MANAGING WAREHOUSE RESOURCE AND TRANSPORTATION PLAN STABILITY USING THE FLEXIBLE REQUIREMENTS PROFILE TECHNIQUE

by

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A thesis submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfilment of the requirements
for the degree of Master of Science in
Engineering Management

Charlotte

2023

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ABSTRACT

SHIVANI GURUNATH. Managing Warehouse Resource and Transportation Plan Stability using the Flexible Requirements Profile Technique

(Under the direction of DR. ERTUNGA C. OZELKAN)

In today's ever-changing markets, maintaining an effective and adaptable supply chain is essential for any organisation, especially in view of the current business environment's uncertainty and the continuously changing and rising demands of customers. Supply chains have always been susceptible to disruptions. Demand fluctuations is one of the main uncertainty factors in today's business world. Demand uncertainty can cause frequent changes in production plan which can lead to the increase of instability in the production and distribution system, and result in a surplus or deficiency in inventories and resources. (Inman and Gonsalvez, 1997; Metters and Vargas, 1999). Frequently revising plans and making extra efforts to deal with system uncertainties cause anxiety/nervousness in production environments. (Lee et al., 1997)

To deal with this nervousness, various strategies and models have been created for production planning. Previous studies show that strategies like frozen horizon (Kadipasaoglu and Sridharan,1995) , lot sizing techniques (Zhao et al., 2001), forecasting beyond the planning horizon (Blackburn et al., 1986), flexible requirement profile (Srinivasan, 2005) can be applied to minimize the plan instability (nervousness).

Literature shows that nervousness/stability has been addressed for production planning but not many models are available for transportation/warehouse planning. While traditional warehouse resource and transportation planning methods focus on cost minimization, they do not seem to provide a formal means to manage plan stability along with cost.

In this study, we aim to close this research gap by developing a new Warehouse Resource and Transportation Planning (WRTP) model that considers plan stability, incorporating the Flexible Requirements Profile (FRP) technique called here the WRTP-FRP. The proposed **WRTP-FRP** is compared to a traditional WRTP as a baseline that minimizes cost without the consideration of stability, using numerical experiments based on cost and stability performances.

Keywords: Warehouse Planning, Transportation Planning, Plan Stability, Plan Nervousness, Flexible Requirements Profile (FRP).

DEDICATION

I would like to dedicate this thesis to my family, advisor and teachers who have been extremely helpful and supportive throughout my journey.

ACKNOWLEDGMENTS

I express my sincere gratitude to my advisor, Dr. Ertunga C. Ozelkan, who has supported me throughout my masters' journey by helping me navigate through all the obstacles and challenges. He was always patient with me and provided valuable resources that helped me find solutions to any problems that arose. His constant support was instrumental in the success of my research. I would also like to extend my thanks to the Engineering Management program, and I am very grateful to Dr. Agnes G. Ozelkan and Dr. Vishnu G. Prabhu for their generosity in serving on my committee and providing me with helpful feedback and guidance to enhance my research.

I would like to give special thanks to my parents: Gurunath HS and Sunitha Gurunath, whose never-ending love and support have been my driving force throughout my journey. Despite being continents away, their unwavering encouragement has always inspired me to work towards achieving my goals and making them proud.

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APP Aggregate Production Planning

FRP Flexible Requirements Profile

MILP Mixed-Integer Linear Programming

MRP Material Resource Planning

WRTP Warehouse Resource and Transportation Planning

CHAPTER 1: INTRODUCTION

The growing competitive demands on the global market and the rapid advancements in information technology has brought supply chain in the forefront of the business practices of most manufacturing and service organizations. The main focus of supply chain planning is the coordination and integration of a company's major business operations, from the acquisition of raw materials to the distribution of finished goods to the customer. The decision-making process in these extremely intricate and interconnected networks can be broken down according to the time horizons (Gupta & Maranas, 1999). In recent years, supply chain management issues have received a lot of attention due to growing market competitiveness, shortened product lifecycles, and quick technological advancements (Kouvelis et al., 2006). Unprecedented occurrences like the COVID-19 outbreak and the ongoing crisis in Ukraine has yet again brought attention to the vulnerabilities of worldwide supply chains (Allam et al.,2002). The current issues in supply chain management have been worsened by fast emerging and changing client expectations, expanded market opportunities, complex international issues, and other elements. The global nature of marketplaces have compelled businesses to develop supply chain networks that are less centralised and more flexible to shifting market conditions. Maintaining an effective and adaptable supply chain is essential for any organisation, especially in light of the current business environment's volatility and the continuously changing and rising demands of customers. Various sources of uncertainty can be identified in these systems.

Demand volatility is a primary cause of uncertainty in a supply chain network. Demand uncertainty is a circumstance that can occur at any time, with or without a pandemic and cause companies to scramble for solutions to keep their supply chains running smoothly. Based on the timeframes over which these uncertainties affect the system, they are classified as short-term and long-term uncertainties (Subrahmanyam, Pekny, & Reklaitis, 1994). Short-term uncertainties include day-to-day processing fluctuations, cancelled or expedited orders, equipment malfunction, etc. Long-term uncertainties include changes in production and transportation rate over extended periods of time, seasonal variations in demand, and price fluctuations of raw materials and finished goods. Underestimating such uncertainties and its impact leads to the planning decisions that can raise serious threats to the company and its supply chain. For instance, product demand is one of the main sources of uncertainty in any production-distribution system. Failure to account for significant demand fluctuations could result in either excessive inventory holding costs or unfulfilled consumer demand, which would result in a loss of market share (Petkov & Maranas, 1997).

Organizations have created a variety of solutions to deal with those problems, which call for a significant amount of internal resources. Building inventories or having an overly large production capacity are two common ways people have tried to deal with uncertainty. This is known as make to stock, where the demand uncertainty is handled by inventories. The cost of maintaining inventory goes up with the make to stock production method. Another strategy is to "freeze" the master production schedule (MPS), which prohibits modifications to the MPS for a defined amount of time (referred to as the "frozen period") in order to prevent production planning from being disrupted (Xie et al., 2003; Kadipasaoglu and Sridharan, 1995; Zhao and Lee, 1993). It is shown that implementing a frozen horizon can calm the manufacturer's nerves, but because it is poorly responsive to changing demand, it is prone to build-up or adversely allow shortages (Zhao and Lee, 1993). The Flexibility Requirements Profile (FRP) offers an alternative solution to reduce nervousness and enhance flexibility by implementing dynamic flexibility limits on the planned production, controlling the variability of production levels over the planning horizon. Unlike rigid constraints on planned production quantities during fixed time periods, FRP permits adjustments to the master production schedule to some extent to manage uncertainties. This approach aims to enforce adaptable flexibility bounds or limits on the planned production to enable changes that align with the evolving production requirements. (Demirel et al, 2018).

The evolution of the global economy over the last ten years has fundamentally altered how businesses operate. One of the biggest changes is that the primary function of storage in the supply chain is no longer restricted to maintaining a huge amount of stock. Instead, small quantities of goods are delivered promptly from a significantly wide variety of stock keeping unit (SKU) throughout its supply chain (Berg & zijm, 1999).

Resource planning is an ability to anticipate needs and create a strategy for efficiently planning, allocating, and utilising resources and workforce competencies. In fast paced environments like warehouse operations, it is essential that we strategically plan the needed resources to effectively perform at the desired level. The rising demand on distribution centres has made it extremely important for warehouse management to deliver quicker turnarounds from receiving to shipping while ensuring accurate inventory efficiency.

Warehouse management systems are designed to support all resources, from the simple movement and storage of commodities within a facility to the complex configuration, such as inventory tracking and maintaining. The idea that warehouses and fulfilment centres are just places to store goods is losing ground. According to (O'Reilly ,2015) historical warehouses were considered of as "a fixed, immovable force that acted as the nexus for any distribution network.". Now their role in supply chain is utilised as a resource to give stability and support for expanding organisations. The most common resources in warehouse operations are workforce and inventory. Scheduling of labour in accordance with the needs of the warehouse operations deliverables, is one of the typical issues in resource planning. In this research, we aim to build an optimal and responsive FRP warehouse planning system taking into account of labour and inventory resources along with the transportation costs for a network.

A network consist of nodes and these nodes are connected through links called arcs. All these networks are used to send some kind of information or resources from one node to another node which we generally call flow. In manufacturing, a flow network is a combination of physical facilities such as supply nodes, transhipment nodes and demand nodes. Optimal network design of such flows is crucial for the operation of the supply chain since a good logistic distribution network can reduce transportation costs and raise service standards (Marmolejo, Rodríguez, Cruz-Mejía & Saucedo, 2016).

One of the most fundamental transportation network models is the shortest path model, which is used to find the shortest route between two nodes in a transportation network. The shortest path model has been applied to various transportation systems, including vehicle routing, public transit, and air traffic control systems (Dijkstra et.,1959; Orda et., 1990). Another important transportation network model is the minimum cost flow model, which is used to find the optimal flow of goods or people in a transportation network, subject to constraints such as capacity limits and demand requirements. The minimum cost flow model has been applied to various transportation systems, including logistics and supply chain management, as well as urban transportation planning (Ford et., 1956; Bazaraa et., 2011). In contrast, the maximum cost flow model aims to find the maximum flow of goods or people in a transportation network, subject to constraints such as capacity limits and demand requirements. The maximum cost flow model has been used to study transportation systems such as freight transportation, where maximizing the flow of goods is a crucial objective (Ahuja et al., 1993; Goldberg et al., 1988).

1.1 Summary of Expected Research Contributions

The objective of this research is to integrate mathematical optimisation and the flexible warehouse resource and transportation planning research to fill the gap between the conventional WRTP and practices of flexible warehouse resource and transportation planning. Hence, the proposed model provides a general framework to achieve optimal warehouse resource and transportation planning under FRP. Main contributions of his research objective are:

- Develop a new mathematical programming model that includes FRP constraints.
- Compare the FRP-based optimization scheme with the traditional WRTP problem.
- Assess the impact of flexibility bounds using a numerical study, and
- Conduct a comparative study via an experimental design to analyze the trade-off between the cost and warehouse resource and transportation plan stability under various flexibility bound scenarios.

CHAPTER 2: LITERATURE REVIEW

Numerous warehouse resource and transportation planning studies are available in the literature. In this chapter we review the literature on warehouse resource and transportation planning problems and flexible planning under rolling horizons. We first review the related literature in the warehouse resource and transportation planning area from different perspectives. We start with mathematical programming of warehouse resource and transportation planning and then continue with the rolling horizon approach. We also review some mitigation strategies for dealing with the issue of nervousness in the supply chain.

2.1 Mathematical Programming Models in Warehouse Resource and Transportation Planning

Warehouse and transportation planning are critical components of supply chain management, and efficient planning can help organizations reduce costs, increase productivity, and enhance customer service levels. Mathematical programming models have been extensively used to optimize these planning processes, resulting in improved decision-making and reduced operating costs.

One of the primary areas where mathematical programming models are applied is workforce management. Effective workforce planning is essential for efficient warehouse operations, and mathematical models have been developed to optimize workforce scheduling, task assignment, and performance measurement (Sarmiento et al., 2013). These models consider factors such as worker skills, task requirements, and workloads to develop optimal schedules that minimize labour costs and maximize efficiency.

Inventory control is another key area where mathematical programming models are applied in warehouse resource planning. Inventory management is a critical aspect of warehouse operations, and mathematical models have been developed to optimize inventory control policies, such as reorder points, safety stock levels, and inventory turnover rates (Barahona et al., 2007). These models consider factors such as demand variability, lead times, and holding costs to develop optimal inventory control policies that ensure adequate stock levels while minimizing inventory costs.

Vehicle routing is another area where mathematical programming models are commonly applied in transportation planning. Vehicle routing problems involve optimizing the routes of delivery vehicles to minimize transportation costs, reduce delivery time, and improve customer service levels. Mathematical models have been developed to optimize vehicle routing, considering factors such as vehicle capacity, delivery time windows, and delivery locations (Grazia, 2018; Josepha et al., 2010). These models aim to develop optimal routing solutions that minimize transportation costs while ensuring timely delivery of goods.

2.1.1 Rolling Horizon Model

Rolling horizon models are the ones where planning is done iteratively and each plan consists of planning periods which has real information about the current period's model parameters while future values are estimated. The application of rolling horizon modelling to solve real time transportation problems can be seen in (Yang, Jaillet and Mahmassani,1998).

The current focus of supply chain planning is the coordination and integration of a company's major business operations, from the acquisition of raw materials to the distribution of finished goods to the customer. These extremely intricate and interconnected networks' decision-making process can be broken down based on the time horizons taken into consideration (Gupta & Maranas, 1999).

A rolling horizon is a time-dependent model that is repeatedly solved, with the planning interval moving forward in time with each solution step. Rolling horizon models are one of the most prominent topics in planning literature. Baker (1977) is one of the earliest studies to look at rolling horizon models' efficacy in the context of production planning. The initial conditions for inventories and backlogs, as well as demand projections, are updated based on the most current actual values during each cycle, and production schedules are prepared for subsequent time frames. In order to give updated plans, rolling horizon planning dynamically incorporates new information. (Yücel and Çanakoğlu,2021) provide a comprehensive overview of rolling horizon models in optimization, including their advantages, limitations in production planning, scheduling, and transportation. (Watling et al.,2015; Zhen et al.,2016) propose a rolling horizon approach for dynamic network design in transportation planning. The research demonstrates that the suggested approach can handle capacity and demand constraints successfully and offer more solutions than conventional static models.

2.1.2 Nervousness (Instability)

Plan instability, also known as nervousness syndrome, has been widely studied in the literature. Researchers such as Carlson et al. (1979) and Kropp et al. (1983, 1984) have proposed various modified Wagner-Whitin algorithms and heuristics to model MRP nervousness, focusing on setup changes and related costs during rescheduling. Blackburn et al. (1985, 1986, 1987) have discussed strategies for dealing with MRP nervousness and have identified demand uncertainties and the planning model as possible causes. They compared different strategies such as "freezing decisions within the planning horizon," "lot-for-lot policy," "safety stocks," "forecast beyond the planning horizon," and "change cost procedure," but found that each has mixed results or yields suboptimal solutions. According to their comparative results, buffer stock is the best strategy to address nervousness, but this comes with the cost of increased inventory, while the lot-for-lot strategy is the least effective one.

Highly uncertain demand generally results in frequent update of production and transportation planning from one planning period to an another, which not only causes nervousness and instability in production environment but also the fluctuations in inventory level can be the major cost driver. Frequent alterations to plans can result in disruptions such as conflicts in scheduling and issues with capacity utilization (Inman and Gonsalvez, 1997). These changes made to production plans can lead to both an increase in inventory and material holding costs, as well as under or overutilization of resources. Several studies show that demand uncertainty in supply chains can cause adverse effects like bullwhip effect, leading to inventory shortages or excesses (Inman and Gonsalvez, 1997; Niranjan et al., 2011). One area that bullwhip effect causes serious cost implications is production planning and scheduling (Metters, 1997; Lee et al., 1997).

While several studies have focused on the negative impacts of nervousness and the importance of stable plans in production planning, there is a limited amount of research specifically on warehouse resource management planning. However, some studies have discussed the significance of stable plans in this context. Agrawal and Smith (2006) emphasizes the importance of stable workloads for improving labor productivity and reducing turnover rates. Additionally, Chandra and Grabis (2006) found that a stable planning horizon can help mitigate nervousness and improve inventory management in warehouse operations. By reducing the frequency of production and shipment plan changes, inventory levels can be better controlled and overall warehouse performance can be improved.

Overall, the literature suggests that nervousness in warehouse resource management planning can have significant negative impacts on inventory, but that implementing stable planning strategies, such as a rolling horizon model, can help mitigate these effects and improve overall performance. Throughout this dissertation we will use the nervousness and instability terms interchangeably.

2.1.3 Empirical Strategies

To deal with this nervousness, it is essential to have flexible production and transportation systems that can quickly adapt to changes in demand. While it may be challenging to accurately predict future demand, industries can use historical data, market research, and other forecasting techniques to develop informed estimates. This can help them plan for potential scenarios and adjust production accordingly. Some older strategies that are advised to deal with demand variability include safety stocks and safety lead times. Safety stock decreases the amount of instability at the lower levels of the product structure by allowing organizations to withstand demand swings by absorbing the changes at the top level. High inventory holding costs come with a high safety stock level, yet it could increase the master production schedule (MPS) stability without compromising customer service. Yano and Carlson (1987) observed that if rescheduling occurs rarely, safety stock can be a good defence against demand fluctuations. Although safety stock below a particular level could minimize instability and reduce cost, Sridharan and LaForge (1989) came to the conclusion that nervousness could be observed if stock levels were not appropriately chosen.

To deal with this nervousness, various strategies and models have been created for production planning. Among these some of the common strategies are frozen horizon

(Kadipasaoglu and Sridharan,1995) , lot sizing techniques (Zhao et al., 2001) , and forecasting beyond the planning horizon (Blackburn et al., 1986). Flexible Requirement Profile (Srinivasan, 2005) (which forms the basis of this thesis study and will bw covered in more details in subsequent sections), is a yet another more recent strategy, which relaxes the rigid "freeze" requirements in frozen horizon through changing bounds in time. While each of these empirical methods has produced findings that are largely encouraging, they also highlight the need for high forecast quality and low levels of demand fluctuation in order to achieve robustness in MRP models.

2.1.4 Warehouse Resource

The literature describes warehouses as locations with planned space for handling and storing various materials and goods. They are also necessary for supply chains to have a seamless product flow (De Koster et al., 2017).The processing and storing of items in warehouse operations is a key component of competitive supply chains (Pereira et al., 2020). Moreover, warehouses greatly influence the performance of the supply chain and the degree of customer service (Gue and Meller, 2014). Additionally, three different types of warehouses have been described: contract, production, and distribution warehouses (Berg et al., 1999). Distribution warehouses are primarily concerned with the storage and shipping of deliverables from a supplier to a customer, production warehouses, as their name implies, are production facilities for various product types, such as raw materials or finished goods, and lastly, contracted warehouses handle warehouse tasks for a number of different clients (Berg et al., 1999). In this study, we aim to optimise distribution warehouse resource and transportation planning while managing plant stability.

Warehousing is frequently required to carry out standard logistical tasks like inventory management, order product mixing, cross docking, and customer support (Coyle, Bardi, & Langley, 2003). Such processes need the use of significant company resources including storage space, material handling equipment, and employees. (Ballard 1996) addressed the idea that better accuracy and customer service will arise from a warehouse's optimal use of its space and resources. However, the attention paid by researchers in resource management in warehouse operation is relatively limited.

2.1.5 Warehouse Resource Management

Warehouse management, which includes the storage, movement, and tracking of commodities inside a warehouse, is an essential part of supply chain management (Cohen & Lee, 1988). Effective warehouse management is essential for meeting customer demand, minimizing inventory costs, and improving supply chain performance. The efficient distribution and use of human resources in the warehouse to accomplish organizational goals is part of the crucial supply chain process. The process entails determining the competences and skills needed for particular warehouse tasks and appointing employees with those skills to those activities. In order to improve productivity and accomplish organizational objectives, effective warehouse workforce management makes sure that the right people are working on the right tasks at the right time.

Many components of the process, including workforce planning, scheduling, and training, have been the subject of research in the field of warehouse workforce management. For instance, anticipating future warehouse hiring needs and creating plans to address those requirements are both part of workforce planning. Researchers have studied various techniques for warehouse workforce planning, such as demand forecasting and supply forecasting, and their impact on warehouse performance (Bechet, 2017). According to the literature, efficient workforce planning for warehouses can assist businesses in filling positions, lowering employee turnover, and improving productivity.

Scheduling is another critical aspect of workforce management. Researchers have investigated the effects of different warehouse scheduling methods, including shift scheduling and task scheduling, on employee satisfaction and productivity (Cayirli et al., 2009). Overall, effective warehouse human resource management, in general, necessitates a thorough comprehension of organizational objectives and personnel capabilities. It involves implementing best practices and technologies for labor planning, scheduling, and training in warehouses in order to maximize efficiency and meet organizational goals.

2.1.6 Flexible Requirement Profile

A concept called the Flexible Requirement Profile (FRP)-based planning was created to allow for changes in production plans while still keeping a certain level of control. (Srinivasan, 2004). The concept of flexible fencing is used to keep production plans within a range defined by lower and upper flex-limits or bounds. The fundamental concept behind FRP is to create flexible "fences" around production plans, allowing for changes within a specific range without totally disrupting the plan. These fences can be modified in response to shifting conditions, such as changes in demand, the availability of materials, or the production capability (Huang et al. ,2003). (Demirel, et al. , 2018) showed that FRP-based rolling horizon Aggregate Production Planning (FRP-APP) models can be formulated and solved using mixed-integer linear programming (MILP). Based on two industry-based numerical studies, (Demirel et al. ,2018) demonstrated that FRP-APP has the potential to generate production plans that are more stable yet cost effective as compared to the traditional APP models. In a subsequent study, Torabzadeh and Ozelkan (2021) proposed Fuzzy-FRP-APP models to represent the demand uncertainty better. Ozelkan et al. (2023) proposed a bi-objective APP (BO-APP) model and compared it to the FRP-APP model. They concluded that like the FRP-APP, the BO-APP model can be very effective managing plan stability. While there are FRP-APP models, none of these models have considered warehouse and transportation aspects in the supply chain, which is the aim and contribution of this current study. With the help of the FRP concept, warehouse managers may modify resource levels, such as labour and equipment, based on changes in demand and other variables. Efficient warehouse resource and transportation planning are crucial for the success of supply chain management.

2.2 Summary and Conclusions

As seen in the literature review, there are no studies that focus on cost and stability simultaneously in warehouse and transportation management. Therefore, in this study, we aim to address this research gap by developing a new warehouse resource and transportation planning (WRTP) model that incorporates the FRP technique, called WRTP-FRP. By using WRTP-FRP, we can effectively manage plan stability and ensure that production plans remain within prescribed lower and upper bounds. To evaluate the performance of WRTP-FRP, we will compare it to a traditional WRTP model that solely focus on cost minimization, without considering stability. We will conduct numerical experiments to evaluate the cost and stability performance of both models. Our aim is to provide a formal method of handling plan stability along with cost minimization in warehouse resource and transportation planning.

CHAPTER 3: MODEL AND METHODOLOGY

This chapter begins by demonstrating the dynamic formulation of the conventional WRTP model. Subsequently, the FRP approach is introduced, which optimizes both plan cost and plan stability. Additionally, we demonstrate the application of this approach to a rolling horizon process. While the analysis presented in this chapter focuses on a single product, it is worth noting that the framework we provide can be extended to encompass multiple products with ease.

3.1 Warehouse Resource and Transportation Planning Model (WRTP)

The proposed approach is to solve the warehouse and transportation planning through mathematical optimization. Our underlying idea is to create a dynamic optimization plan that minimizes warehouse and transportation related costs. In specific, the proposed model is an warehouse and transportation planning problem that employs a deterministic optimization model to find optimal values for shipment levels, workforce size, shipment quantities, and inventory and backorder levels for the current and next N periods. The optimal plans are computed on a rolling basis, and there is an optimal plan for each period in the planning horizon. The following parameters and decision variables below are used in the model.

Indices:

N: number of periods in the planning horizon

T: number of periods in the rolling horizon

Z: Number of nodes in the supply network

U: Number of nodes in supplier network

V: Number of nodes in consumer/retailer network

X: Number of nodes in warehouse network

n :Index for planning horizon, n = 0, … , N

t : Index for rolling horizon, t = 1, … , T

i: Any node that is origin/source of material movement, i= 1,…., Z j: Any node that is destination/sink of material movement, j=1,…., Z

Parameters:

c^W: labour cost of a regular worker per period

c^H, c^L: hiring and layoff costs per worker, respectively

c_{ij}: transportation cost

h : unit inventory holding cost

b : unit backlog cost

ϑ: total number of working hours in a week

m^R : maximum number of units shipped per worker per period

I : Initial inventory

W : Initial workforce

Variables:

$S_{t,n,ij}$: n-step ahead shipment level planned

$I_{t,n,j}$: n-step ahead inventory level planned

$B_{t,n,j}$: n-step ahead backorder level planned

$W_{t,n,j}$: n-step ahead workforce size planned

$H_{t,n,j}$: n-step ahead planned hiring level

$L_{t,n,j}$: n-step ahead planned layoff level

$d_{t,n,ij}$: n-step ahead demand forecasted at period t

Note that for all n related parameter, n = 0 represents the current period t and actual values, while n > 0 corresponds to future planning periods.

Model and Notation:

Let M = { 1,…, Z} denote the set of indices for all the supplier plants, consumer plants and warehouses in a network. Let P={1,…,U}, Q={1,…,V} and R={1,….,X} respectively denote the sets of indices for supplier plants, consumer plants and warehouses.

The total cost of the shipment is given by:

$$\sum_{i \in M} \sum_{j \in M} c_{ij} . S_{ij} \qquad 3.1$$

The MILP formulation of the warehouse resource and transportation planning (WRTP) can be formulated as follows;

$$Minimise \sum_{n=0}^{N} \Big(\sum_{j \in R} (c^{w} . \vartheta . W_{t,n,j} + c^{H} H_{t,n,j} + c^{L} . L_{t,n,j} + h . I_{t,n,j} + b . B_{t,n,j}) + \sum_{i \in M} \sum_{j \in M} c_{ij} . S_{t,n,ij} \Big) \qquad 3.2$$

Subject to:

Initial inventory:

$$\sum_{i \in \mathrm{P}} \sum_{j \in \mathrm{R}} S_{t,0,ij} = d_{t,0,j} + I_{t,0,j} - B_{t,0,j} - I_{t-1,0,j} + B_{t-1,0,j} \qquad \forall i \in P \text{ and } j \in R \qquad 3.3$$

$$\sum_{i \in \mathrm{P}} \sum_{j \in \mathrm{R}} S_{t,n,ij} = d_{t,n,k} + I_{t,n,j} - B_{t,n,j} - I_{t,n-1,j} + B_{t,n-1,j} \qquad \forall n = 1,2 \dots, N \quad \forall i \in P, j \in R \text{ and } k \in Q \qquad 3.4$$

End Inventory:

$$I_{t,n,j} \geq I \qquad \forall n = 1,2 \dots, N \qquad \forall j \in R \qquad 3.5$$

Workforce:

$$W_{t,n,j} = W_{t-1,n,j} + H_{t,n,j} - F_{t,n,j} \qquad \forall n = 1,2, \dots, N \quad \forall j \in R \text{ where } j = 1,2 \dots, J \qquad 3.6$$

Shipment capacity:

$$\sum_{i\in P}\sum_{j\in R} S_{t,n,ij} + \sum_{j\in R}\sum_{k\in Q} S_{t,n,jk} \leq m^R W_{t,n,j} \qquad \forall n = 1,2,\dots,N \qquad 3.7$$

Demand constraint:

$$\sum_{i\in R}\sum_{j\in Q} S_{t,n,ij} = d_{t,n,j} \qquad \forall n = 1,2,\dots,N \qquad 3.8$$

Capacity constraint:

$$\sum_{i\in P}\sum_{j\in R} S_{t,n,ij} \leq Plant\ capacity \qquad \forall n = 1,2,\dots,N \qquad \forall i \in P\ and\ j \in R \qquad 3.9$$

$$S_{t,n,ij} \geq 0 \qquad \forall n = 1,2,\dots,N \qquad \forall i\ and\ j \in M \qquad 3.10$$

$W_{t,n}, H_{t,n}, F_{t,n}$ are integers. *3.11*

$$I_{t,n,j}, B_{t,n,j}, W_{t,n,j}, H_{t,n,j}, F_{t,n,j} \geq 0 \qquad \forall n = 1,2,\dots,N \qquad \forall j \in R \qquad 3.12$$

At each period t, the objective is to minimise the overall projected cost over the current cost (n=0) and next N periods. The objective function consists of the labour cost, hiring/layoff cost, inventory holding cost, and backorder cost. Inventory Balance is provided through constraints (3.3-3.4) where the realised or forecasted demand plus the ending inventory equals the total shipment plus the ending inventory from the previous period. *Workforce* constraint (3.6) ensures that the total workforce in period *t* equals to total workforce in the previous period (*t*-1), plus the net change in the workforce during period *t*. The net change is based on hiring or laying-off workers. *Capacity* constraint (3.9) ensures that the total shipment in period *t* will not exceed the available shipment capacity.

3.2 Flexible Requirements Profile (FRP)

To facilitate comparison, we will briefly introduce the FRP-APP model as defined by Demirel et al. (2018). This model employs FRP to keep production plans within acceptable flexibility levels. Specifically, the n-step ahead production plan (n = 1,2,.. N) in an FRP-based plan is subject to dynamically changing lower and upper bounds. The concept of planning fences has been transformed into flex-limits and are represented as $\pm F_n$ such that $F_1 \leq F_2 \leq F_3 \leq \dots \leq F_N$, where N is the number of periods in planning horizon. The FRP bounds are updated dynamically during each planning iteration. By enforcing flex-limits in production plans, the model increases the ability to respond to demand fluctuations and smooths out production and inventory levels. Figure 3.1 illustrates incremental flex-limits of 1%, 2%, and 3%, where flexibility increases over the planning horizon. Due to its shape, this is also referred to as the planning funnel by Demirel et al. (2018).

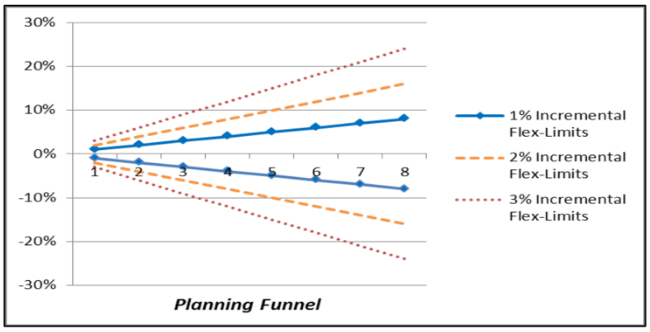


Figure 3.1 Application of Flex-Limits in the Planning Horizon.

Let $LB_{t,n}$ and $UB_{t,n}$ denote lower and upper production bounds on P during the planning period.

To compute the iteration at time t, the shipment bounds for t+1 are updated as follows.

Lower Bounds: $LB_{t+1,n} = max\{LB_{t,n+1}, P_{t-1,n+1}(1-F_n)\} \quad n = 0,1,\ldots,N-1$ *3.13*

Upper Bounds: $UB_{t+1,n} = \min\{UB_{t,n+1}, P_{t-1,n+1}(1+F_n)\} \quad n = 0,1,\ldots,N-1$ *3.14*

The lower and upper bounds of n = N are set as $LB_{t+1,n} = -\infty$ and $UB_{t+1,n} = +\infty$. With this update, the planning at t is completed and the time rolls into the next period t+1. As a result, the following FRP-based constraint is enforced on the production levels:

$$FRP\ Bounds: LB_{t,n} \leq P_{t,n} \leq UB_{t,n} \quad n = 0,1,\ldots,N \qquad 3.15$$

Hence, the FRP-APP formulation can be formally stated as follows :

FRP-APP = APP + FRP Constraints (3.13-3.15)

In our research, we will employ a similar concept to ensure that our warehouse resource and transportation plans. Given that our warehouse does not involve production, we will implement FRP constraints for the warehouse inflow, which aims to optimize both plan cost and plan stability. To formalize our approach, we present it as follows:

Lower Bounds: $LB_{t+1,n,ij} = \max\{LB_{t,n+1}, S_{t-1,n+1,ij}(1-F_n)\}$ 3.16

$$n = 0,1,\ldots N-1 \quad \forall i \in P \; and \; j \in R$$

Upper Bounds: $UB_{t+1,n,ij} = \min\{UB_{t,n+1}, S_{t-1,n+1,ij}(1+F_n)\}$ 3.17

$$n = 0,1,\ldots N-1 \quad \forall i \in P \; and \; j \in R$$

FRP: $LB_{t,n,ij} \leq S_{t,n,ij} \leq UB_{t,n,ij} \quad \forall n = 1,2,\ldots,N \quad \forall i \in P \; and \; j \in R$ 3.18

WRTP-FRP = WRTP + FRP Constraints (3.16-3.18)

3.3 Rolling Horizon Implementation

In rolling horizon environments, planning is an ongoing process that involves analysing the current situation and anticipating future demands, while making decisions that only come into effect in the initial period. As time progresses, the planning process is constantly updated, and decisions are revised based on new information about demand. This rolling over of the horizon allows for greater adaptability and responsiveness to changes in demand patterns. It recognizes that forecasts for distant future periods are less reliable and more expensive than those for near future periods, so plans are adjusted accordingly. Figure 3.2 illustrates how planning elements are interconnected between time t-1 and time t, demonstrating the continuous nature of the rolling horizon planning approach.

Rolling Horizon iteration t=1,...T	Planning horizon n=1,....N																	
	1	0	1	2	...	n-1	n	n+1	...	N-1	N							
	2		0	1	2	...	n-1	n	n+1	...	N-1	N						
	...			...			...				...		...					
	t-1				0	1	2	...	n-1	n	n+1	...	N-1	N				
	t					0	1	2	...	n-1	n	n+1	...	N-1	N			
	t+1						...			...				...		...		
	...																	
	T-1							0	1	2	...	n-1	n	n+1	...	N-1	N	
	T								0	1	2	...	n-1	n	n+1	...	N-1	N

Figure 3.2:Illustration of Updates from Period t-1 to t

3.4 Computational Study

In this section, a comprehensive analysis on the performance of the WRTP-FRP model will be presented. The data structure and the two performance metrics are presented first, followed by the major findings, and experimental examination of the models to determine the elements that have an impact on their performance.

3.4.1 Data Structure

We use three sets of data corresponding to Textile (Leung, Wu et al. 2003, Demirel 2014), Automotive parts (Sillekens, Koberstein et al. 2011, Demirel 2014) and Wood & Paper production (Mirzapour Al-E-Hashem, Malekly et al. 2011) as shown in Table 3.1. It should be noted that the values marked by * are missing values in each case and calculated using the mean values of the same parameters in other cases.

These data sets follow a different structure in terms of production, inventory and labour related costs and times.

Table 3.1: Cost and Capacity, Three Case Studies

Parameter	**Textile**	**Automotive Parts**	**Wood & Paper**
Production cost($/unit)	6.41	1.8	9.03*
Inventory cost per unit per week ($/unit)	1.92	0.18	5
Backorder cost per unit per week ($/unit)	3.85	3.6	2
Labour cost ($/person-hour)	0.80	11.16	18
Hiring cost ($/person)	12.82	3571	40
Layoff cost ($/person)	15.38	14286	70

3.5 Types of Network Used in This Study

In our study, we examine six different network configurations, each with varying numbers of supplier, consumer, and warehouse nodes. We assume that all of the supplier plants are working with 100% capacity.

The first network configuration included two supplier nodes, one warehouse node, and two consumer nodes with no direct connections between supplier and consumer (2-1-2).

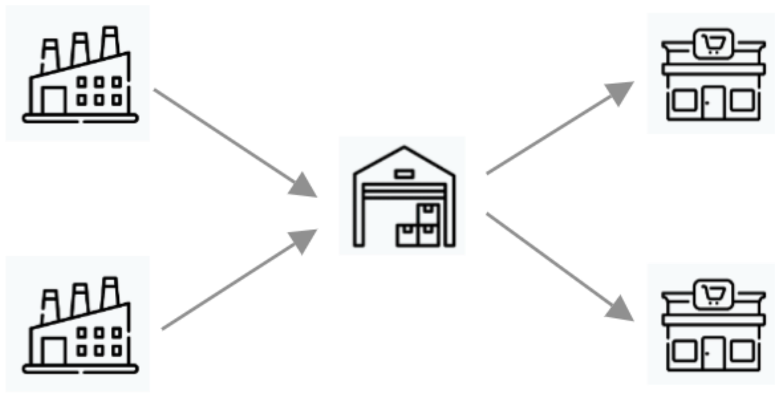


Figure 3.3: 2-1-2 Network

The second network configuration also had two supplier nodes, one warehouse node, and two consumer nodes, but this time with direct connections between suppliers and consumers (2-1-2-D).

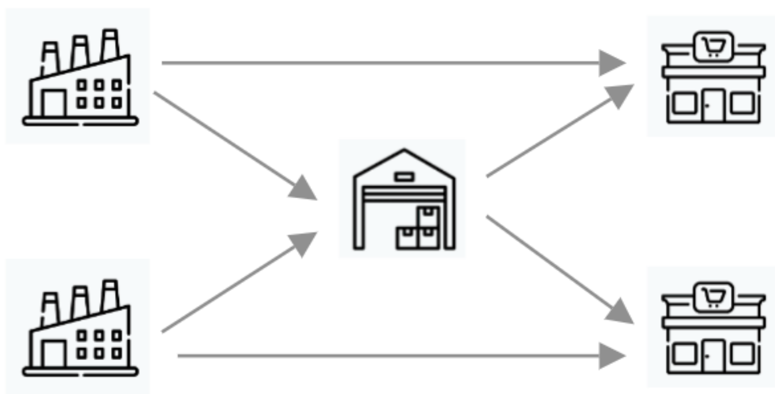


Figure 3.4:2-1-2-D Network

The third network configuration had two supplier nodes, two warehouse nodes, and two consumer nodes with no direct connections between supplier and consumer (2-2-2).

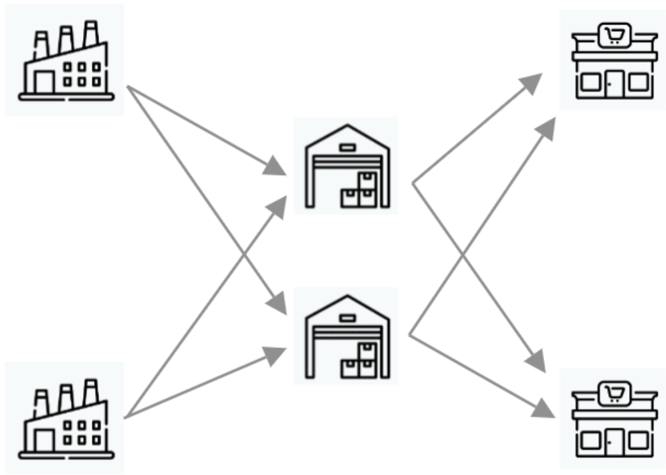


Figure 3.5: 2-2-2 Network

The fourth network configuration had two supplier nodes, two warehouse nodes, and two consumer nodes with direct connections between suppliers and consumers (2-2-2-D).

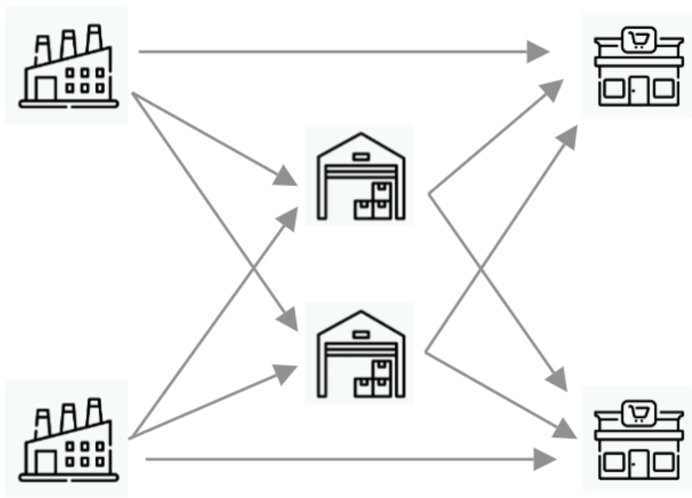


Figure 3.6: 2-2-2-D Network

The fifth network configuration had two supplier nodes, two warehouse nodes, and two consumer nodes with no direct connections between supplier and consumer (2-2-3).

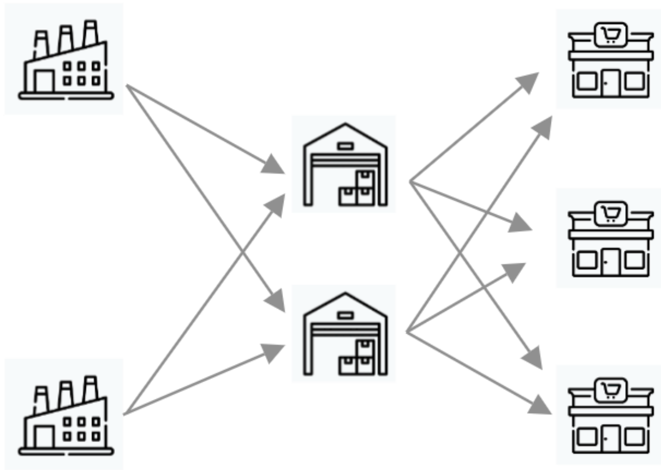


Figure 3.7:2-2-3 Network

The sixth network configuration had two supplier nodes, two warehouse nodes, and three consumer nodes with direct connections between suppliers and consumers (2-2-3-D).

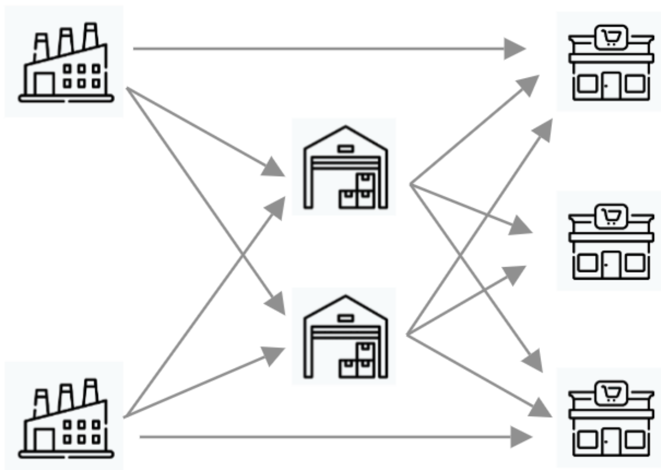


Figure 3.8: 2-2-3-D Network

The cost of transporting goods between suppliers, warehouses, and consumers can vary greatly across different industries. The transportation cost between the supplier, warehouse and consumer nodes for different industries are given in below tables. We use transportation cost data between networks for Wood & Paper (Leung, Wu et al. 2003, Demirel, 2014), as shown in Table 3.2.

Table 3.2: Transportation Costs for Wood & Paper Industry

	3	4	5	6	7	8
1	0.036	0.058	0.072	0.065	0.014	0.029
2	0.065	0.043	0.086	0.036	0.029	0.014
3	0.095	0.115	0.072	0.151	0.13	0.144
4			0.079	0.108	0.05	0.072

The transportation costs between nodes in the textile industry were estimated based on research by (Leung, Wu et al., 2003), which suggested that transportation costs are typically 5% of production cost per unit. Our study used this assumption to calculate the transportation costs between different nodes in the supply chain, and the findings were presented in Table 3.3.

Table 3.3: Transportation Costs for Textile Industry

	3	4	5	6	7	8
1	0.3205	0.372	0.641	0.577	0.124	0.258
2	0.577	0.381	0.763	0.3205	0.258	0.124
3	0.833	1.022	0.641	1.342	0.443	1.282
4			0.703	0.961	0.445	0.641

A study conducted by (CSCMP, 2019) revealed that logistics costs constitute approximately 9.9 % of total sales in the automotive industry. In our case study, we have assumed that the demand is equivalent to sales and have generated the corresponding transportation cost data, which is presented in the Table 3.4.

Table 3.4: Transportation Costs for Automotive Industry

	3	4	5	6	7	8
1	0.094	0.151	0.188	0.169	0.036	0.075
2	0.169	0.112	0.223	0.094	0.075	0.036
3	0.248	0.3	0.188	0.394	0.339	0.188
4			0.206	0.282	0.130	0.0275

The initial inventory is assumed to be 100 units and the initial workforce is set based on the realized demand in the first period of each planning iteration. Each employee regularly works 8 hours per day, 5 days per week.

We use the demand generation formulation introduced by (Demirel, 2014) where the demand is assumed to follow a seasonal behaviour according to the following formulation:

$$D_t = (a + bt)S_t + e_t \qquad 3.19$$

Where D_t is the demand value at time period t, a is the baseline parameter, b is the trend component, S_t is the seasonal factor at time period t, and e_t is the random error component with a normal distribution N (0, σ^2). The variation in the values of demand generation components could result in various demand scenarios. Table 3.5 represents the magnitude of four demand generation components (Demirel,2014). As each of 4 main components in (3.19) has 2 levels, 16 demand scenarios would be generated.

Table 3.5: Demand Generation Components Values

Component	**Low**	**High**
Baseline	1000 units	3000 units
Trend	20 units	100 units
Seasonality	$\pm$ 0.1	$\pm$ 0.3
Magnitude of error	Std = 50	Std = 100

We will be using the same demand scenarios for all case studies as the 16 demand scenarios have variation combinations for demand values and it has the potential to give an overview of the effect of different cost structures on the WRTP-FRP and WRTP models performance. Table 3.6 presents these scenarios and levels of parameters used for generation of each scenario.

Table 3.6: Demand Scenarios

Scenario No	Baseline	Trend	Seasonality	Magnitude of error
1	Low	Low	Low	Low
2	Low	Low	Low	High
3	Low	Low	High	Low
4	Low	Low	High	High
5	Low	High	Low	Low
6	Low	High	Low	High
7	Low	High	High	Low
8	Low	High	High	High
9	High	Low	Low	Low
10	High	Low	Low	High
11	High	Low	High	Low
12	High	Low	High	High
13	High	High	Low	Low
14	High	High	Low	High
15	High	High	High	Low
16	High	High	High	High

For the crisp models and taking into account the generated demand as the historical data, the Multiplicative Holt-Winter (Triple Exponential Smoothing) forecasting approach is used to predict the demand values of the future periods.

This forecasting technique considers all demand generation formulation components, each of which has a unique parametric-based formulation. Baseline, Trend, and Seasonality and the anticipated demand formulation is as follows:

$$Base: L_t = \alpha\left(\frac{D_t}{S_{t-s}}\right) + (1-\alpha)(L_{t-1} - T_{t-1}) \tag{3.20}$$

$$Trend: T = \beta(L_t - L_{t-1})) + (1-\beta)T_{t-1} \tag{3.21}$$

$$Seasonality: S_t = \Upsilon\,(D_t) + (1 - \Upsilon)S_{t-s} \tag{3.22}$$

$$Forecast: F = (L_t + mT_t)S_{t+m-s} \tag{3.23}$$

In the above formulation, s is the seasonality length, and m denotes the number of future periods for which the forecasting is done. In addition, α, β, $\Upsilon\ \epsilon[0,1]$ are the smoothing parameters. Each demand scenario is forecasted using the above formulation, and is used in crisp models as the forecasted demands. For each demand scenario, we aim to do the planning for the current period and N = 8 periods ahead in each planning iteration (n = 0,1, … ,8) and repeat the planning for T = 50 rolling horizon iterations (t = 1, … ,50). As a result, the Mean Square Error (MSE) of the projections is initially calculated using the anticipated demand for each period and its actual demand generated using the demand generation formulation. Once all of the forecasts have been completed, we utilize MSE minimization to get the best values for α, β, and Υ, as well as the more trustworthy forecast values that will be used in our test issues later on.

3.6 Performance Measures

The first performance measure is the total current cost for n = 0 (actual cost) over all planning iterations. Please note that this cost performance measure is related to but different from the cost objective function defined in the optimization models as it just considers the summation of actual costs over all planning iterations as shown in the formula below:

Actual Cost:

$$Minimise \sum_{t=1}^{T} (\sum_{j \in R} (c^{w}.W_{t,0,j} + c^{H} H_{t,0,j} + c^{L}.L_{t,0,j} + h.I_{t,0,j} + b.B_{t,0,j}) + \sum_{i \in M} \sum_{j \in M} c_{ij}.S_{t,0,ij}) \qquad 3.24$$

The second measure, called plan variability, is defined to capture the stability/nervousness in production and transportation plans. There have been a few attempts to quantify nervousness in transportation planning. In some earlier studies, nervousness is defined in terms of cost, and included in the objective function (Carlson et al., 1979). Non-monetary nervousness measures have considered changes in production quantities and changes in number of setups extensively (Sridharan and LaForge 1989; Kimms, 1998; Jeunet and Jonard, 2000). Measures that consider multiple criteria simultaneously, such as changes in production quantities and differences between new and old order due dates, are also available (Ho and Ireland, 1998). We define plan stability as the difference between the planned shipment levels versus the actual shipment in a rolling horizon environment. The overall plan stability in the planning horizon is calculated according to the following formula;

$$\sum_{t=2}^{T} \sum_{i \in M} \sum_{j \in M} \frac{(\sum_{n=1}^{N} |s_{t-1,n,ij} - s_{t,n-1,ij}|)}{T \times N} \tag{3.25}$$

Where T is the number of evaluation periods. This definition is based on the I_p – norm, where p is the compensation parameter such that $1 \leq p \leq \infty$. In this study, we use full compensation, i.e. p=1, which represents the distance between two consecutive N-period shipment plans (De Kok and Inderfurth, 1997).

3.7 Computational Results

We conduct our numerical experiments using the Python programming language and the GUROBIPY solver. Comparisons between the WRTP models with and without FRP are made within the context of planning costs and stabilities. There are 16 (2^4) demand scenarios available that represent the two levels (low and high) of four demand factors (Table 3.5). The computations give different results for the wood & paper, automotive and textile industries, but in majority of the cases optimization-based FRP approach return more favourable outputs. For the purpose of this analysis, we consider that all supplier plants are functioning at maximum capacity.

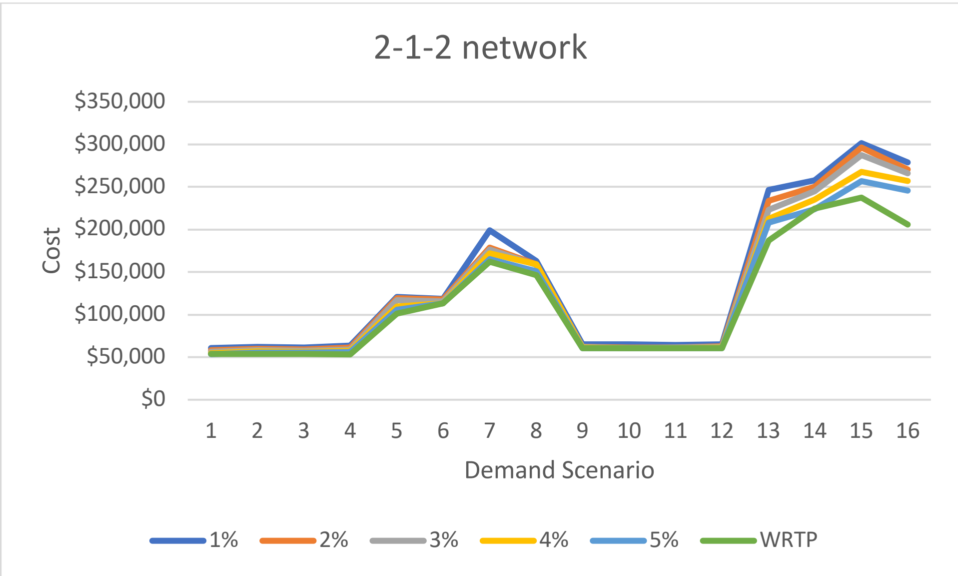
Industry 1: Wood & Paper Industry

Figures 3.9 and 3.10 display the results of total cost for the wood & paper industry under the 16 demand scenarios in different networks. The cost gap among the flex-limits appears to be very small in all the networks. “No-flex-limits” case yields slightly lower costs than the model with flex limits in majority of the demand scenarios.

Our study revealed that, although the difference may be slight, WRTP-FRP models in all networks consistently resulted in higher costs than WRTP models across all five flex-limits categories examined. As we introduced FRP into the WRTP model and decreased the flex limit from 5% to 1%, we observed a corresponding increase in costs. In fact, our analysis showed that the highest costs were associated with the WRTP-FRP model operating under a 1% flex limit.

By observing Figure 3.9, we can see that the (2-1-2-D) yields slightly lesser cost in scenarios with high level of trend (13-16) than the other network without direct connection between supplier and consumer nodes therefore minimising the warehouse resources and the total cost. However, in both cases we see that WRTP models yields lower cost than the WRTP-FRP model under different flex limits. Per our observation, in one warehouse network, WRTP approach displays more favourable results with an average cost of 19.4% and 18.83% less expensive when compared to WRTP-FRP model with 1% flex limit for (2-1-2) and (2-1-2-D) network respectively.

The (2-2-2) and (2-2-2-D) model resulted in the similar analysis. (2-2-2-D) networks performs better than (2-2-2) network however in this comparison, 96% of the cases in WRTP-FRP models in both the networks consistently resulted in higher costs than WRTP models across all five flex-limits categories examined. Per our observation, in two warehouse network, WRTP approach displays more favourable results with an average cost of 22.57% and 31.25% less expensive when compared to WRT-FRP model with 1% flex limit for (2-2-2) and (2-2-2-D) network respectively.



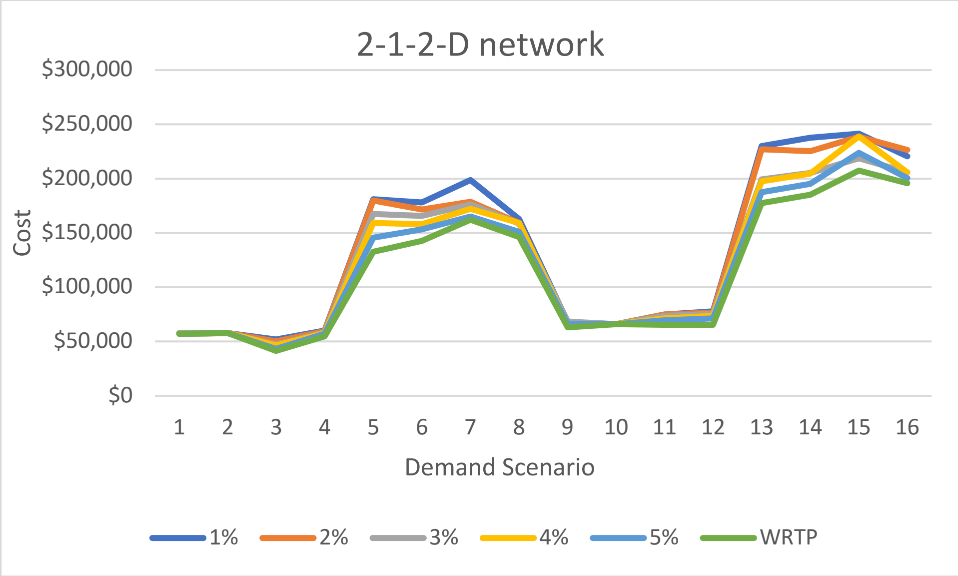
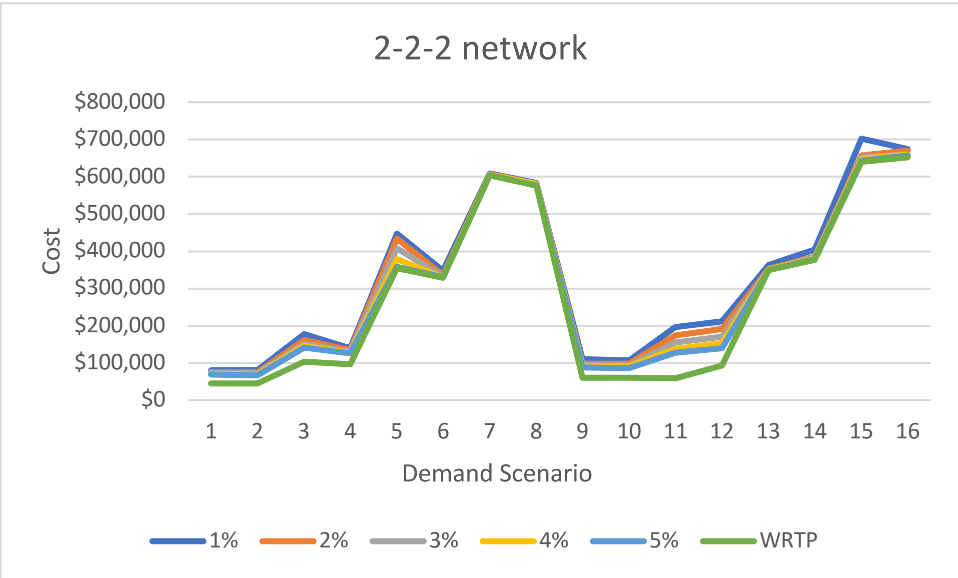


Figure 3.9: Cost Graphs in Wood & Paper Industry with 1 Warehouse Network



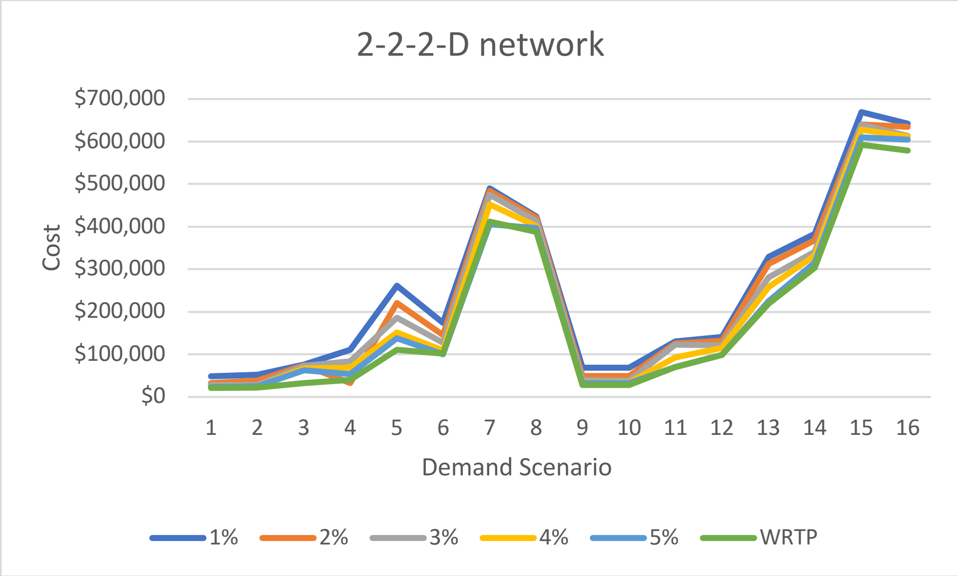
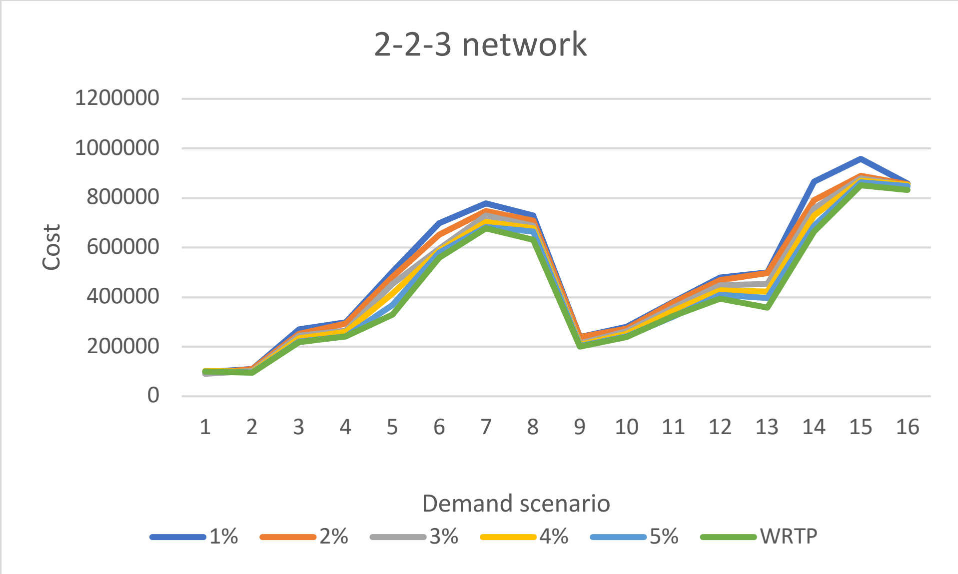


Figure 3.10: Cost Graphs in Wood & Paper Industry with 2 Warehouses Network

Further analysis using (2-2-3) and (2-2-3-D) networks, we observed that the latter outperformed the former. As expected, our comparison revealed that the WRTP-FRP models consistently resulted in higher costs than the WRTP models, regardless of the five flex-limits categories examined in both networks. Our findings showed that the WRTP approach yielded more favourable results in a two-warehouse, three-consumer network, with an average cost that was 22.06% and 15.44% less expensive compared to the WRT-FRP model with a 1% flex limit for the (2-2-3) and (2-2-3-D) networks, respectively.



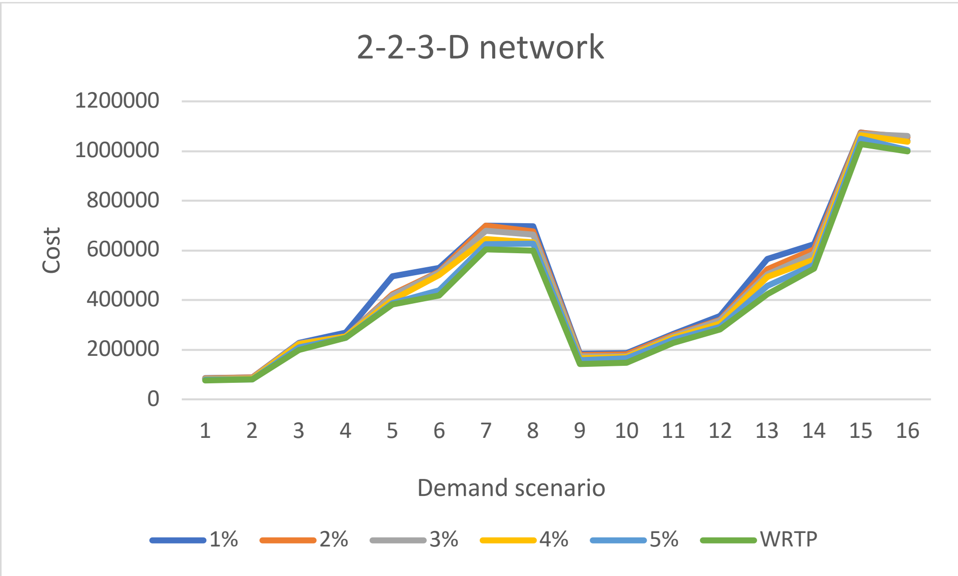


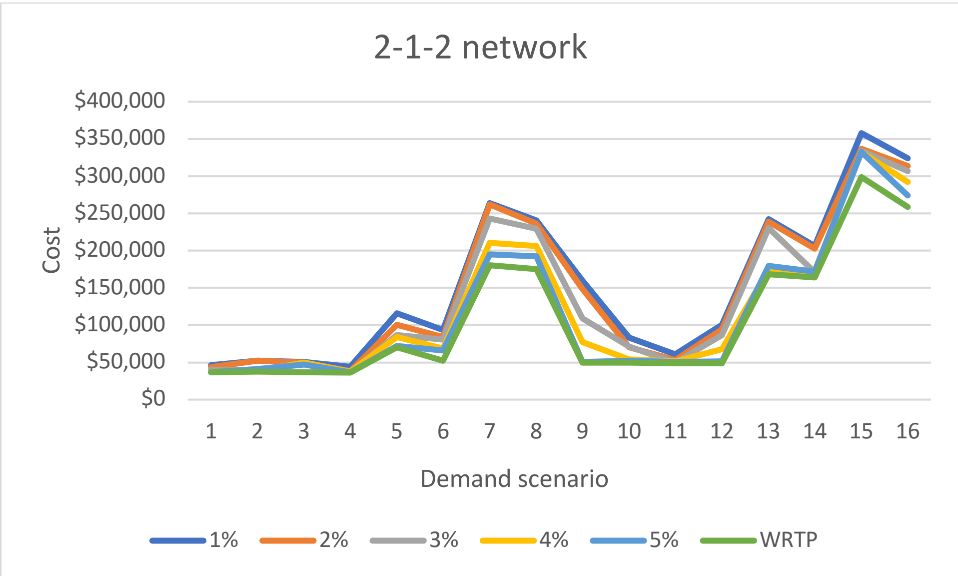
Figure 3.11: Cost Graphs in Wood & Paper Industry with 3 Customers Network

Industry 2: Textile Industry

Figure 3.12- 3.14 displays the results of total cost for the textile industry under the 16 demand scenarios in different networks. The cost gap among the flex-limits appears to be slightly higher than the Wood & Paper industry and yet “no-flex-limits” case yields lower costs in all the demand scenarios. The WRTP approach consistently resulted in lower costs than the WRTP-FRP model across all five flex-limits categories examined where higher costs were associated with model operating under a 1% flex limit. Per our observation, in one warehouse network, WRTP approach displays more favourable

results with an average cost of 43% and 40.38% when compared to WRT-FRP model with 1% flex limit for (2-1-2) and (2-1-2-D) network respectively.

The (2-2-2) and (2-2-2-D) model resulted in the similar analysis as seen in Figure 3.13. (2-2-2-D) networks performs better than (2-2-2) network however in this comparison, 98% of the cases in WRTP-FRP models in both the networks consistently resulted in higher costs than WRTP models across all five flex-limits categories examined. Based on our analysis, we found that the WRTP approach outperformed the WRT-FRP model with a 1% flex limit in a two-warehouse network. Specifically, we observed average cost of 22.52% and 21% cheaper for the (2-2-2) and (2-2-2-D) network configurations, respectively, when using the WRTP approach.



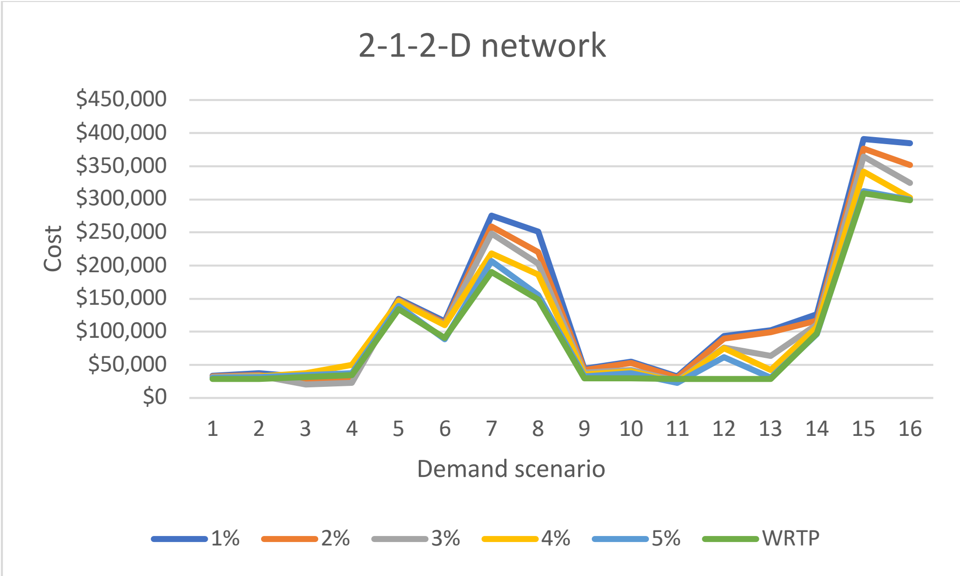
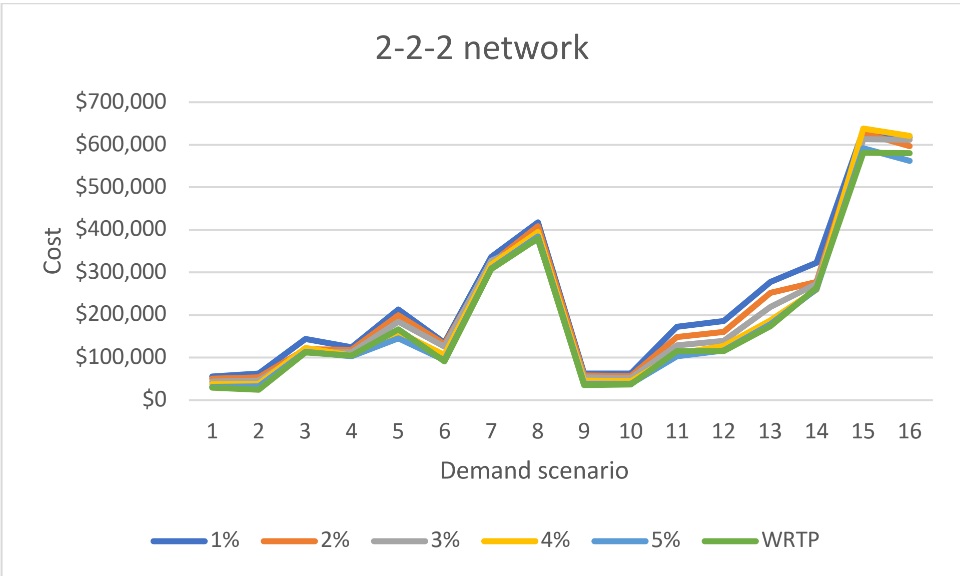


Figure 3.12: Cost Graphs in Textile Industry with 1 Warehouse Network



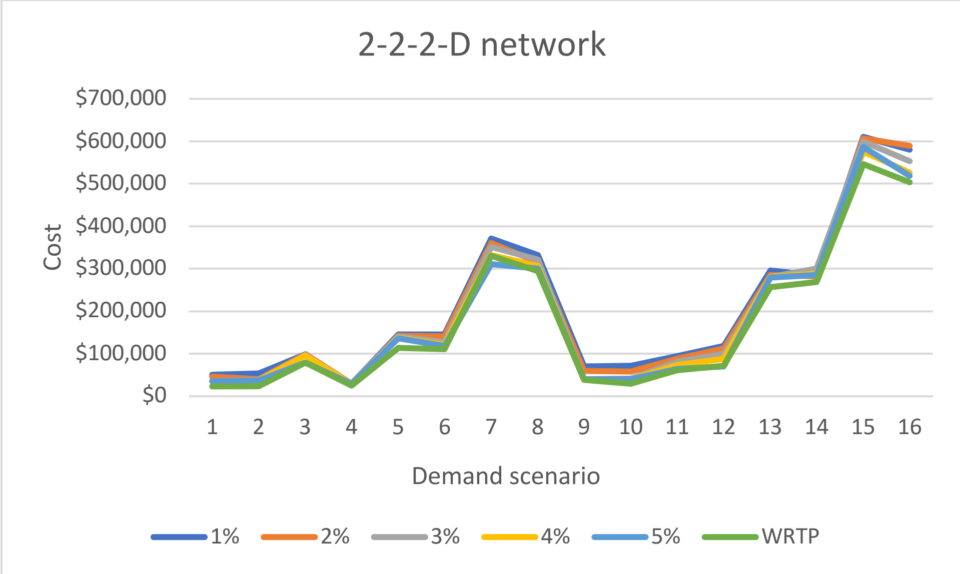
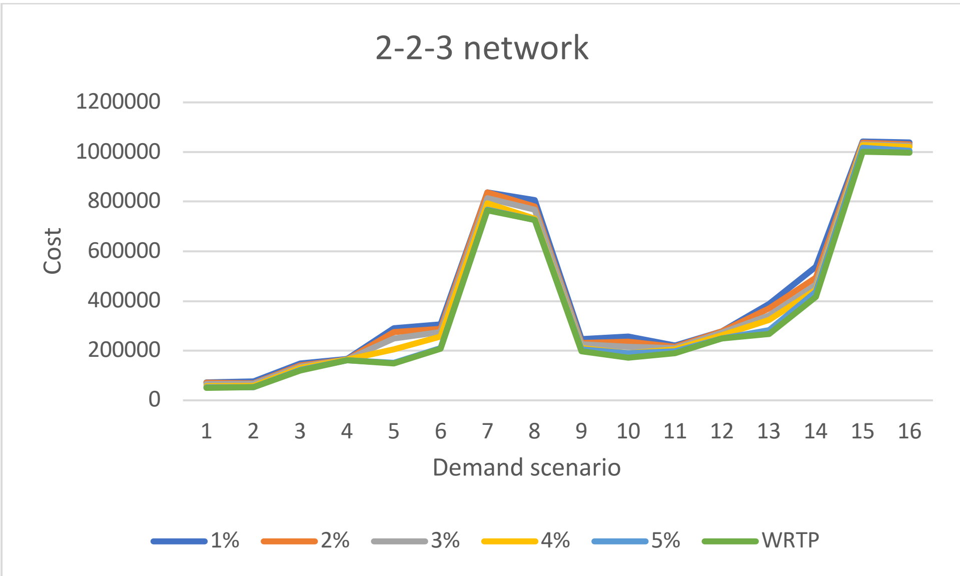


Figure 3.13: Cost Graphs in Textile Industry with 2 Warehouses Network

Using the (2-2-3) and (2-2-3-D) networks, we found that the WRTP-FRP models consistently resulted in higher costs than the WRTP models, regardless of the five flex-limits categories examined. Our data showed that the WRTP approach yielded cost savings of 17.3% and 17.51% for the (2-2-3) and (2-2-3-D) networks, respectively, in a three-consumer, two-warehouse network.



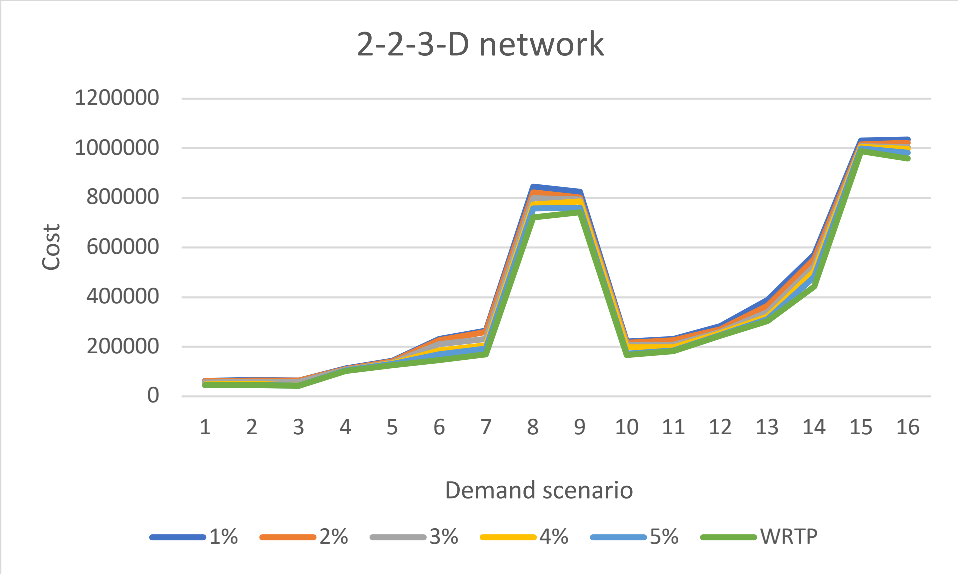
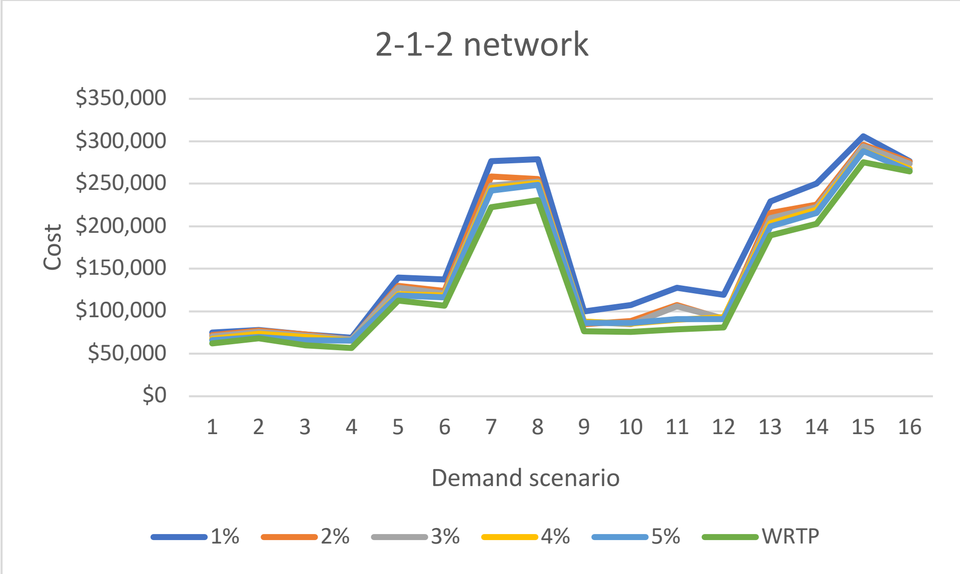


Figure 3.14: Cost Graphs in Textile Industry with 3 Consumers Network

Industry 3: Automotive Industry

Figures 3.15 - 3.17 present the total cost outcomes for the automotive industry across 16 different demand scenarios and networks, with a particular focus on the impact of flex limits. Same as previous, the cost differences between the various flex limit scenarios are relatively small across all networks. Moreover, the model that assumes no flex limits is shown to result in slightly lower costs than the model that includes flex limits in the majority of the demand scenarios.

Our study findings demonstrate that the WRTP-FRP even for Automotive industry models resulted in higher costs compared to the WRTP models, consistently across all networks and flex-limits categories. As we reduced the flex limit from 5% to 1% and incorporated FRP into the WRTP model, we noticed a corresponding increase in costs. Notably, the highest costs were found with the WRTP-FRP model operating under a 1% flex limit, according to our analysis.



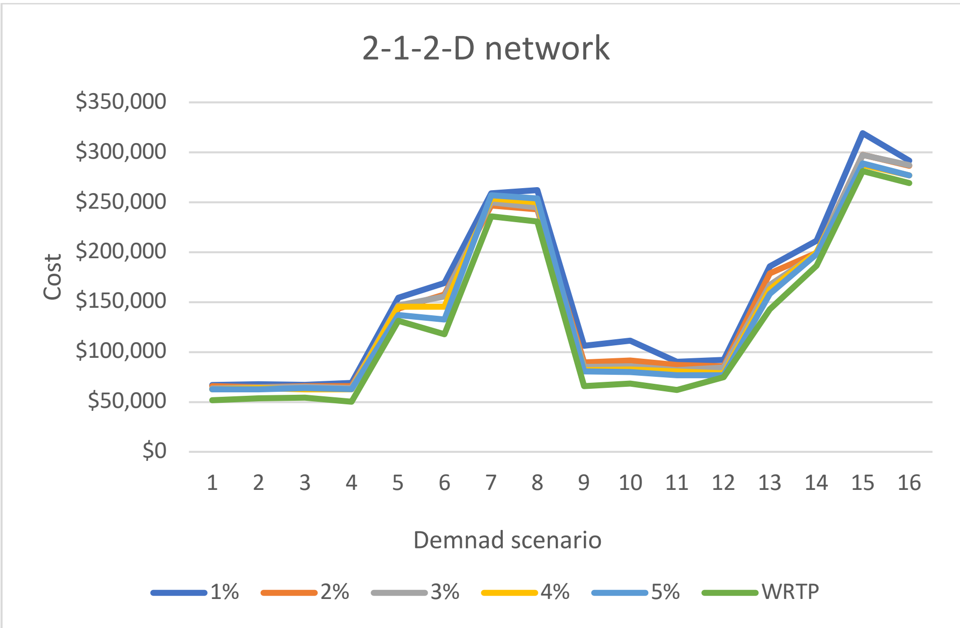
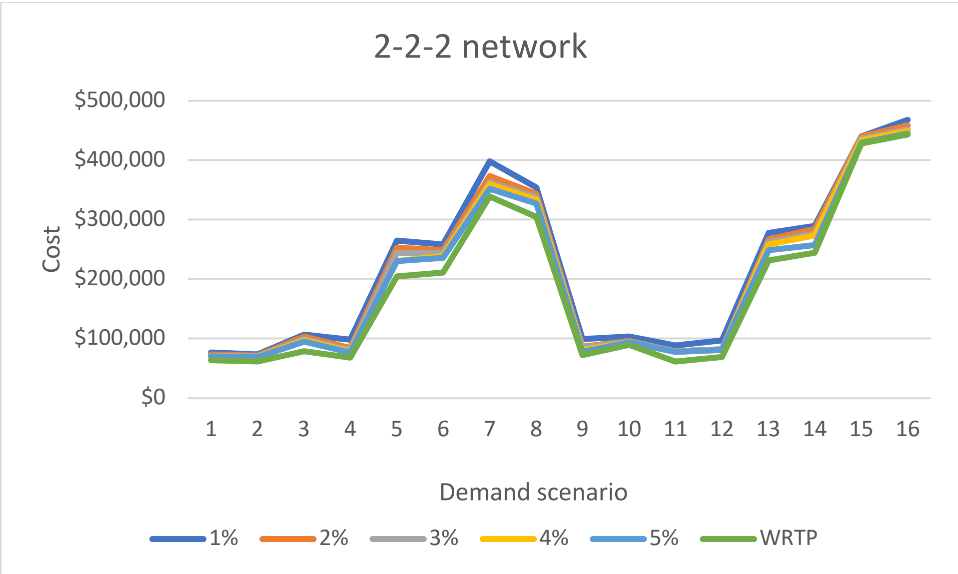


Figure 3.15: Cost Graphs in Automotive Industry with 1 Warehouses Network

Figure 3.16 highlights that the (2-1-2-D) network yields slightly lower costs compared to the network without a direct connection between supplier and consumer nodes. The direct connection node eliminates the need for warehouse resources, which minimizes the total cost. However, the WRTP models consistently outperform the WRTP-FRP models under different flex limits in both network types. In one-warehouse networks, the WRTP approach leads to average savings of 22.22% and 21.58% compared to the

WRTP-FRP model with a 1% flex limit for the (2-1-2) and (2-1-2-D) networks, respectively.

Similar observations were made for the (2-2-2) and (2-2-2-D) models, where the (2-2-2-D) network performs better than the (2-2-2) network. Nevertheless, the WRTP models consistently produce lower costs compared to the WRTP-FRP models across all five flex-limits categories in both network types. In two-warehouse networks, the WRTP approach results in average savings of 17.51% and 14% compared to the WRTP-FRP model with a 1% flex limit for the (2-2-2) and (2-2-2-D) networks, respectively.



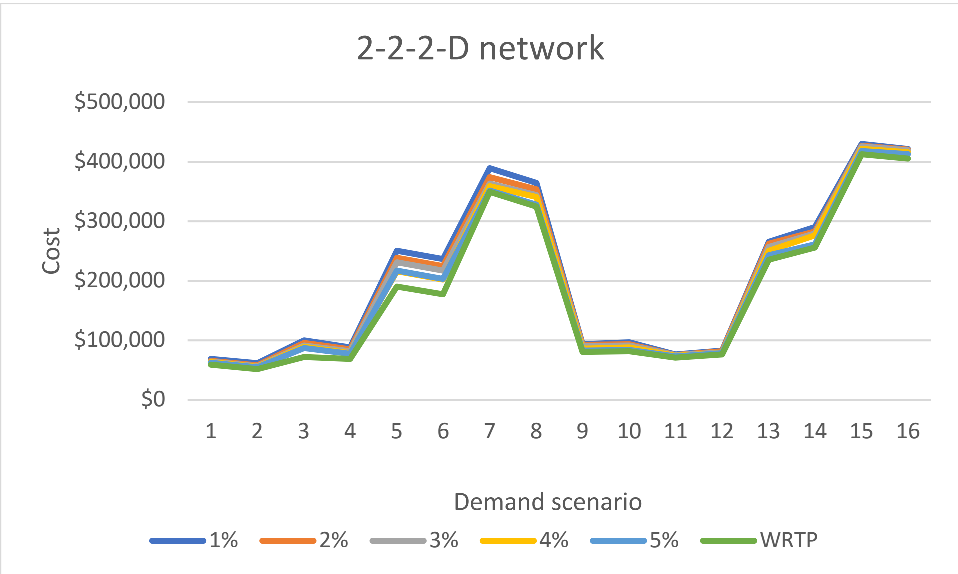
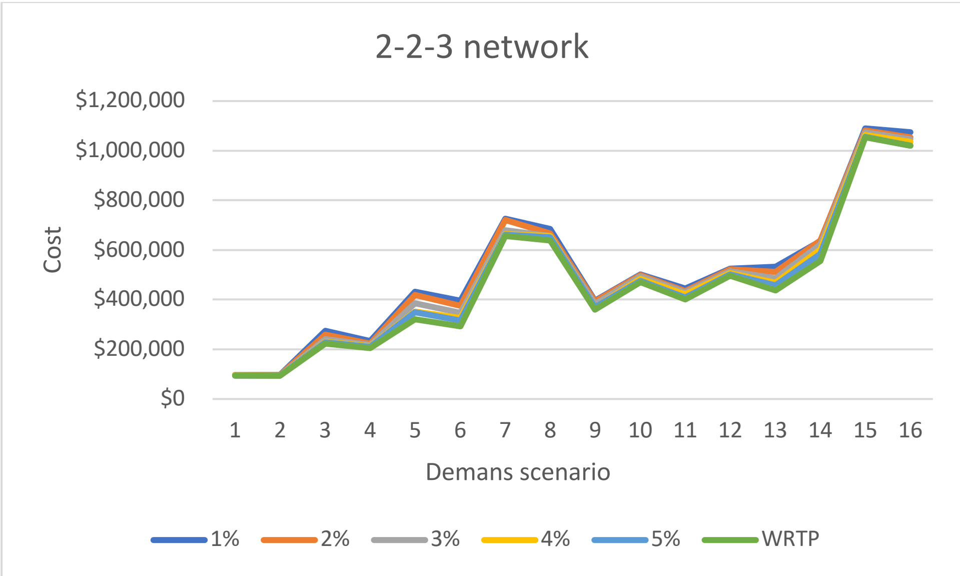


Figure 3.16: Cost Graphs in Automotive Industry with 2 Warehouses Network

Our analysis of the (2-2-3) and (2-2-3-D) models showed that the (2-2-3-D) network outperformed the (2-2-3) network, and the WRTP models consistently resulted in lower costs compared to the WRTP-FRP models across all five flex-limits categories in both network types. Notably, the WRTP approach yielded cost savings of 11.3% and 9.01% for the (2-2-3) and (2-2-3-D) networks, respectively, in two-warehouse networks.



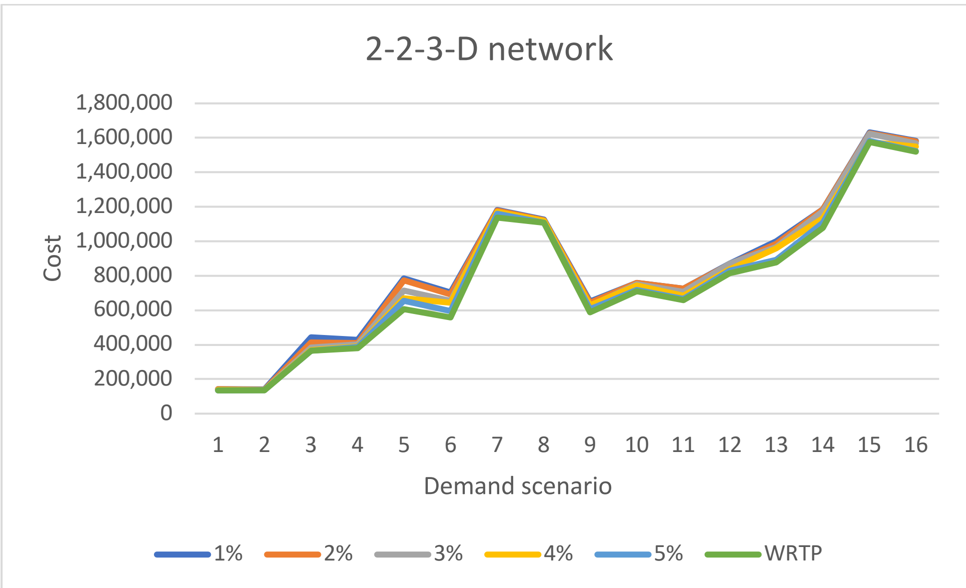
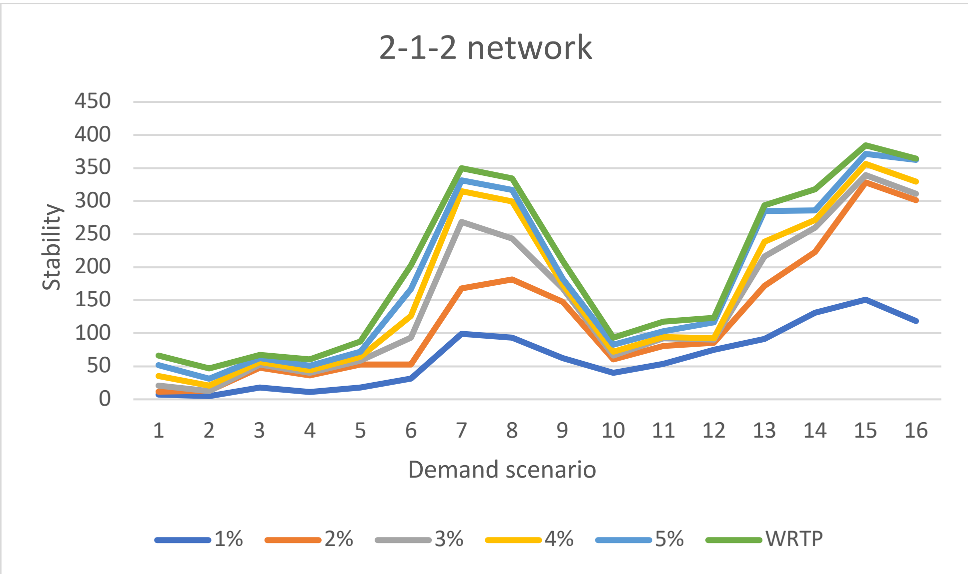


Figure 3.17: Cost Graphs in Automotive Industry with 3 Consumer Network

Our study found that the presence of flex-limits has a significant impact on the second performance measure, plan variability. As expected, smaller flex-limits resulted in lower plan variability. Surprisingly, we observed that using 5% flex-limits displayed similar plan variability to no-flex limits for the majority of cases, suggesting that warehouse resource and transportation plan bounds with 5% flex-limits may be redundant and that the problem becomes ordinary warehouse and transportation planning (WRTP).

For Industry Type 1, in the WRTP-FRP approach for (2-1-2) network, 3% flex limits show 25% reduction in plan variability when compared to the no-flex-limits. This number increases to 68% with the implementation of 1% flex-limits (Figure 3.18).WRTP-FRP model in other networks return very similar variability results. For example, (2-1-2-D) network, 3% flex limits show 12% reduction in plan variability when compared to the no flex-limits. This number increases 62% with the implementation of 1% flex limits. Traditional warehouse and transportation planning in (2-1-2) and (2-2-2) network without flex-limits constantly have the highest variability with an average value of 197 and 184, which is thrice as high as on average than WRTP-FRP with 1% flex-limits.



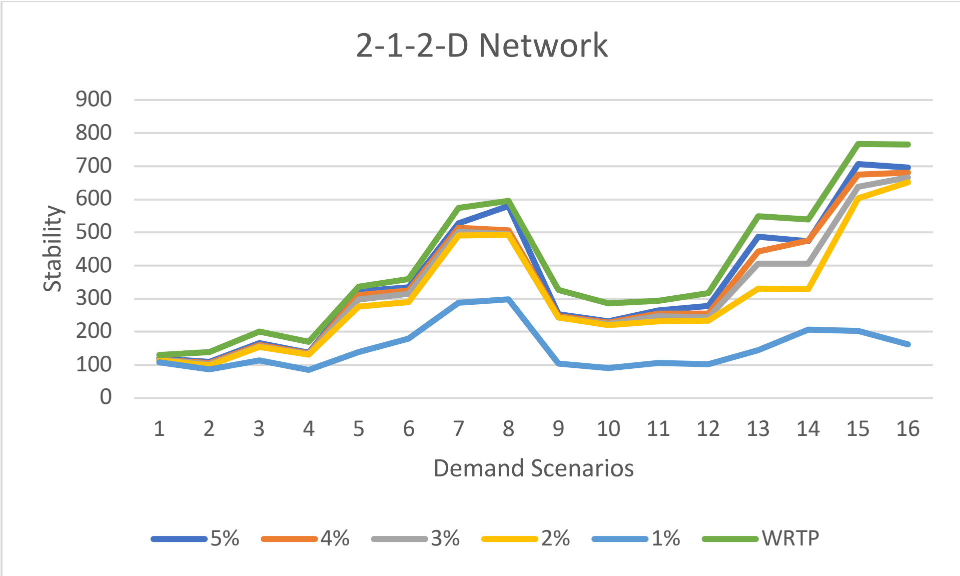
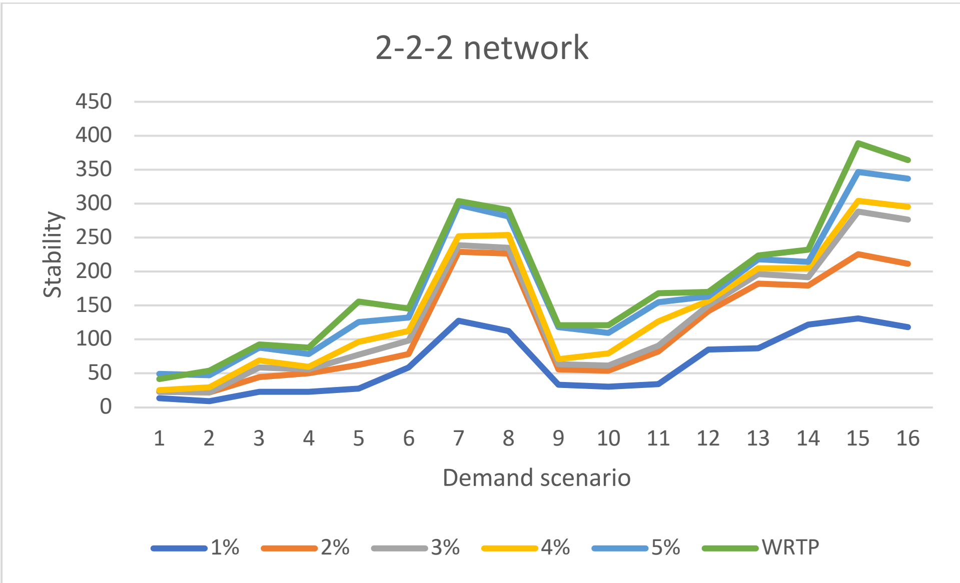


Figure 3.18:Stability Graphs in Wood & Paper Industry with 1 Warehouse Network



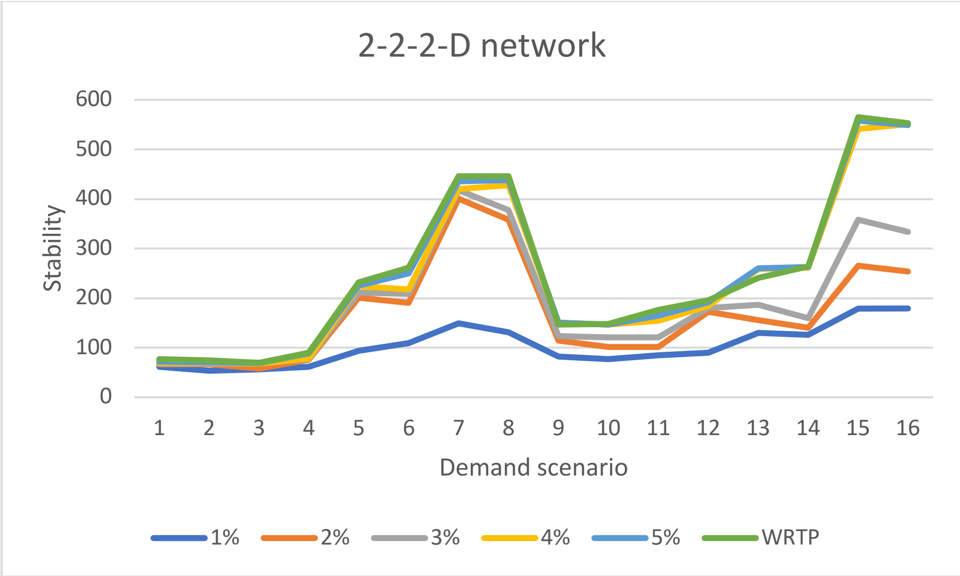
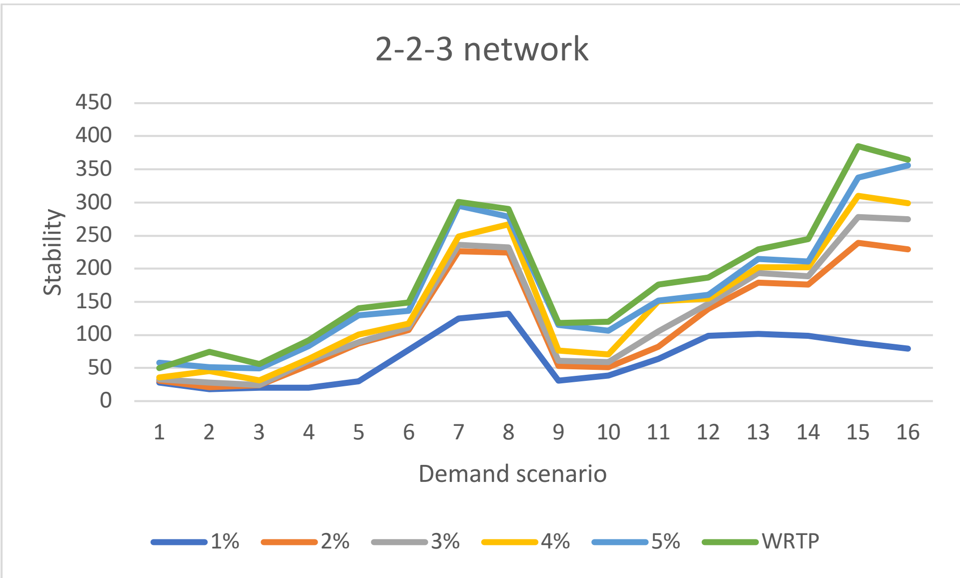


Figure 3.19: Stability Graphs in Wood & Paper Industry with 2 Warehouses Network



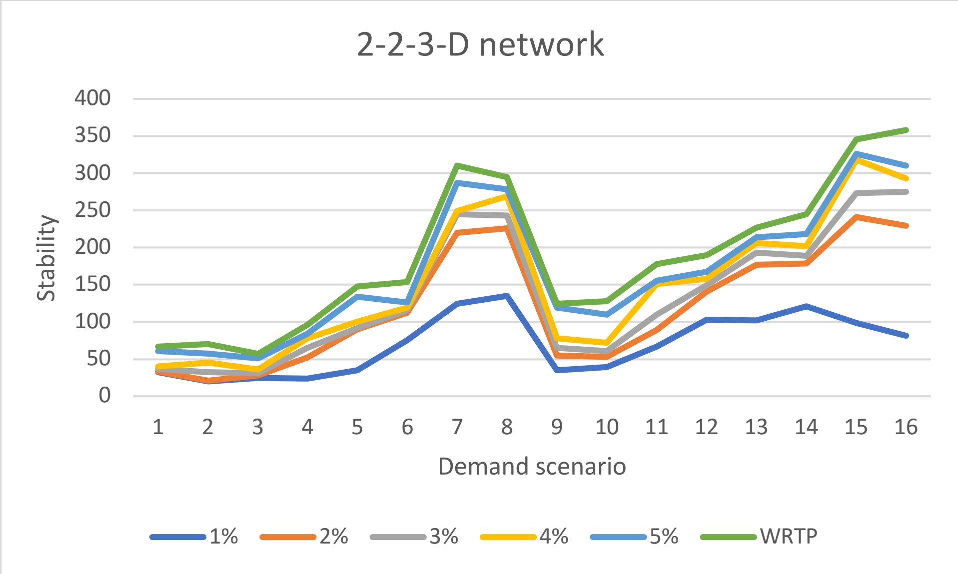


Figure 3.20: Stability Graphs in Wood & Paper Industry with 3 Consumers Network

Similarly, in the WRTP-FRP approach for (2-2-2) and (2-2-2-D) network, 3% flex limits show 27% and 23% reduction in plan variability when compared to the no-flex-limits. This number increases to 65% and 59% with the implementation of 1% flex-limits (Figure 3.19).

Our study showed that the WRTP-FRP approach with 3% flex limits in (2-2-3) and (2-2-3-D) networks resulted in a 28% and 27% reduction in plan variability, respectively, compared to no flex-limits. This reduction increased to 64.7% and 62% with the implementation of 1% flex-limits, as shown in Figure 3.20. These findings highlight the effectiveness of the WRTP-FRP approach in reducing plan variability and improving the efficiency of three-consumer networks.

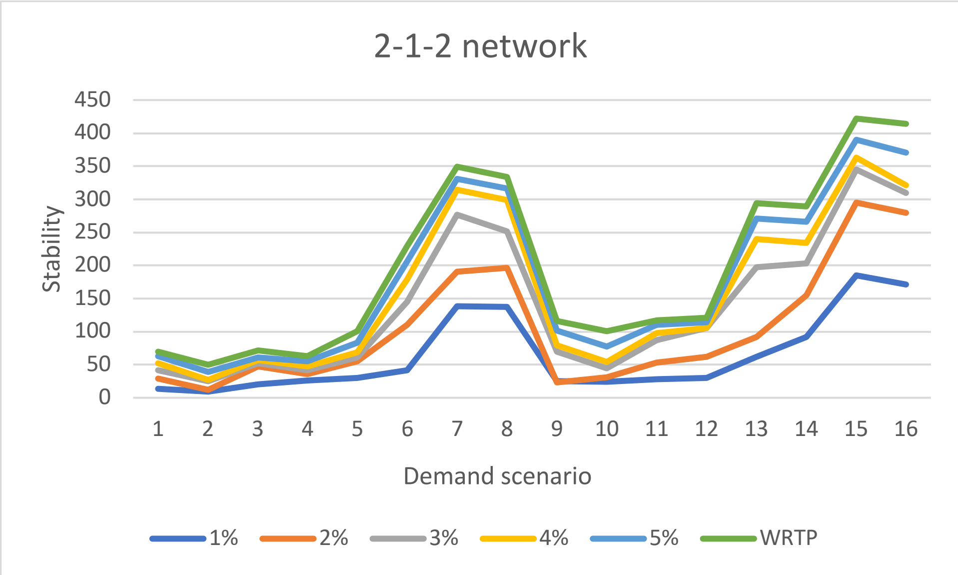
For Industry Type 2, both (2-1-2) and (2-2-2) network return very similar stability results as shown in Figure 3.21 and Figure 3.22 . For example, in (2-1-2) and (2-1-2-D) networks, 3% flex-limits show respectively 28% and 23% reduction in plan variability on average when compared to the no-flex limits. Similarly, (2-2-2) and (2-2-2-D) networks show 21% and 24% reduction in plan variability for the same 3% flex limits. This number increases to 68%, 51%, 59% and 56% respectively. Traditional WRTP model without flex limits constantly have the highest variability with an average value of 276 which is twice as high as on average than WRTP-FRP with 1% flex limits across all the networks.

In the case of three-consumer networks as shown in Figure 3.23, our analysis revealed similar outcomes. Specifically, we found that implementing the WRTP-FRP approach with 3% flex limits in (2-2-3) and (2-2-3-D) networks resulted in a 20.3% and 24.68% reduction in plan variability, respectively, compared to not having flex-limits. With the implementation of 1% flex-limits, the reduction in plan variability increased to 58.75% and 59.76%.These results provide further evidence of the effectiveness of the WRTP-FRP approach in reducing plan variability and enhancing the efficiency of three-consumer networks.

In Industry Type 3, both the (2-1-2) and (2-2-2) network types exhibit similar stability results, as depicted in the Figure 3.24 and 3.25. Specifically, implementing 3% flex-limits leads to a reduction of plan variability by 20% and 21% on average in the (2-1-2) and (2-1-2-D) networks, respectively, compared to no-flex limits. Likewise, the (2-2-2) and (2-2-2-D) networks demonstrate a reduction of 20% and 22% in plan variability for the same 3% flex limits, respectively. Notably, the plan variability further reduces to 49%, 52%, 49%, and 47%, respectively when flex-limit was reduced to 1%. It is important to highlight that the traditional WRTP model without flex limits consistently exhibits the highest variability, with an average value of 287, which is twice as high as the WRTP-FRP model with 1% flex limits across all networks.

We found that the outcomes were similar for networks with three consumers. The WRTP-FRP approach, when implemented with 3% flex limits in (2-2-3) and (2-2-3-D) networks, led to a 21.2% and 24.25% decrease in plan variability, respectively, compared to not having flex-limits. With the implementation of 1% flex-limits, the reduction in plan variability increased to 48.09% and 49.93%, as shown in Figure 3.26. These results provide further evidence of the efficacy of the WRTP-FRP approach in minimizing plan variability and improving the effectiveness of networks with three consumers.

When comparing different flex-limits, it was observed that larger flex-limits led to increased plan variability, higher transportation costs, and smaller inventory levels. This is because highly uncertain demands result in higher variability in costs, plan variability, and actual shipment levels. The main drivers of demand uncertainty are trends and seasonality. Scenarios 7-8 and 15-16 have high trend and seasonality patterns of demand, and the flex-limits had a significant impact on stability performance for these scenarios. On the other hand, scenarios 5-6 and 13-14 have high trend and low levels of seasonality, and we observed larger differences between different flex-limits for these scenarios.



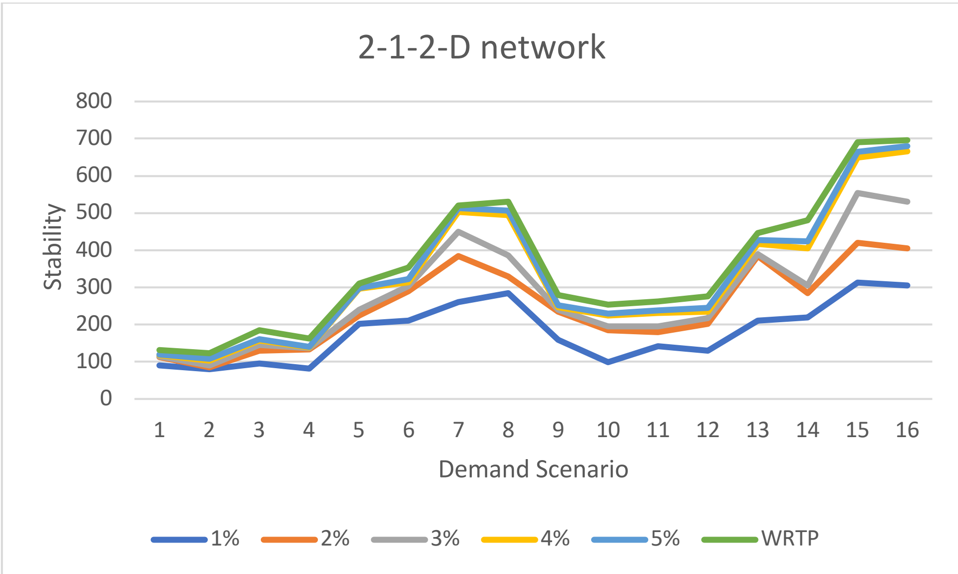
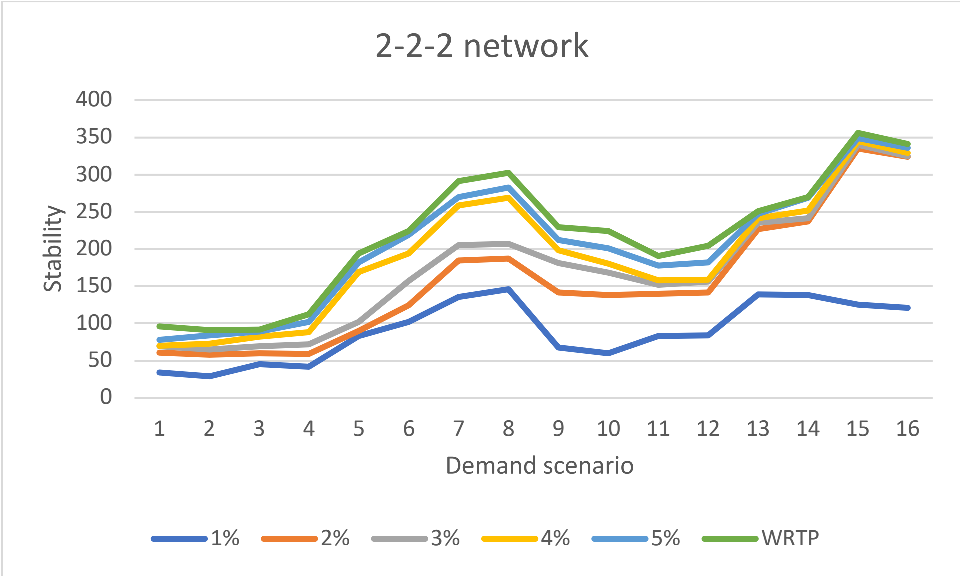


Figure 3.21: Stability Graphs in Textile Industry with 1 Warehouse Network



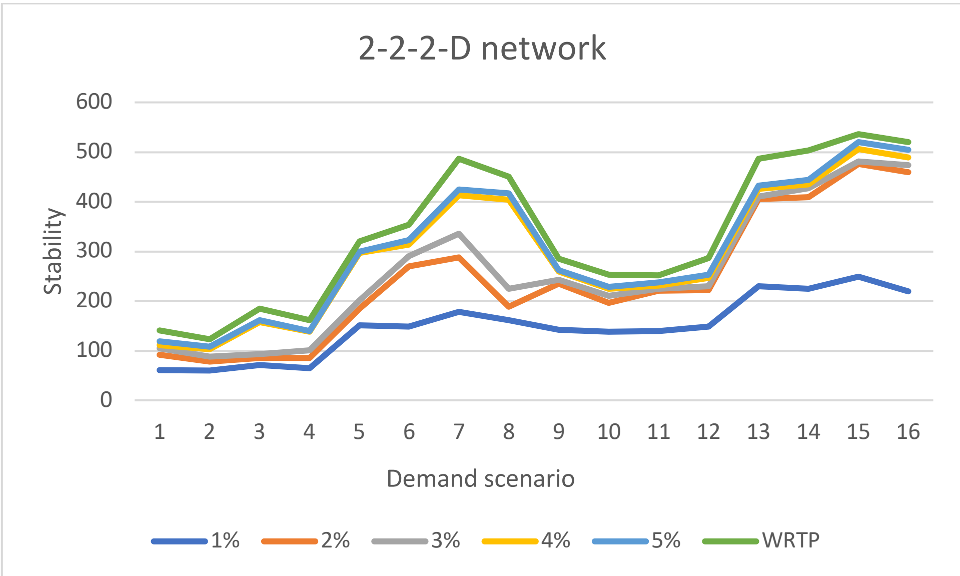
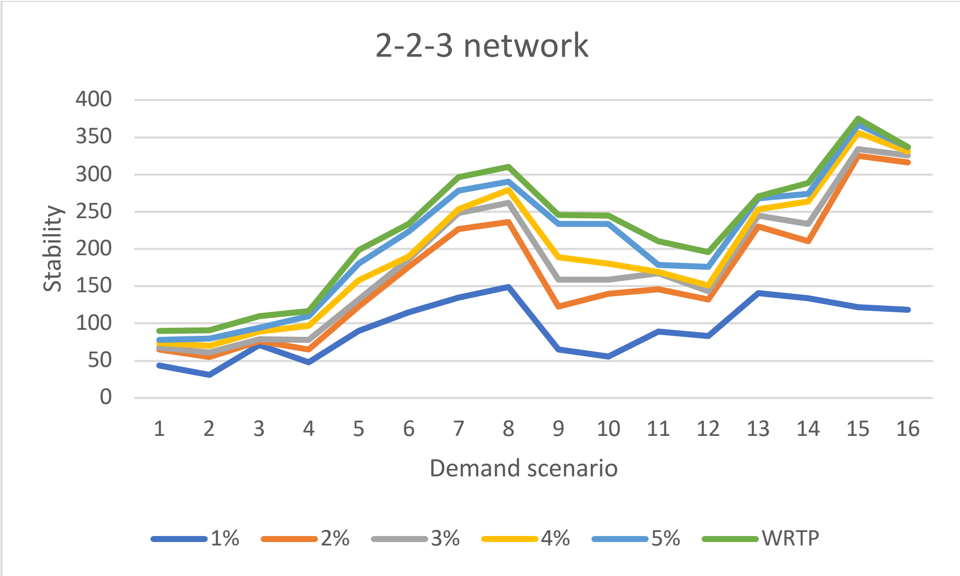


Figure 3.22: Stability Graphs in Textile Industry with 2 Warehouses Network



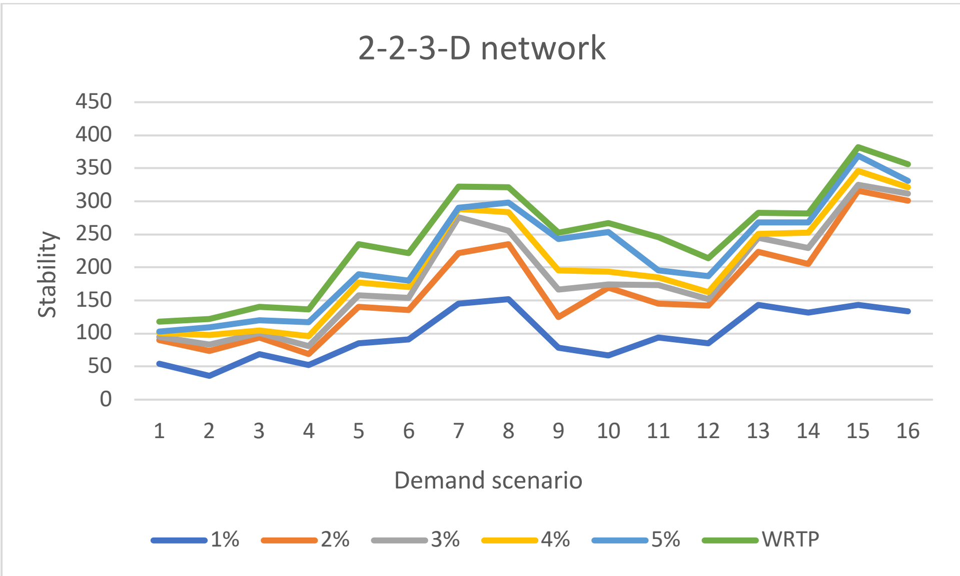
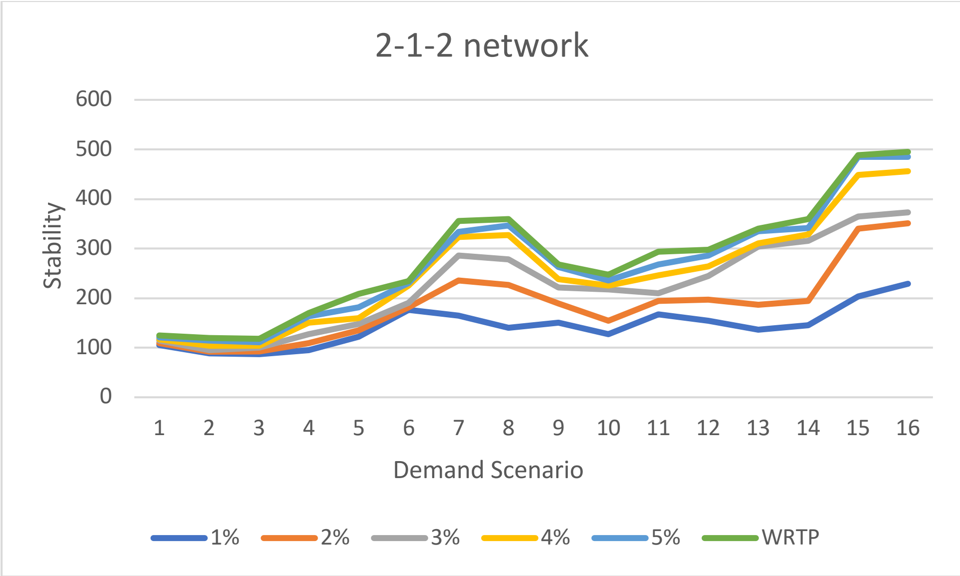


Figure 3.23: Stability Graphs in Textile Industry with 3 Consumers Network



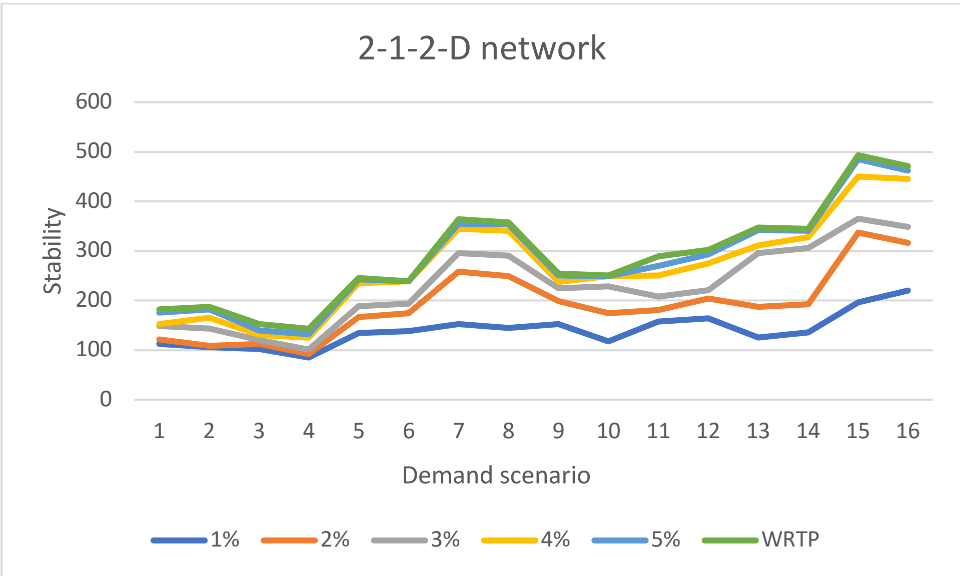
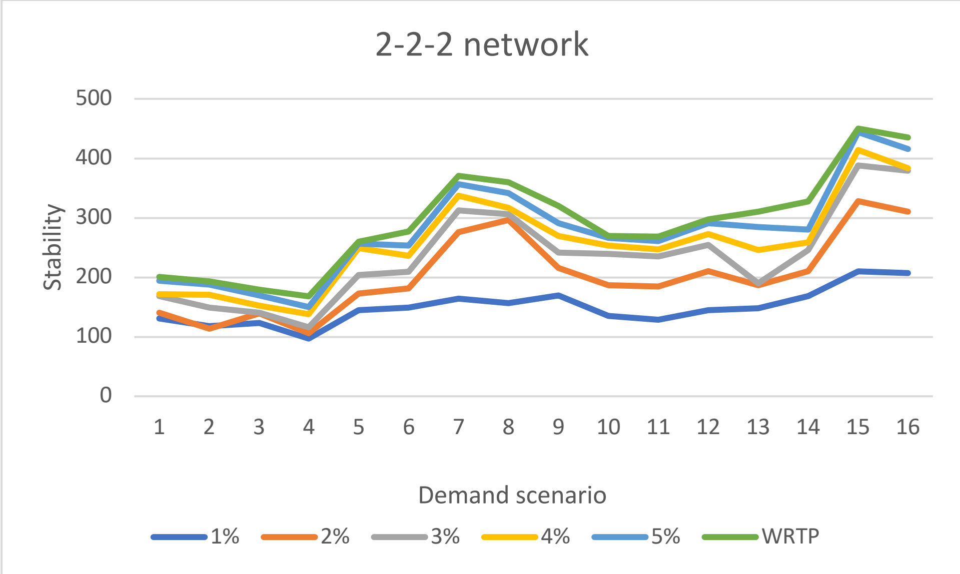


Figure 3.24: Stability Graphs in Automotive Industry with 1 Warehouse Network



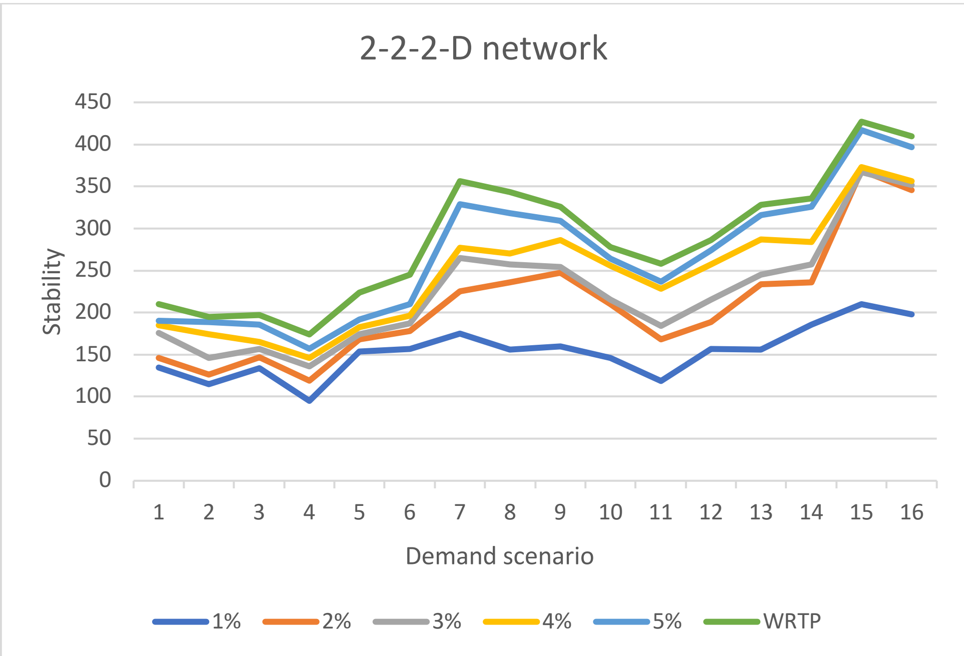
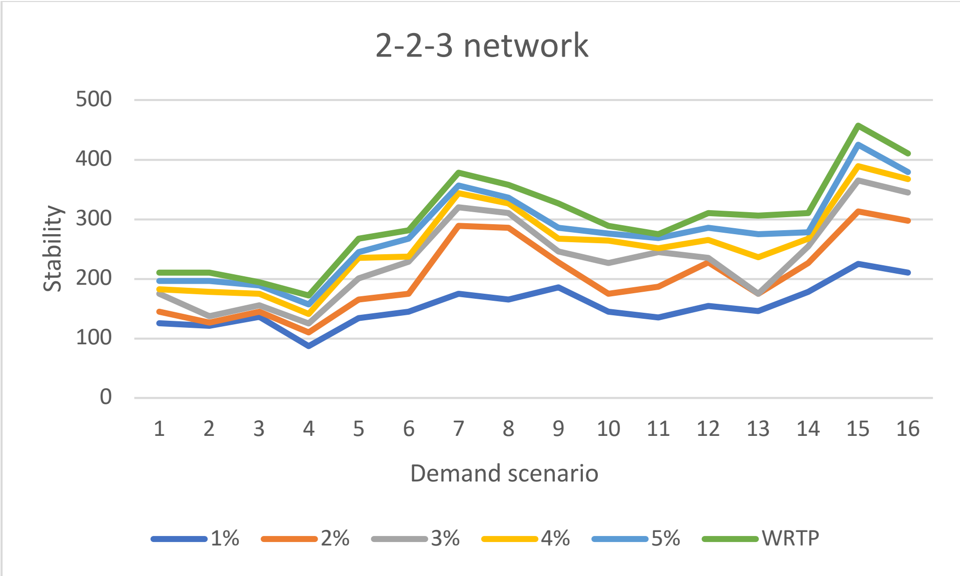


Figure 3.25: Stability Graphs in Automotive Industry with 2 Warehouses Network



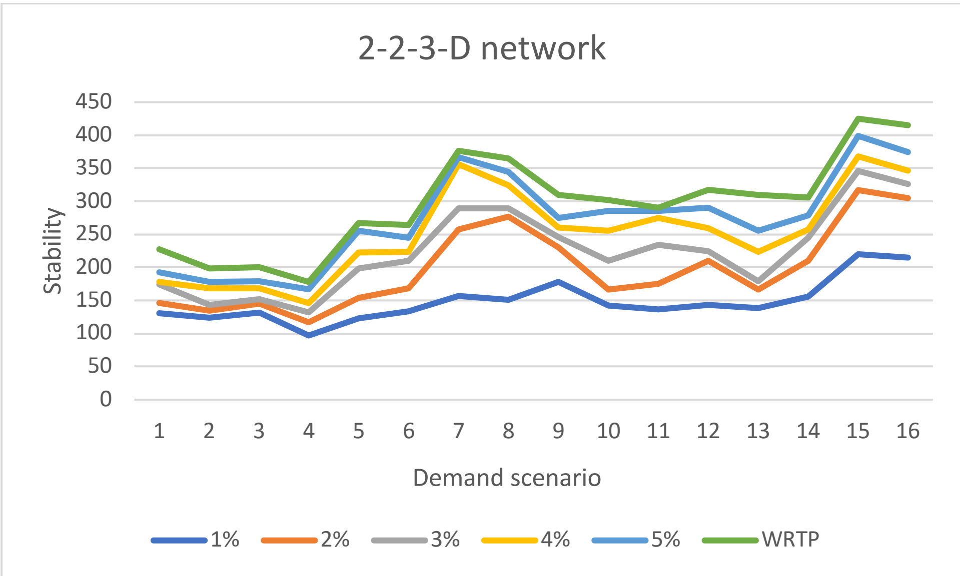
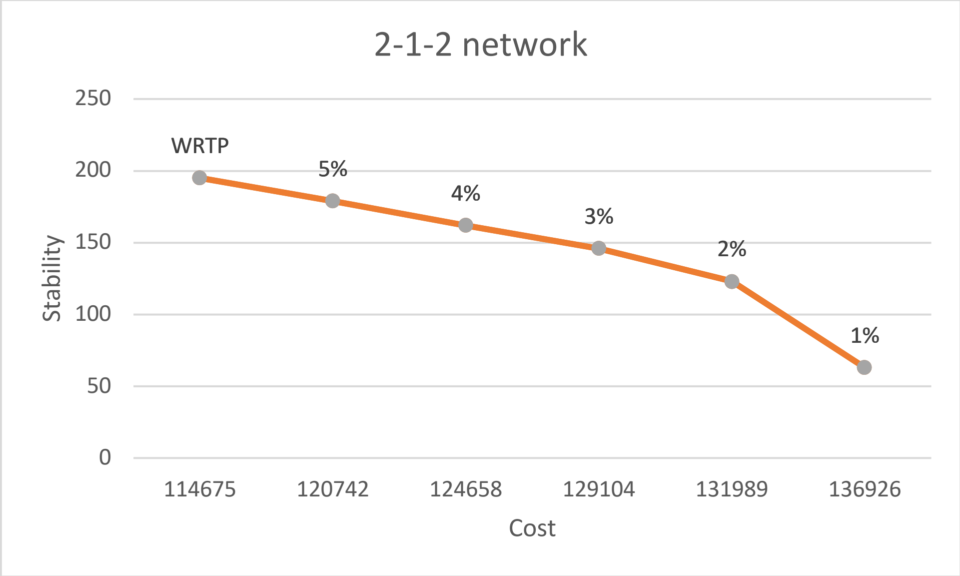


Figure 3.26: Stability Graphs in Automotive Industry with 3 Consumers Network



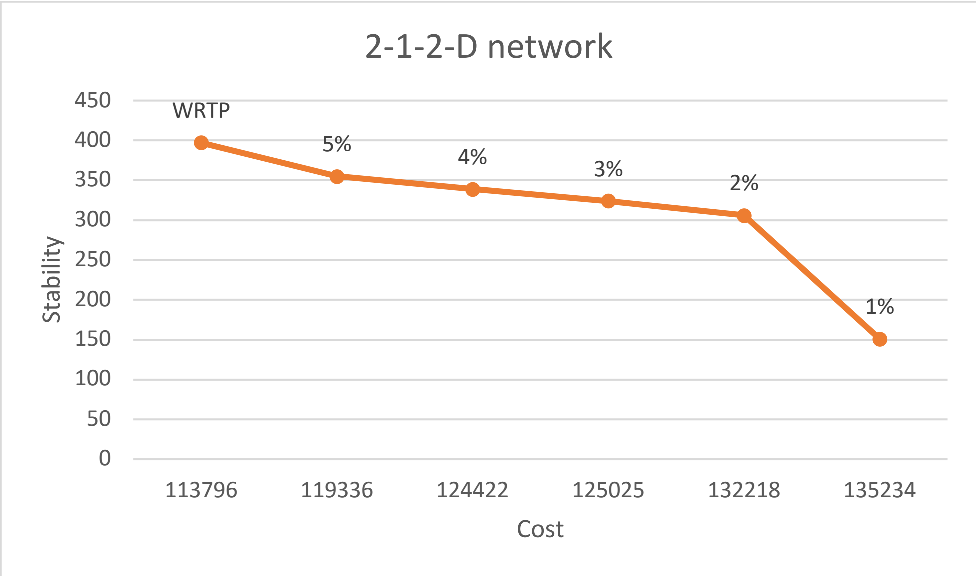
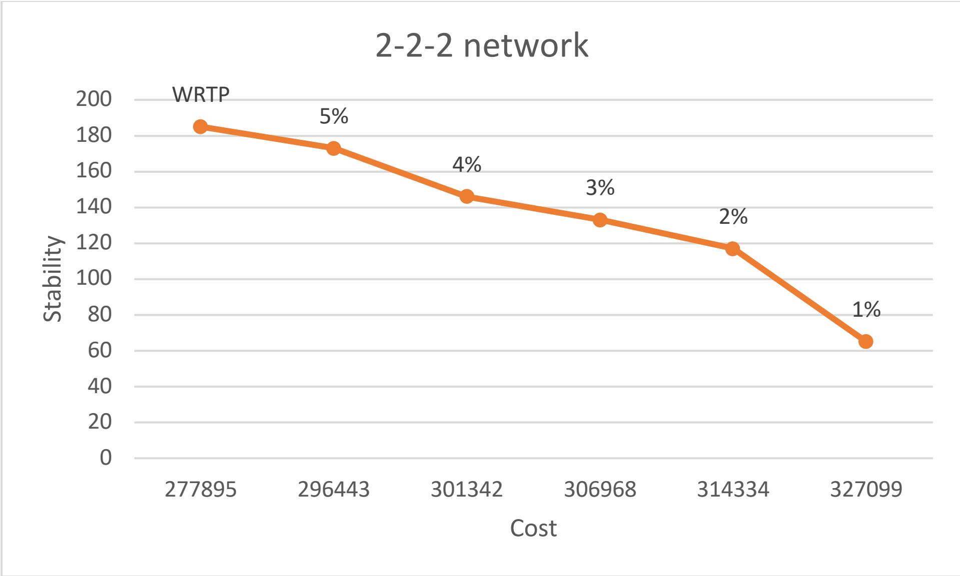


Figure 3.27: Pareto Graph of Stability vs. Cost, Wood & Paper Industry for 1 Warehouse Network



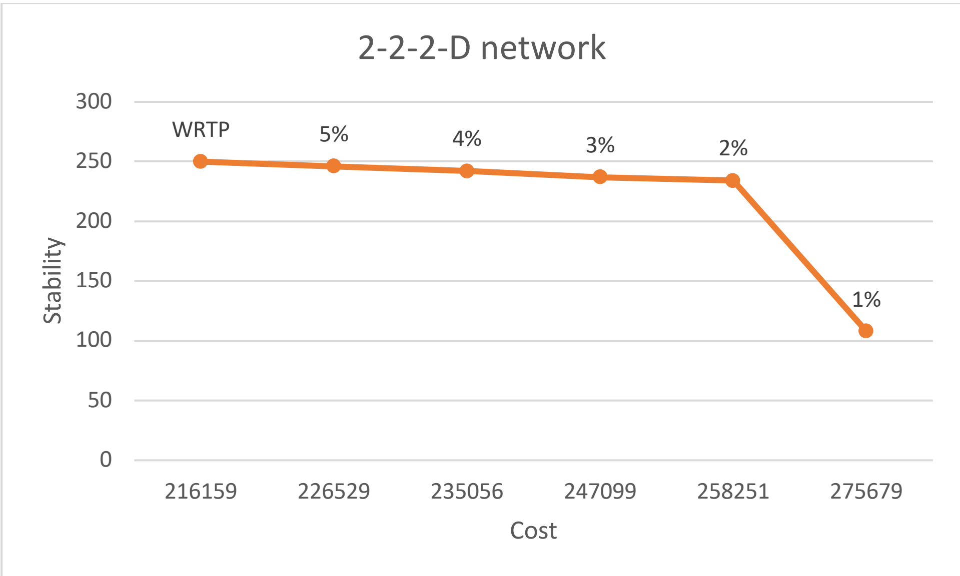
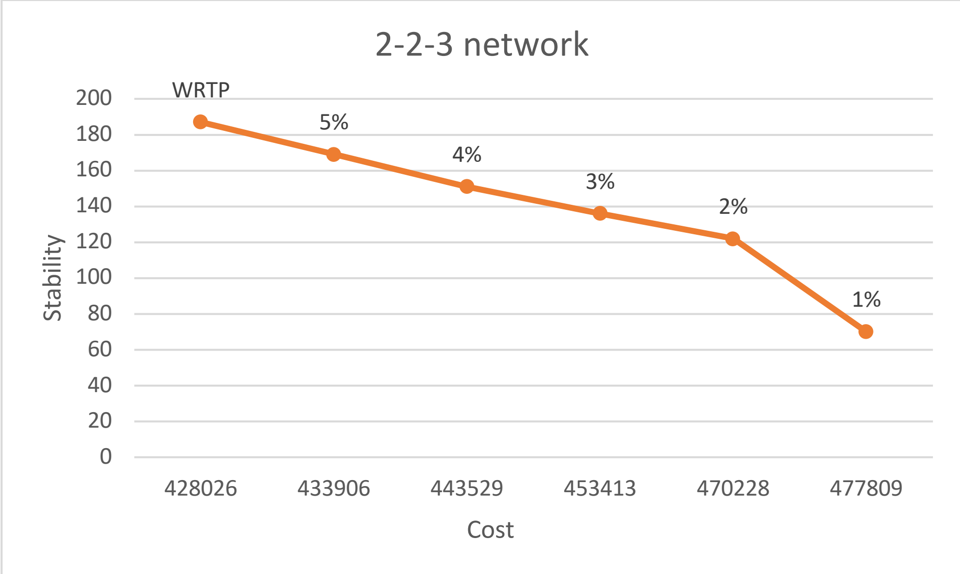


Figure 3.28: Pareto Graph of Stability vs. Cost, Wood & Paper Industry for 2 Warehouses Network



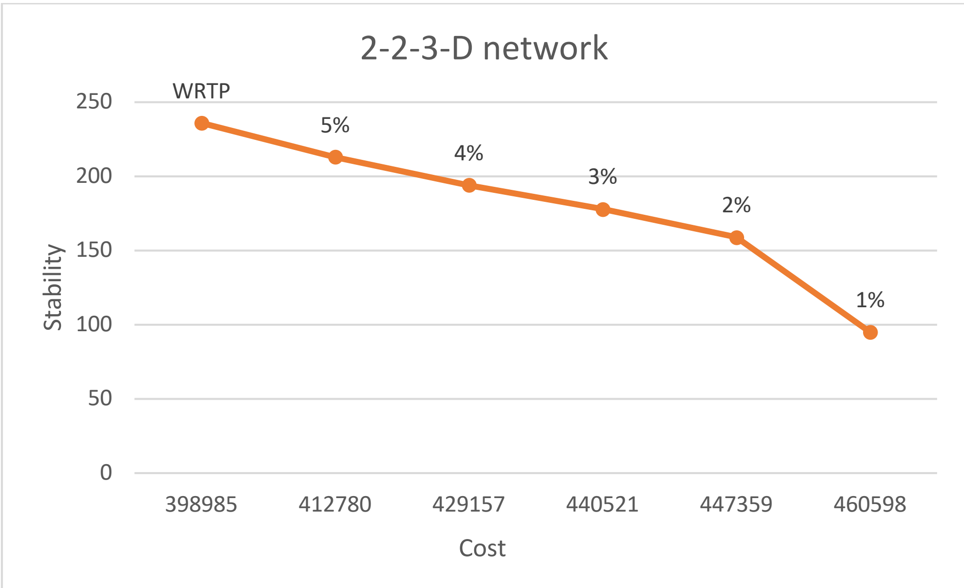
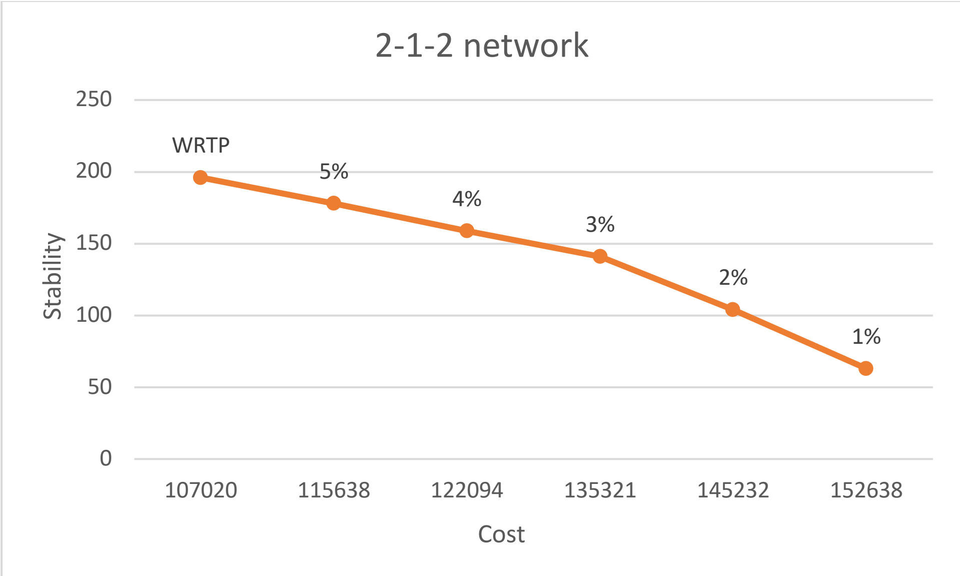


Figure 3.29: Pareto Graph of Stability vs. Cost, Wood & Paper Industry for 3 Consumers Network



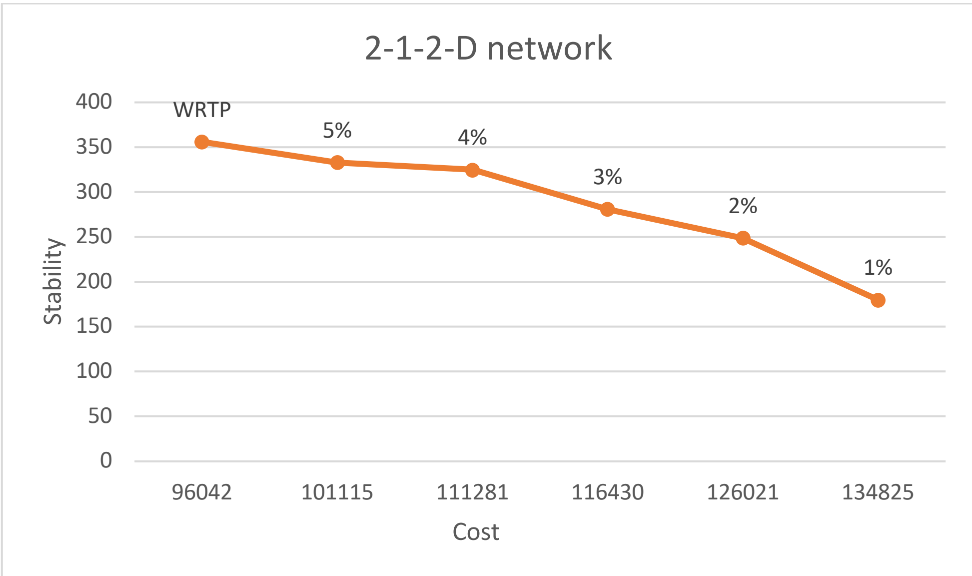
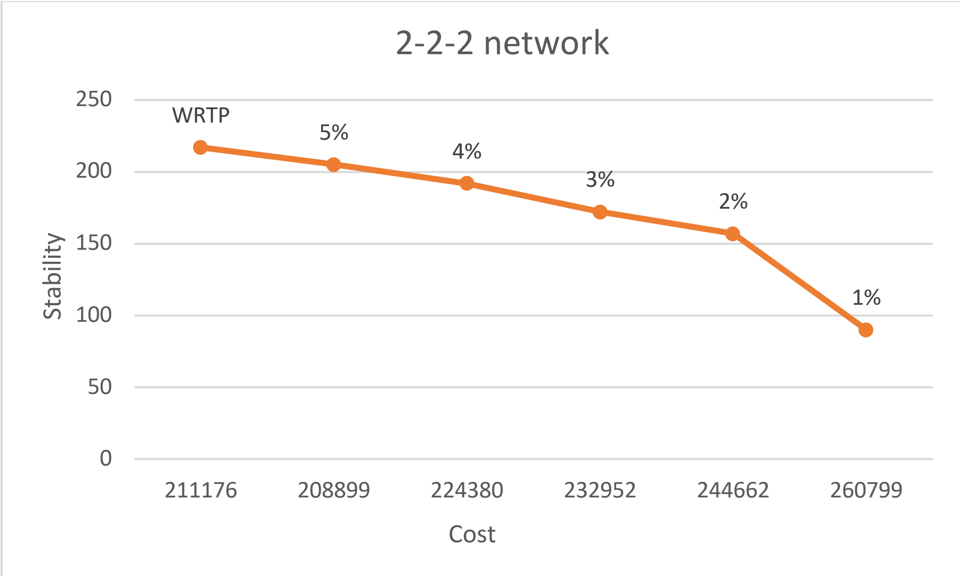


Figure 3.30: Pareto Graph of Stability vs. Cost, Textile Industry for 1 Warehouse Network



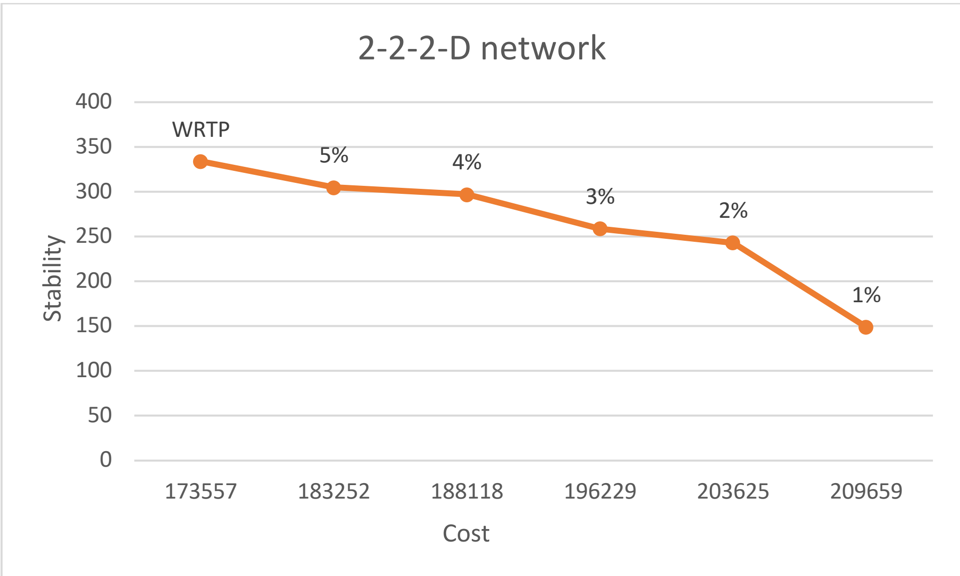
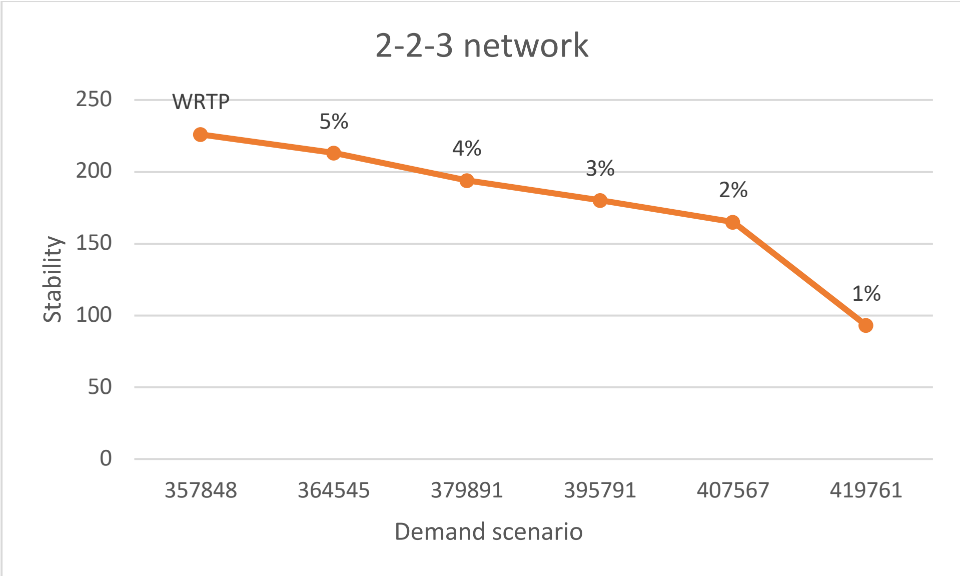


Figure 3.31: Pareto Graph of Stability vs. Cost, Textile Industry for 2 Warehouses Network



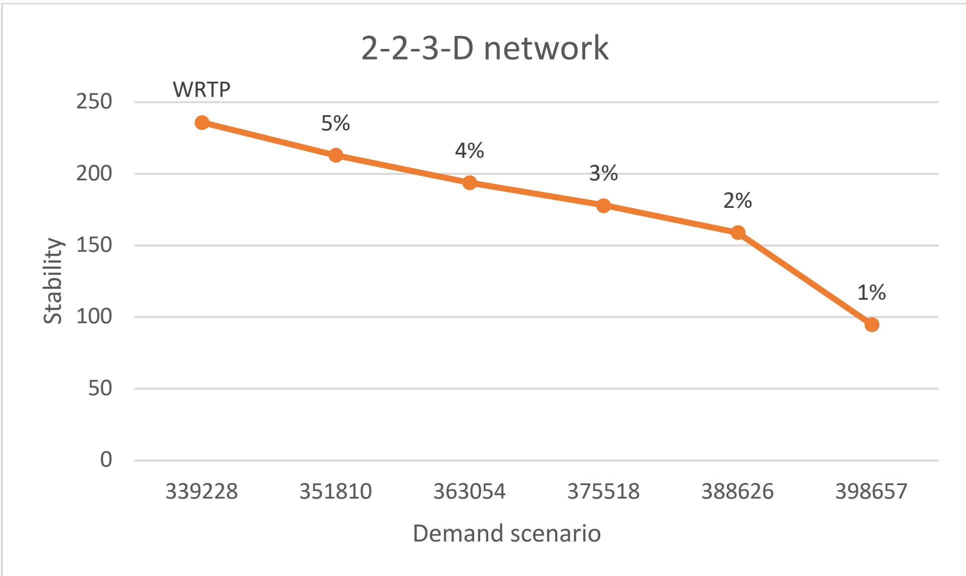
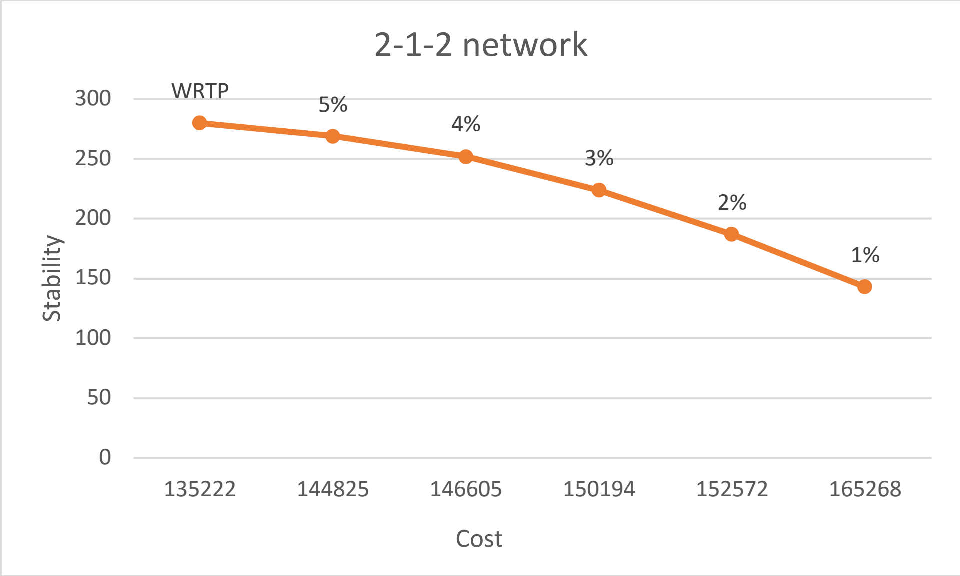


Figure 3.32: Pareto Graph of Stability vs. Cost, Textile Industry for 3 Consumers Network



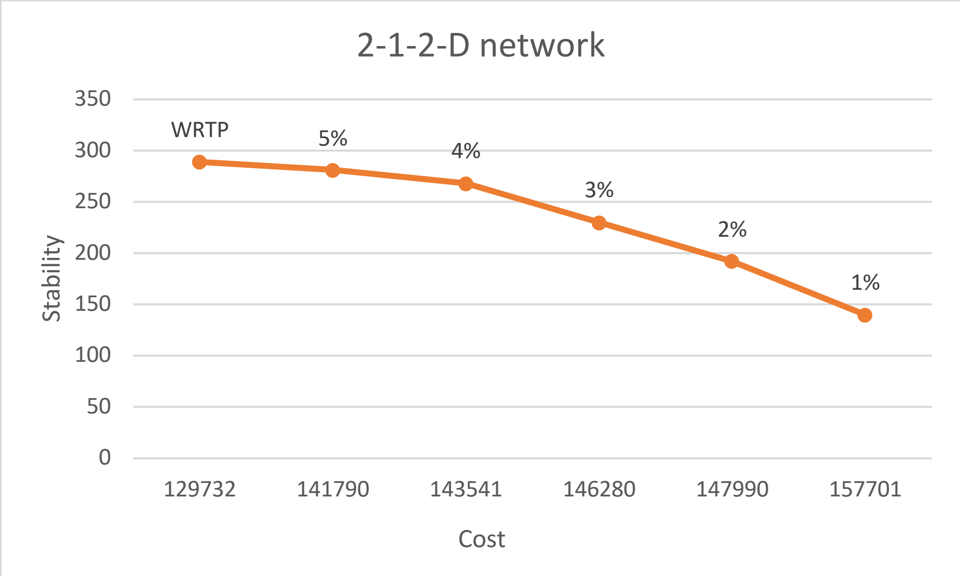
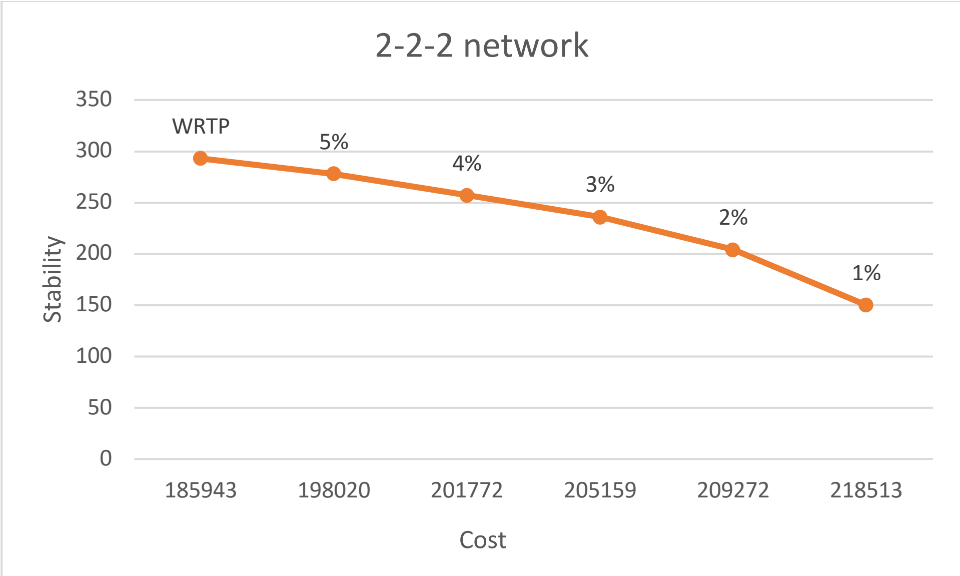


Figure 3.33: Pareto Graph of Stability vs. Cost, Automotive Industry for 1 Warehouse Network



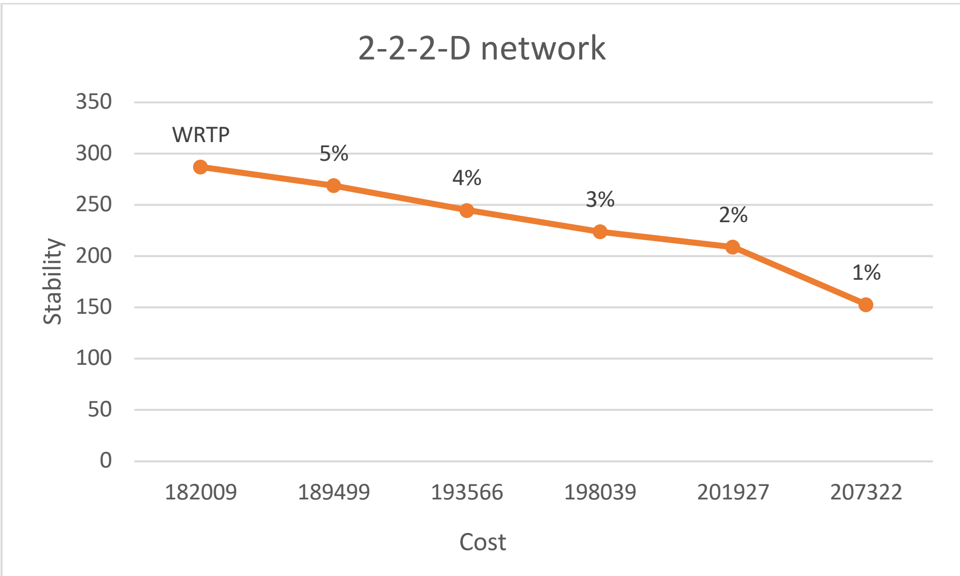
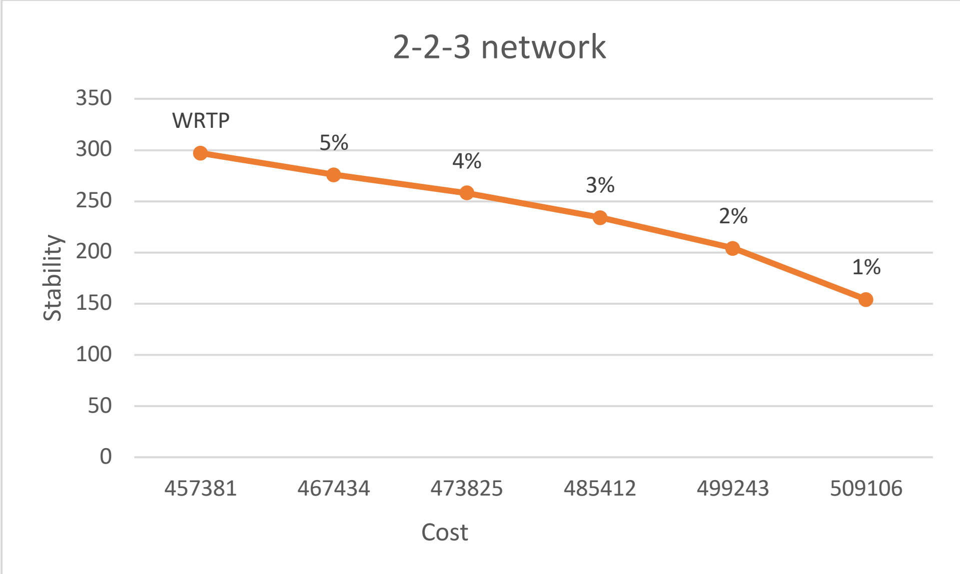


Figure 3.34: Pareto Graph of Stability vs. Cost, Automotive Industry for 2 Warehouses Network



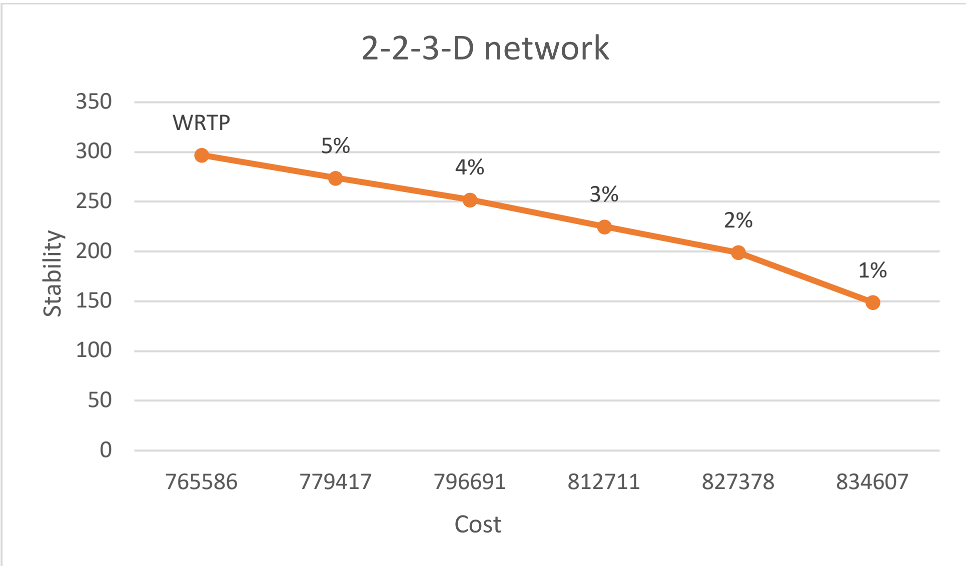


Figure 3.35: Pareto Graph of Stability vs. Cost, Automotive Industry for 3 Consumers Network

The Pareto analysis between cost and stability in different networks and industries is illustrated in Figure 3.27 to Figure 3.35. The analysis reveals that, while the WRTP models consistently offer lower costs compared to the WRTP-FRP models in all networks, the latter provides higher stability across all demand scenarios. Specifically, the implementation of the 1% flex-limit in the FRP models resulted in higher stability compared to other flex-limits. The stability of the 5% flex-limit model is comparable to that of the WRTP model without any flex-limit. This suggests that there is a trade-off between cost and stability when incorporating FRP in the model. However, since the increase in cost is not significant, incorporating FRP models is beneficial as it reduces nervousness in planning due to minor changes in demand or supply. In other words, the implementation of FRP models provides a more stable plan and reduces the impact of demand or supply changes on the plan, which can be useful for industries that require high levels of stability in their planning. The results of the analysis have important implications for decision-makers in the industry who need to balance cost and stability considerations when designing their supply chain planning models.

Supply chain planning is subject to various uncertainties such as demand fluctuations, supply disruptions, and unexpected changes in lead times. These uncertainties lead to nervousness in the planning process, making it difficult to maintain a stable plan. The flexibility provided by the FRP models can help address this nervousness and provide stability to the planning process. By allowing for a certain level of flexibility in warehouse resource and transportation plans, FRP models can accommodate changes in demand or supply without causing major disruptions. This can help reduce the costs associated with frequent plan changes and can also improve customer satisfaction by ensuring timely delivery of products. Therefore, incorporating FRP models into supply chain planning can be beneficial for industries that face high demand volatility or have shorter product life cycles.

Table 3.7: Cost Comparison Between Industries at 1% flex-limit and no flex-limit

Network type	Flex limit	Wood & Paper industry	Textile Industry	Automotive Industry
2-1-2	1%	$136,926	$152,638	$165,268
	No flex	$114,675	$107,020	$135,222
2-1-2-D	1%	$135,234	$134,825	$157,701
	No flex	$113,796	$96,042	$129,732
2-2-2	1%	$308,480	$260,799	$218,512
	No flex	$218,006	$211,176	$185,943
2-2-2-D	1%	$254,429	$209,659	$207,322
	No flex	$190,440	$173,557	$182,009
2-2-3	1%	$477,809	$411,636	$509,105
	No flex	$428,026	$362,598	$457,381
2-2-3-D	1%	$458,723	$393,094	$490,945
	No flex	$419,235	$347,915	$450,344

Table 3.8: Stability Comparison Between Industries at 1% flex-limit and no flex-limit

Network type	Flex limit	Wood & Paper industry	Textile Industry	Automotive Industry
2-1-2	1%	63	65	143
	No flex	195	196	280
2-1-2-D	1%	151	180	140
	No flex	397	356	289
2-2-2	1%	65	90	150
	No flex	185	217	293
2-2-2-D	1%	104	149	153
	No flex	249	334	287
2-2-3	1%	66	101	165
	No flex	186	236	250
2-2-3-D	1%	112	167	180
	No flex	250	268	294

Table 3.7 and Table 3.8 depict the cost comparison between different industries using the WRTP model with no flex-limit and WRTP-FRP model with a 1% flex-limit. Interestingly, the results reveal that regardless of the industry type, the WRTP model without a flex-limit yields marginally lower costs when compared to the WRTP model with a 1% flex-limit. However, when we consider the stability between these models, it becomes evident that the WRTP-FRP model with a 1% flex-limit exhibits greater stability across all demand scenarios when compared to the WRTP model without a flex-limit. This highlights the existence of a trade-off between cost and plan stability, suggesting that organizations need to carefully weigh their options to achieve the desired balance between these two competing objectives.

3.7.1 Networks Under Supplier Plant Capacity

In this part, we delved deeper into the impact of supplier plant capacity on the cost savings achieved through the warehouse relocation and transportation planning (WRTP) approach in the Wood & Paper, Textile , and Automotive industries. Our additional analysis focused on supplier plants that were operating at under 60% and 80% capacity for 1 warehouse network.

While the cost graphs displayed a similar trend to the ones without considering supplier plant capacity, our findings revealed a slight increase in total cost. Specifically, in the

Wood & Paper industry, we observed that one warehouse network using the WRTP approach at 1% flex-limit and no flex-limit achieved an average total cost of $143,081 and $118,131, operating at 60% supplier plant capacity. This represented an increase in average total cost by $6,155 and $3,456, respectively, when compared to the model that assumed 100% supplier plant capacity. However, the average total cost slightly reduced when we increased the capacity from 60% to 80% but still the model with 100% supplier plant capacity had the lowest average total cost at all flex-limits as shown in Figure 3.36.

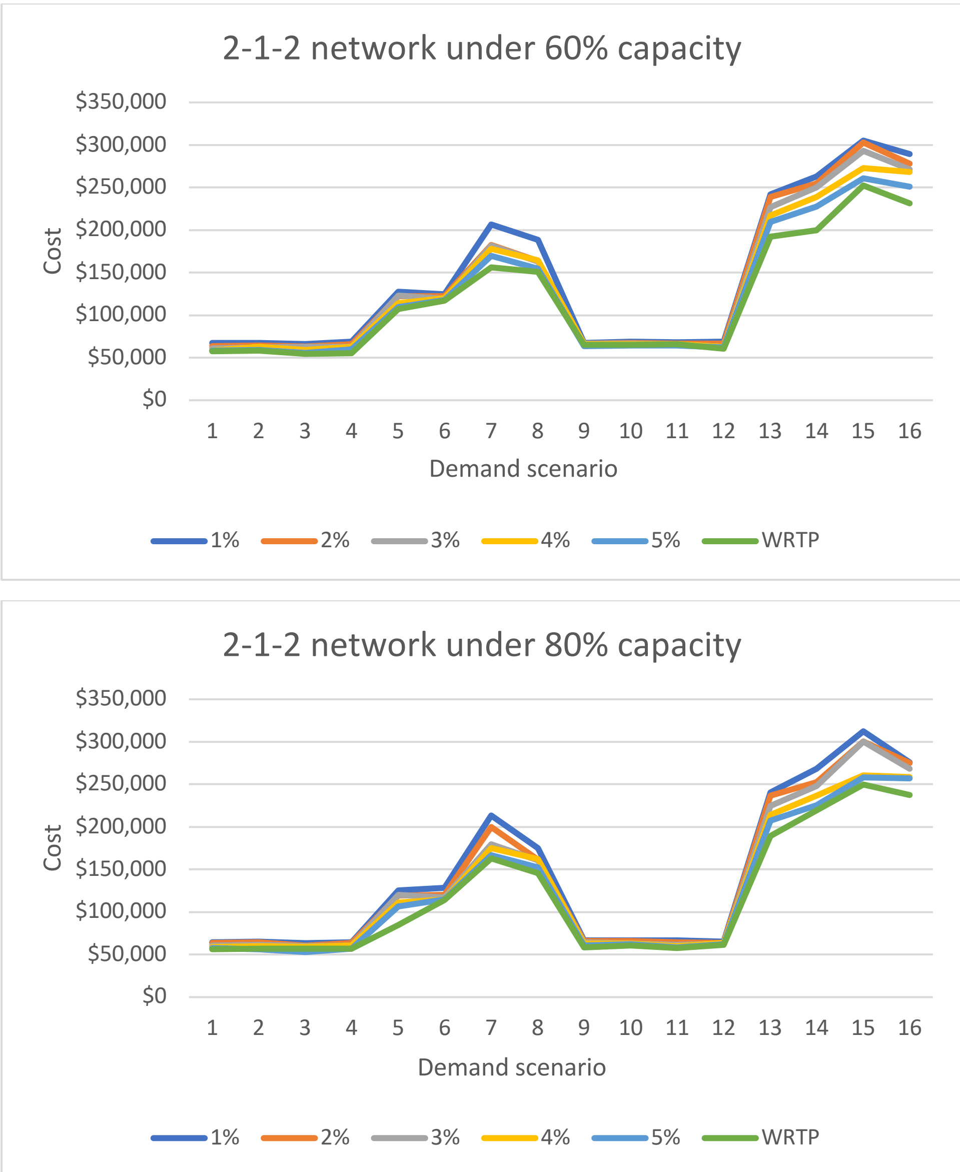
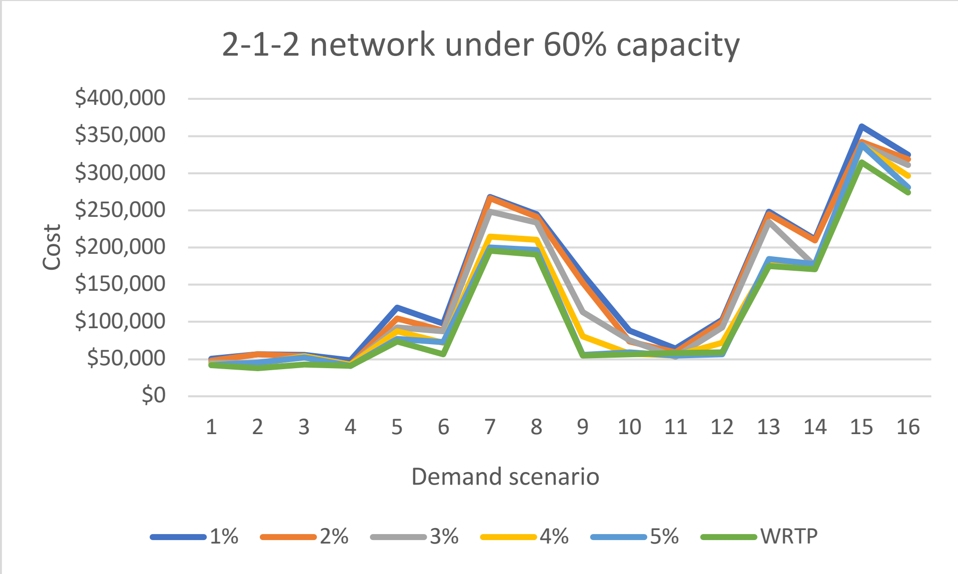


Figure 3.36: Cost Graphs in Wood & Paper Industry with 60%-80% Supplier Plant Capacity



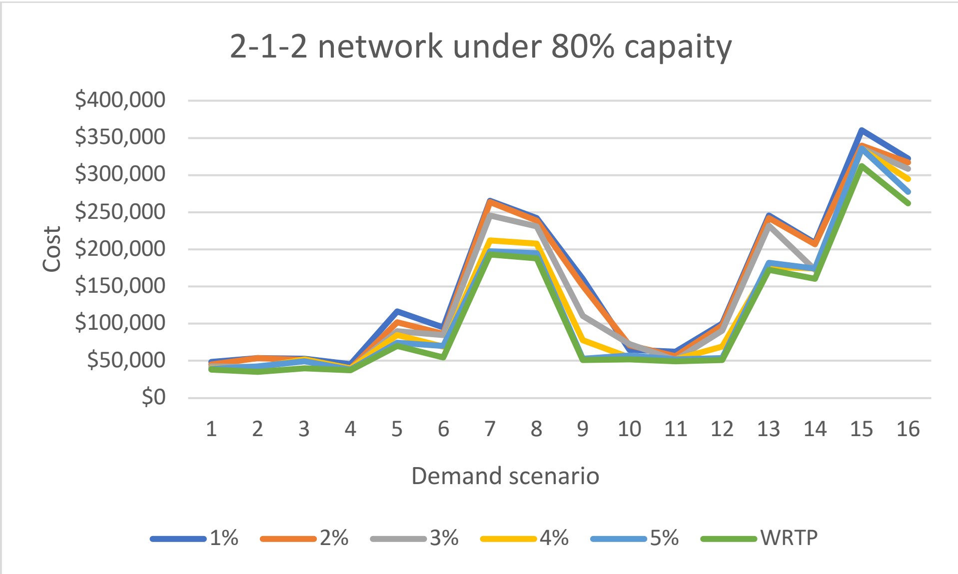
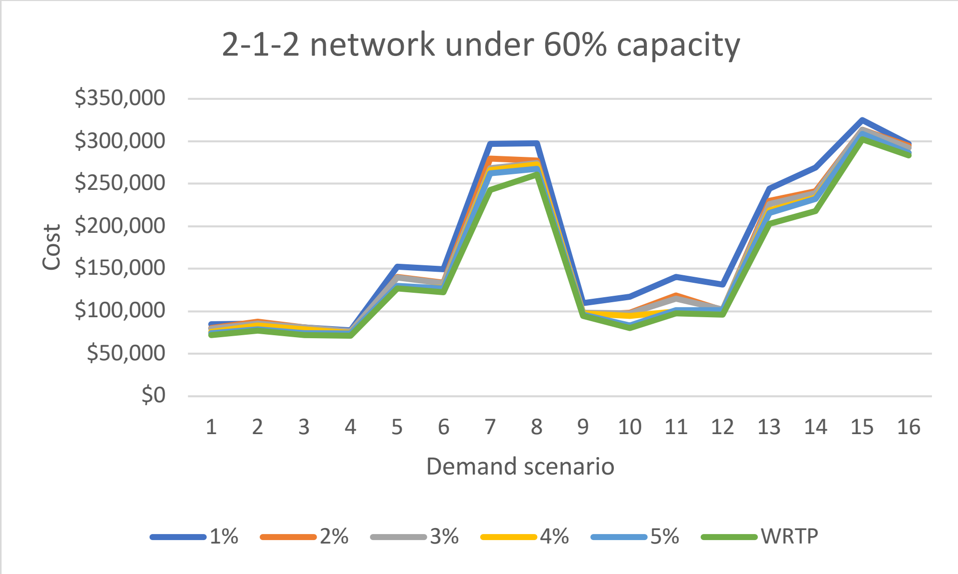


Figure 3.37: Cost Graphs in Textile Industry with 60%-80% Supplier Plant Capacity



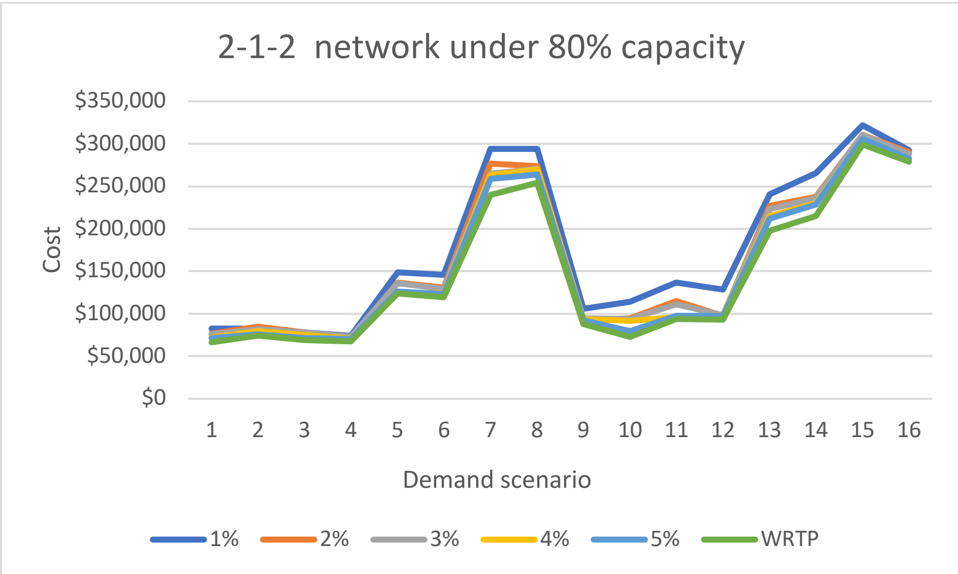


Figure 3.38: Cost Graphs in Automobile Industry with 60%-80% Supplier Plant Capacity

Our analysis also explored the impact of supplier plant capacity on cost savings in the Textile and Automotive industries, using the WRTP approach under different flex-limits. In the Textile industry, we found that models operating under 60% and 80% supplier plant capacity with a flex-limit of 1% resulted in an increase of average total cost by $3,964 and $1,952 , respectively, as compared to the model that assumed 100% supplier capacity as shown in the Figure 3.37. Nevertheless, the WRTP approach still produced lower costs than the models that used different flex limits.

Similarly, in the Automotive industry, we observed an increase in average total cost of $6,617 and $2,653 for models operating at 60% and 80% supplier plant capacity under 1% flex-limit, respectively, as compared to the model that assumed 100% supplier capacity, using the WRTP approach as shown in the Figure 3.38.

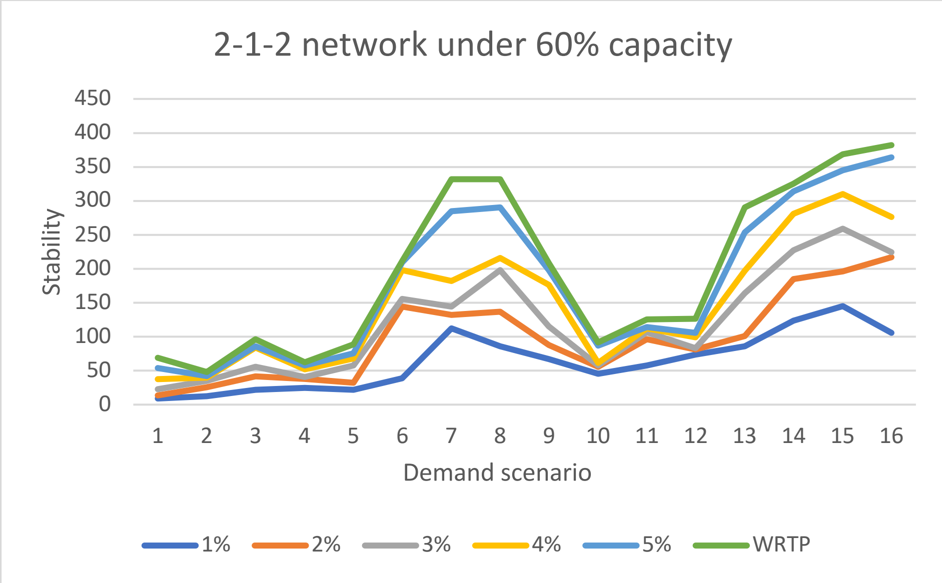
As demonstrated earlier, the presence of flex-limits has a significant impact on the plan variability even for model running under certain supplier plant limit. The results obtained for one warehouse network under 60% and 80% capacity is as follows.

As expected for all industries, WRTP-FRP model with 1% flex-limit has better stability than the model without any flex-limits. These results demonstrate the importance of considering supplier plant capacity in optimizing warehouse resource and transportation planning in various industries. Even though the WRTP approach may experience a slight decrease in cost savings when supplier plants operate at lower capacities, it still outperforms other WRTP-FRP models that use different flex limits.

In our analysis of the Wood & Paper Industry operating at 60% and 80% supplier plant capacity, as expected, we found that implementing flex-limits in the WRTP approach can significantly reduce plan variability. Specifically, using a 3% flex-limit resulted in a 38% and 28% reduction in plan variability, respectively, when compared to the model with no flex-limits. By implementing a 1% flex-limit, these numbers increased even further to 67% and 66%, respectively (as shown in Figure 3.39).

As in our previous findings, we observed that the traditional warehouse and transportation planning model without flex-limits consistently had the highest variability, with an average of 217. This was three times as high on average than the WRTP-FRP model with a 1% flex-limit. Furthermore, we observed similar variability results in other industries using the WRTP-FRP models, as illustrated in Figure 3.40 and Figure 3.41.

These findings further emphasize the importance of incorporating flex-limits in the WRTP approach for warehouse network optimization, especially in situations where supplier plant capacity may be limited. By doing so, decision-makers can reduce plan variability and increase the stability of model, leading to significant cost savings and improved profitability.



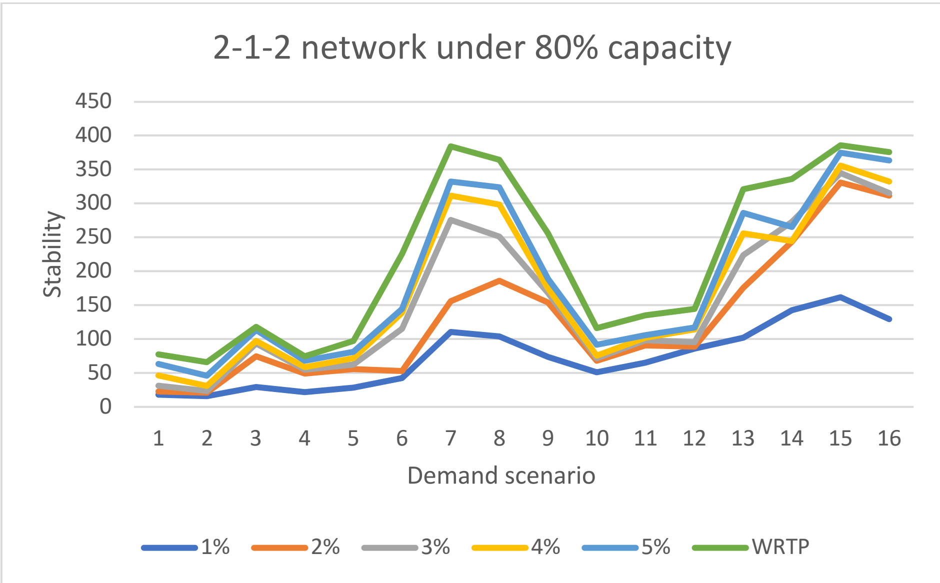
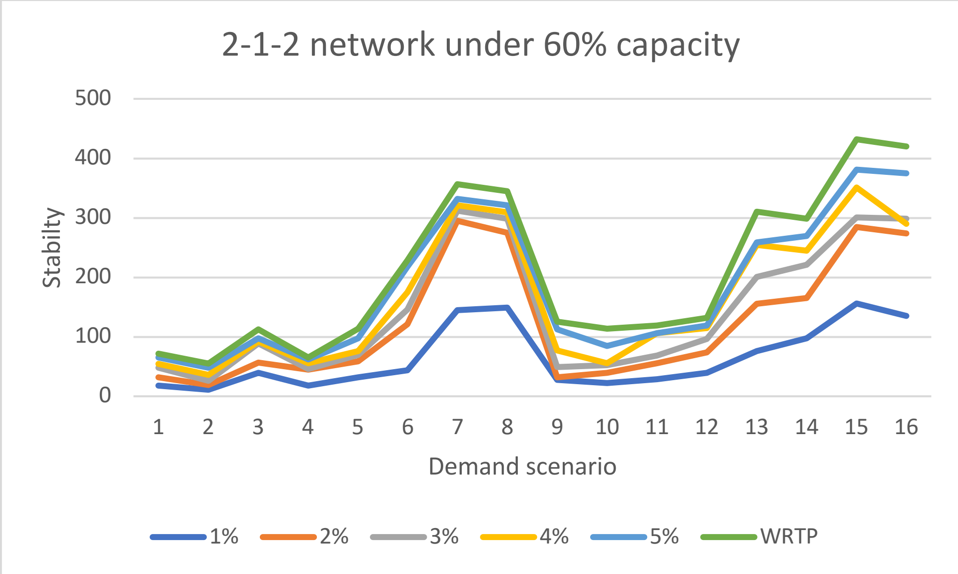


Figure 3.39:Stability Graphs in Wood & Paper Industry with 60%-80% Supplier Plant Capacity



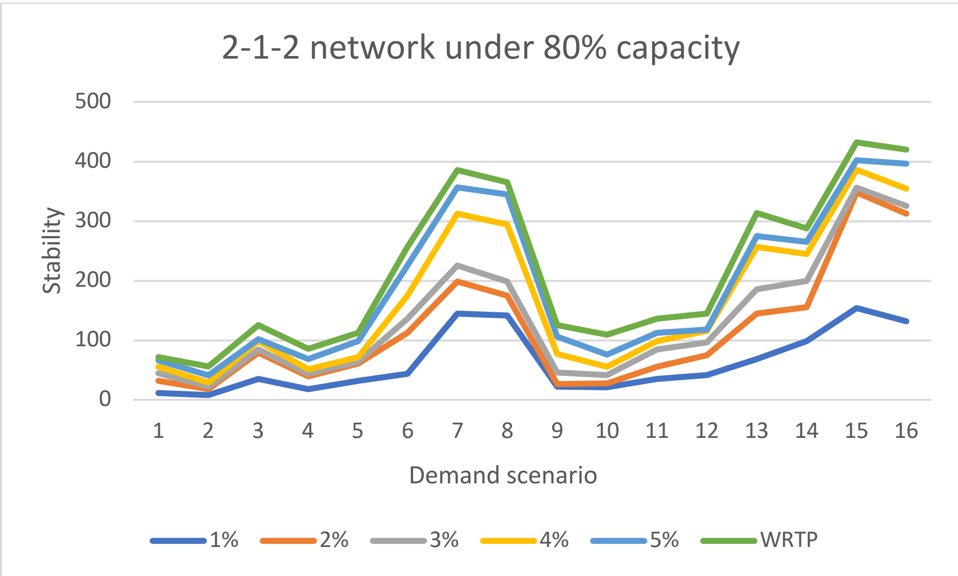
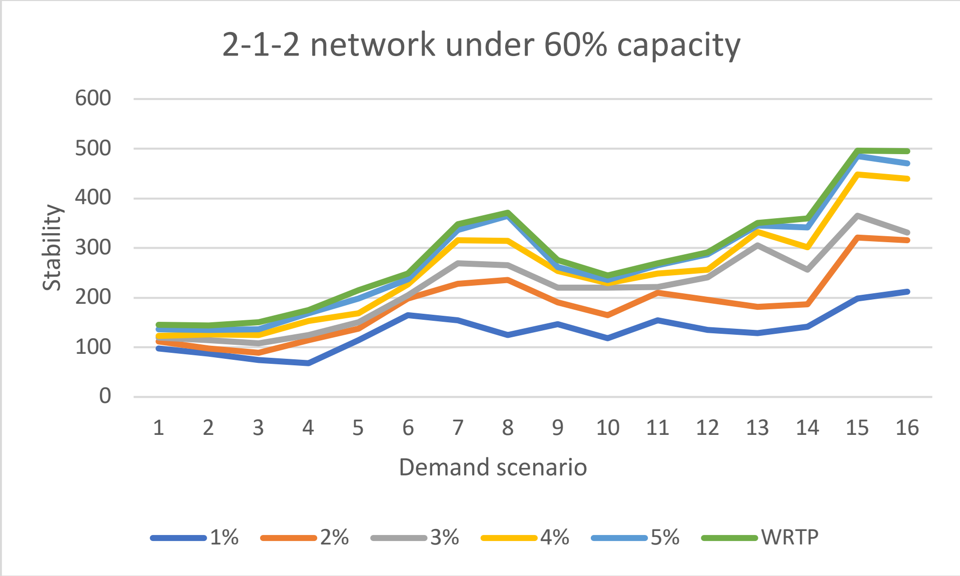


Figure 3.40: Stability Graphs in Textile Industry with 60%-80% Supplier Plant Capacity



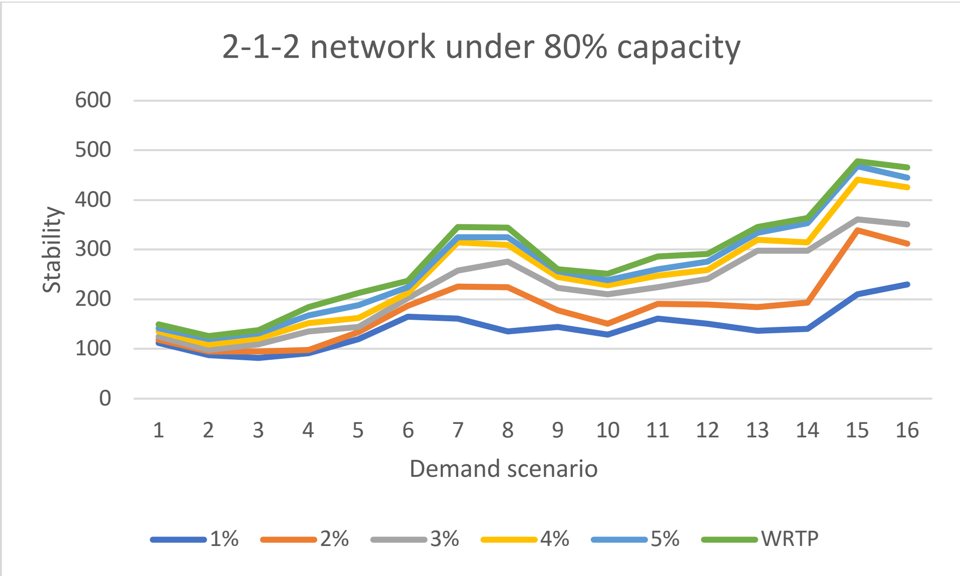


Figure 3.41: Stability Graphs in Automotive Industry with 60%-80% Supplier Plant Capacity

CHAPTER 4: SUMMARY AND CONCLUSIONS

4.1.1 Summary

This research explores the use of flexibility requirements profile (FRP) in warehouse and transportation planning to strike a balance between cost and plan stability. A mixed-integer linear programming (MILP) model is developed to solve the FRP-based warehouse and transportation planning (WRTP-FRP) problem in a rolling horizon framework, enabling the determination of optimal plans for warehouse and transportation operations. The model aims to minimize costs associated with warehouse and transportation operations, including inventory holding, transportation, and workforce costs, over the planning horizon while integrating constraints that reflect the FRP requirements. Experimental data from three industry types, namely a Wood & Paper industry, a Textile Industry and an Automotive Industry case, is used to perform a computational study.

4.2 Conclusions

The overall results suggest that the proposed WRTP-FRP method has given favourable results in warehouse resource and transportation planning stability when flex-limits are enforced, with a slight increase in the total cost when compared with the traditional WRTP without FRP.

Comparison of the proposed WRTP-FRP model with WRTP showed that the cost and stability performance of WRTP-FRP models are dependent on the flex-limits enforced. The results suggest that WRTP-FRP models with 1% - 3% flex-limits yield more promising stability results. In particular, the use of a 1% flex-limit appears to result in the most stable plans, although this may come at the potential cost of increased plan costs. Therefore, it is important for organizations to carefully consider the appropriate flex-limits when implementing WRTP-FRP models to balance stability and cost considerations.

Other influential factors on both cost and stability measures are industry and demand forecast related parameters. Among the demand parameters, demand trend emerged as the most influential parameter and demand seasonality and demand error/uncertainty came next. When the demand trend, demand seasonality and demand uncertainty increase, the instability increases as expected, but again WRTP-FRP model seem to perform relatively well compared to the traditional WRTP model that does not consider stability.

The enforced flex-limits also acknowledge that the tight bounds provide better smoothing effect on shipment and inventory levels. The results suggest that the WRTP-FRP approach can assist organizations in achieving a level of stability while still preserving their economic interests. Particularly, industries with short product lifecycles or exposed to significant demand fluctuations can potentially benefit from implementing the WRTP-FRP approach.

In addition to the importance of stable and collaborative warehouse resource and transportation planning, our research also found that the effectiveness of these planning models can differ according to the industries in which they are being used. Therefore, it is necessary to carefully consider the specific needs and priorities of each industry and make informed decisions on whether to implement these models. This requires a comprehensive understanding of the industry's operations, supply chain network, and customer demands. By taking into account these factors and using subjective judgments, industry leaders can determine the appropriate flex-limits to use in their warehouse and transportation planning, which can significantly impact the performance and cost-effectiveness of their supply chain.

The WRTP-FRP formulation offers flexibility to decision-makers by allowing them to prioritize either stability or cost based on their preferences. However, it is important to note that all solutions within the Pareto optimal set are equally acceptable mathematically, and the ultimate decision should be made by the decision-makers' subjective judgments and priorities. The WRTP-FRP formulation offers decision makers and planners a flexible approach to setting limits on production changes across the planning horizon. This dynamic method can be adjusted to different levels of flexibility over time, providing additional flexibility to the decision-making process.

Our analysis suggests that utilizing WRTP-FRP models with tighter flexibility bounds (1%-3%) can help control stability while still achieving cost-effective plans. Based on these findings, we recommend planners considering these models as a potential solution.

4.3 Assumptions and Limitations

It is important to note that the study presented in this work has a few limitations that must be taken into account. One of the major assumptions made in the study is the independence of demand forecasts, which may not reflect the complex interdependence among multiple products in real-world manufacturing environments (Baykal-Gursoy and Erkip, 2010). Moreover, the study assumes the availability of resources to adjust the workforce levels, which may not always be feasible due to budgetary constraints and regulatory restrictions. Additionally, the use of fractional factorial experiments to analyse the relationship between the smoothing constants and forecast quality may not provide a comprehensive understanding of the topic.

Furthermore, it is crucial to mention that the data used in this study is limited to three sets of data from three different industries, which may not represent the broader industry. In addition, the study employs a simple network for its model, which may not reflect the complex nature of real-world supply chain networks.

Despite these limitations, the findings of the study suggest significant potential for improvement in terms of plan stability and cost savings for the three sample industry scenarios. Nonetheless, it is important to carefully consider these limitations when interpreting the results of this study and applying them to real-world manufacturing environments.

4.4 Future Direction

- *Multi-product planning*: Also, as this research considers the single product case, future research could also include multi-products cases where there could exist shared resources, setups as well as demand correlations among some or all products.
- *Different mathematical models*: While we have utilized the WRTP-FRP technique to build our model, other techniques could be utilized such as bi-objective models, multi-stage planning, and the fuzzy stochastic model.

- *Complex networks*: Supply chain networks can be highly complex, with many different nodes, processes, and stakeholders involved in the production, transportation, and delivery of goods or services. In this study, a simple network model was used to represent the supply chain, which may not fully capture the complexity of real-world supply chain networks. Future research could focus on applying this to real-world supply chain networks.
- *Other modes of transport:* In our research, we utilized trucks as the mode of transportation for goods or services in the supply chain. However, it is important to note that in real-world supply chain networks, different modes of transport can be used, including air, rail, sea, or a combination of these modes. Each mode of transport has its own advantages and disadvantages, which can impact the efficiency and cost-effectiveness of the supply chain. Therefore, future research could focus on exploring the use of different modes of transport and their impact on the overall performance of the supply chain network.
- Implement in real company: In our research, we generated demand and used industry data available in the literature to develop and test our model. However, it is important to note that the actual demand for goods or services in real-world supply chain networks can be influenced by a variety of factors, such as economic conditions, consumer behaviour, and market trends, which may not be fully captured in our model. Therefore, future research could focus on applying our model to real industry data to check the robustness of the model and its ability to accurately predict the demand for goods or services in a given supply chain network.

4.5 Managerial Insights

Similar to production planning, warehouse resource and transportation planning are critical for organizations that seek to achieve a lean supply chain. The efficient utilization of warehouse resources and effective transportation planning not only improve the internal operations of the organization but also the overall supply chain's performance (Frazelle, 2002).

Nervousness, or variability, in warehouse and transportation planning can lead to increased lead times, excess inventory, and higher transportation costs. Therefore, it is essential to create a robust warehouse and transportation plan that emphasizes stability and minimizes variability.

To achieve this, collaboration between internal departments, suppliers, and customers is critical. Warehouse and transportation planning should involve all stakeholders to eliminate uncertainties that restrict operational performance (Vachon & Klassen, 2006; Lamming & Hampson, 2016). This collaborative effort can lead to the development of a leaner and more efficient supply chain, eliminating the bullwhip effect (Christopher & Peck, 2004).

In summary, organizations that prioritize stable and collaborative warehouse resource and transportation planning can improve their operational efficiency, reduce costs, and enhance their overall supply chain's performance (Wang, Yan, & Zhang, 2021). It is also important to make industry-specific considerations while implementing warehouse resource and transportation planning models. By prioritizing stable and collaborative planning efforts and leveraging industry insights, organizations can improve their operational efficiency, reduce costs, and enhance their overall supply chain performance.

REFERENCES

Ahuja, R. K., Magnanti, T. L., & Orlin, J. B. (1993). Network Flows. Englewood Cliffs NJ: Prentice-Hall.

Allam, Z.; Bibri, S.E.; Sharpe, S.A. The Rising Impacts of the COVID-19 Pandemic and the Russia–Ukraine War: Energy Transition, Climate Justice, Global Inequality, and Supply Chain Disruption. *Resources* 2022, *11*, 99. https://doi.org/10.3390/resources11110099

Baker, K. R., 1977. An experimental study of the effectiveness of rolling schedules in production planning. Decision Sciences, 8, 19-27.

Baumann, N., & Skutella, M. (2009). Earliest arrival flows with multiple sources. Mathematics of Operations Research, 34(2), 499–512.

Baykal-Gursoy, M., & Erkip, E. (2010, May). The Impact of Node Density and Transport Protocols on the Performance of Wireless Ad Hoc Networks. In 2010 IEEE International Conference on Communications (ICC) (pp. 1-5). IEEE.

Bazaraa, M. S., Jarvis, J. J., & Sherali, H. D. (2011). Linear programming and network flows. John Wiley & Sons.

Bechet, T. P. (2017). Strategic staffing: A comprehensive system for effective workforce planning. AMACOM Div American Mgmt Assn.

Blackburn, J. D., Kropp, D. H., Millen, R. A. (1985). MRP system nervousness: causes and cures. Engineering Costs and Production Economics, 9, 141-146.

Blackburn, J. D., Kropp, D. H., Millen, R. A. (1987). Alternative approaches to schedule instability: a comperative analysis. International Journal of Production Research, 25(12), 1739- 1749.

Blackburn, J.D., Kropp, D.H., & Millen, R.A., 1986. A comparison of strategies to dampen nervousness in MRP systems. Management Science, 32(4), 413-429.

Bondarouk, T., & Ruel, H. J. M. (2019). Electronic human resource management: challenges and opportunities. International Journal of Human Resource Management, 30(5), 743-756.

Buzacott, J. A., and Shanthikumar, J. G., 1994. Safety stock versus safety time in MRP controlled production systems. Management Science, 40(12), 1678-1689.

Carlson, R C., Jucker, J. V., & Kropp, D. H., 1979. Less nervous MRP systems: a dynamic economic lot-sizing approach. Management Science, 25(8), 754-761.

Cayirli, T. & Veral, E. (2009). Outpatient scheduling in health care: A review of literature. Production and Operations Management. 12. 519 - 549. 10.1111/j.1937-5956.2003.tb00218.x.

Christopher, M., & Peck, H. L. (2004). Building the Resilient Supply Chain. International Commerce Review, 4(1), 39-44.

Council of Supply Chain Management Professionals (CSCMP). (2019). State of Logistics Report. https://cscmp.org/

Coyle, J. J., Bardi, E. J., & Langley, C. J. (2003). The management of business logistics: A supply chain perspective. South-Western/Thomson Learning.

de Kok, T., and Inderfurth, K., 1997. Nervousness in inventory management: Comparison of basic control rules. European Journal of Operational Research, 103, 55-82.

De Koster, R., Le-Duc, T., & Roodbergen, K. J. (2007). Design and control of warehouse order picking: A literature review. *European journal of operational research*, *182*(2), 481-501.

Demirel E., Ertunga C. Özelkan, and Churlzu Lim. (2018). "Aggregate planning with Flexibility Requirements Profile." International Journal of Production Economics 202: 45-58.

Demirel, E. (2014). "Flexible Planning Methods and Procedures with Flexibility Requirements Profile." The University of North Carolina at Charlotte, Charlotte, NC.

Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. Numerische Mathematik, 1(1), 269-271.

F. Barahona, Francisco & Chowdhary, Pawan & Ettl, Markus & Huang, P. & Kimbrel, T. & Ladányi, Laszlo & Lee, Young & Schieber, B. & Sourirajan, K. & Sviridenko, M. & Swirszcz, Grzegorz. (2007). "Inventory allocation and transportation scheduling for logistics of network-centric military operations," in IBM Journal of Research and Development, vol. 51, no. 3.4, pp. 391-407, May 2007, doi: 10.1147/rd.513.0391.

Ford, L. R., & Fulkerson, D. R. (1956). Maximal flow through a network. Canadian Journal of Mathematics, 8(3), 399-404.

Frazelle, E. (2002). World-Class Warehousing and Material Handling. McGraw-Hill Education. ISBN-13: 978-0071376002.

Glockner, G. D., & Nemhauser, G. L. (2000). A dynamic network flow problem with uncertain arc capacities: Formulation and problem structure. Operations Research, 48(2), 233–242.

Goh, M., & Lim, J. (2020). A conceptual model of warehouse workforce allocation for order picking efficiency. International Journal of Production Research, 58(7), 1921-1937.

Goldberg, A. V., & Tarjan, R. E. (1988). A new approach to the maximum-flow problem. Journal of the ACM, 35(4), 921-940.

Gupta, A., & Maranas, C. D. (1999). A hierarchical Lagrangean relaxation procedure for solving midterm planning problems. Industrial and Engineering Chemistry Research 38, 1937/1947.

Huang, G.Q., Lau, J.S., & Mak, K.L. (2003). The impacts of sharing production information on supply chain dynamics: A review of the literature. *International Journal of Production Research, 41*, 1483 - 1517.

Inman, R. R., and Gonsalvez, D., 1997. Measuring and analysing supply chain schedule stability: a case study in the automotive industry. Production Planning & Control, 8(2), 194-204.

Josefa Mula., David Peidro., & Manuel Díaz-Madroñero, Eduardo Vicens,. (2010). Mathematical programming models for supply chain production and transport planning. European Journal of Operational Research, 204(3), 377-390.

K Kadipasaoglu, S. N., and Sridharan, V., 1995. Alternative approaches for reducing schedule instability in multistage manufacturing under demand uncertainty. Journal of Operations Management, 13(3), 193-211.

Khodayifar, S. (2021). Minimum cost multicommodity network flow problem in time-varying networks: By decomposition principle. Optimization Letters, 15(3), 1009–1026.

Klinz, B., & Woeginger, G. J. (2004). Minimum-cost dynamic flows: The series–parallel case. Networks, 43(3), 153–162.

Kropp, D. H. and Karlson, R. C. (1984). A lot-sizing algorithm for reducing nervousness in MRP systems. Management Science, 30(2), 240-244.

Kropp, D. H., Karlson, R. C., Jucker, J. V. (1983). Heuristic lot-sizing approaches for dealing with MRP system nervousness. Decision sciences, 14(2), 156-169.

L.R. Ford, and D.R. Fulkerson, "A simple algorithm for finding maximal network flows and an application to the Hitchcock problem," Canadian Journal of Mathematics, vol. 9, 1957, pp. 210-218.

Lamming, R., & Hampson, J. (2016). The green supply chain: An introduction to the development of environmentally sustainable supply chains and the potential associated with their management.

M. Grazia Speranza (2018). Trends in transportation and logistics. European Journal of Operational Research, 264(3), 830-836.

Marmolejo, J.A., Rodríguez, R., Cruz-Mejía, O. and Saucedo, J. (2016) Design of a distribution network using primal-dual decomposition. Mathematical Problems in Engineering, Volume 2016, Article ID 7851625, 9 pages, http://dx.doi.org/10.1155/2016/7851625

Metters, R., 1997. Quantifying the bullwhip effect in supply chains. Journal of Operations Management, 15(2), 89-100.

Niranjan, T. T., Wagner, S. M., and Aggarwal, V., 2011. Measuring information distortion in real-world supply chains. International Journal of Production Research, 49(11), 3343- 3362.

O'Reilly, J. (2015). Building a smarter warehouse. Inbound Logistics, 18(5), 104-108

Orda, A., & Rom, R. (1990). Shortest-path and minimum-delay algorithms in networks with time-dependent edge-length. Journal of the ACM, 37(3), 607–625.

Ozelkan, E. & Torabzadeh, S. & Demirel, E. & Lim, C. (2023). Bi-Objective Aggregate Production Planning for Managing Plan Stability. Computers & Industrial Engineering. 178. 109105. 10.1016/j.cie.2023.109105.

Öztürkoğlu, Ö., Gue, K. R., & Meller, R. D. (2014). A constructive aisle design model for unit-load warehouses with multiple pickup and deposit points. *European Journal of Operational Research*, *236*(1), 382-394.

Pereira, C. M., Anholon, R., Rampasso, I. S., Quelhas, O. L., Leal Filho, W., & Santa-Eulalia, L. A. (2020). Evaluation of lean practices in warehouses: an analysis of Brazilian reality. International Journal of Productivity and Performance Management.

Petkov, S. B., & Maranas, C. D. (1997). Multiperiod planning and scheduling of multiproduct batch plants under demand uncertainty. Industrial and Engineering Chemistry Research 36, 4864.

Philpott, A. B. (1990). Continuous-time flows in networks. Mathematics of Operations Research, 15(4), 640–661.

Sarmiento, R., Sáenz, M. J., & Cerdá, J. (2013). A mixed-integer programming approach for workforce scheduling in a cross docking platform. International Journal of Production Economics, 142(2), 326-336.

Sridharan, V., and LaForge R.L., 1989. The impact of safety stock on schedule instability, cost and service. Journal of Operations Management, 8(4), 327-347.

Srinivasan, M., 2005, Streamlined: 14 Principles for Building& Managing the Lean Supply Chain, Thomson Business and Professional Publishing.

Subrahmanyam, S., Pekny, J. F., & Reklaitis, G. V. (1994). Design of batch chemical plants under market uncertainty. Industrial and Engineering Chemistry Research 33, 2688.

Torabzadeh S. &. Ozelkan E. , 2021. "Fuzzy aggregate production planning with flexible requirement profile for plan stability in uncertain environments," European Journal of Industrial Engineering, Inderscience Enterprises Ltd, vol. 15(4), pages 514-549.

Vachon, S., & Klassen, R. D. (2006). Extending green practices across the supply chain: the impact of upstream and downstream integration. International Journal of Operations & Production Management, 26(7), 795-821.

Van den Berg, J. P., & Zijm, W. H. (1999). Models for warehouse management: Classification and examples. International journal of production economics, 59(1-3), 519-528.

Wang, L., Yan, Y., & Zhang, J. (2021). Logistics operation mode and energy consumption of cold chain logistics based on big data. Energy Reports, 7, 2388-2393.

Watling, D. P., Bennett, S., & Wang, Y. (2015). Warehouse order picking with time window constraints: Problem properties, models and solution approaches. International Journal of Production Economics, 159, 92-105.

Xie, J., Zhaob, X., Lee, T.S. (2003). Freezing the master production schedule under single

Yang, J., Jaillet, P., Mahmassani, H.S.: On-line algorithms for truck fleet assignment and scheduling under real-time information. Transportation Research Record 1667, 107–113 (1998)

Yano, C. A. and Carlson, R. C. (2987). Interaction between frequency of rescheduling and the role of safety stock in material requirements planning systems. International journal of production research, 25(2), 221-232.

Yano, C. A., and Carlson, R. C., 1987. Interaction between frequency of rescheduling and the role of safety stock in material requirements planning systems. International Journal of Production Research, 25(2), 221-232.

Yücel, E., & Çanakoğlu, E. (2021). A novel heuristic for the two-echelon inventory routing problem. Journal of Cleaner Production, 294, 126158.

Zhao, X., and Lee, T.S., 1993. Freezing the master production schedule for material requirements planning systems under demand uncertainty. Journal of Operations Management, 11(2), 185–205.

Zhen, L. & Li, H. (2022). A literature review of smart warehouse operations management. Frontiers of Engineering Management. 9. 10.1007/s42524-021-0178-9.