5. Additionally, these four demand points were also only interacted with each other resulting in $\binom{4}{2}+\binom{4}{2}=12$ runs and resulting dispersion value interactions. The other points selected were compared with each other providing $\binom{12}{2}=66$ runs and dispersion value interactions. This ensures that we are challenging the system with enough differing demand classifications (ADI, CV^2, and Mean Level values) resulting in a larger range of IOD values in order to reveal insights into the dispersion interactions. The specific values are shown in Table 5.1.

Except for the number of realizations, which was increased to 500, the rest of the model parameters are held constant from Table 4.1.

5.2 Method

Based on the demand input point selections, we empirically estimate the corresponding IOD values for each heterogeneous product using the t^* and n^* selected in Chapter 3. The model developed by Doudnikoff (2021) was adapted to handle products of heterogeneous demand to generate the demand, forecast, and evaluation of the total number of backorders in the network, producing 78 experimental runs (March 2022). The total average number

Table 5.1: ADI, CV^2, Mean Level Values, and Demand Classification for points selected in the experimental study.

ADI	CV^2	Mean Level	Demand Classification
Initial Exploration			
1.16	0.24	3.48	Smooth
1.16	0.74	3.48	Erratic
1.16	0.24	5.22	Smooth
1.16	0.73	5.22	Erratic
1.48	0.24	4.44	Intermittent
1.48	0.73	4.44	Lumpy
1.48	0.24	6.66	Intermittent
1.48	0.73	6.66	Lumpy
Expanded Study			
1.25	0.25	3.75	Smooth
1.25	2.0	3.75	Erratic
1.25	3.5	3.75	Erratic
1.25	5.0	3.75	Erratic
2.0	0.25	6.0	Intermittent
2.0	2.0	6.0	Lumpy
2.0	3.5	6.0	Lumpy
2.0	5.0	6.0	Lumpy
3.5	0.25	10.5	Intermittent
3.5	2.0	10.5	Lumpy
3.5	3.5	10.5	Lumpy
3.5	5.0	10.5	Lumpy

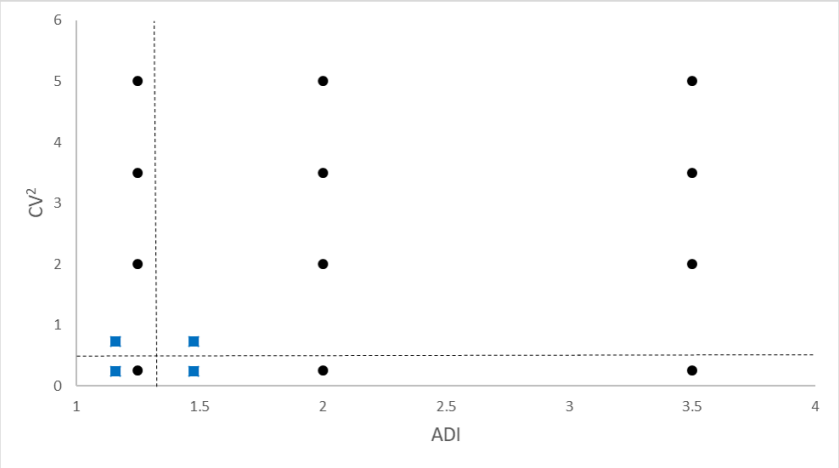

Figure 5.1: (color online) CV^2 and ADI Values utilized for Experimental Runs. Dashed lines represent the demand classification cut-off values from Syntetos et al. (2005). Blue squares represent previously studied demand parameters from Chapter 4 that only interacted with each other.

of backorders for these runs was compared to the difficulty index, which is the value of the interaction of the empirically estimated IODs for each of the distinct demand input parameters. The dispersion interactions provide this difficulty index which is a measure of how hard the set of demand difficulty is within the system, which we define as $D_{k_{i,j}}$ for $k \in \{1,2,3,4,5\}$ for the following interactions:

$$D_{1(i,j)} = (d_i + d_j), \tag{5.1}$$

$$D_{2(i,j)} = \left|d_i - d_j\right|, \tag{5.2}$$

$$D_{3(i,j)} = (d_i + d_j)/2, \tag{5.3}$$

$$D_{4(i,j)} = \lambda_i d_i + \lambda_j d_j, \text{ and} \tag{5.4}$$

$$D_{5(i,j)} = \text{Mean Level}_i\, d_i + \text{Mean Level}_j\, d_j. \tag{5.5}$$

for all pairs of products i, j where $i \neq j$. The notation λ_i, λ_j represents the estimated arrival rate for products i and j with $i \neq j$.

Equation (5.1) was selected as an interaction because it produces a difficulty index that is the sum of the individual dispersion values from the product demand, which is a measure of the combined variation of each product. The difficulty index generated from Equation (5.2) is the difference in the demand variation of each product. Equation (5.3) was selected as an interaction as it provides a difficulty index that is the arithmetic mean of the two IOD values. Knowing that the demand is a stationary point process over time, we generate a difficulty index from Equation (5.4) that is the sum of the IODs weighted by the product's sample arrival rate. Lastly, Equation (5.5) was selected because it results in a difficulty index that is the sum of the weighted IOD by the product's mean level of non-zero demand.

We then analyzed the correlation between the resultant difficulty index and the average total number of backorders, and then applied a regression analysis to determine whether or not the difficulty index was a valuable predictor for the backorders. Using a five fold cross validation technique, the data sets for each regression analysis were split into a training set consisting of 80% of the data, and test set consisting of the other 20% used to calculate the RMSE.

5.3 Results and Analysis

5.3.1 Linear Regression

The difficulty indices are analyzed for each of the $D_{k_{i,j}}$'s. From the histograms shown in Figure 5.2 we see that each of the difficulty indices are skewed right. Difficulty index D_3 was omitted, since the average of the dispersion values results in identical characteristics as D_1 multiplied by a scalar value.

We plot each of the $D_{k_{i,j}}$'s to allow for a visual understanding of how the average total number of backorders relate to each of the difficulty indices. In Figure 5.3, we see that for each of the difficulty indices, as we increase in difficulty index the number of backorders in the networks generally increases. Additionally, we notice that as the difficulty index increases there is a greater variation in the average total number of backorders.

The correlation values for each of the plots is captured in Table 5.2. Each of the difficulty indices show that they are highly correlated with the average total number of backorders in the No AM network under heterogeneous demand.

A linear regression analysis was performed on each of the difficulty indices, $D_{k_{i,j}}$. A first-order linear model was chosen as a simple linear regression model that can provide

insight into whether the dispersion interaction is a significant predictor of the average total number of backorders:

$$BO_{Total} = \beta_0 + \beta_1 D_{k_{i,j}} + \varepsilon_{BO_{Total}}, \tag{5.6}$$

where $\varepsilon_{BO_{Total}} \sim N(0, \sigma^2)$.

The resulting R^2, RMSE, and p-values for each of the $D_{k_{i,j}}$'s is listed in Table 5.3. Since the $D_{k_{i,j}}$ value was used as the only predictor for the response variable we are not surprised to find that they are all statistically significant. Based on the R^2 value we see that in interactions D_1, D_3, D_4, and D_5 that the majority of the variation in the backorders is explained by the difficulty index. Using the RMSE as the selection criteria we would say that interactions D_5, D_4, and D_3 appear to be the best performing in providing a difficulty measure that predicts the number of backorders. Figure 5.4 shows the linear trend line plotted against the data, calculated from the regression analysis.

The corresponding residual and Q-Q plots were evaluated to determine whether or not the assumptions for use of the linear regression model hold. The resulting residual and Q-Q plots for difficulty index D_1, shown in Figure 5.5, reveal several issues with the assumptions for linear regression. The first is that comparing the residuals to the fitted values in the model, they are heavily skewed right and not evenly distributed about the mean. Additionally, the Q-Q plot shows a heavy tail skewed right that does not fall along the Normal line. This means that the residuals are not Normally distributed and that the linear regression model does not explain all the positive trend we see when plotting the average total number of backorders by the difficulty index value from D_1.

Analyzing the additional residual and Q-Q plots for all the difficulty indices, we notice similar issues. Figure 5.6 shows the residual and Q-Q plots for D_4, and we see that the residual versus fitted values are skewed right and not randomly distributed about the mean of 0. Additionally, in the residuals versus leverage plot we notice that we have an influential point that falls outside the Cook's distance line. The presence of the influential points has an impact on the slope of the regression line, and affects the parameter estimate calculated for β_1.

All of the residual plots for the additional difficulty indices are found in Appendix D.

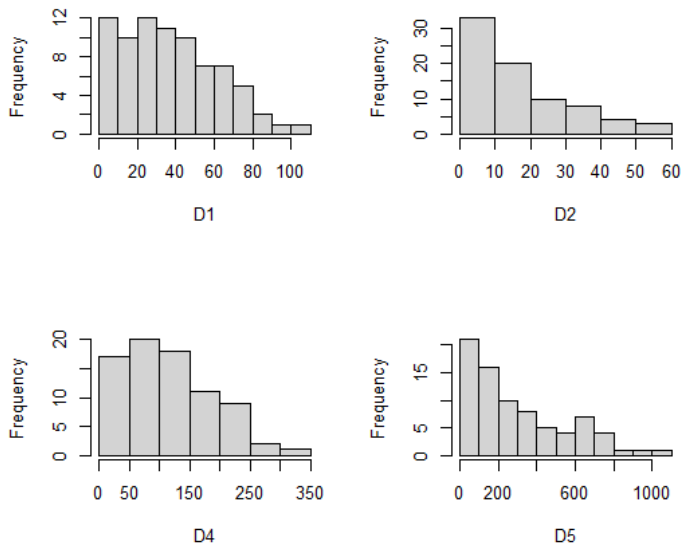

Figure 5.2: Histogram Plots of the Difficulty Index for D_k for $k \in \{1,2,4,5\}$.

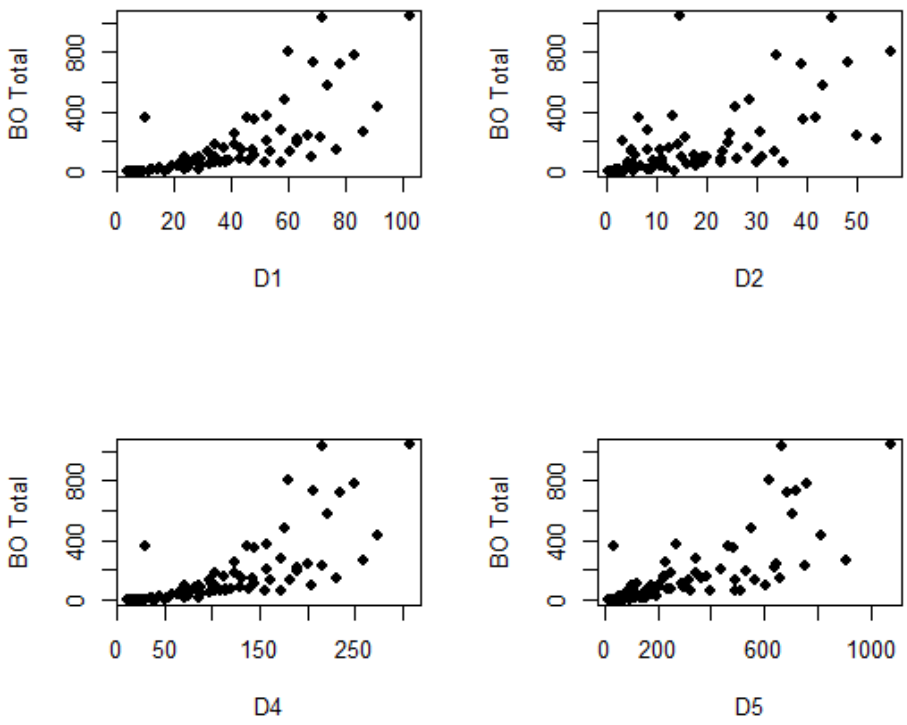

Figure 5.3: Backorders by Difficulty Index for D_k for $k \in \{1,2,4,5\}$.

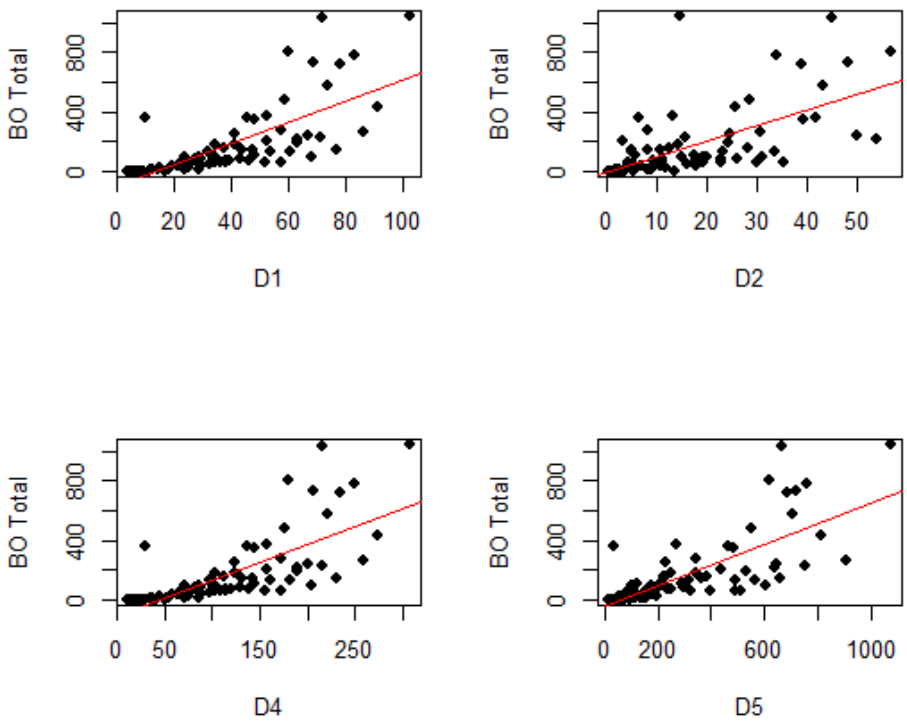

Figure 5.4: Backorders by Difficulty Index with Lines of Best Fit for each of the Difficulty Indices $D_{k_{i,j}}$ for $k \in \{1,2,4,5\}$.

Table 5.2: Correlation of Backorders with Difficulty Index by D_k

Difficulty Index	Correlation
D_1	0.73
D_2	0.63
D_3	0.73
D_4	0.78
D_5	0.75

Table 5.3: Linear regression analysis of backorders by difficulty index measure. 5-fold cross-validation with alpha = 0.05.

Difficulty Index	R^2	RMSE	p-value for β_1
D_1	0.528	167.765	5.07E-14
D_2	0.399	190.23	5.77E-10
D_3	0.528	166.959	5.07E-14
D_4	0.530	164.219	4.36E-14
D_5	0.556	157.137	4.82E-15

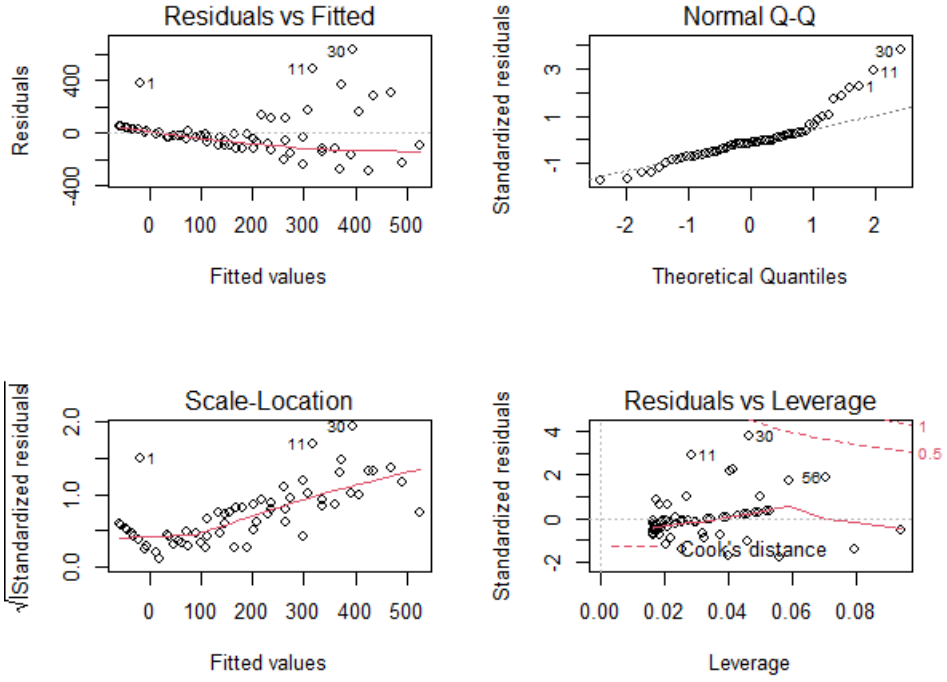

Figure 5.5: First Order Linear Model Residuals and Q-Q Plots for Difficulty Index D_1.

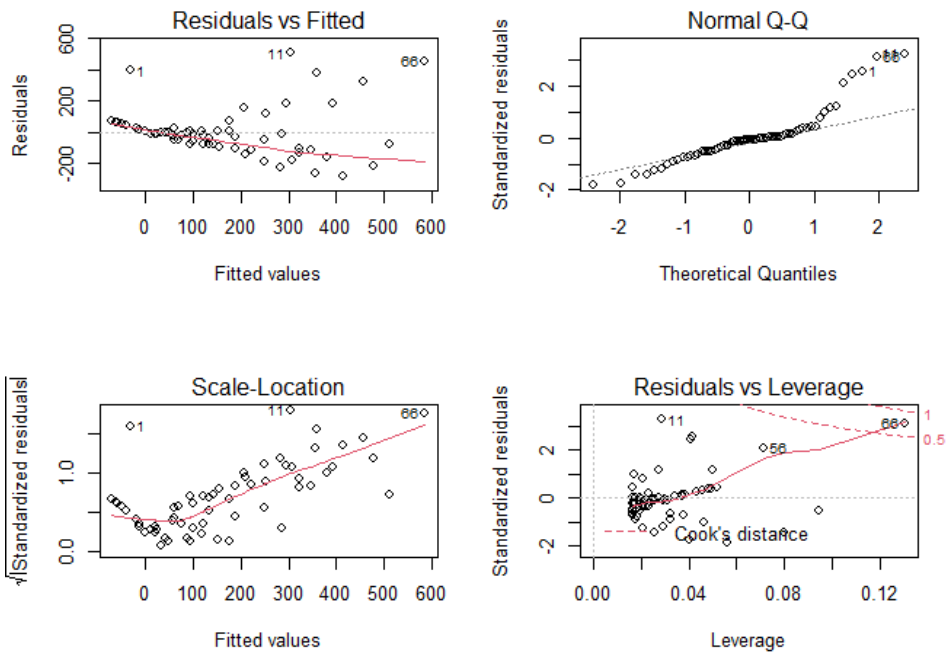

Figure 5.6: Residuals and Q-Q Plots for Difficulty Index D_4.

5.3.2 Quadratic Regression — Full Quadratic

From Figure 5.3, we identify that the data may exhibit a quadratic trend. A full second order regression is performed on the data for each of the difficulty indices against the average total number of backorders:

$$BO_{Total} = \beta_0 + \beta_1 D_{k_{i,j}} + \beta_2 D^2_{k_{i,j}} + \varepsilon_{BO_{Total}}. \tag{5.7}$$

The statistical results are contained in Table 5.4. From this analysis we see that the difficulty indices D_3, D_4, and D_5 may be useful as the majority of the variation of the backorders is explained, and the p-values for the quadratic term, $D^2_{k_{i,j}}$, are statistically significant. The residuals and Q-Q plots for this regression model are analyzed and all still exhibit some of the issues that were noted with the first order linear regression model. The residuals versus fitted values are still skewed right and the standardized residuals seem to fall further from

Table 5.4: Full quadratic regression analysis of backorders by difficulty index measure. 5-fold cross-validation with $\alpha = 0.05$.

Difficulty Index	**R^2**	**RMSE**	**p-value for β_1**	**p-value for β_2**
D_1	0.583	155.35	0.859	0.00245
D_2	0.405	176.211	0.192	0.37
D_3	0.583	151.444	0.859	0.00245
D_4	0.582	159.092	0.860	0.00305
D_5	0.583	155.44	0.338	0.0303

the Normal line on the Q-Q plot, exemplified for difficulty index D_1 shown in Figure 5.7. All of the residual plots are contained within Appendix D.

5.3.3 Quadratic Regression — Partial Quadratic

From the full quadratic model, we showed that the difficulty index measure squared, $D^2_{k_{i,j}}$ was shown to be statistically significant as a predictor while the $D_{k_{i,j}}$ first order was not. However the residuals still exhibit heteroscedasticity and the assumption that the residuals are Normally distributed did not hold. The next step in the analysis is to evaluate the partial quadratic and fit a quadratic regression to the dispersion interaction term $D^2_{k_{i,j}}$ only. The partial quadratic model is defined as:

$$BO_{Total} = \beta_0 + \beta_1 D^2_{k_{i,k}} + \varepsilon_{BO_{Total}}. \tag{5.8}$$

The results of the regression analysis are listed in Table 5.5. There is no significant change in the R^2 or MSE is noted, and as the only predictor the $D^2_{k_{i,j}}$ is shown to be a statistically significant predictor. The residuals and Q-Q plots for this regression model show no improvement over the full second order quadratic, and the assumptions do not hold. For comparison the D_1 residual plots are shown in Figure 5.8.

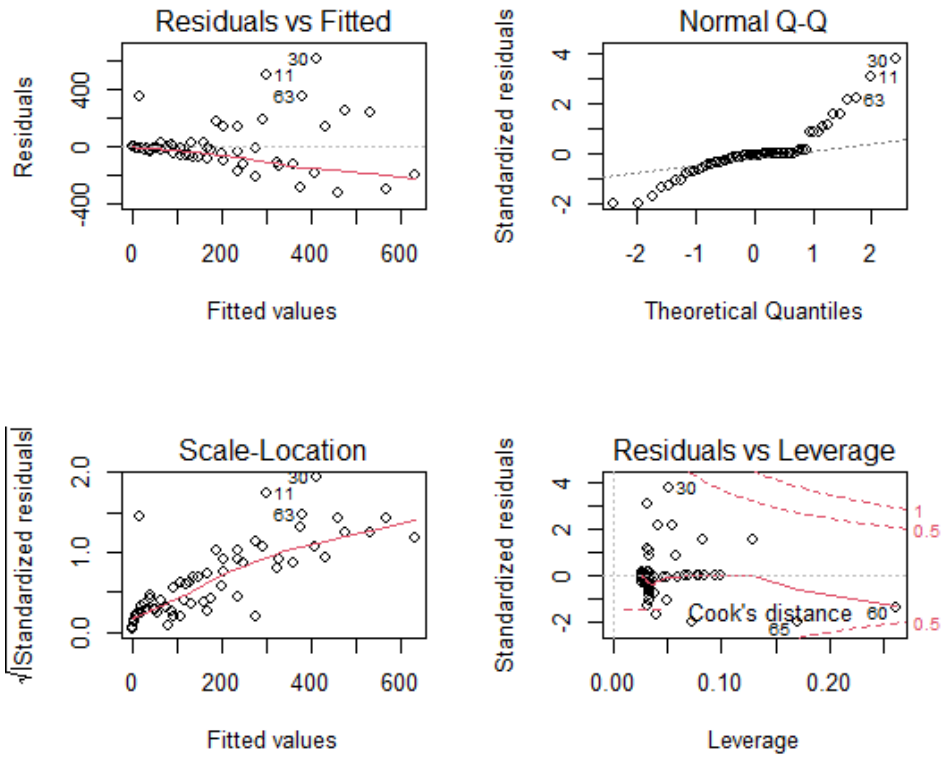

Figure 5.7: Residuals and Q-Q Plots for Full Quadratic Regression Model of Backorders by Difficulty Index D_1^2 and D_1.

Table 5.5: Partial quadratic regression analysis of backorders by difficulty index measure. 5-fold cross-validation with $\alpha = 0.05$.

Difficulty Index	**R^2**	**RMSE**	**p-value for β_1**
D_1	0.583	154.739	4.55E-16
D_2	0.391	169.47	9.21E-10
D_3	0.583	157.912	4.55E-16
D_4	0.582	152.267	4.83E-16
D_5	0.578	151.211	6.90E-16

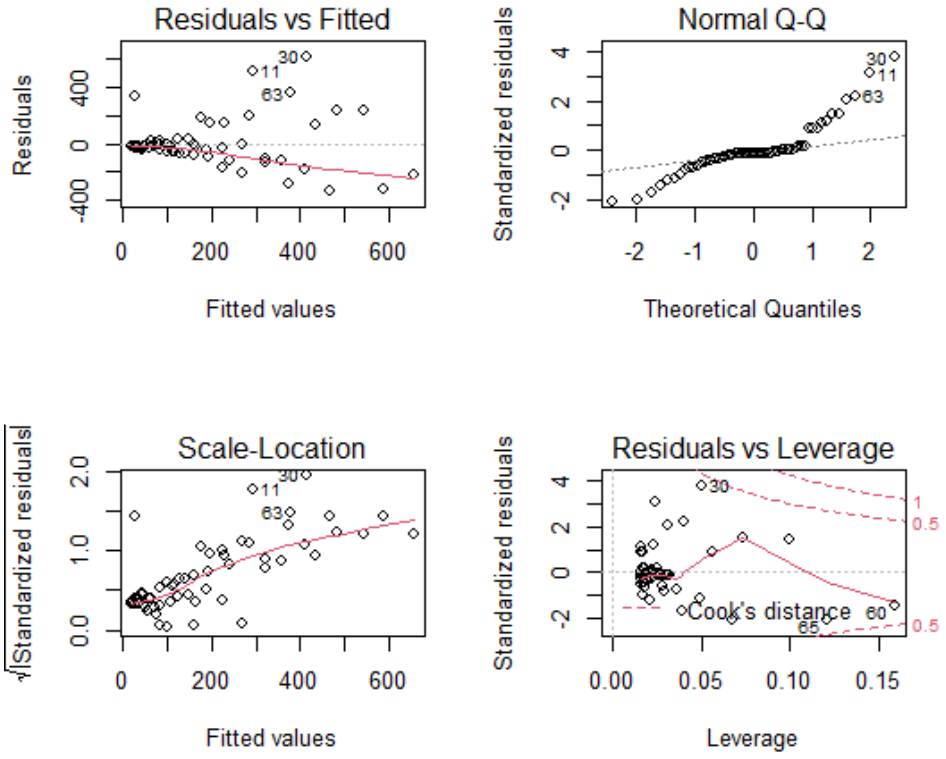

Figure 5.8: Residuals and Q-Q Plots for Partial Quadratic Regression Model of Backorders by Difficulty Index D_1^2 .

Table 5.6: Linear Additive regression analysis of backorders by difficulty index measure with sum of mean level values. 5-fold cross-validation with $\alpha = 0.05$.

Difficulty Index	R^2	RMSE	p-value for β_1	p-value for β_2	VIF
D_1	0.532	162.579	1.75E-10	0.416	1.81
D_2	0.426	192.589	4.40E-07	0.0614	1.269
D_3	0.532	164.58	1.75E-10	0.416	1.81
D_4	0.532	162.48	1.36E-10	0.354	1.842
D_5	0.611	150.874	1.53E-13	0.00166	2.587

5.3.4 Linear Regression — Additive Model with Sum of Mean Level Values

Based on Equation (2.1), we know that there is a natural relationship between the denominator of the IOD values and the mean level of the demand. We hypothesize that the mean level of the total demand may affect the difficulty of the demand within the network. From this the next step is to create an additive linear regression model that models the average total number of backorders as a function of the dispersion interaction value $D_{k_{i,j}}$ added with the sum of the mean level ($ML_{i,j}$) values:

$$BO_{Total} = \beta_0 + \beta_1 D_{k_{i,j}} + \beta_2 (ML_i + ML_j) + \varepsilon_{BO_{Total}}. \tag{5.9}$$

These results are listed in Table 5.6. From these results we see that the $D_{k_{i,j}}$ is shown to be statistically significant as a predictor and in the case of dispersion interaction D_5 the sum of the mean levels is also statistically significant. Since D_5 is the interaction of the dispersion value weighted by the mean level it is intuitive that there are issues with collinearity between these two predictors in the model due to Equation (2.1). This is why the variance inflation factor (VIF) increases to approximately 2.6. Overall there is improvement in the residual plots with the assumption that the residuals are Normally distributed. However, the residuals versus fitted values still show that they are skewed to the right. For reference, the residuals and Q-Q plots for this regression model for the D_1 interaction are shown in Figure 5.9.

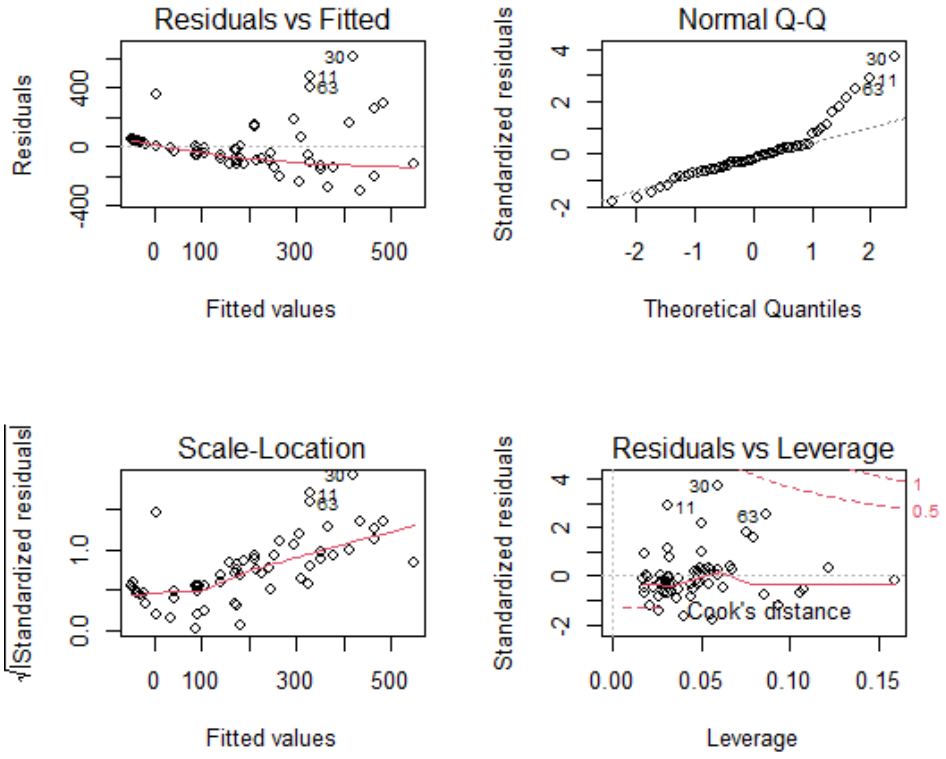

Figure 5.9: Residuals and Q-Q Plots for Additive Linear Regression Model from Equation (5.9) and D_1.

5.3.5 Linear Regression — Box-Cox Transform of Backorders as function of Difficulty Index

To address the heteroscedasticity that we found in the residuals of the linear regression model, we utilize the Box-Cox Transformation by transforming the response variable, average total number of backorders (Millard 2022). The optimal hyperparamater λ is determined by the maximum log likelihood shown in Figure 5.10. The results are described within Table 5.7. We see from these results that the Box-Cox transform model shows all of the D_j predictors as statistically significant and we see a substantial increase in the R^2 values for indices D_1, D_3, D_4, and D_5. For these interactions approximately 70% of the variation in the backorders is explained by the difficulty index for the underlying demand classifications. Additionally, an analysis of the residual plots and Q-Q plot show that the assumptions for the regression model hold and that the residuals are normally distributed. This provides strong evidence that this would be an acceptable method to compare the difficulty indices as an explanation for the number of backorders. Figure 5.11 presents the residuals and Q-Q plots for D_1 in this regression model.

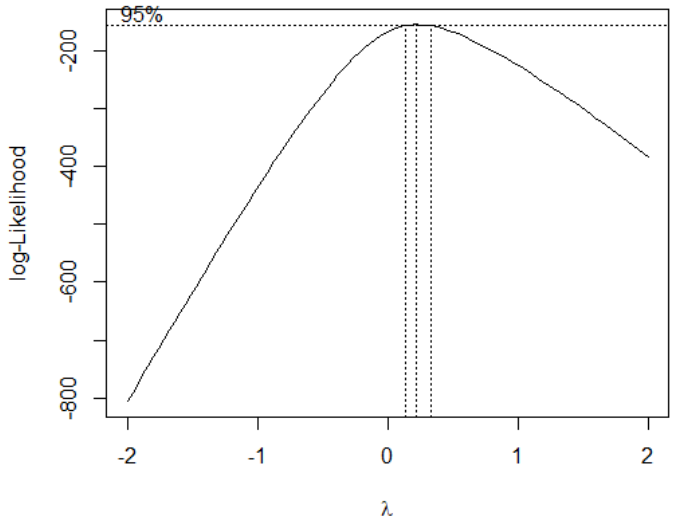

Figure 5.10: Maximum Likelihood Plot for λ Values for Box-Cox Transform of Backorders. Optimal $\lambda = 0.2626$.

Table 5.7: Linear Regression Analysis of Box-Cox Transform of the Backorders as a function of Difficulty Index, $\alpha = 0.05$, $\lambda = 0.2626$.

Difficulty Index	**R^2**	**RMSE**	**p-value for β_1**
D_1	0.736	2.942	2.20E-16
D_2	0.530	3.989	2.86E-13
D_3	0.761	2.827	<2.20E-16
D_4	0.732	2.859	<2.20E-16
D_5	0.672	3.410	<2.20E-16

5.4 Findings

We see from the heteroscedasticity in the first order linear regression model's residual plots and deviations from the Normal line in the Q-Q plots for the difficulty indices $D_{k_{i,j}}$ for $k \in \{1,2,3,4,5\}$ that the assumptions for the first order linear regression model do not hold. Analyzing the full quadratic, partial quadratic, and linear additive model did not significantly improve upon the first order linear regression, in terms of addressing the heteroscedasticity. However, when applying the Box-Cox transform, we showed that the heteroscedasticity issue in the residuals was absolved and that the difficulty indices D_1, D_3, and D_4 are the most prominent candidates to show that the difficulty index is a valid measure for explaining demand difficulty's effect on the total number of backorders within the SPSC network.

While the difficulty index may be a significant predictor for the average number of backorders in the network, it does not fully explain the positive trend noted in Figure 3.3. This shows that there are other factors present within the SPSC network that determine the difficulty of the network present.

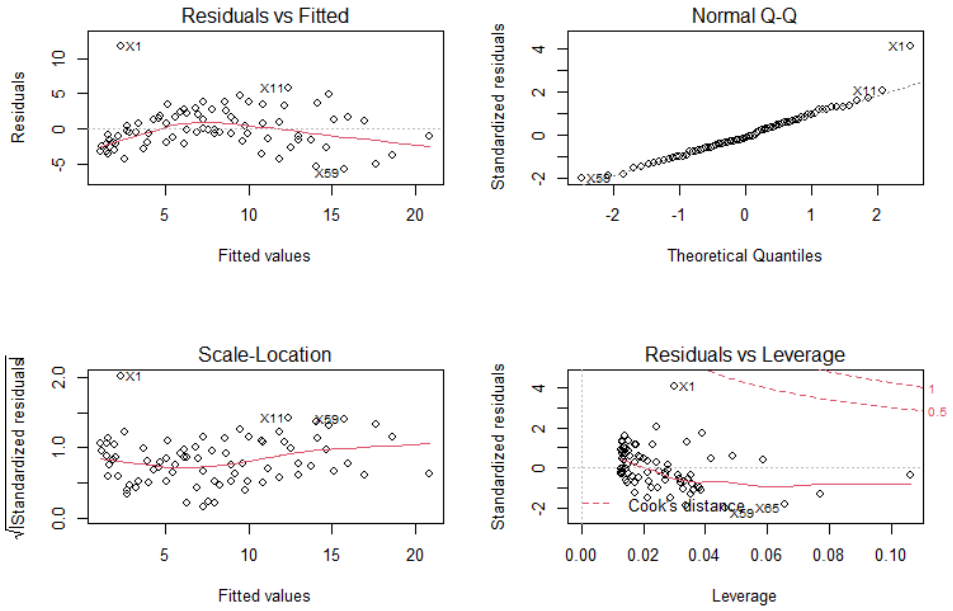

Figure 5.11: Residuals and Q-Q Plots for Box-Cox Transform Linear Regression Model of Backorders by Difficulty Index D_1.

CHAPTER

6

CONCLUSIONS

6.1 Summary of Results

The goal of this research is to determine whether the IOD value and difficulty index generated from the interaction of IOD values is an adequate measure for describing the demand difficulty in the AM SPSC Network, based on the performance metrics of average total cost and average total number of backorders. This work empirically estimates the IOD value for demand input parameters (ADI, CV^2, and Mean Level), incorporating the demand characteristics of spare part demand. It then takes an exploratory analysis into the IOD for a single (homogeneous) demand classification in an AM capable network and compares this measure through four of the network configurations (No AM, Full AM, Centralized, and Distributed) and compares this value to the performance metrics. After identifying several implications to utilizing the measure in AM enabled networks, we proposed mathematical interactions of the IOD values resulting in a difficulty index that was analyzed for a larger range of heterogeneous spare parts demand classifications. This resultant difficulty index was evaluated against the average total number of backorders within the No AM network configuration. Regression analysis of the Box-Cox transform reveals that difficulty indices

D_1, D_4, and D_5 are the most promising in terms of providing a difficulty measure for demand in the AM enabled SPSC.

Using the demand classification proposed by Syntetos et al. (2005) and a model used for AM in a SPSC network designed by McDermott (2020) and expanded by Doudnikoff (2021), we empirically estimate the IOD value for the given demand input parameters. In empirically estimating the IOD value, we determine the ideal time (t^*) and the ideal number of realizations (n^*), based on a 0.01 tolerance for convergence. This allows us to consolidate the demand classification input parameters into a single value based on the ADI, CV^2, and Mean Level values.

We then analyze a homogeneous dual product AM enabled network comparing the average total costs and the average total backorders for the No AM, Full AM, Centralized, and Distributed AM network configurations against the empirically estimated IOD values for a set of demand classifications adopted from McDermott et al. (2021). Our findings show that the IOD value was not adequate for describing difficulty in terms of total costs due to the varying cost components driven by the demand input parameters. As the demand increased in mean level, there was a proportional scaling up of difficulty in the total costs based on production, inventory carrying, and transportation costs. This showed that the IOD value was not an appropriate measure in describing the difficulty faced by each of the network configurations in terms of cost. However, in terms of the average total number of backorders faced by each system, we did see evidence of the IOD value being an acceptable measure of difficulty to describe the network. Additionally, we showed that the incorporation of AM into the SPSC network reduced the variability of the network described by the IOD value.

From our study of dual products under homogeneous demand, the IOD value accounted for the majority of the variability in the No AM network configuration. Since our research objective was to determine whether the interaction of IOD values would be an acceptable measure to describe difficulty in the heterogeneous demand network, we only looked at two products of heterogeneous demand in the No AM network configuration. We proposed then evaluated five separate IOD value interactions that provided a difficulty index ($D_{k_{i,j}}$) for each of the corresponding IOD values and varied the range of demand inputs to cover a larger range of demand classifications, consistent with previously studied literature (McDermott 2020; Syntetos and Boylan 2001). An initial comparison of the backorders versus the difficulty indices showed that there is a high correlation under heterogeneous demand in the No AM network configuration.

We performed a first order linear regression analysis of backorders as a function of the difficulty index $D_{k_{i,j}}$, and analyzed the results for each of the indices. An analysis of the

residual plots and Q-Q plots from each of the difficulty indices showed that our fundamental assumption for the linear regression analysis did not hold due to heteroscedasticity in the residual versus fitted plots for each of the dispersion interactions. Also, the Q-Q plots revealed that our residuals were not Normally distributed. This showed that the difficulty indices, $D_{k_{i,j}}$, do not fully explain the positive trend that we identified in the backorders versus the difficulty index. A full second order quadratic, partial quadratic, and linear additive model were also analyzed, and did not show improvement in terms of our regression assumptions.

However, when we applied the Box-Cox transform to the average total number of backorders, we were able to correct the heteroscedasticity issue in all of our difficulty indices, $D_{k_{i,j}}$. From there, we select the sum-based (D_1), or weighted sum using demand arrival rate or mean level (D_4, D_5), interactions as our most prominent candidates in determining a difficulty index based on the IODs to characterize demand difficulty in terms of backorders within the SPSC network.

Although the difficulty indices showed that they explain part of the difficulty in the SPSC network, there are other factors such as network design, production capacities, lead times, and transportation concerns as well that may contribute to the number of backorders in the network.

6.2 Limitations

There are several limitations associated with this study in addition to the limitations proposed in Doudnikoff (2021). They are described below:

1. **Two Product Analysis**

   The model used was incorporated from Doudnikoff (2021), and adapted to study only two products under heterogeneous demand. In reality a typical supply chain may consist of a much larger number of SKUs of spare parts, with varying demand classifications. The two products were chosen as this allows us to study the effect of heterogeneous demand in the SPSC under simplified conditions.

2. **Comparable AM Capacity in the Network**

   In our pilot study from Chapter 4, the AM capacity at each of the AM enabled network configurations was varied from 1 to 4 at each AM enabled location. In our network there are five possible AM capable locations and so with an AM capacity of 1, the Full

AM network would have five AM machines compared to the Distributed AM network that only had two AM machines. Since our study was focused on how the IOD value described the performance of the network in terms of total cost and backorders, we were not concerned with the ensuring the AM capacities were equivalent throughout. However, to study the difficulty indices comparatively across different network configurations the least common multiple for number of AM machines in the network would be required as the AM capacity given the current source code (March 2022).

3. **Coverage of Total Demand Space**

   For the experiment in Chapter 5, we looked at 16 points within the demand space (ADI, CV^2) that were consistent with the values explored in previous research (McDermott et al. 2021; Doudnikoff 2021). From these demand points we were unable to distinguish which dispersion value interaction is the best in determining a difficulty index that can be used to describe the total number of backorders.

4. **Unable to Distinguish Best Difficulty Index**

   Since the experiment only examined two products and looked at only 16 distinct points in the ADI, CV^2, and mean level demand space, we were unable to distinguish which of the difficulty indices was the best for describing demand difficulty.

6.3 Future Work

Although our research showed that the difficulty index did not fully describe the difficulty of the heterogeneous demand network, based on our results, difficulty indices D_1,D_4, D_5—the sum based, or weighted sum using demand arrival rate or mean level—appear to be the most promising measures. This is due to their interpretability and overall performance when evaluated using linear regression analysis and Box-Cox transformation. They had the lowest MSE values compared to the other difficulty indices, when using regression on the Box-Cox transformation on the data. Follow on research should look at incorporating additional measures for difficulty in the network and performing regression analysis to see which ones are most statistically significant, and identify whether the measures exhibit any signs of multicollinearity with additional predictor variables.

In our analysis, we saw that as the difficulty index increased the variation in the average total number of backorders began to increase. Our study looked at a total of 20 separate tuples of demand input parameters, however increasing the range of ADI, CV^2, and Mean

Level values may reveal more beneficial insights that were not identified in this research. Specifically, it may be useful to repeat the analysis using demand parameters from an industrial data set.

The overarching goal of this research was to reduce the dimensionality when analyzing multiple products of heterogeneous demand in the AM enabled SPSC. Incorporating more than two products and evaluating the dispersion interactions may provide further insights into the validity of the difficulty index to describe the network. This could then be extended into evaluating for AM enabled networks including a Full, Centralized, and Distributed network. However, to appropriately compare results the AM capacity of the network must be a least common multiple so that the total number of machines present in the system is constant throughout.

In previous work by McDermott (2020, p.45-48), assertions about the best AM configuration were drawn from given homogeneous demand types, determined by their ADI and CV^2 values. Overlaying the corresponding IOD values based on these same demand input parameters would show what ranges of IOD favor a particular network configuration.

Determining the best method for determining a difficulty index based on the dispersion values allows for future application in operational planning and guidance for AM opportunities within SPSC networks. The model adapted from Doudnikoff (2021) may be adapted to fit differing SPSC network, however there are many inputs and operational conditions that must be accounted for by stakeholders such as AM machine costs, printing costs, lead times, transportation costs, network structure, etc. Having a definitive difficulty index allows for application as a heuristic to determine whether or not AM may be beneficial in certain parts of the network, based only on the demand data of the spare parts. From this, the resultant difficulty index can be found based on the IODs of the spare parts effectively determining the areas for AM implementation into the network to decrease demand difficulty, making AM implementation more effective.

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APPENDICES

APPENDIX

A

ACRONYMS AND DEFINITIONS

A summary of all acronyms and definitions is documented in Table A.1.

Table A.1: List of acronyms and associated definitions.

Acronym	**Definition**
ADI	Average demand interval
AM	Additive manufacturing
BO	Backorder
CV^2	Squared coefficient of variation
DC	Distribution center
IOD	Index of dispersion
MILP	Mixed integer linear program
ML	Mean level of demand
MSE	Mean squared error
MTO	Make-to-order
MTS	Make-to-stock
RMSE	Root mean squared error
(s,S)	Reorder point and order-up-to level inventory policy
SBA	Syntetos & Boylan approximation
SCOR	Supply chain operations reference
SES	Simple exponential smoothing
SKU	Stock-keeping-unit
SL	Service location
SMA	Simple moving average
VIF	Variance inflation factor

APPENDIX

B

EMPIRICALLY ESTIMATING DISPERSION FOR INTERMITTENT DEMAND

B.1 Index of Dispersion

Figure B.1 shows the IOD value for three separate trials over a 25 day time horizon with an ADI = 1.5, $CV^2 = 2.5$, and ML = 3.

B.2 Change in Index of Dispersion

Figures B.2–B.5 detail the change in the IOD Value $I(t) - I(t-1)$ over a 60 day time horizon with an ADI = 1.5, CV^2 =2.5, and ML = 3 for 500, 5,000, and 50,000, and 500,000 repetitions for 3 separate trials.

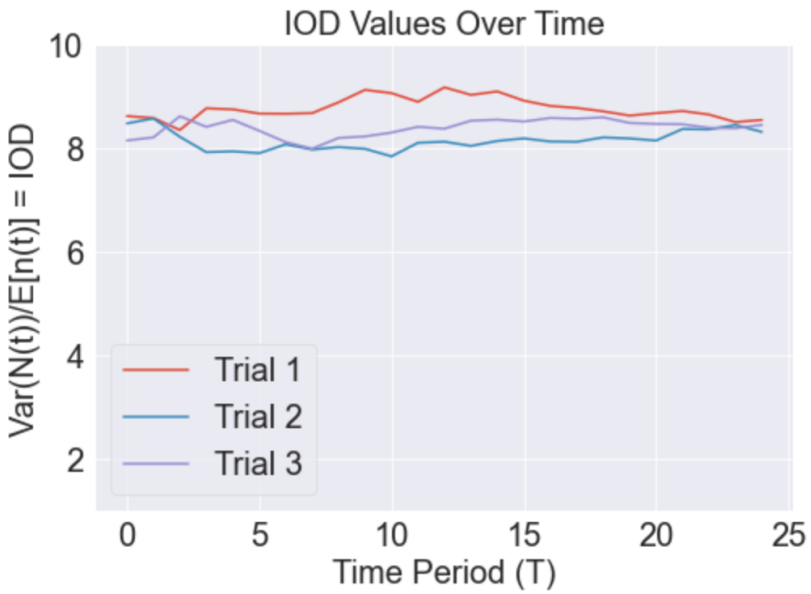

Figure B.1: (color online) IOD Values over 25 day time horizon. ADI = 1.5, $CV^2 = 2.5$, ML = 3

B.3 Days to Convergence

For the initial look at the number of days to convergence we utilized the average demand classification criteria from McDermott (2020). Tables B.1–B.3 show the time in days to convergence within the specified tolerance levels for their respective number of replications.

B.4 Empirical Estimates of the Index of Dispersion

The heat maps in Figures B.6–B.9 detail the IOD value over a range of ADI and CV^2 values for varying MLs of 3.0, 3.5, 4.0, and 5.0.

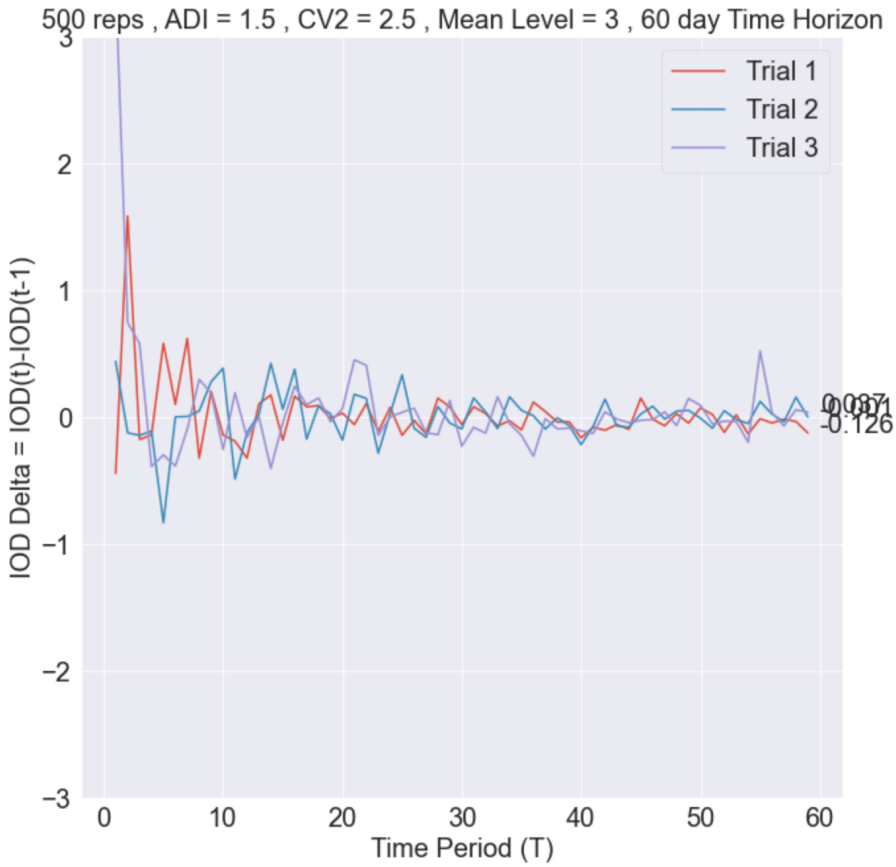

Figure B.2: (color online) IOD Delta over 60 day time horizon, 500 realizations.

Table B.1: Days to Convergence by Tolerance Level for 500 Replications

Demand Classification	**Tol = 0.01**	**Tol = 0.001**	**Tol = 0.0001**
Smooth	61	78	357
Erratic	61	64	697
Lumpy	61	100	203
Intermittent	66	116	276

Table B.2: Days to Convergence by Tolerance Level for 5,000 Replications

Demand Classification	**Tol = 0.01**	**Tol = 0.001**	**Tol = 0.0001**
Smooth	61	69	189
Erratic	61	61	241
Lumpy	61	68	186
Intermittent	66	85	226

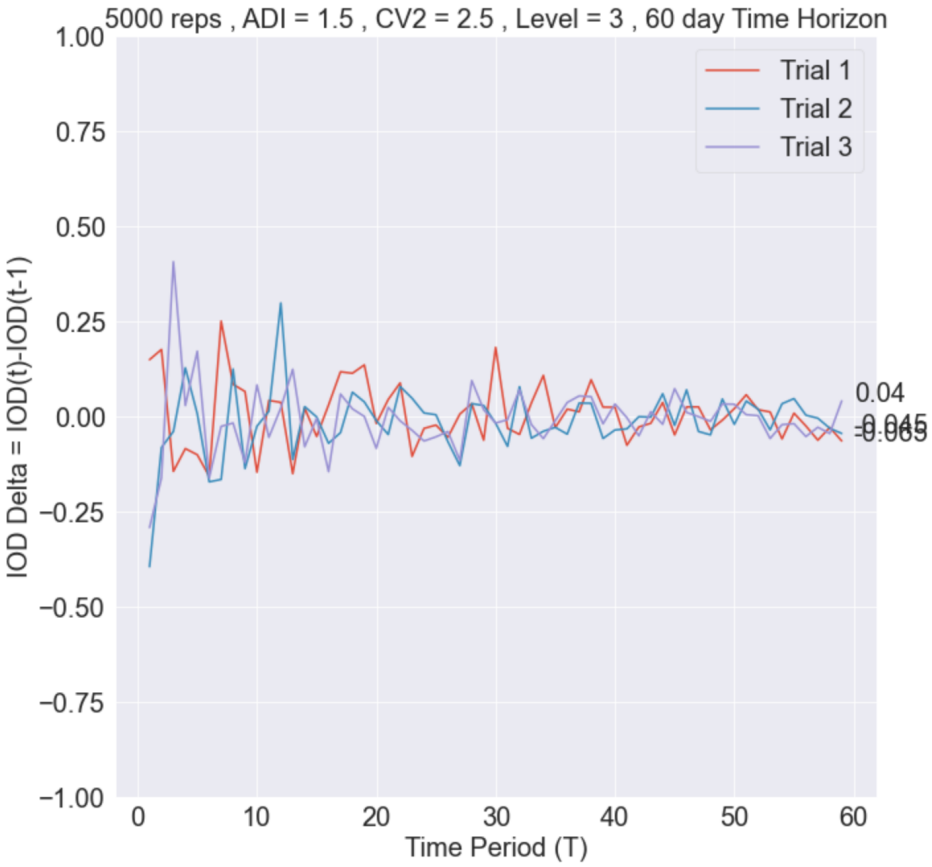

Figure B.3: (color online) IOD Delta over 60 day time horizon, 5,000 realizations.

Table B.3: Days to Convergence by Tolerance Level for 50,000 Replications

Demand Classification	**Tol = 0.01**	**Tol = 0.001**	**Tol = 0.0001**
Smooth	61	61	196
Erratic	61	70	192
Lumpy	61	61	215
Intermittent	66	74	259

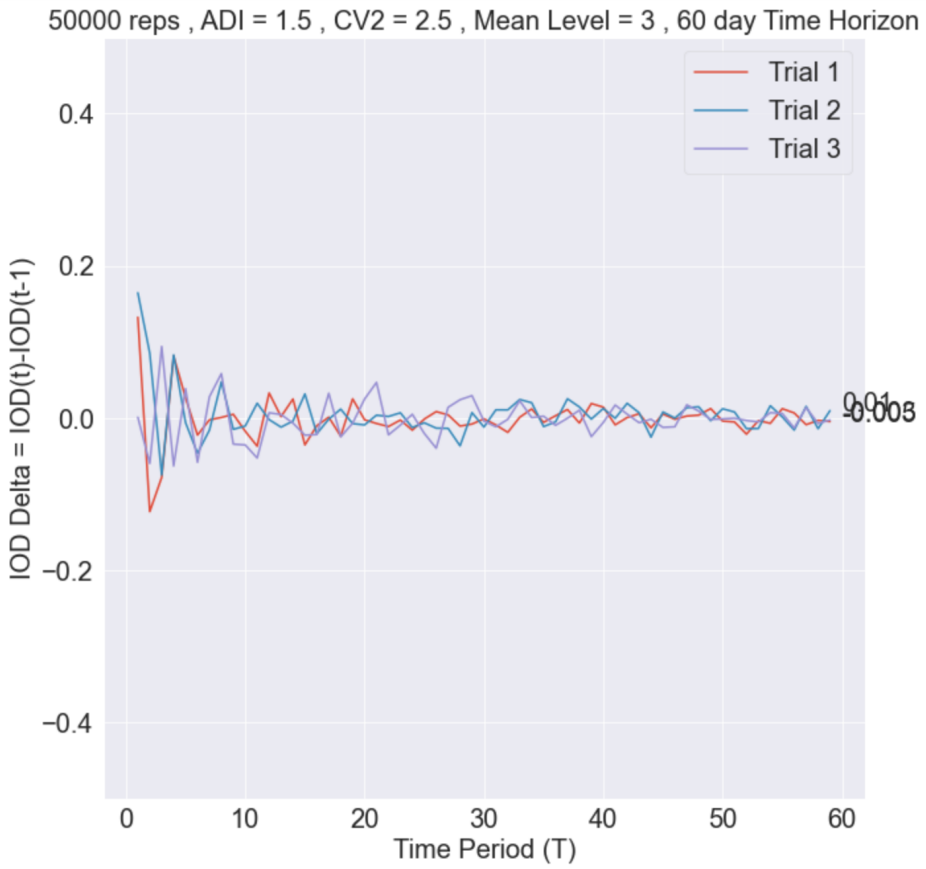

Figure B.4: (color online) IOD Delta over 60 day time horizon, 50,000 realizations.

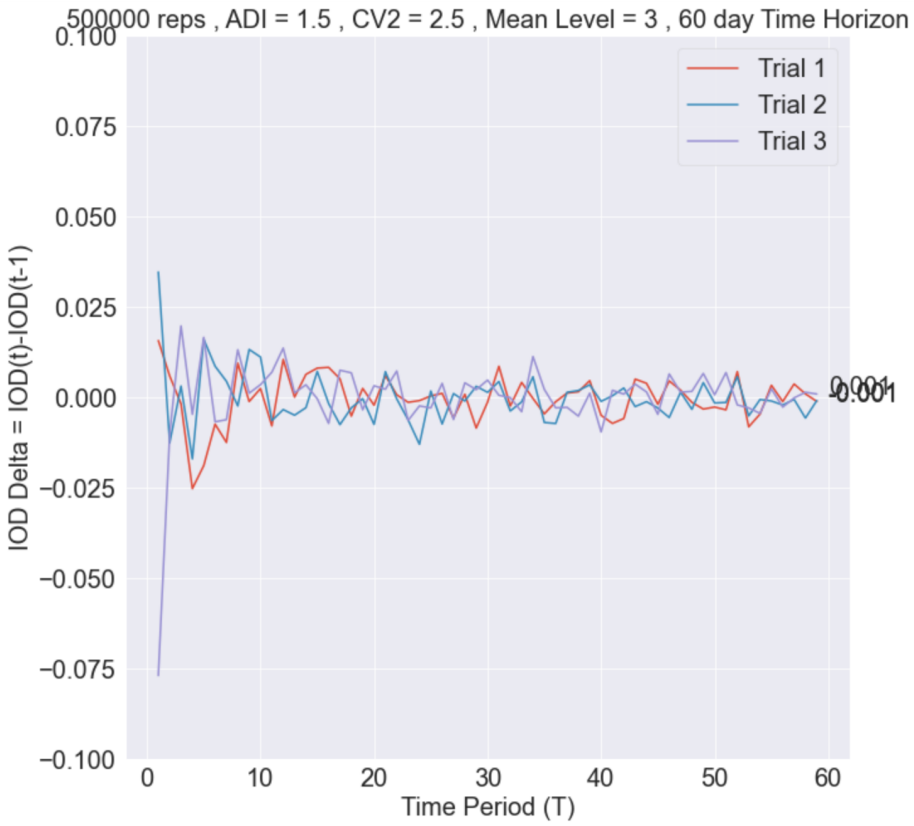

Figure B.5: (color online) IOD Delta over 60 day time horizon, 500,000 realizations.

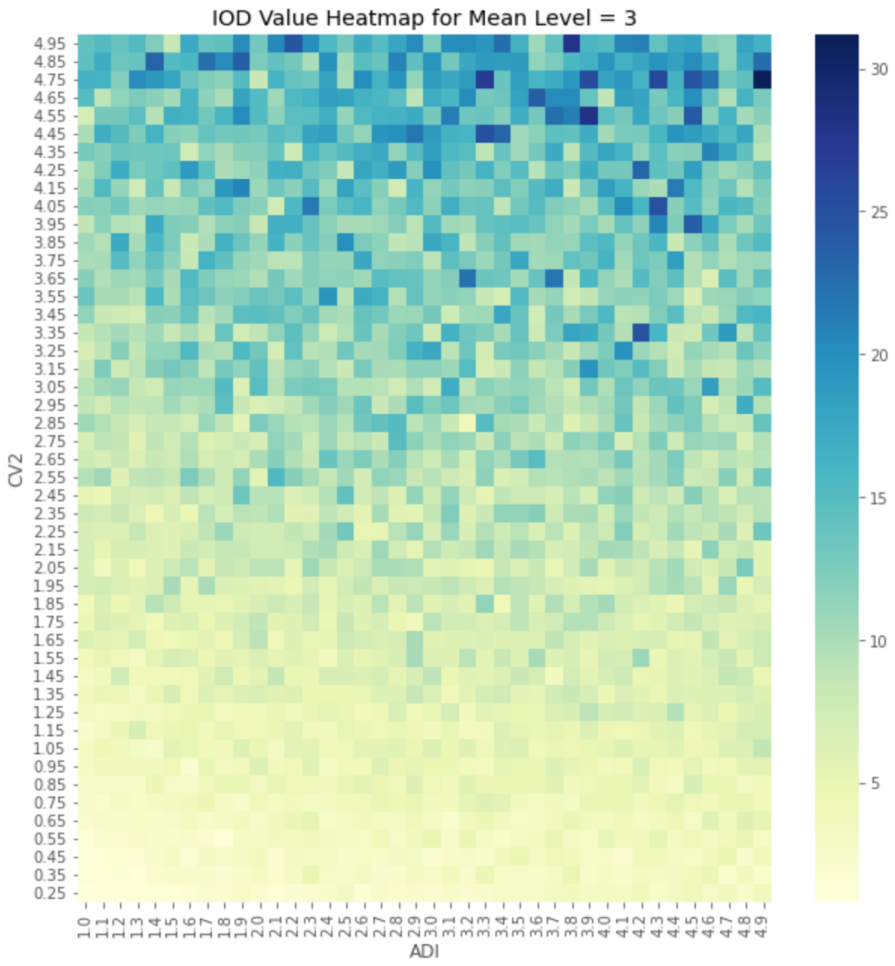

Figure B.6: (color online) Heatmap of Dispersion Value by ADI and CV^2 for Mean Level = 3.0.

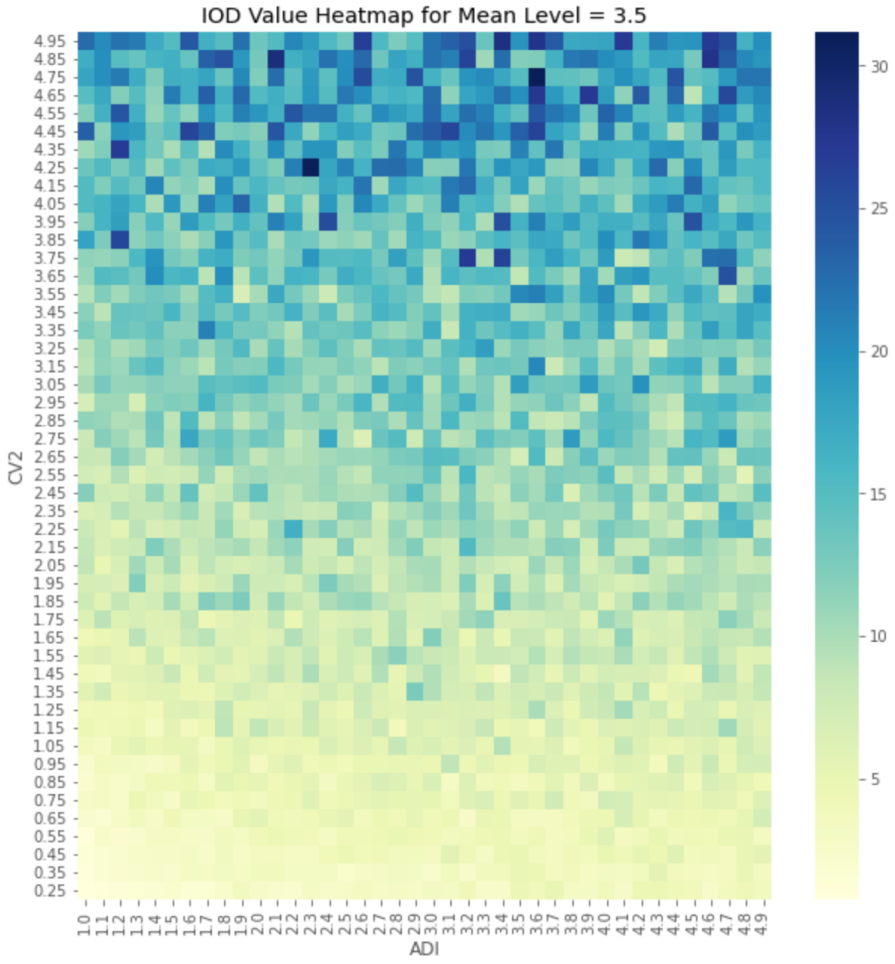

Figure B.7: (color online) Heatmap of Dispersion Value by ADI and CV^2 for Mean Level = 3.5.

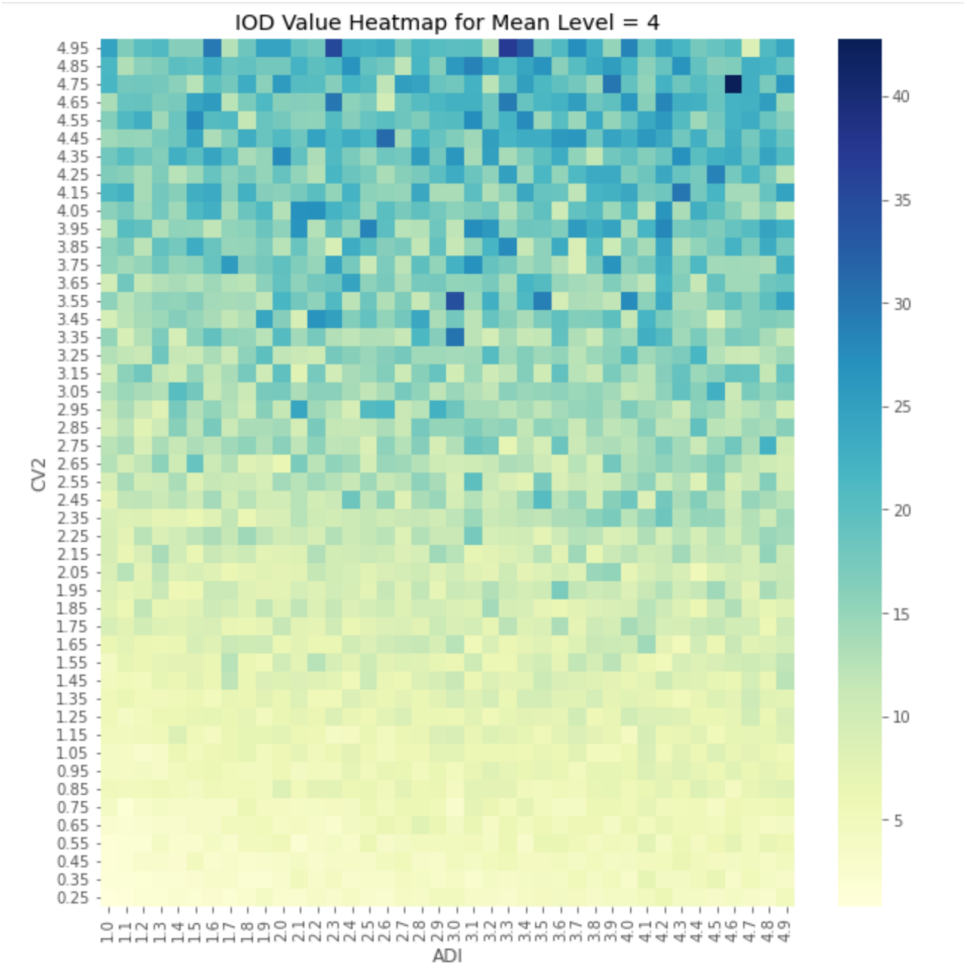

Figure B.8: (color online) Heatmap of Dispersion Value by ADI and CV^2 for Mean Level = 4.0.

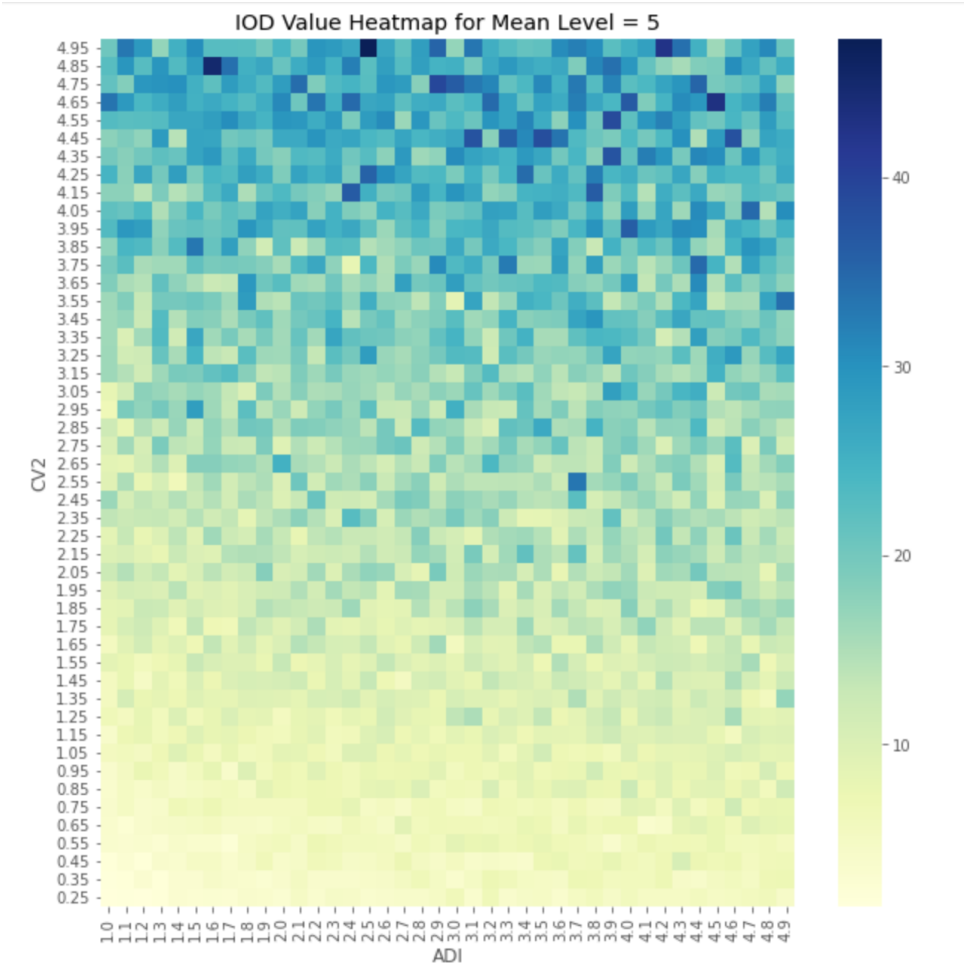

Figure B.9: (color online) Heatmap of Dispersion Value by ADI and CV^2 for Mean Level = 5.0.

APPENDIX

C

RESIDUAL PLOTS FOR HOMOGENEOUS DEMAND STUDY

C.1 Linear Regression Models' Residual Plots

The following plots are the residual plots for each of the linear regression models performed in Chapter 4. The residual plots for the No AM, Full AM, Centralized AM, and Distributed AM configurations are shown in Figure C.1, Figure C.2, Figure C.3, and Figure C.4, respectively.

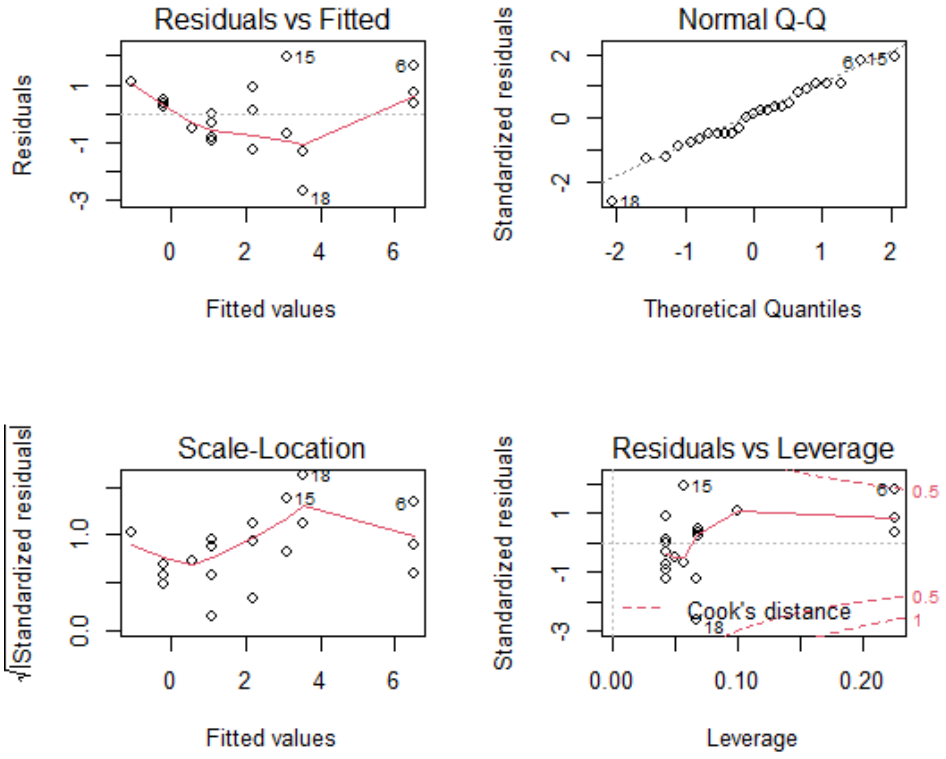

Figure C.1: Residuals and Q-Q Plots for Regression Analysis of Backorders by IOD Value for products of homogeneous demand in No AM Network Configuration.

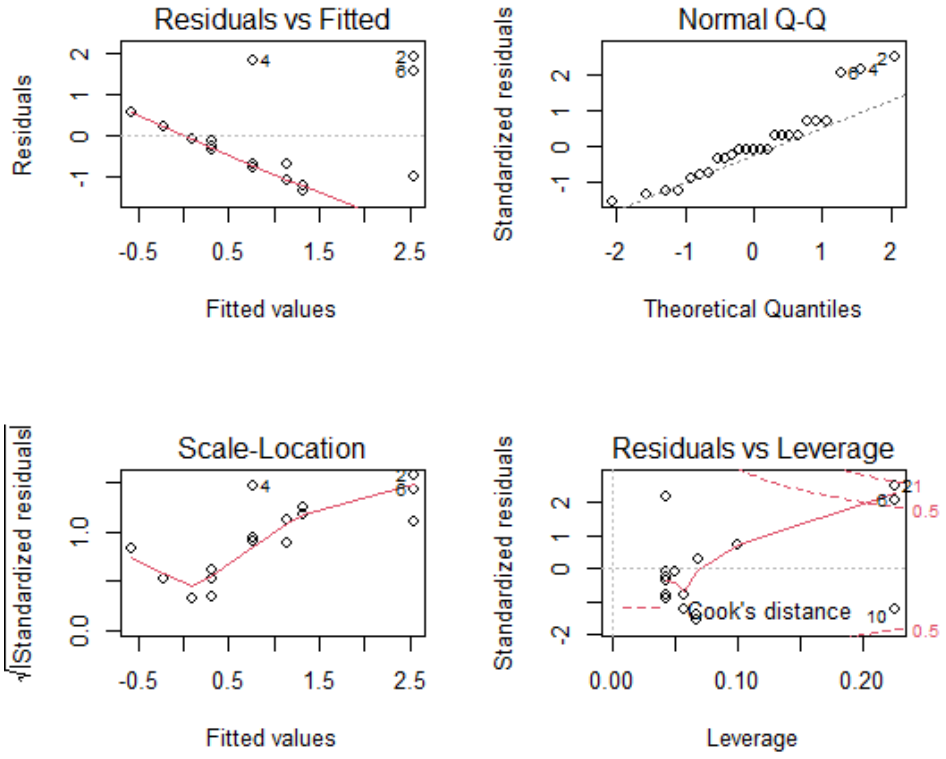

Figure C.2: Residuals and Q-Q Plots for Regression Analysis of Backorders by IOD Value for products of homogeneous demand in Full AM Network Configuration.

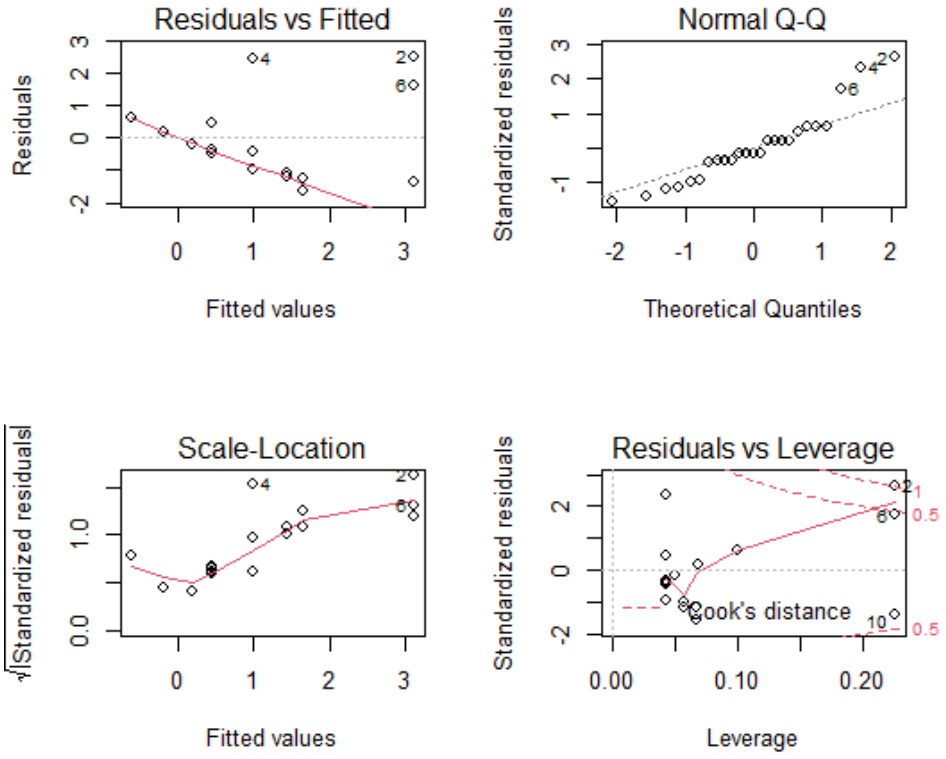

Figure C.3: Residuals and Q-Q Plots for Regression Analysis of Backorders by IOD Value for products of homogeneous demand in the Centralized AM Network Configuration.

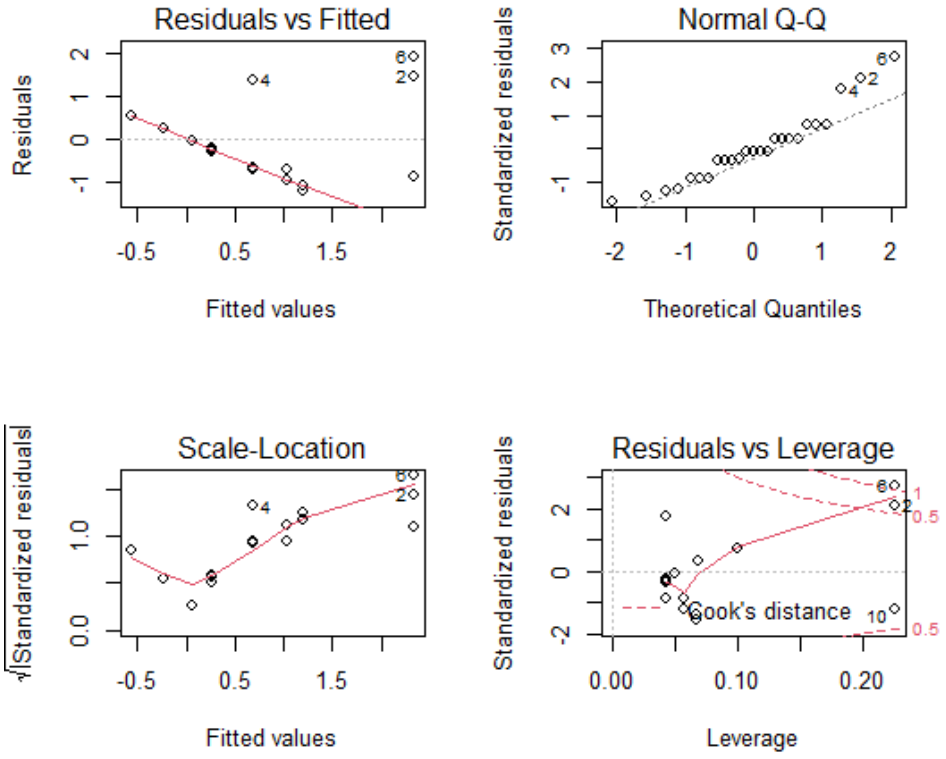

Figure C.4: Residuals and Q-Q Plots for Regression Analysis of Backorders by IOD Value for products of homogeneous demand in the Distributed AM Network Configuration.

APPENDIX

D

SUPPLEMENT TO HETEROGENEOUS DEMAND STUDY

D.1 Dispersion of Superposition Demand Process

Similar to the analysis in Chapter 5, the superposition dispersion is also calculated by combining the resulting demand data used from each of the heterogeneous demand input parameters and then calculating the resulting IOD. Let $\{N_i(t),\ t \geq 0\}$ and $\{N_j(t),\ t \geq 0\}$ be the counting processes for the number of demands by time t for products i and j, respectively. The the superposition demand process is obtained by $\{N_S(t),\ t \geq 0\}$ where

$$N_S(t) = N_i(t) + N_j(t), \tag{D.1}$$

which permits using

$$D_0 = \frac{\mathrm{Var}(N_S(t))}{\mathrm{E}[N_S(t)]}, \tag{D.2}$$

to assess the total demand difficulty.

Figure D.1 shows the plot of the average total number of backorders by the IOD super-

Table D.1: Linear regression analysis of backorders by IOD superposition value. 5-fold cross-validation, $\alpha = 0.05$.

R^2	RMSE	p-value for β_1
0.56	162.538	5.16E-14

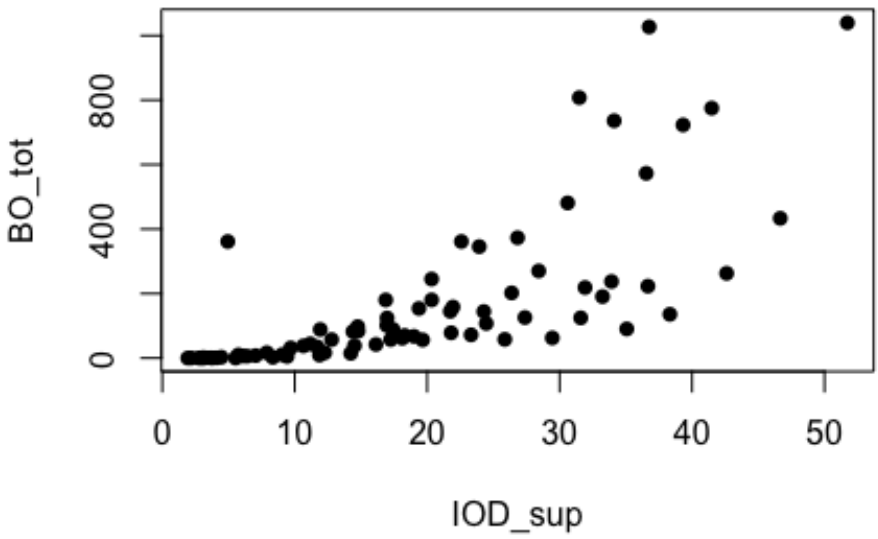

Figure D.1: Average total number of Backorders by IOD Superposition Value

position. A 5-fold cross validation linear regression analysis of the average total number of backorders by the IOD superposition value was performed and the results are detailed in Table D.1. The residual plots for the regression analysis is shown in Figure D.2.

D.2 Linear Regression Residual Plots

Figures D.3–D.6 provide the linear regression residual plots for each of the difficulty indices D_2, D_3, D_4, D_5, respectively.

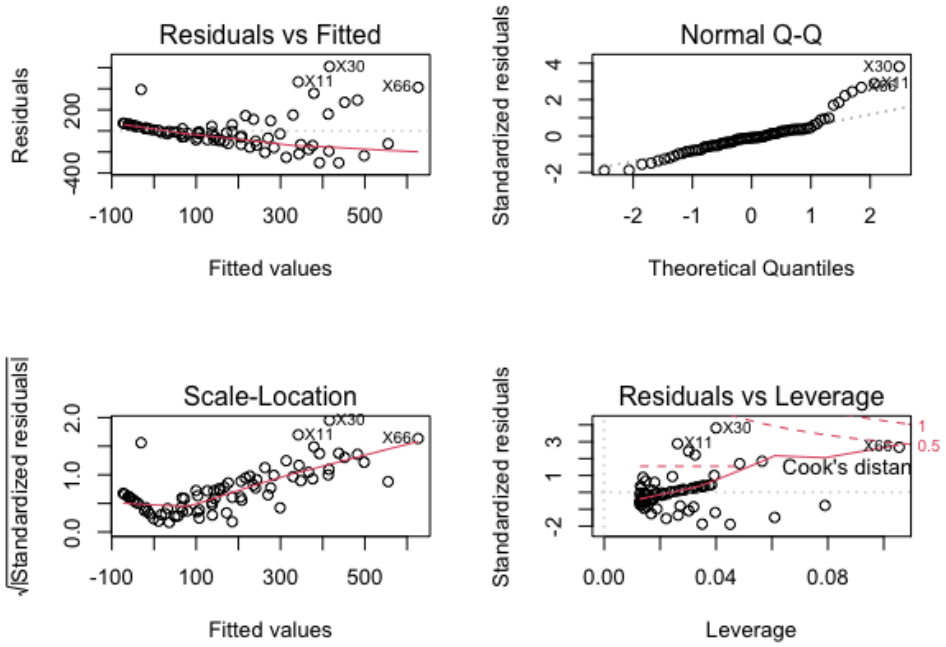

Figure D.2: Residuals and Q-Q Plots for Regression Analysis of Backorders by IOD Superposition Value.

D.3 Full Quadratic Regression Residual Plots

Figures D.7–D.10 provide the full quadratic regression residual plots for each of the difficulty indices D_2, D_3, D_4, D_5, respectively.

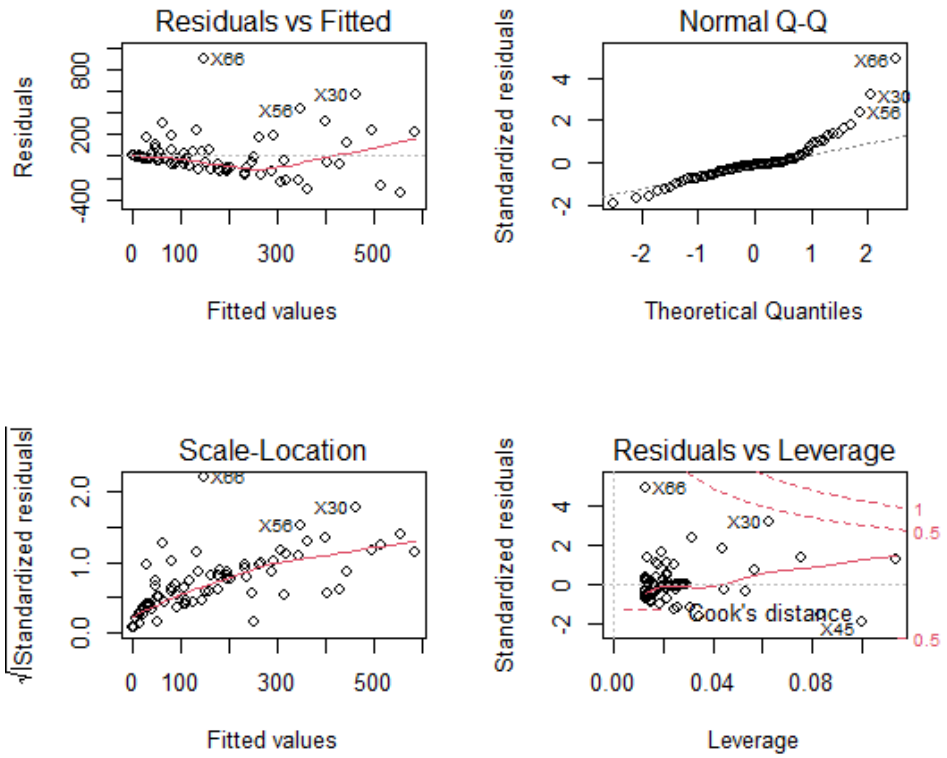

Figure D.3: First Order Linear Model Residuals and Q-Q Plots for Difficulty Index D_2.

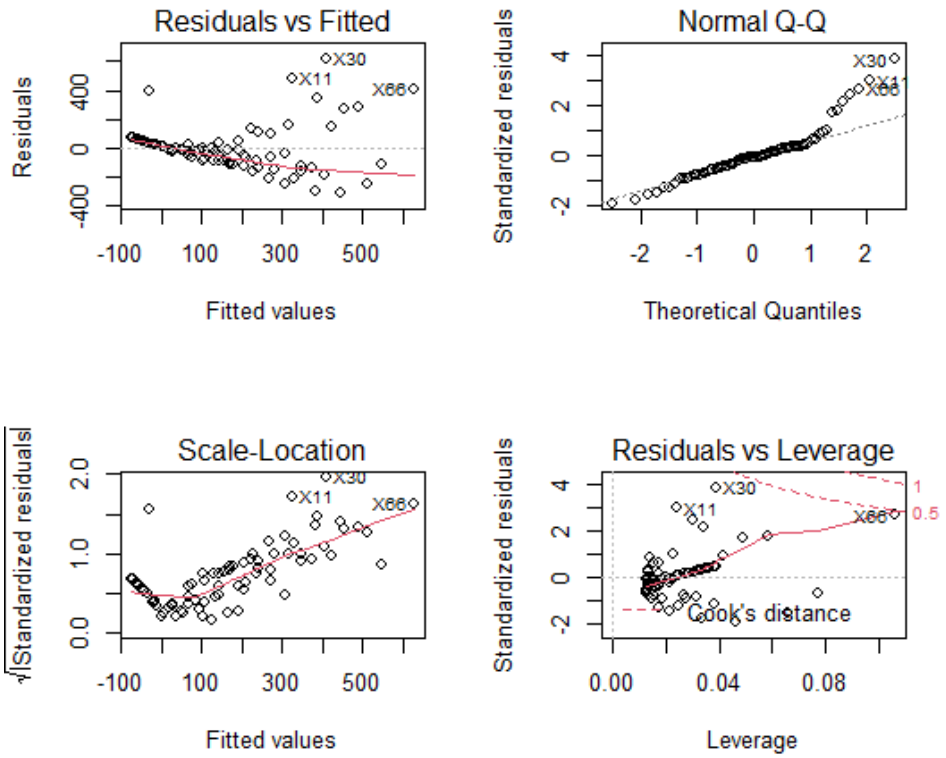

Figure D.4: First Order Linear Model Residuals and Q-Q Plots for Difficulty Index D_3.

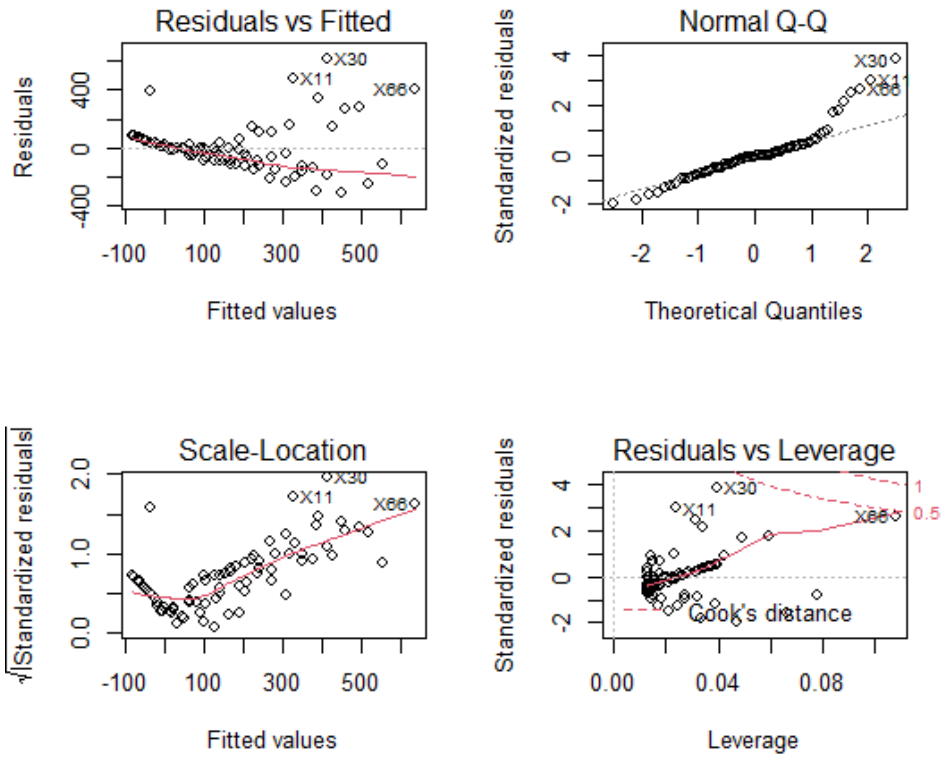

Figure D.5: First Order Linear Model Residuals and Q-Q Plots for Difficulty Index D_4.

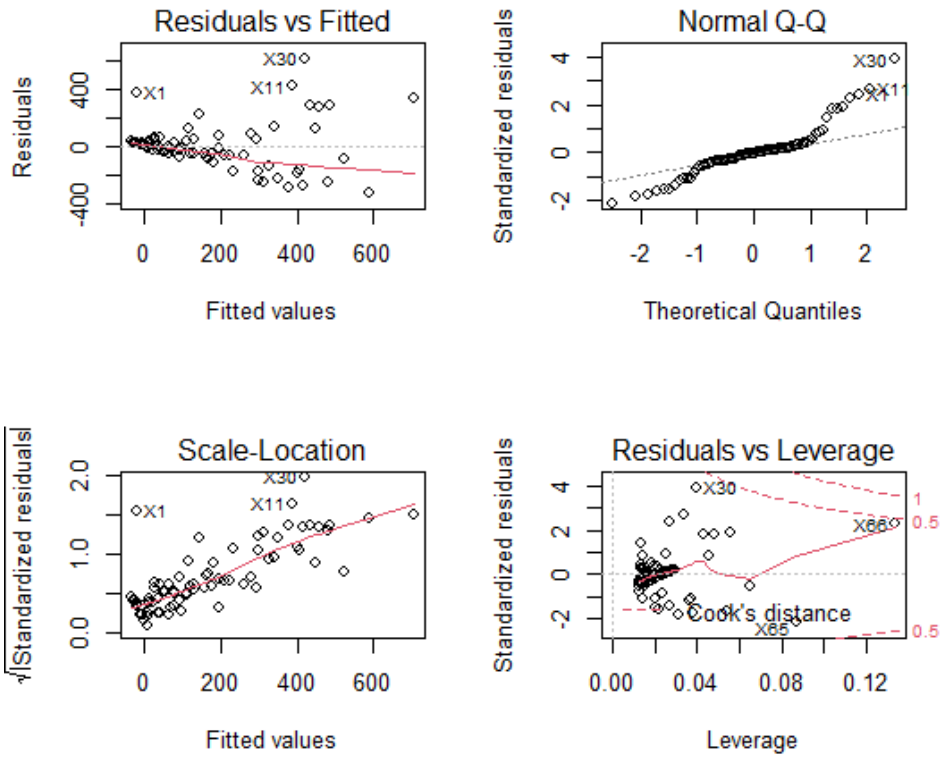

Figure D.6: First Order Linear Model Residuals and Q-Q Plots for Difficulty Index D_5.

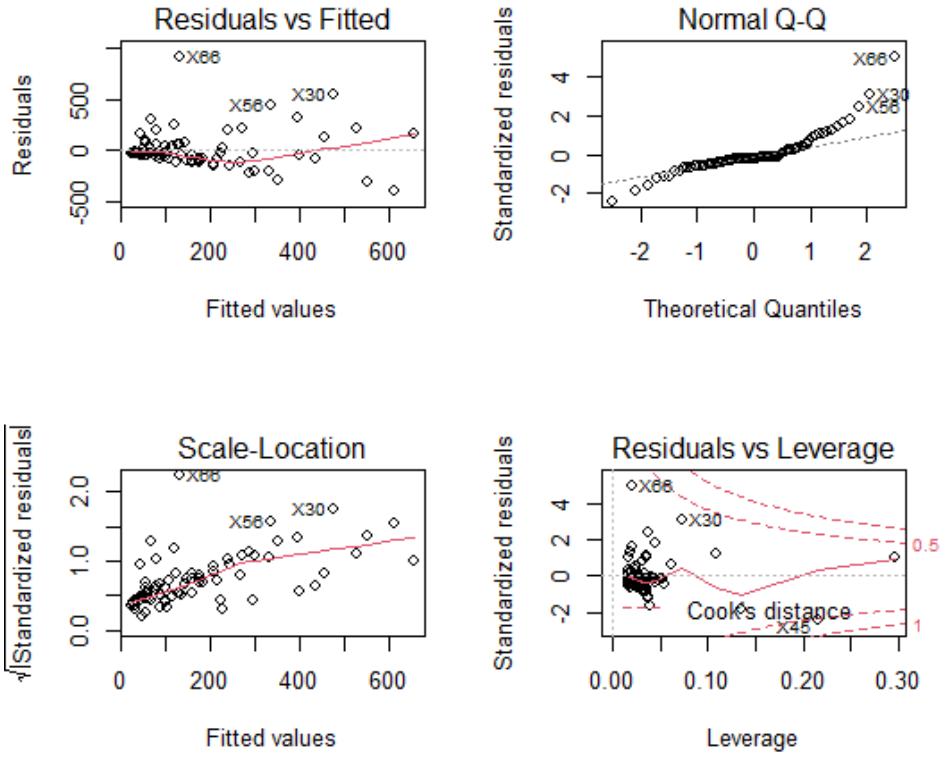

Figure D.7: Residuals and Q-Q Plots for Full Quadratic Regression Model of Backorders by Difficulty Index D_2^2 and D_2.

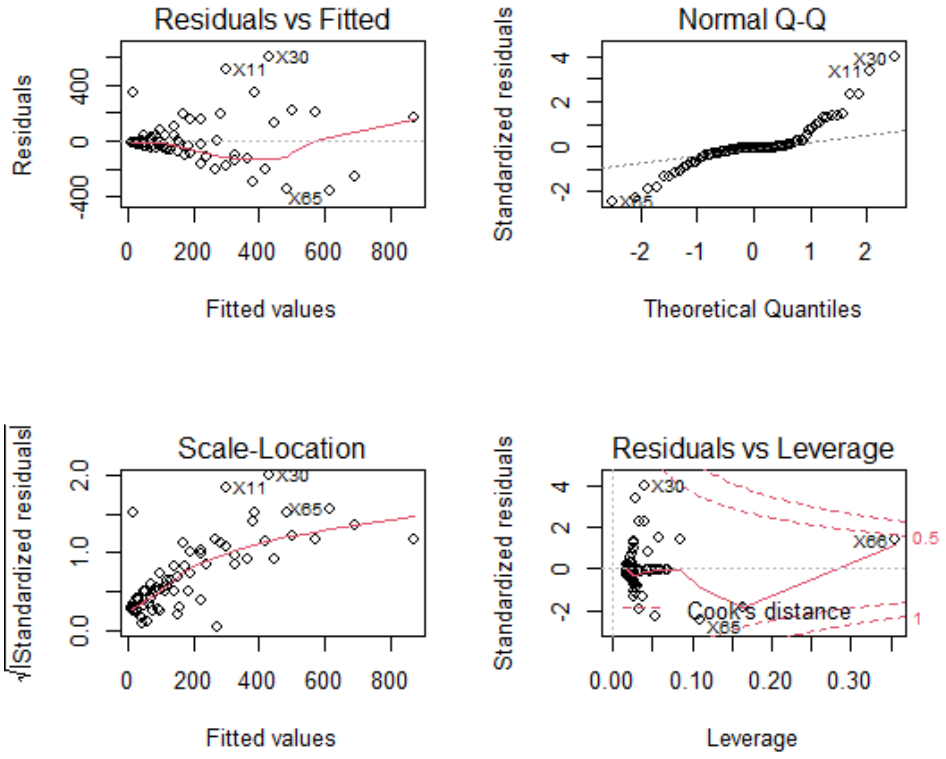

Figure D.8: Residuals and Q-Q Plots for Full Quadratic Regression Model of Backorders by Difficulty Index D_3^2 and D_3.

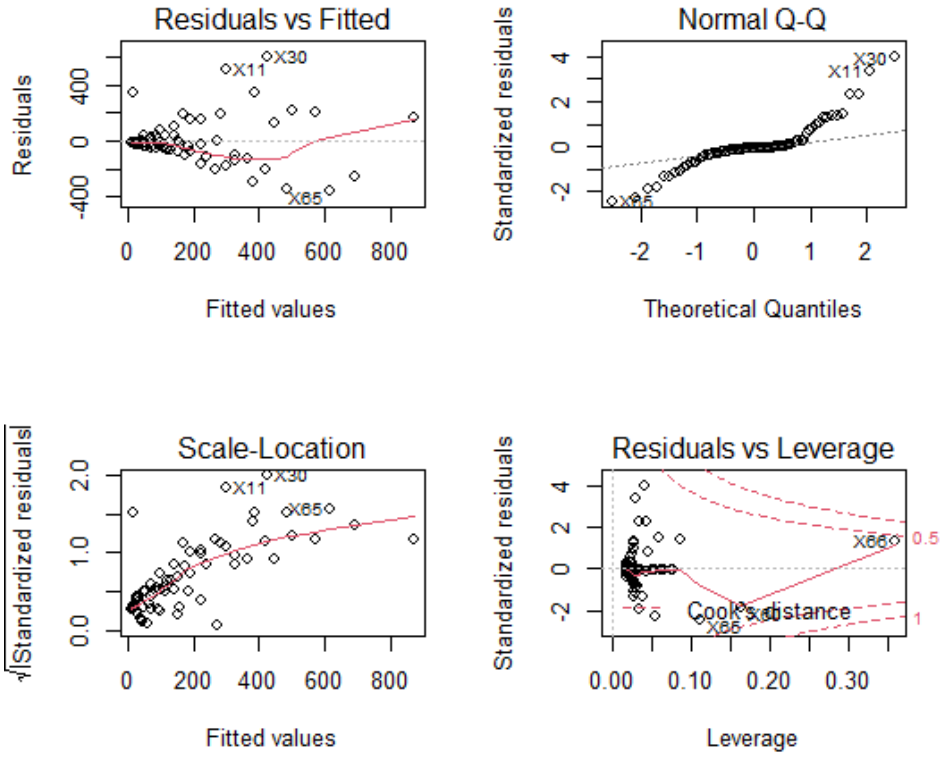

Figure D.9: Residuals and Q-Q Plots for Full Quadratic Regression Model of Backorders by Difficulty Index D_4^2 and D_4.

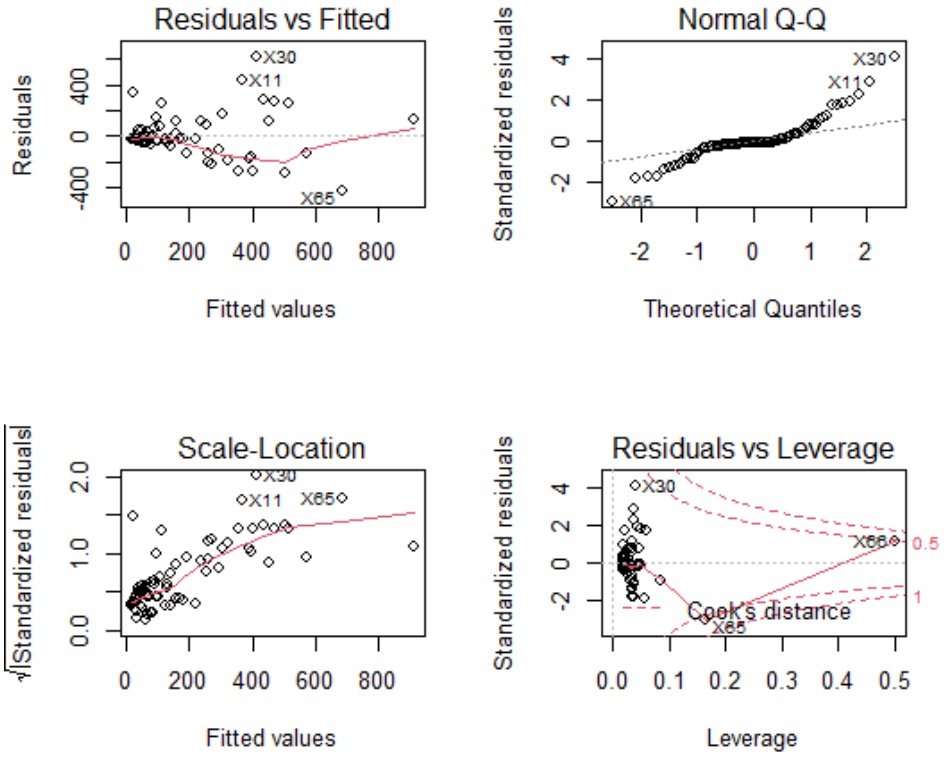

Figure D.10: Residuals and Q-Q Plots for Full Quadratic Regression Model of Backorders by Difficulty Index D_5^2 and D_5.

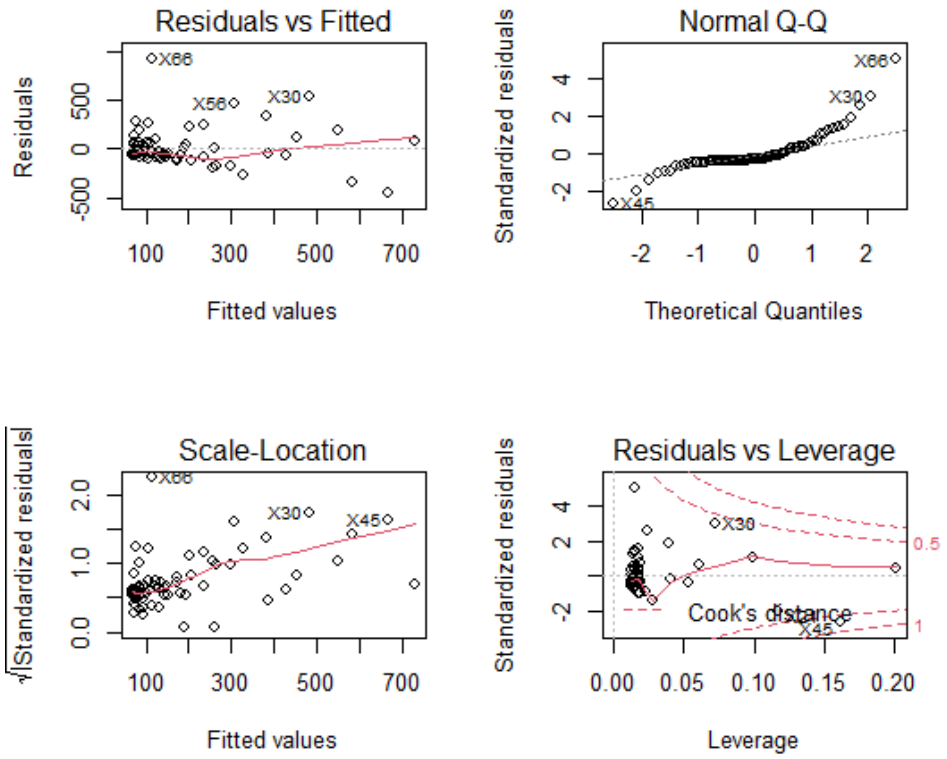

Figure D.11: Residuals and Q-Q Plots for Partial Quadratic Regression Model of Backorders by Difficulty Index D_2^2.

D.4 Partial Regression Residual Plots

Figures D.11–D.14 provide the partial quadratic regression residual plots for each of the difficulty indices D_2, D_3, D_4, D_5, respectively.

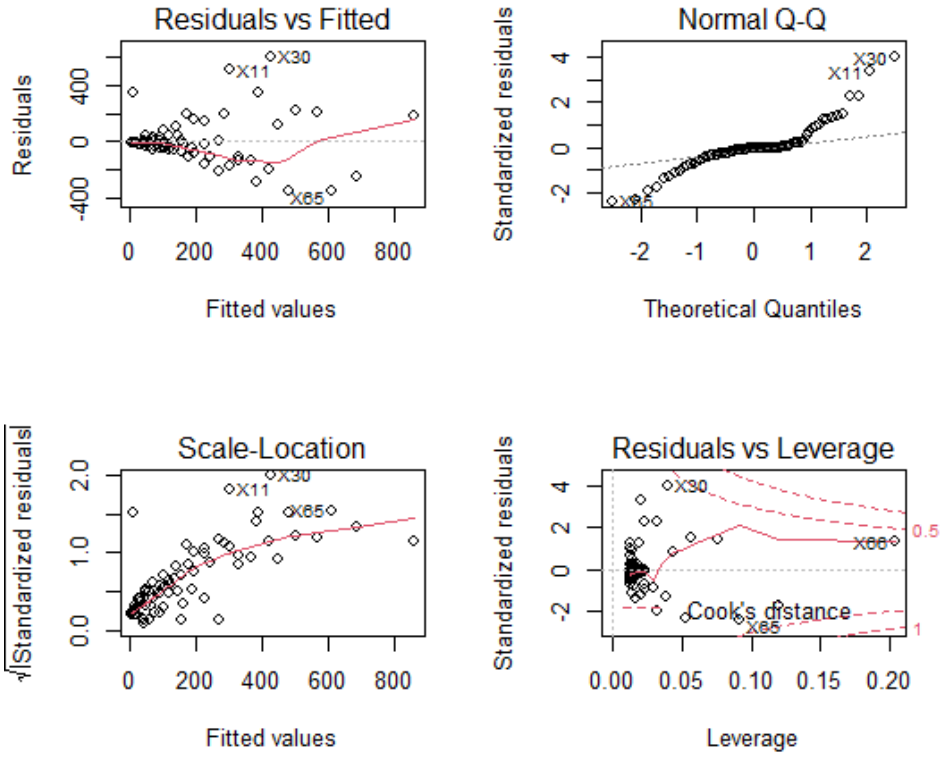

Figure D.12: Residuals and Q-Q Plots for Partial Quadratic Regression Model of Backorders by Difficulty Index D_3^2.

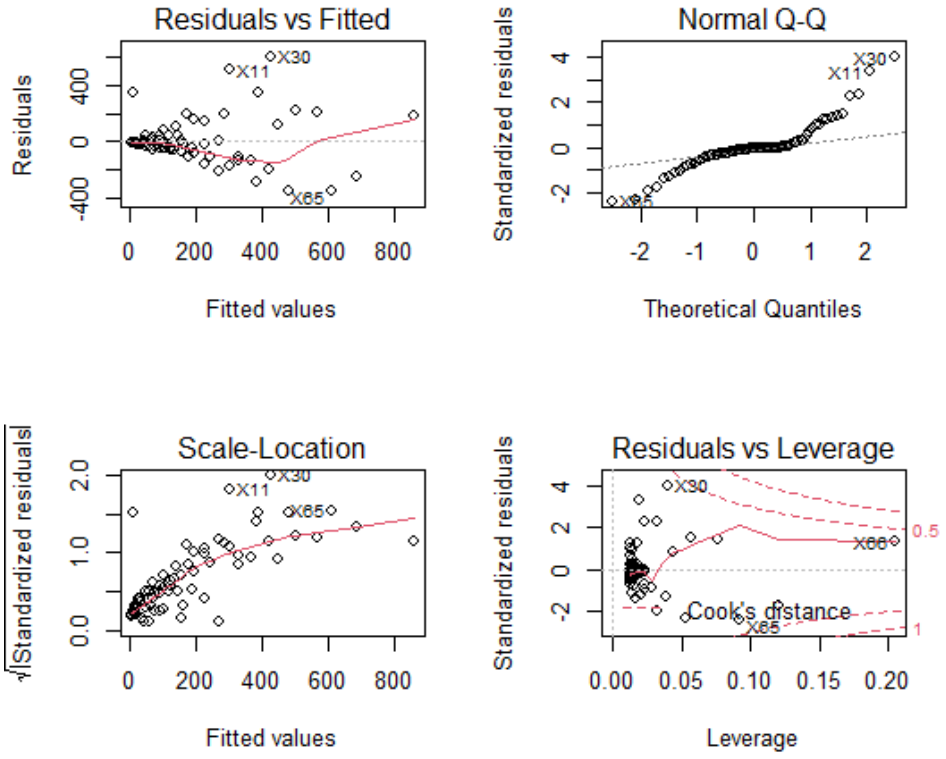

Figure D.13: Residuals and Q-Q Plots for Partial Quadratic Regression Model of Backorders by Difficulty Index D_4^2.

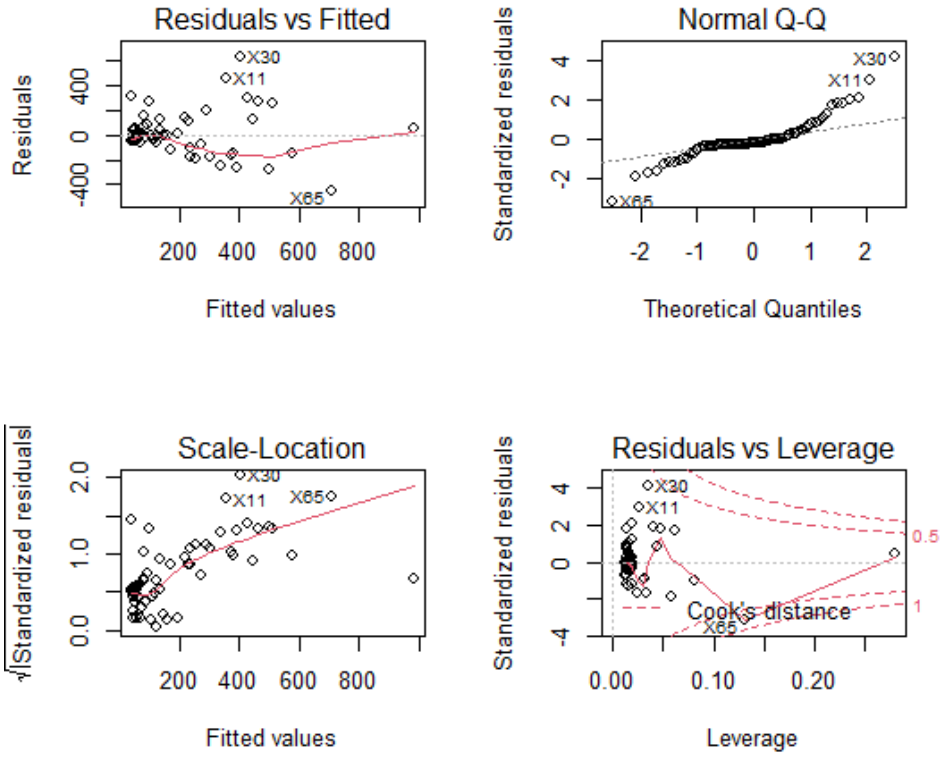

Figure D.14: Residuals and Q-Q Plots for Partial Quadratic Regression Model of Backorders by Difficulty Index D_5^2.

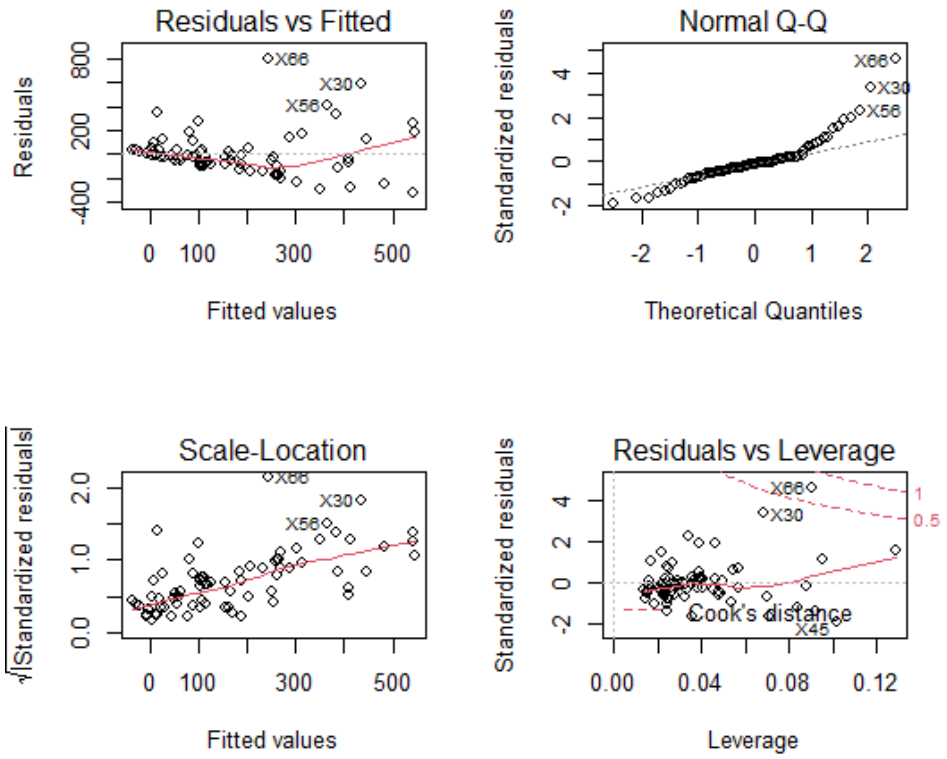

Figure D.15: Residuals and Q-Q Plots for Additive Linear Regression Model from Equation 5.9 and D_2.

D.5 Linear Additive Model Regression Residual Plots

Figures D.15–D.18 provide the linear additive model regression residual plots for each of the difficulty indices D_2, D_3, D_4, D_5, respectively.

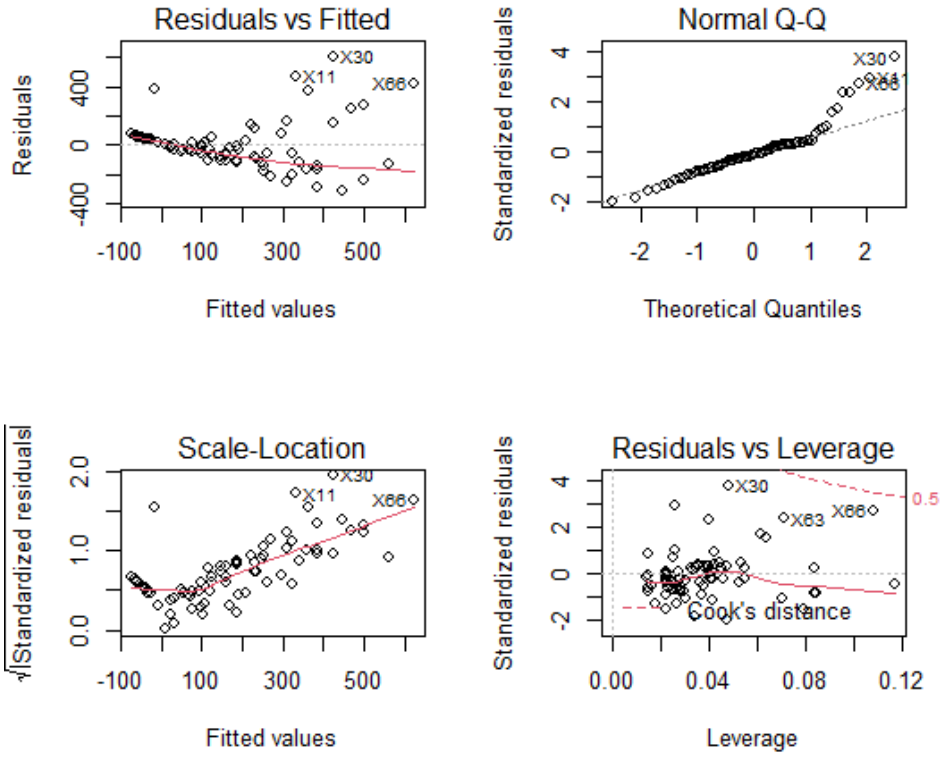

Figure D.16: Residuals and Q-Q Plots for Additive Linear Regression Model from Equation 5.9 and D_3.

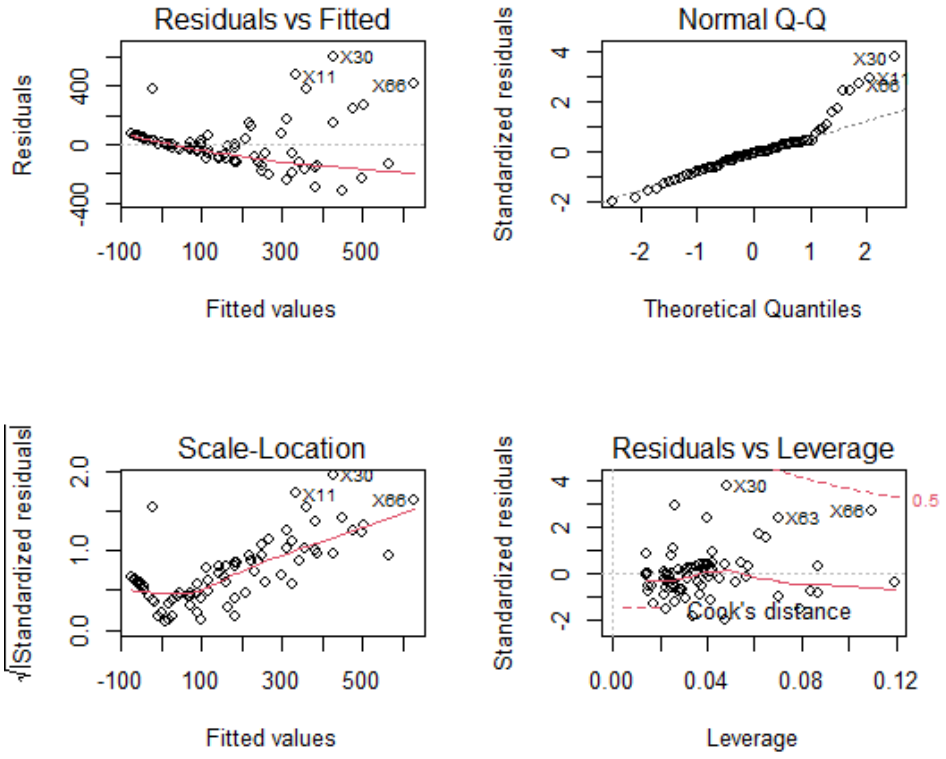

Figure D.17: Residuals and Q-Q Plots for Additive Linear Regression Model from Equation 5.9 and D_4.

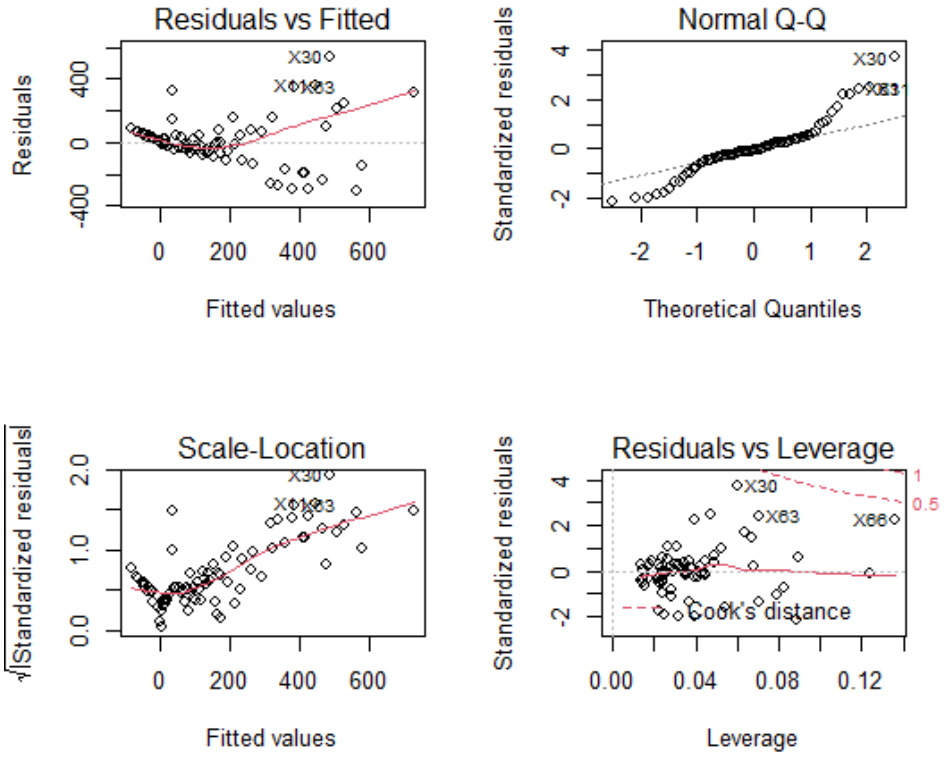

Figure D.18: Residuals and Q-Q Plots for Additive Linear Regression Model from Equation 5.9 and D_5.

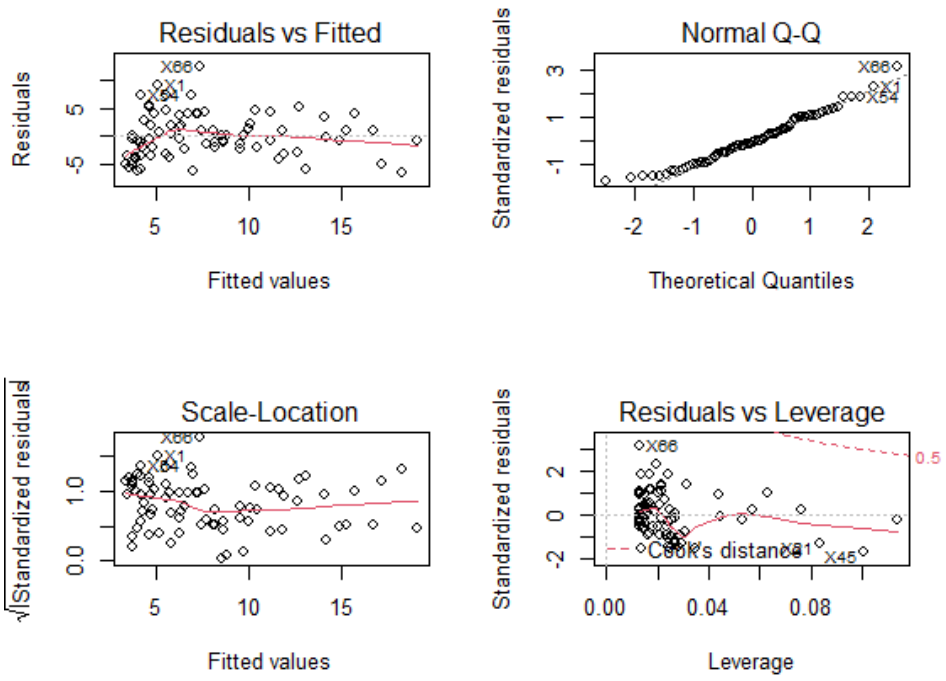

Figure D.19: Residuals and Q-Q Plots for Box-Cox Transform Linear Regression Model of Backorders by Difficulty Index D_2.

D.6 Box-Cox Transform Linear Regression Residual Plots

Figures D.19–D.22 provide the Box-Cox transform linear regression residual plots for each of the difficulty indices D_2, D_3, D_4, D_5, respectively.

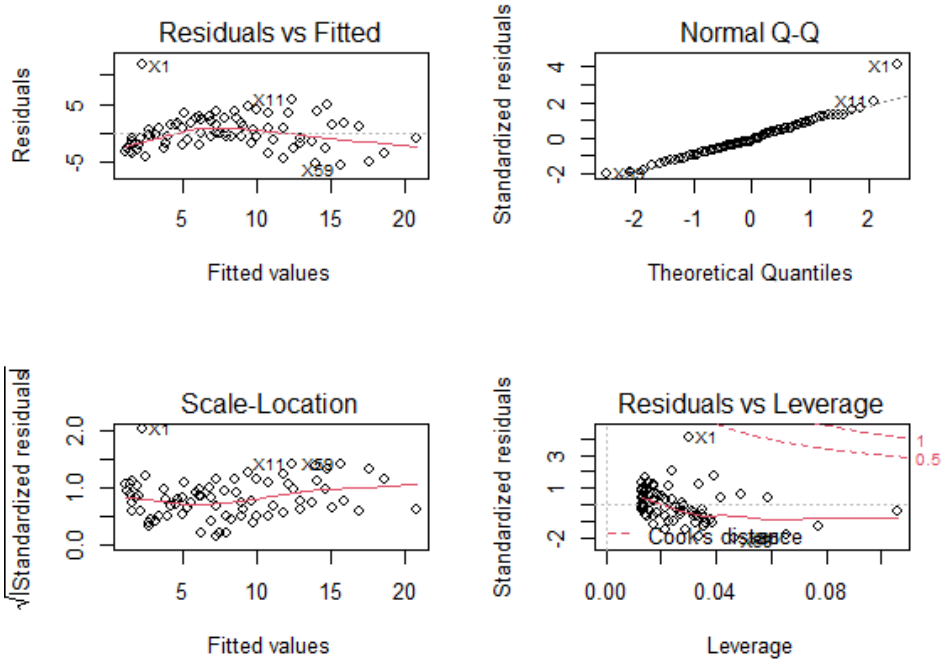

Figure D.20: Residuals and Q-Q Plots for Box-Cox Transform Linear Regression Model of Backorders by Difficulty Index D_3.

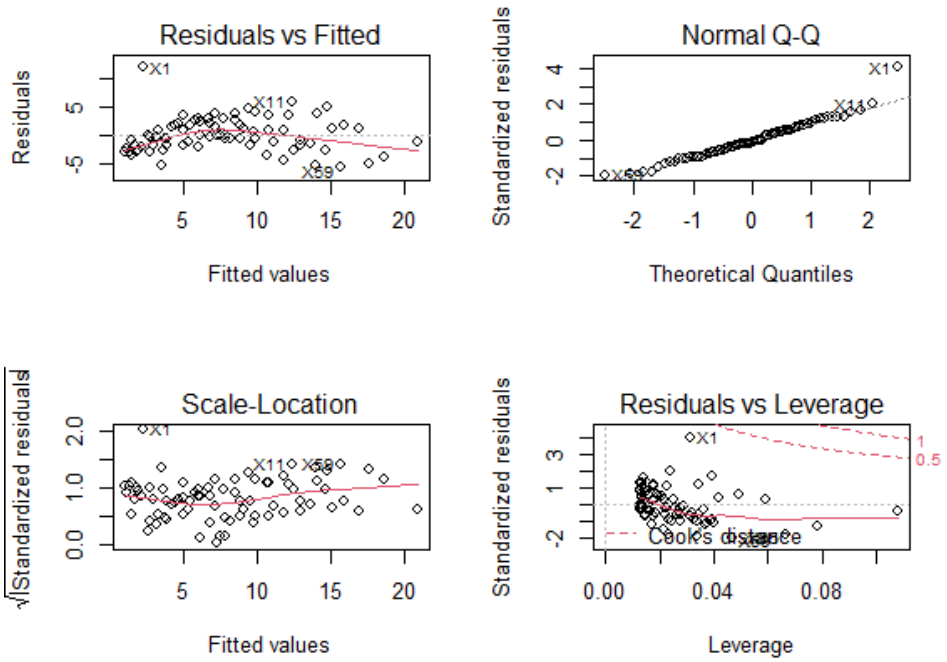

Figure D.21: Residuals and Q-Q Plots for Box-Cox Transform Linear Regression Model of Backorders by Difficulty Index D_4.

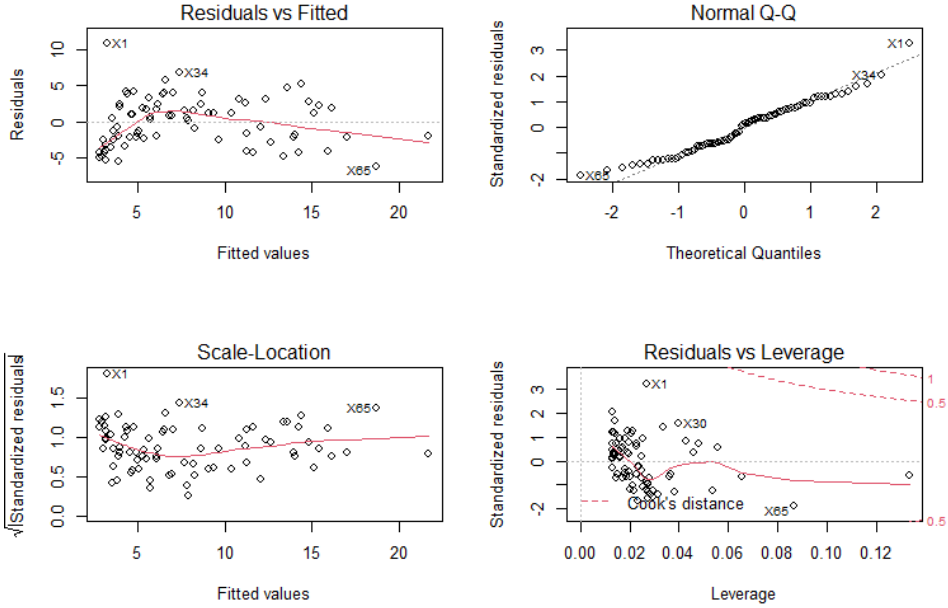

Figure D.22: Residuals and Q-Q Plots for Box-Cox Transform Linear Regression Model of Backorders by Difficulty Index D_5.