FLEXIBLE PLANNING METHODS AND PROCEDURES WITH FLEXIBILITY REQUIREMENTS PROFILE

by

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ABSTRACT

EDIL DEMIREL. Flexible planning methods and procedures with Flexibility Requirements Profile. (Under the direction of Dr. E. C. OZELKAN and Dr. C.LIM)

Uncertainties in supply and/or demand combined with rolling horizon planning necessitate flexibility in a dynamic production planning process. In rolling horizon planning, production plans are revised when new information becomes available after time rolls forward on the planning horizon. Frequent adjustments to production plans can lead to the increase of instability in the production system, and result in a surplus or deficiency in production resources. These frequent replanning adjustments and extra efforts to cope with uncertainties in the system lead to syndrome referred to as *nervousness*.

Frozen horizon and other planning approaches attempt to provide insights on how to mitigate nervousness. However, most of the existing studies do not consider the flexibility aspect in production plans, or provide only partial flexibility to handle the fluctuating demand. In this research, we propose to study mathematical optimization for *Flexibility Requirements Profile (FRP)* that is designed to mitigate nervousness by enforcing bounds on production plans in order to maintain a desired degree of flexibility. Instead of 0% flexibility in the frozen horizon planning and 100% flexibility in the make to order planning, the proposed FRP optimization model allows the trade-off between conflicting planning objectives, stability and responsiveness of the production system.

In this dissertation, we first evaluate the effectiveness of the proposed mathematical optimization having FRP constraints by comparing its performance with that of ad-hoc

implementation of FRP under a variety of experimental scenarios when conducting aggregate planning. In specific, we compare the production plans in a rolling horizon environment by evaluating the total costs and plan stability over the evaluation horizon. Then we extend our research to a mathematical optimization model that simultaneously optimizes conflicting objectives. Although FRP has been discussed in aggregate planning problems without optimization, none of the existing studies analyze the tradeoff between cost and plan stability under the presence of FRP. We fill these gaps by developing a bi-objective mixed-integer linear programming model using a compromise programming approach. Finally, we utilize these mathematical optimization models to demonstrate how stability in planning can facilitate leanness in system operations.

The numerical results show that aggregate planning with FRP can consistently identify stable production plans without significantly sacrificing the cost objective. Flexibility bounds increase the responsiveness to demand fluctuations, provide manufacturers and suppliers a better visibility in forecasting, and have a smoothing effect on production and inventory levels. Overall, this dissertation research aims to contribute to the production planning area by introducing new optimization models to mitigate nervousness and help practitioners and researchers to build optimal and responsive planning systems by creating balanced trade-offs between those conflicting planning objectives.

DEDICATION

To my family,

and my grandfathers, Cumali Demirel and Turhan Turaylar, who are waiting for me, for an interval, somewhere very near, just around the corner.

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CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

In recent years, the supply chain management problems have gained a great deal of attention due to increasing market competition, shortened product lifecycles, and rapid technology changes (Kouvelis et al., 2006). The global nature of the markets have forced companies to move towards decentralized supply chain networks that require more responsiveness to changing market conditions and requirements. A traditional supply chain network is made up of many diverse players including suppliers, manufacturers, distribution centers, retailers, etc. These players have different goals depending on their function within the supply chain, and many of these goals are conflicting by nature. For example, manufacturers prefer to maintain a steady production rate and predictable throughput levels, whereas retailers' main focus is on responding to changing demand quickly to meet customer requirements as well as avoiding backorders or piled-up inventories. Due to the fluctuations in demand, the retailer (customer) will not be willing to commit to long term purchasing, and in turn, this might require frequent changes in the production rates (Figure 1.1). This typical conflict is a good indicator of how difficult it is to simultaneously optimize supply chain operations. In order to return higher profit margins while maintaining high customer service levels, organizations are required to have optimal, adaptable, and robust supply chain planning strategies that can find balanced trade-offs between those conflicting planning objectives.

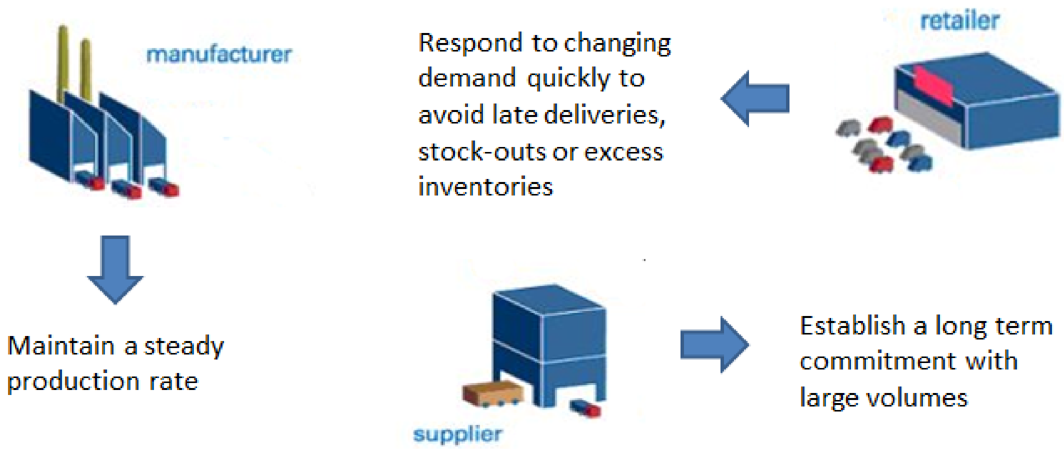


Figure 1.1: Supply chain players & objectives.

A fundamental source of uncertainty in a supply chain network is demand volatility. The variation in demand causes a propagating information distortion (upstream) in supply chains, also known as *bullwhip effect*, and creates adverse effects such as excess inventories, backorders and inefficient use of resources (Lee et al., 1997). One area that bullwhip effect causes serious cost implications is production planning and scheduling (Metters, 1997; Lee et al., 1997). Most production planning systems operate in this type of an uncertain world, and are exposed to a great deal of demand uncertainty. As planning organizations get more visibility and obtain accurate information about future demand, they tend to revise and update their production plans. Especially in rapidly changing markets, demand uncertainty causes excessive plan changes in short periods and leads to a general state of confusion and anxiety. This phenomenon is called as *nervousness*, or lack of planning stability, and increases the frequency of replanning activities, which induces further uncertainty into the production plan (de Kok and Inderfurth, 1997). Frequent adjustments to the production plans changes can typically lead to increases in production costs, reduced productivity, lower customer service level and responsiveness to demand, and a general state of confusion at the shop floor (Hayes and Clark, 1985). On a greater scale, excessive changes can hinder *Material Requirements Planning* (MRP) systems and leverage bullwhip effect (Lee et al., 1997).

The uncertainties in planning make organizations' efforts inefficient. To address those issues, organizations have developed numerous strategies, which require considerable amount of internal resources. A traditional attempt to cope with uncertainties is to build inventories or have excessive production capacity. This is known as *make to stock*, where the demand uncertainty is handled by inventories. The make to stock production strategy increases the inventory holding costs. Another approach is to freeze the *master production schedule* (MPS), where no changes are allowed in the MPS for a predetermined time period, called frozen period, to avoid disruption in production planning. While implementing a frozen horizon can reduce the manufacturer's nervousness, it is poorly responsive to changing demand, and hence, can easily result in pile-up or adversely allow shortages.

A similar concept to frozen horizon is *time fences* (Costanza, 1996). The idea is to establish limits on the amount of change to MPS. Time fences are usually employed in combination with frozen horizons, where MPS is frozen for a prespecified time period and then, beyond the horizon time fences with varying limits are established. We propose the application of an alternative approach to mitigate the nervousness syndrome. Flexibility Requirements Profile (FRP) is an alternative stabilizing approach that enforces flexibility bounds on production plans so that planned production quantities remain within a lower and upper bounds. When time rolls to the next planning period, those bounds are dynamically updated to reflect revised demand forecasts and plans.

In this dissertation, we focus on developing planning models that are robust yet responsive to changing customer demand while avoiding anxiety within the organization due to large plan changes from one planning period to another. Although the main emphasis will be on production planning problems, we believe that the contributions will not be limited to production environments. The frameworks developed here are generic and can be applied to any planning problem. The rest of this chapter is organized as follows. In the next section, we first provide a list of expected contributions of our research, and then give an overview of previous work about production planning problems under rolling horizon models. Section 1.3 gives further background of *Mixed Integer Linear Programming* (MILP) that will be used throughout this dissertation. In the last section of this chapter, we outline the rest of the thesis.

1.2 Summary of Expected Research Contributions

Developing FRP-based flexible planning models in rolling-horizon environments can be considered as the main research contribution of this dissertation. In particular, the following research accomplishments are made:

Objective 1 & Contributions:

The first objective is to integrate mathematical optimization and the flexible production planning research to fill the gap between the conventional aggregate planning and practices of flexible production planning. Hence, proposed models provide a general framework to achieve optimal production plans under FRP. Main contributions of this research objective are:

- Develop a new mathematical programming model that incorporates FRP constraints.
- Compare the FRP-based optimization scheme with the traditional aggregate production planning.
- Assess the impact of flexibility bounds using a numerical study, and
- Conduct a comparative study via an experimental design to analyze the tradeoff between the cost and production plan stability under various flexibility bound scenarios.

Objective 2 & Contributions:

The second objective is to incorporate two conflicting planning goals into a single criterion. As opposed to traditional production planning systems that rely on single criterion such as cost minimization or profit maximization, we formulate a model that integrates conflicting interests and seeks to reduce both of them simultaneously. Contributions of the second objective are:

- Integrate FRP into the production plan using a multi-objective programming model and develop a bi-objective MILP model that considers cost and plan stability terms simultaneously.
- Assess the efficacy of FRP under multiple conflicting criteria.
- Present a comparative study of costs and stability performances among the single objective FRP model, the bi-objective approach without FRP, and the combination of two methods.

- Solve the problem with different set of flex-limits and observe how flex-limits with different magnitudes respond to uncertain demand.
- Build a Pareto frontier for the decision maker by varying weights of objectives.
- Apply statistical tests to identify the significant parameters in the FRP-based planning process.

Objective 3 & Contributions:

As the third objective, we will discuss stability in planning from the lean thinking perspective and its use in achieving lean operation systems. To address this objective we will:

- Explore stability's role in planning and eliminating non-value added activities such as unnecessary inventory and overproduction through the utilization of FRP.
- Compare FRP-embedded planning schemes with aggregate planning models that implement frozen horizon through a numerical study and analyze stability and FRP's contributions to the lean value chain.
- Investigate the relationship between the stability and lean systems. Assess the sensitivity of its impact under different manufacturing conditions and industry settings.

1.3 Previous Work on Aggregate Production Planning (APP)

APP problems concern about the allocation of available resources to respond demand requirements. The goal is to minimize the overall cost over a planning horizon by adjusting production, inventory and workforce levels while satisfying demand needs. APP's goal is to anticipate customer needs and come up with an optimal set of decisions concerning the current and future resources (Sipper and Bulfin Jr., 1997). The aggregate production plan provides guidelines for MPS. According to APICS, MPS expresses what to produce in a more detailed level and provides information related to production configurations, quantities, and dates. MPS then becomes an input for the MRP. Due to demand uncertainty and other external and internal anomalies (disruptions), the MRP system has to be regularly updated by replanning MPS. The effectiveness of MPS is positively correlated with the production efficiency on the shop floor. A well-established MPS will not only help companies to utilize their resources more efficiently but also reduce the overall production costs and increase their throughput. Due to its critical role in establishing production efficiency, APP has become a vital component in business operations. Many solution methodologies, from enumeration based ad-hoc methods to mathematical programming, are used to solve APP problems. We will provide more information regarding these solution approaches in Chapter 2.

Two essential components in the production planning procedure are the *forecast (time) horizon* and the *planning (study) horizon*. In a traditional planning setting, forecast horizon is the total number of periods where future demands are estimated. On the other hand, planning horizon shows how distant in the future that the planning is concerned. Typically, the number of periods in the planning horizon is fixed for each decision point. *Rolling horizon planning* has been frequently used in production planning problems since the early 1950 to provide predictive guidance for planning environments (Modigliani and Hohn, 1955). In rolling horizon planning production plans are revised and updated as new or more accurate information is available. This gives a chance to review plans on a continuous basis and increase the planning accuracy. In rolling horizon planning, in each decision point, the planning problem is solved over a predetermined time period, by considering the current state of production as well as the future demand events, but only the decisions in the initial period are actually implemented. In the next decision point, the production plans are revised as new information becomes available after time rolls forward on the planning horizon.

Previous research efforts concerning rolling horizon planning provide a few different insights. First and foremost is the diminishing effect of forecast on production plans. Although longer planning horizons provide greater visibility to planners, the forecasts in the distant future tend to be less accurate and more expensive. This phenomenon is analyzed in many different studies (Wagner and Whitin, 1958; Baker and Peterson, 1979; Federgruen and Tzur, 1994) over the years and eventually formed the forecast horizon theory, which suggests that forecast in the distant future have no effect on the decisions of the current period. Another frequently discussed topic is the frequency of replanning. Frequent replanning increases the firm's chance to incorporate more recent information on a timely manner, which can be an important strategic advantage under uncertainty. However, frequent replanning will also cause frequent changes in production plans, and hence, may increase the instability. Main consensus on this issue is that frequent replanning is not desirable from the cost perspective. However, there are a few contrary observations to this common belief. Chung and Krajewski (1986) showed that less frequent planning vs. rolling one period at a time do not reflect a significant difference in terms of projected costs. Lin et al. (1994) added that the degree of efficacy of replanning frequency is based on multiple parameters such as product cost structure, MPS unit change cost, the cumulative lead time and the length of frozen interval.

1.4 Nervousness Syndrome

(Lee et al., 1997) observed that the variation in demand causes a propagating information distortion towards upstream in supply chains, also known as bullwhip effect, and creates adverse effects such as higher costs, excess inventories/backorders and inefficient use of resources. The uncertainty and variability within the demand also cause excessive plan changes in short periods and leads to a general state of confusion, mistrust and loss of confidence in the planning system, which is referred to as nervousness (de Kok and Inderfurth, 1997). Frequent changes in plans cause various disruptions such as scheduling conflicts and capacity utilization issues in the production systems (Inman and Gonsalvez, 1997; Metters and Vargas, 1999). These changes in production plans not only increases inventory and material holding costs but also lead to under or overutilization of resources. There are two commonly applied concepts as a proactive tool against nervousness. These are *Production Smoothness* and *Plan Stability* (Graves, 2006).

1) *Production Smoothness* is interested in the variability of the production output. It investigates the changes in the production over the planning horizon by measuring the variance of production output. Production smoothing is achieved through in advance production and inventory accumulation, which makes it preferable when inventory carrying costs are low. Another viable option to accomplish smoothing is to alter the demand pattern through efforts such as pricing and promotion. (Kamien and Li, 1990)
2) *Plan Stability* is concerned with the variance of planned revision, and can be defined as the changes in the planned production versus actual production from one period to another as time rolls on the planning horizon.

The impacts of nervousness and the importance of having stable production plans are mentioned in several studies. Carlson et al. (1979) are one of the first to touch upon that issue in their study, where they used a modified Wagner-Whitin algorithm to increase the emphasis on stable production plans and schedules by including the cost of cancelled setups. As time has gone by, many researchers have agreed on the necessity of emphasizing and establishing stability even if that could mean having less optimal solutions in terms of cost. We will provide more information about the approaches that have been proposed to minimize the instability (nervousness) under rolling horizon plans in Chapter 2. Throughout this dissertation we will use the nervousness and instability terms interchangeably.

1.5 Mixed-Integer Linear Programming in APP

In this section, we briefly describe the usage of *mixed integer-linear programming* (MILP) in APP and include the important points that will be useful for the remainder of the dissertation. MILP is an optimization problem with a linear objective function and linear constraints where some of the variables take only integer values. MILP formulations are used in many real-world supply chain and aggregate production planning problems. Most of those problems are formulated in accordance with the classical approach, where the planning horizon is divided into discrete time periods. In each time period a set of constraints have to be satisfied. The first principal set of constraints is responsible from maintaining the conservation of material flow. The second set represents the total amount of capacity available for each resource in the system (Missbauer and Uzsoy, 2011). To visualize this formulation let us define the following parameters and variables.

D_t : demand for product in period t

up_t : cost of producing one unit of product in period t

h_t : cost of holding one unit of product in period t

C_t : production capacity available in period t

P_t : total amount of product produced in period t

I_t : total amount of product hold in inventory at the end of period t

$t = 1, \ldots, T$ index of time period

Then the classical planning formulation can be shown as follows:

$$\text{Minimize } \sum_{t=1}^{T} \left(up_t P_t + h_t I_t \right) \tag{1.1}$$

$$\text{Subject to: } D_t = P_t - I_t + I_{t-1} \qquad \forall t \tag{1.2}$$

$$P_t \leq C_t \qquad \forall t \tag{1.3}$$

$$P_t, I_t \geq 0 \qquad \forall t \tag{1.4}$$

The objective function (1.1) considers minimizing the total production and inventory holding cost over a planning horizon. (1.2) is responsible from maintaining the inventory balance, whereas (1.3) ensures that production will not exceed the capacity. This finite horizon single product linear programming model is used as a basis for the production planning models developed throughout this dissertation.

1.6 Multi-Objective Programming in APP

An optimization problem, in which several objectives are considered, is called a multi-objective programming (optimization) problem. The classical multi-objective optimization problem can be described in the following form;

$$\text{Minimize } \left\{ f_1(x), f_2(x).....f_Z(x) \right\} \tag{1.5}$$

$$\text{Subject to: } g_i\left(x\right) \geq 0, \qquad i = 1, 2, ..., j \tag{1.6}$$

$$x \in \Omega \tag{1.7}$$

Where $\left\{ f_1(x), f_2(x).....f_Z(x) \right\}$ represent the attributes that are involved the decision making process and j is total number of inequality constraints. The underlying idea is to optimize all objectives simultaneously.

Multi-objective optimization problems have been extensively investigated and multiple approaches were presented. These approaches are usually classified according to the availability of preference information provided by the decision maker (Miettinen, 1999). Solution methods for multi-objective optimization can be categorized as the following (Kalyanmoy, 2001).

1) Preference methods

Preference methods are divided into two. *A priori methods* are considered when the decision maker's preferences are known in advance and these preferences are used to find one preferred Pareto-optimal solution. *A posteriori methods* use decision maker's preferences over different objectives to generate a set of Pareto optimal solutions. They often rely on the idea of scalarization and transform the original multi-objective problem into a series of scalarized single objective sub problems.

2) Non-preference methods

Unlike the preference methods, non-preference methods do not require preferences articulated by DM and could generate one or more Pareto-optimal solutions without any inputs from the DM. Let us review some of the most frequently used multi objective optimization methods in supply chain and production planning problems.

1.6.1 Weighted-Sum Method

In the weighted-sum method, multiple objectives are transformed to a one single overall objective by multiplying each objective with a decision maker supplied weight. It is easy to implement and produces good results within convex sets. For mixed optimization problems (min-max), we need to convert all the objectives into one type. Weighted- sum is often used when preferences are set in prior. The classical interpretation of the method is as follows:

$$\text{Minimize } \sum_{i=1}^{k} w_i f_i\left(x\right) \tag{1.8}$$

$$\text{Subject to: } \sum_{i}^{k} w_i = 1, w_i \geq 0, i = 1, ..., k \tag{1.9}$$

$$x \in \Omega \tag{1.10}$$

Where scalars w_i are the weights of each objective *i* and the multiple objectives are transformed to single objectives by varying the weight vector *w*.

1.6.2 Compromise Programming

Compromise programming seeks to find a solution point that is closest to a utopia (ideal) point. The utopia point is considered as infeasible in the decision space because of the conflicting nature of the individual objectives and the decision maker has to find a compromise solution between the final solution and the utopia point. The utopia vector (point) contains the best possible values of each criterion, and as opposed to goal programming, the utopia point in compromise programming is not a target established by the DM’s own views. The distance measure used in compromise programming is the family of L_p metrics. p stands for the decision maker’s compensation between deviations, where p variates between 1 (full compensation) and ∞ (no compensation). The classical CP formulation can be formulated as (e.g., Chen et al., 1999):

$$\text{Minimize } \left\| f\left(x\right)-U\right\| \tag{1.11}$$

$$\text{Subject to: } x\in\Omega \tag{1.12}$$

Where $\| \ \|$ denotes the metric of choice and U corresponds to the utopia (ideal) point.

For a weighted L_p - metric, the formulation can be shown in the following form:

$$\text{Minimize}\left(\sum_{i=1}^{N}\left(w_i\left|f_i(x)-u_i\right|\right)^p\right)^{1/p} \tag{1.13}$$

$$\text{subject to: } x\in\Omega, \tag{1.14}$$

Where p is the compensation parameter and w_i are objective weights, $w_i \geq 0, i=1...N.$

As shown in (1.13), in full compensation $\left(\text{i.e. } p=1\right)$ deviations from the ideal point are taken into account in direct proportion to the magnitude of that respective object. On the contrary, when the p is equal ∞, the L_p metric can be transformed into a linear programming model, which is also known as Tchebycheff distance. In this case, only the objective with the largest deviation is taken into account to generate non-dominated points. The transformation can be shown as following:

$$\text{Minimize } \left\| f_i\left(x\right)-u_i\right\|_{\infty}^{w} \tag{1.15}$$

$$\text{where } \left\| f_i\left(x\right)-u_i\right\|_{\infty}^{w} = \max_{i=1,\dots,M}\left\{w_i\left|f_i\left(x\right)-u_i\right|\right\}$$

(1.14) will reformulate as:

$$\text{Minimize } n^* \tag{1.16}$$

$$\text{Subject to: } w_i\left(f_i(x)-u_i\right)\leq n^* \tag{1.17}$$

$$\text{Subject to: } x\in\Omega, \tag{1.18}$$

Where $n^*=\max_{i=1,\ldots,M}\left\{w_i\left|f_i(x)-u_i\right|\right\}$ because we know that by construction $\left|f_i(x)-u_i\right|=\left(f_i(x)-u_i\right)\geq 0, i\in M$.

1.6.3 Epsilon-Constraint Method

The epsilon-constraint (ε-constraint) approach, which is introduced by Haimes et al., 1971, keeps only one of the attributes in the objective function and treats all the remaining attributes as a set of inequality constraints that need to be satisfied. Each inequality constraint is bounded by an epsilon vector, and each vector corresponds to a point in the Pareto frontier. As the magnitude of the epsilon vector changes, tradeoffs between objectives can be reached and a pareto-front can be built. One significant advantage of ε-constraint over weighted-sum method is that it can deal with both convex and non-convex sets. As a drawback, choosing an appropriate value for epsilon vector can be a challenge and would require us to know the decision space of objectives in advance. The problem formulation appears below:

$$\text{Minimize } f_i(x) \tag{1.19}$$

$$\text{Subject to: } f_n(x)\leq\varepsilon_n, n=1,2,..,N\left(n\neq i\right) \tag{1.20}$$

$$x\in\Omega \tag{1.21}$$

1.7 Dissertation Outline

The remainder of this dissertation is organized as follows. Chapter 2 provides a comprehensive review of the relevant literature. Specifically, we present a review of aggregate planning problems, rolling horizon procedures, and stability in production planning. The rest of the chapter discusses mathematical optimization and multi-objective programming in planning problems. In the beginning of Chapter 3, Flexibility Requirements Profile is introduced, and FRP-embedded aggregate planning is described with an illustrative example. The rest of the chapter presents our proposed MILP formulation integrated with FRP as well as the experimental design that we created to test the efficacy of the procedure in different industrial settings.

Chapter 4 includes the implementation of multi-objective programming in rolling horizon models and the analysis of resulting FRP-embedded bi-objective optimization models. A thorough analysis and discussion of an experimental design scheme is also presented. Chapter 5 focuses on production plan stability and its integration to lean system operations. We, specifically analyzed lean waste items and reduce these items through the utilization of FRP. Chapter 6 summarizes our work, as well as explains the limitations of our study and presents possible directions for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

In this chapter, we review the literature on aggregate production planning problems and flexible planning under rolling horizons. In the first subsection, we talk about the use of mathematical programming in APP. Later, we provide information about rolling horizon models and the approaches that were presented to mitigate the instability (nervousness) in production plans. At the end of the chapter, we present the most frequently used multi-objective optimization methods in APP problems.

2.2 Mathematical Programming Models in Aggregate Planning Problems

APP problems concern about the allocation of available resources to respond demand requirements. The goal is to minimize the overall cost over a finite time horizon by adjusting production, inventory and workforce levels while demand requirements are satisfied. The critical role of production planning in business operations has motivated practitioners and researchers to study production planning methodology.

The use of mathematical programming in APP has started in the 1950's. Holt et al. (1955) and Holt et al. (1956) applied linear decision rules to find optimal production and workforce levels while minimizing the total costs. Researchers have slowly built upon those models and, since then, a wide range of mathematical models for APP problems has been presented in the literature.

About this matter, Nam and Logendran (1992) provided a comprehensive study that cites more than 100 sources and classify the cited models as optimal and near-optimal solutions. Traditional APP problems are formulated to consider discrete periods over a planning horizon with the objectives of minimizing production-related (workforce, production, inventories and backorders) costs or maximizing profit. In each period, there are a set of decisions to be made while satisfying the constraints at an aggregate level. Although a great variety of approaches are available, linear programming (LP) and mixed integer-linear (MILP) are found to be the widely used approaches for APP problems (Hung and Leachman, 1996; Gnoni et al., 2003, Missbauer and Uzsoy, 2011). For further review, we refer readers to a recent study by Mula et al. (2010), where a comprehensive list of existing studies is provided.

2.3 Rolling Horizon Models

One of the most notable subjects in the area of planning literature is rolling horizon models. Baker (1977) is one of the first studies to investigate the effectiveness of rolling horizon models in the context of production planning. The purpose of the study was to optimize finite horizon models in infinite horizons using concave costs and implementing the procedure on a rolling basis. The results suggested that rolling schedules are quite efficient but the demand pattern and length of the planning horizon had significant impact on the effectiveness of rolling schedules. McClain and Thomas (1977) further investigated the effect of the length of planning horizon through simulation and found that while the length of planning horizon has significant impact on cost performance, cost does not improve monotonically as the planning horizon is extended. Similarly, Baker and Peterson (1979) studied the effects of the length of planning horizon, forecast uncertainty and the periodicity of demand in rolling schedules under uncertain demand. Carlson et al. (1982) analyzed the cost performance of a rolling procedure and observed better cost performance when the planning horizon length equals or multiple integers of the natural economical order quantity (EOQ) cycle.

2.4 Mitigating Nervousness (Instability)

Many studies have shown that the changes in demand propagates through the supply chain and creates undesirable effects such as bullwhip-effect or schedule nervousness (instability) (Inman and Gonsalvez, 1997; Niranjan et al., 2011). Rolling horizon models provide a vast body of literature regarding these issues. According to Chand et al. (2002) who present a classified bibliography about rolling horizon models, various approaches were applied to minimize the instability (nervousness). Some of these proposed approaches are presented below.

2.4.1 Empirical Strategies

Safety stock and safety lead times are examples of earlier methods, which are recommended to cope with demand variability. Safety stock let organizations to handle demand swings by absorbing the changes at the top level, which reduces the amount of instability at the lower levels of the product structure. A high safety stock level could improve the stability of the MPS without degrading customer service, but it incurs high inventory holding cost. Yano and Carlson (1987) observed that safety stock is a viable option against demand variations if the frequency of rescheduling is low. Sridharan and LaForge (1989) concluded that although safety stock below certain levels could eliminate instability and reduce cost, nervousness can be seen if stock levels are not determined carefully. Buzacott and Shanthikumar (1994) recommended using safety stock over safety lead time when forecast accuracy is low due to frequent input changes from customers.

Other strategies that have been investigated to handle instability include; lot sizing techniques (Zhao et al., 2001), forecasting beyond the planning horizon (Blackburn et al., 1986), and incorporating cost of schedule changes (Carlson, 1979; Blackburn et al., 1986). A relatively recent study to by Pujawan (2004) considered modeling instability by directly looking into field observations in a manufacturing environment. While all of these empirical approaches have returned somewhat favorable results, they also underline the necessity of having high forecast quality and low levels of demand variability to obtain robustness in MRP models.

2.4.2 Frozen Horizons

Freezing the production schedule is another recommendation that is addressed in multiple studies. Blackburn et al. (1986), who proposes a simulation model, have found frozen horizons to be more effective than safety stock in rolling horizon plans. Sridharan and Berry (1990) provides a framework for comparing methods for freezing the MPS, and concludes choice of an appropriate method to freeze the MPS is critical. Kadipasaoglu and Sridharan (1995) have applied three strategies under demand uncertainty and found that freezing is the best approach to reduce nervousness in multi-level MRP systems. While frozen horizons are effective in establishing a certain degree of stability, costs are found to be dramatically increased when the frozen horizon is being applied over more than 50% of the planning horizon (Sridharan et al., 1987; Sridharan and Berry, 1990). Zhao and Lee (1993) further added that frozen horizons may increase costs in the presence of uncertain demand. A similar conclusion was derived by Meixell (2005), where frozen schedules were not found cost effective in industries with highly optioned products like the automotive industry.

2.4.3 Flexible Fences

Planning-using "planning-flex fences" has been discussed in several industry oriented books. It has been conceptually discussed in Costanza's work (1996), and later in an updated version of his book, fences are described as "the bounds that allow plus and minus percentage changes to a total demand within a particular time period". Another conceptual example can be found in Graves's (2006) study, where the frozen horizon is employed in the initial periods of the production schedule, and then time fences become effective for certain of period time. In Srinivasan's book (2005), the same concept is called *flexible requirements profile* and the planning methodology is referred to as *rate-based planning*. While this book provides a basic computational example, none of these references took a research approach to investigate when FRP can be useful or not and they did not utilize planning-flex fences under an optimization scheme.

2.5 Multi-Objective Optimization in APP

The earliest works on APP have used conventional objectives such as minimizing production and distribution costs, or maximizing profits. The emphasis was on single, cost-oriented objectives due to the difficulty in addressing and quantifying non-monetary objectives. Through the theoretical developments in multi-objective decision-making and multi-attribute utility theory (Keeney and Raiffa, 1976; Zeleny, 1982), multi-objective optimization in supply-chain planning has obtained considerable attention and a variety of relevant studies have been presented. Some examples are in production planning and scheduling (Loukil et al., 2005), operational supply chain planning (Sabri and Beamon, 2005), supplier selection (Amid et al., 2006), network capacity and design (Altiparmak et al., 2006).

Goal programming is one of the earlier approaches to tackle the multiple conflicting criteria. Lee (1973) applied this approach with conventional goals such as minimizing inventory and overtime costs and maximizing sales. Masud and Hwang (1980) compared goal programming with other approaches including step method and sequential multiple objective problem solving. Lee and Hung (1989) considered goal programming in flexible manufacturing systems, where production rate, machine utilization, and throughput time minimization are considered as the conflicting criteria. More recently, Wang and Fang (2001) analyzed the trade-off between maximizing the profit and minimizing the changes in the workforce. Wang and Liang (2004) further considered minimizing the rate of change in labor levels and minimizing total production costs. Chern and Hsieh (2007) proposed a heuristic algorithm with the goals of minimizing delay, outsourcing and total costs in the supply chain. Other objectives that were considered in multi-objective problems include order fulfillment rates and total delivery time (Gjerdum et al., 2001; Liang, 2008). Among the several methods for solving multi-objective optimization problems, goal programming, the weighted sum, compromise programming and the epsilon-constraint methods are the most widely used and applied through different industries (Ozelkan and Duckstein, 2000; Cheng et al., 2004; Guillien et al., 2005). For further review, one can refer to a recent study by Mula et al. (2010), where a comprehensive list of existing studies in regard to mathematical programming models for supply chain production planning is presented.

2.6 Summary and Conclusions

In this chapter, we briefly reviewed the literature pertaining to mathematical programming in production planning. Our primary focus was on the models that have utilized linear and integer programming. Next, we reviewed the rolling horizon decision making procedures as well as the studies related to the nervousness (instability) in production plans. Finally, we discussed the methods that are used to address the nervousness syndrome and showed the shortcomings of these approaches. A general observation we made is that the variety of existing studies related to flexible planning in rolling horizon models is quite limited. While existing research provides valuable insights into the nervousness phenomenon, the scope of previous studies is somewhat limited and only considers certain approaches. In the next chapter, we begin the formulation of our FRP-based mathematical optimization model and address those shortcomings.

CHAPTER 3: AGGREGATE PLANNING WITH FLEXIBILITY REQUIREMENTS PROFILE AND EMPIRICAL ANALYSIS

3.1 Introduction

In this chapter we describe FRP and its implementation on a rolling horizon procedure first. Following that, we present the dynamic formulation of mathematical models that we work with in our analysis. While the analysis in this chapter based on a single product setting, extension to multiple products can be easily achieved by following the framework we provided.

3.2 Flexibility Requirements Profile (FRP)

As briefly mentioned in the literature review section, FRP was conceptualized from the idea of planning fences, and is used to maintain production plans at certain levels with the utilization of certain lower/upper bounds. The bounds are based on parameters called *flex-limits*, and represented as $\pm F_i$ such that $F_1 \le F_2 \le F_3 \le ..... \le F_N$, where N is the number of periods in the planning horizon. While the initial implementation of FRP effectively enforces planning bounds in multiple periods, its use is limited to simple planning schemes (Srinivasan, 2005).

Figure 3.1 illustrates how flex-limits are positioned as the time rolls on the planning horizon. The funnel-like shape of the limits addresses the manufacturer's nervousness; and as the production plan rolls to the next period, the amount of flexibility provided gradually increases.

The FRP will ensure that the deviations in the dynamic planning process stay within the specified ranges while rolling in the planning horizon. The amount of flexibility that is permitted will be higher in distant periods due to higher degrees of uncertainty. Percentages in flex-limits tell us the amount of incremental increase at each period as one move into the future. In the Figure 3.1, three flex-limits cases are provided for visual comparison. While 1% flex-limits provide less variability in production levels, due to lower responsiveness, we will likely see higher variations in inventory levels in the presence of fluctuating demand. Conversely, 5% flex-limits are capable of providing greater flexibility but also have less smoothing effect on production levels.

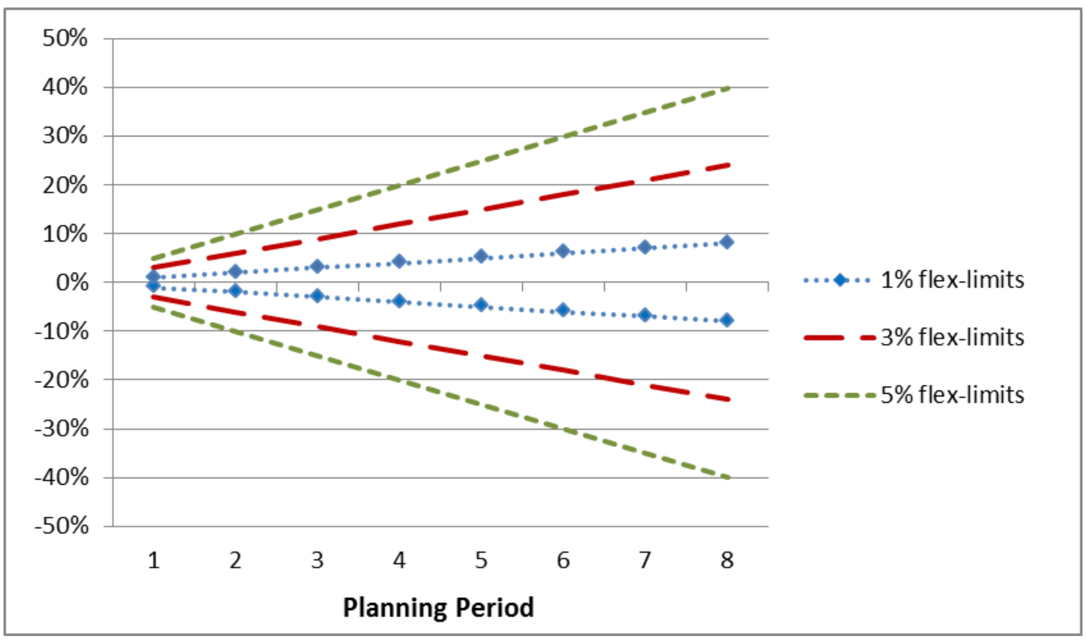


Figure 3.1: Application of flex-limits in the planning horizon.

To be more specific on how FRP works in aggregate planning, suppose that time rolled into a new planning period t from $t-1$, where $i = 0$ represents the current period, while $i > 0$ corresponds to the i-step ahead plan. First the actual demand in period t, $d_{t,0}$

is realized, and then the forecasts, $d_{t,i}$, for i = 1, 2,..., N for the next N periods are updated correspondingly.

Given the updated demand forecasts, initial inventory, and safety stock values, the net requirement of period t is computed by

$$R_{t,0} = d_{t,0} + s - I^{+}_{t-1,0} + I^{-}_{t-1,0}, \tag{3.1}$$

Where $d_{t,0}$ is the realized demand, s is the target level of safety stock, $I^{+}_{t-1,0}$ is the inventory level at period t−1, and $I^{-}_{t-1,0}$ is the backorder level at period t-1. With the net requirements on hand and the planned production levels bounds from the previous period, the current production is determined according to the following equation;

$$P_{t,0} = \max\left[LB_{t,0}, \min\left\{ UB_{t,0}, R_{t,0} \right\} \right], \tag{3.2}$$

Where $LB_{t,i}$ and $UB_{t,i}$ are FRP bounds of the production level in the current period. As we will further discuss below in Equations (3.4) and (3.5), these bounds would have been calculated in the previous period according below. Then based on the production level, actual inventory level is calculated;

$$I_{t,0} = P_{t,0} + I^{+}_{t-1,0} - I^{-}_{t-1,0} - d_{t,0}. \tag{3.3}$$

Starting from this inventory level and using demand forecast, net requirement $\left(R_{t,i}\right)$, planned production level $\left(P_{t,i}\right)$, and planned ending inventory level $\left(I_{t,i}\right)$ are computed as follows for future planning periods $i = 1, 2, \ldots, N$.

$$R_{t,i} = d_{t,i} + s - I^{+}_{t,i-1} + I^{-}_{t,i-1} \tag{3.4}$$

$$P_{t,i} = \max\left[LB_{t,i}, \min\left\{ UB_{t,i}, R_{t,i} \right\} \right] \tag{3.5}$$

$$I_{t,i} = P_{t,i} + I^{+}_{t,i-1} - I^{-}_{t,i-1} - d_{t,i}. \tag{3.6}$$

To complete the iteration at time *t*, the production bounds for $t+1$ are updated as follows.

Lower Bounds: $LB_{t+1,i} = \max\left\{LB_{t,i+1}, P_{t,i}\left(1-F_i\right)\right\} \qquad i = 0,1,...,N-1 \qquad (3.7)$

Upper Bounds: $UB_{t+1,i} = \min\left\{UB_{t,i+1}, P_{t,i}\left(1+F_i\right)\right\} \qquad i = 0,1,...,N-1. \qquad (3.8)$

The lower and upper bounds of $i = N$ 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 $t+1$.

3.2.1 FRP- Illustrative Example

To aid understanding of the FRP scheme, we present an illustrative example next. Suppose that production plans and production bounds used at period *t*-1 are as given in Table 1. Furthermore, assume that that the flex-limit is increased by 3% per period. Before time rolls into the next period *t*, these bounds are updated according to Equations (3.4) and (3.5). For example, the lower bound of production plan for period *t* is either 3% below the previously planned production (i.e., (0.97)(350) = 340), or the old lower bound for period *t* (i.e., 338), whichever is larger. In this way, it is guaranteed that new production bounds are within the old bounds.

Next, when the time rolls into period *t*, these new bounds are enforced when updating the production plan. At period *t*, suppose that that the initial inventory level is 50, (realized) demand at *t* is 380, and forecasted demands for next three periods are 440, 440, and 440 (see Table 3.2). Assume that the safety stock level is zero. In Table 2, columns 3-5 are updated row by row. For example, the net requirement is computed by Equation (3.1). Then, production plan for period *t* is calculated using the net requirement as well as bounds in Table 3.1, which provides the ending inventory level at *t*. From this ending inventory level, the next row for period (*t*+1) is updated. Note that production plan for the last period is unbounded (i.e., bounds are $-\infty$ and $+\infty$) as it is fed into the production plan for the first time.

Table 3.1: Production plan at period *t*-1.

Period	Production Plan	Old Lower Bound	Old Upper Bound	New Lower Bound	New Upper Bound
t-1	312	-	-	-	-
t	350	338	375	max{338, 350*(0.97)} = 340	min{375,350*(1.03)} = 361
t+1	416	370	416	max{370, 416*(0.94)} = 391	min{416, 416*(1.06)} = 416
t+2	388	388	420	max{388, 388*(0.91)} = 388	min{420, 388*(1.09)} = 420

Table 3.2: Production plan made at period *t*.

Period	Demand	Net Requirement	Production Plan	Inventory
t	380	380-50 = 330	max{340,min{330,361}}= 340	10
t+1	440	440-10 = 430	max{391,min{430,416}}= 416	-14
t+2	440	440-(-14) = 454	max{388,min{454,420}}= 420	-34
t+3	440	440-(-34) = 474	max{$-\infty$,min{474,$+\infty$}}= 474	0

After the production planning is complete, the bounds are updated according to Equations (3.4) and (3.5), so that they can be used for the production planning when time rolls into the next period (*t*+1). For example, the lower and upper bounds for (*t*+1) become max {391, 416*(0.97)} = 404 and min {416, 416*(1.03)} = 416, respectively. Similarly, the lower bound and upper bounds for (*t*+3) are max {$-\infty$, 474*(0.91)} = 431 and min {$+\infty$, 474*(1.09)} = 517, respectively.

3.3 Mixed-Integer Linear Formulation

The proposed approach is to solve the FRP-based production planning through mathematical optimization. Our underlying idea is to create a dynamic optimization plan under the presence of FRP that minimizes production-related costs. In specific, the proposed model is an aggregate planning problem that employs a deterministic optimization model to find optimal values for production levels, workforce size, production quantities, and inventory and backorder levels for the current and next N periods under given flex-limits. 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:

$i =$ index of planning horizon, $i = 0,1,...,N$

$t =$ index of planning period, $t = 1,2,...,T$

Parameters:

c^w : labor cost of a regular worker per period

c^O : overtime labor cost of a regular worker per period

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

c^P : material cost per unit product

h : unit inventory holding cost per period

b : unit shortage cost per period

s : prespecified safety stock

th : total number of working hours in a week

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

m^O : maximum number of units produced using overtime per worker per period

N : planning horizon

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

$LB_{t,i}$: *i*-step ahead lower bound on planned production updated at period *t*

$UB_{t,i}$: *i*-step ahead upper bound on planned production updated at period *t*

Variables:

$P_{t,i}$: i-step ahead production level planned at period t

$O_{t,i}$: *i*-step ahead overtime production hours planned at period *t*

$I^{+}_{t,i}$: *i*-step ahead inventory level planned at period *t*

$I^{-}_{t,i}$: *i*-step ahead backorder (shortage) level planned at period *t*

$W_{t,i}$: *i*-step ahead workforce size planned at period *t*

$H_{t,i}$: *i*-step ahead hire level planned at period *t*

$L_{t,i}$: *i*-step ahead layoff level planned at period *t*

Note that *i* = 0 represents the current period *t* and actual values, while *i* > 0 corresponds to future plans.

Formulation:

The MILP formulation of the FRP-based aggregate planning (FRP-AP) can be formulated as follows;

$$\text{Minimize } \sum_{i=0}^{N} c^{W} W_{t,i} + \sum_{i=0}^{N} c^{O} O_{t,i} + \sum_{i=0}^{N} c^{H} H_{t,i} + c^{L} L_{t,i} + \sum_{i=0}^{N} c^{P} P_{t,i} + \sum_{i=0}^{N} h\, I^{+}_{t,i} + \sum_{i=0}^{N} b\, I^{-}_{t,i}) \tag{3.6}$$

$$\text{Inventory: } P_{t,i} = d_{t,i} + I^{+}_{t,i} - I^{-}_{t,i} - I^{+}_{t-1,i} + I^{-}_{t-1,i} \qquad i = 0,1,\dots,N \tag{3.7}$$

$$\text{Workforce:} W_{t,i} = W_{t-1,i} + H_{t,i} - L_{t,i} \qquad i = 0,1,\dots,N \tag{3.8}$$

$$\text{Capacity:} P_{t,i} \le m^R W_{t,i} + m^O O_{t,i} \qquad i = 0,1,\dots,N \qquad (3.9)$$

$$\text{FRP:} LB_{t-1,i+1} \le P_{t,i} \le UB_{t-1,i+1} \qquad i = 0,1,\dots,N \qquad (3.10)$$

$$P_{t,i}, I^+_{t,i}, I^-_{t,i}, W_{t,i}, O_{t,i}, H_{t,i}, L_{t,i} \ge 0 \qquad i = 0,1,\dots,N \qquad (3.11)$$

$$W_{t,i}, H_{t,i}, L_{t,i} \qquad \text{integer} \qquad (3.12)$$

At each time period *t*, the objective is to minimize the overall projected cost over the next *N* periods. The objective function consists of the labor costs, hiring/layoff cost, material cost, backorder (shortage) cost, and inventory holding cost (3.6). For each *t* in the planning horizon, the following constraints apply; *Inventory Balance* is provided through constraint (3.7), where the realized demand in period *t* plus the inventory (or backorder) at the end of period *t*, equals to the total production in period *t* plus the inventory (or backorder) from the previous period *t*-1. *Workforce* constraint (3.8) 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. While *Capacity* constraint (3.9) ensures that the total production in period *t* will not exceed the available production capacity, *FRP* constraint (3.10) stipulates that production will stay within the pre-defined lower and upper production bounds. Note that omission of constraint (3.10) in the APP formulation above would yield a classical APP without flex-limits.

3.4 Rolling Horizon Implementation

In rolling horizon environments, planning is made in each decision period by considering the current state and future demand events but only the decisions of the initial period are actually implemented. Next period, planning process is updated and decisions are revised as new demand information become available. The plans are modified as the horizon gets rolled over since the forecasts in the distant future are less reliable and more expensive than the near future. Figure 3.2 illustrates the relationship of planning elements between time $t-1$ and time t.

Period t-1

0	1	2	…	i	i+1	…	N
$D_{t-1,0}$	$D_{t-1,1}$	$D_{t-1,2}$		$D_{t-1,i}$	$D_{t-1,i+1}$		$D_{t-1,N}$
$P_{t-1,0}$	$P_{t-1,1}$	$P_{t-1,2}$		$P_{t-1,i}$	$P_{t-1,i+1}$		$P_{t-1,N}$
$I_{t-1,0}$	$I_{t-1,1}$	$I_{t-1,2}$		$I_{t-1,i}$	$I_{t-1,i+1}$		$I_{t-1,N}$
	$LB_{t-1,1}$	$LB_{t-1,2}$		$LB_{t-1,i}$	$LB_{t-1,i+1}$		
	$UB_{t-1,1}$	$UB_{t-1,2}$		$UB_{t-1,i}$	$UB_{t-1,i+1}$		

Period t

0	1		… i-1	i	…	N-1	N
$D_{t,0}$	$D_{t-1,1}$		$D_{t-1,i-1}$	$D_{t-1,i}$		$D_{t,N-1}$	$D_{t-1,N}$
$P_{t,0}$	$P_{t,1}$		$P_{t,i-1}$	$P_{t,i}$		$P_{t,N-1}$	$P_{t,N}$
$I_{t,0}$	$I_{t,1}$		$I_{t,i-1}$	$I_{t,i}$		$I_{t,N-1}$	$I_{t,N}$
$LB_{t,0}$	$LB_{t,1}$		$LB_{t,i-1}$	$LB_{t,i}$		$LB_{t-1,N-1}$	
$UB_{t,0}$	$UB_{t,1}$		$UB_{t,i-1}$	$UB_{t,i}$		$UB_{t,N-1}$	

Figure 3.2: Illustration of updates from period t-1 to t.

3.5 Computational Study

In what follows, we first provide a brief description of the underlying demand model and the forecasting method that we implement for our numerical study. An alternative simulation-based solution method to the proposed FRP-embedded APP method is described in Section 4.3. In Section 4.4 and 4.5, we present our experimental design framework and response variables, respectively.

3.5.1 Demand Model & Forecasting Method

Phase 1: Demand Generation

While cost structures were specified by these industry settings, we generated various demand scenarios as follows. Considering the fact that product demands vary over time, and are often subjected to trend and seasonality we assume that the demand series are represented by the multiplicative seasonal model. In specific, the following demand generation function is used to generate demands.

$$Y_t = (a + bt)S_t + \varepsilon_t \tag{3.13}$$

Where a is the baseline component, b is the trend component, S_t is the multiplicative seasonal factor, and ε_t is a random error component that is assumed to be normally distributed with a mean of zero and a standard deviation of σ.

The initial baseline, trend, and/or magnitudes of the seasonal and noise components, and the period of the seasonal variation can be changed to generate various demand patterns and extent of uncertainties. As will be described in Section 4, demand scenario in this study is specified by combination of two levels and four demand components. Two levels, low and high, represent the magnitude of four demand components (baseline, trend, seasonality, and the variance of errors).

Phase II: Forecasting parameter estimation

Demand scenarios generated from this model with various parameter values, are assumed to be actual demands that are observed period by period, where future demands are forecasted based on observed demand data without knowing the underlying parameters. Observing the presence of trend and seasonal variations in the generated demand data, the Holt-Winters method (Chatfield, 1978) is employed as the forecasting method in this study, where the smoothing constants for baseline (α), trend (β), and seasonality (γ) were identified using a sensitivity analysis as described under section 5.1. Previous studies have indicated that the Holt-Winters method adequately captures the trend patterns and/or seasonal swings in demand (Zhang, 2004).

3.5.2 FRP-Based Chase Strategy

To assess the value of the mathematical optimization on cost and stability performances, we also implement a traditional chase strategy (Stevenson, 2007) in conjunction with FRP, called FRP-based chase strategy (FRP-CS). The FRP-CS procedure starts with the realization of the current demand and utilizes the computed demand forecasts for the next periods. The net production requirement is calculated by (3.1), and the current production is determined using the net production requirement and the previously computed lower and upper bounds as (3.2). Then the actual inventory level is calculated using (3.3). If the workforce capacity is not sufficient to meet the demand requirements, we hire new employees as in the chase strategy. Conversely, if the current workforce level is able to meet the demand through regular or overtime hours, we lay off unnecessary employees. The final workforce level is updated according to the workforce balance constraint in (3.8). Similar to the optimization case, the production bounds are updated at the end of each decision period *t*. The FRP-CS approach was modelled using AMPL programming language with the same planning parameters, and demand and forecasting model introduced earlier. A more detailed pseudo code for the simulation procedure is provided in Appendix A.

3.5.3 Experimental Design

In order to investigate variations of performances with respect to problem parameters, we constructed an experimental design with seven factors, each of which two levels as shown in Table 3. A 2^7 full factorial experiment with 5 replications is used in this study. The experimental factors that are investigated consist of the following: solution method, flex-limits, demand components including baseline, trend, seasonality and error, and industry type. Two levels in demand components represent the high and low magnitudes, whereas the levels in flex-limits indicate whether the flex-limits is used or not. The first level, “None”, corresponds to the traditional aggregate planning method, where FRP constraints in equation (3.13) are omitted. “Enforced”, on the other hand, considers the implementation of flexibility bounds. The industry type refers to sample scenarios corresponding to automotive parts and textile cases. The corresponding cost and production rate parameters displayed in Table 5 and are compiled from the cases in Sillekens et al. (2011), Gnoni et al. (2003), and Leung et al. (2003). The original cost data in the literature is converted into American dollars to have a unified comparison with the following conversion rates: $1= HK$7.8= €0.7.

Table 3.3: Experimental factors and their levels.

Factors	**Levels**	
Solution Method	FRP-AP	FRP-CS
Flex Limits	None	Enforced
Demand-Baseline	Low (1000 units)	High (3000 units)
Demand- Trend	Low (20 units)	High (100 units)
Demand-Seasonality	Low +/- 0.1	High +/- 0.3
Demand- Magnitude of Error	Low (σ = 50)	High (σ = 200)
Industry Type	Industry Type 1	Industry Type 2

Table 3.4: 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

Table 3.5: Aggregate planning parameters for selected industries (single product considered).

	Industry Type 1: Textile	**Industry Type 2: Automotive Parts**
Production/Inventory Costs (in $USD)		
Production cost ($/unit)	$ 6.41	$ 1.80
Inventory cost per unit per week	$ 1.92	$ 0.18
Backorder cost per unit per week	$ 3.85	$ 3.60
Labor Costs (in $USD)		
Labor Cost ($/person-hour)	$ 0.80	$ 11.16
Overtime labor Cost ($/person-hour)	$ 1.28	$ 12.28
Hire cost ($/person)	$ 12.82	$ 3,571
Lay-off cost ($/person)	$ 15.38	$ 14,286
Production Rates		
Number of units produced (unit/person-hour)	0.57	16.67

The planning horizon is set as $N = 8$, and the performance is evaluated over 12 periods (i.e., T = 12). The production capacity is determined by the size of the workforce. It is assumed that there is an initial inventory of 100 units, and the initial workforce is set according to the first realized demand in the planning horizon. Each employee works for 8 hours per day. Each demand scenario is replicated five times using randomly generated demand variates. Hence, the total number of experimental runs is $640 = 5 \times 2^7$.

3.5.4 Performance measures

Two performance measures are used in this study. The first measure, Cost, considers the current total cost (t, 0) at each optimal plan and computes a final overall cost over the planning horizon. We would like to remark that the cost measure is different than the objective function described in Equation 3.6 since it only considers the actual realized (current) cost of each production plan in the overall time frame as follows:

$$\sum_{t}^{T}\left(c^W W_{t,0} + c^O O_{t,0} + c^H H_{t,0} + c^L L_{t,0} + c^P P_{t,0} + h I_{t,0}^{+} + b I_{t,0}^{-}\right) \qquad (3.14)$$

The second measure, called *plan variability*, is used to capture the nervousness in production plans. There have been a few attempts to quantify nervousness in production planning. In some of the 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 production levels versus the actual production in a rolling horizon environment. The overall plan stability in the planning horizon is calculated according to the following formula;

$$\frac{\left(\sum_{i=0}^{N}\left|P_{t-1,i}-P_{t,i-1}\right|^{m}\right)^{1/m}}{T\times N} \quad (3.15)$$

This definition is based on the L_m norm for production variability where m is the compensation parameter such that $1\leq m\leq\infty$. m=1 implies full compensation, yielding the sum of absolute deviations from the production plans, and $m=\infty$ yields max, meaning no compensation is allowed (De Kok and Inderfurth, 1997).

3.6 Computational Results

We conduct our numerical experiments using the AMPL programming language and the CPLEX solver. Comparisons between the APP 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 3.4). The computations give different results for the automotive and textile industries, but in majority of the cases optimization-based FRP approach return more favorable outputs. Figure 3.3 displays the results of total cost for the textile industry for both approaches under the 16 demand scenarios. The cost gap among the flex-limits appears to be very small for both approaches. "No-flex-limits" case yields slightly lower costs in demand scenarios with high levels of trend and seasonality (scenarios 7-8 and 15-16). While the difference is relatively small, in all five flex-limits categories, FRP-AP yields lower costs compared to FRP-CS. In this comparison, the highest difference is observed when 1% flex-limits are implemented, where 94% of the cases return results in favor of FRP-AP. The lowest percentage is obtained with 3% flex-limits, where FRP-AP still outperforms FRP-CS in 53% percent of the cases. Per our observations, FRP-AP approach displays more favorable results in 75% of the scenarios with an average savings of $1,752.

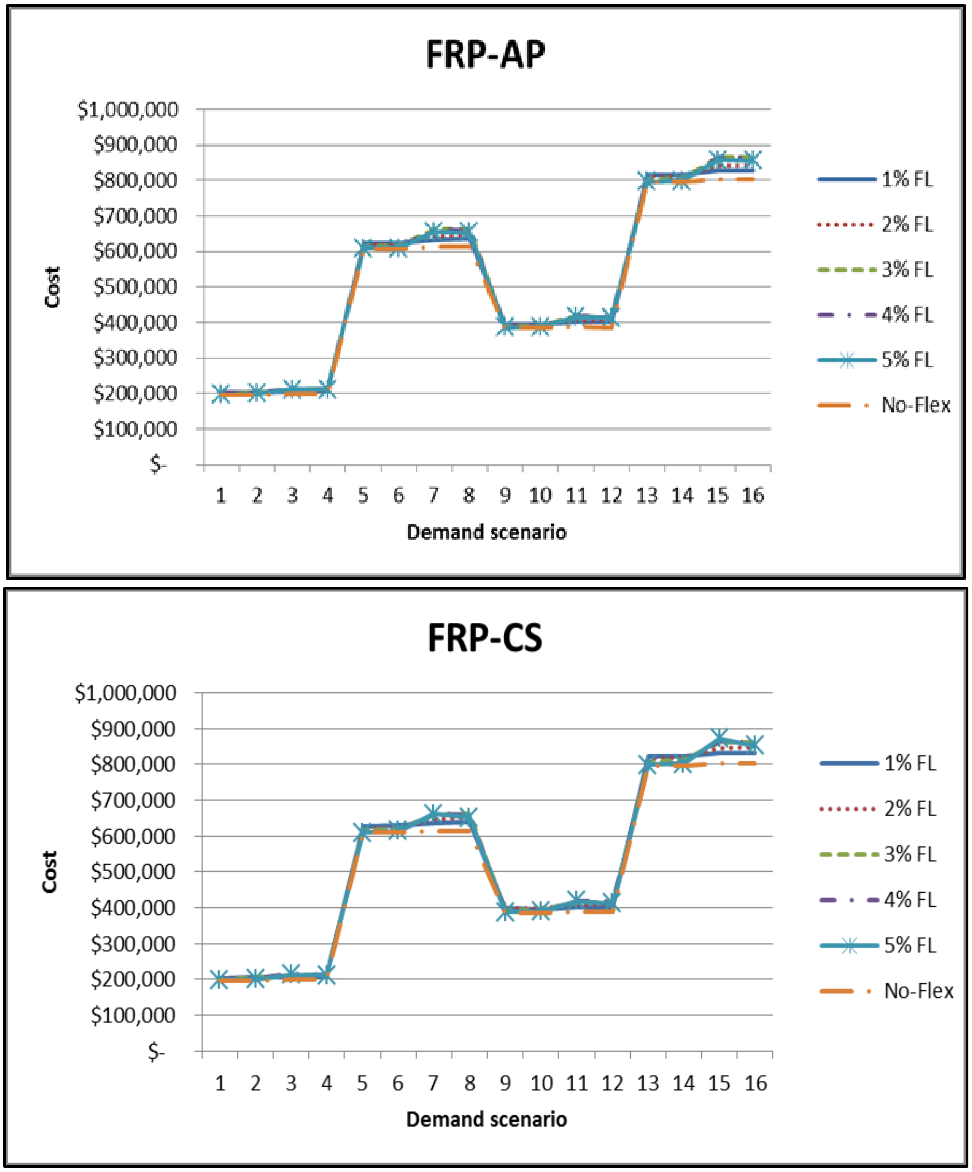


Figure 3.3: Cost Graphs in Industry Type 1: FRP-AP vs. FRP-CS.

By observing cost figures (Figure 3.4) in automotive parts industry we can see that FRP-AP surpasses the FRP-CS approach in terms of performance. Among a total of 480 (i.e., 80 scenarios for each flex-limit case) scenarios, FRP-AP is able to achieve lower costs than those of FRP-CS in all of these, while having an average cost of $187,586. Using

FRP-AP provides $31,749 savings on average amongst all the flex-limits cases. While the savings for 5% flex-limits is $35,838, the savings for 1% flex-limits is found to be $28,332 on average (Table 3.6). This demonstrates that there is a trade-off between the cost and the plan stability. In both approaches, smaller flex-limits yield lower costs in most cases. However, the lowest cost results are obtained in FRP-AP with no-flex limits, which represents the implementation of the traditional aggregate production planning (APP) without FRP. Traditional APP provides 16% and 19% lower costs on average in comparison to FRP-AP with 1% flex-limits and FRP-AP with 3% flex-limits, respectively.

Table 3.6: Average aggregate costs of FRP-CS and FRP-AP for 16 demand scenarios and total amount of savings obtained through FRP-AP.

	1%FL	**2%FL**	**3%FL**	**4%FL**	**5%FL**	**No-FL**	**Average**
FRP-CS	$218,584	$221,329	$225,752	$226,291	$224,826	$199,229	$219,335
FRP-AP	$190,251	$193,309	$195,604	$192,764	$188,988	$164,600	$187,586
Savings	**$28,333**	**$28,020**	**$30,148**	**$33,527**	**$35,838**	**$34,629**	**$31,749**

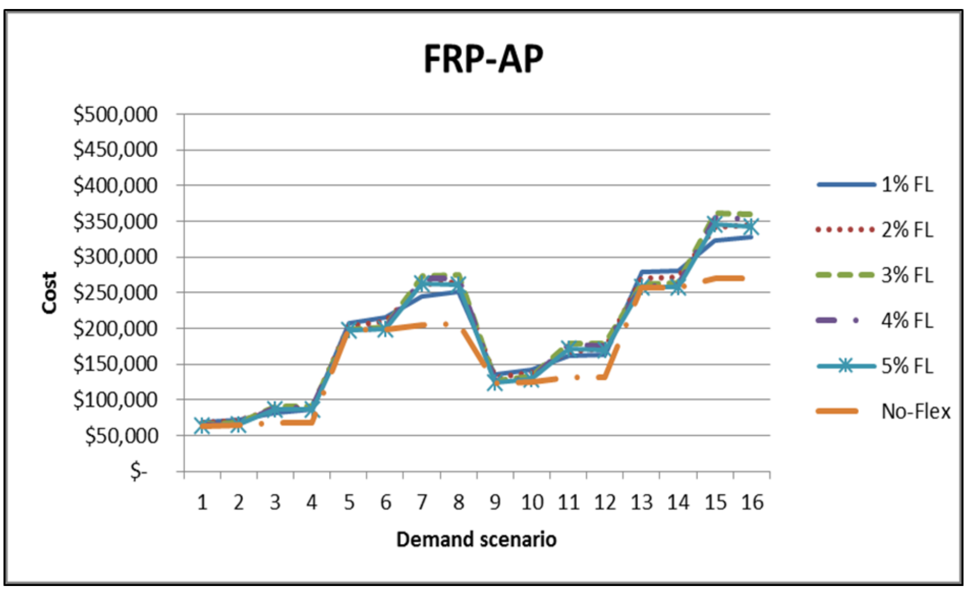


Figure 3.4: Cost Graphs in Industry Type 2: FRP-AP vs. FRP-CS.

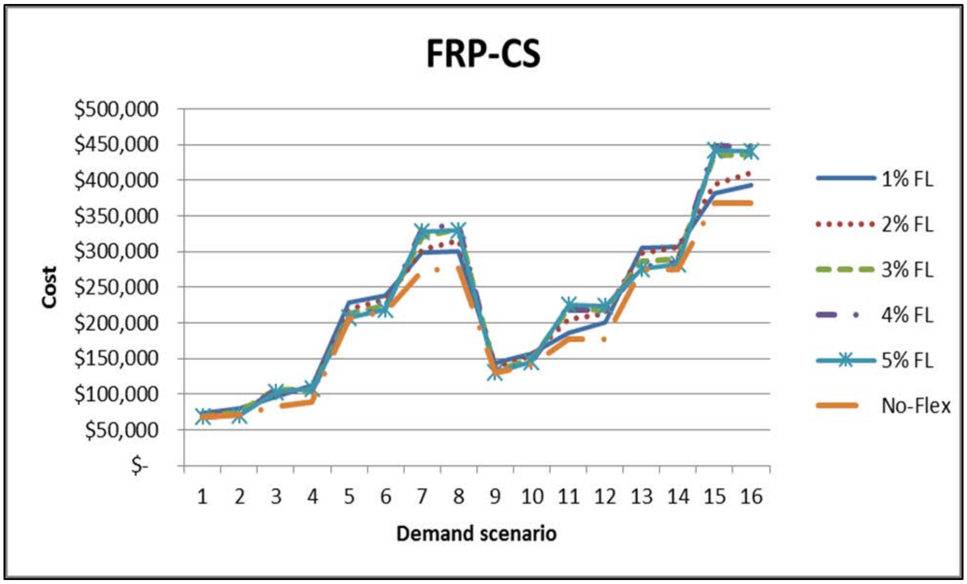
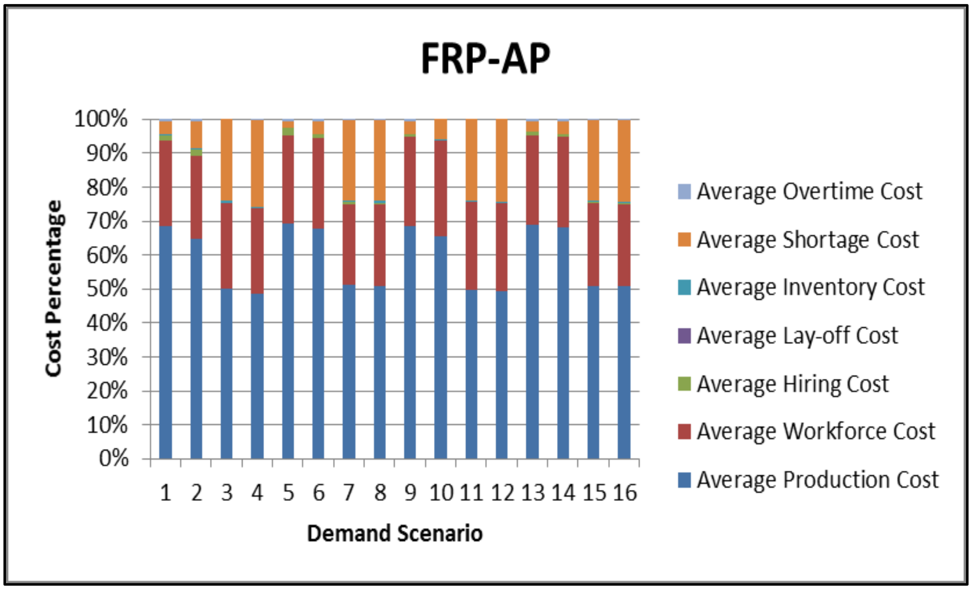
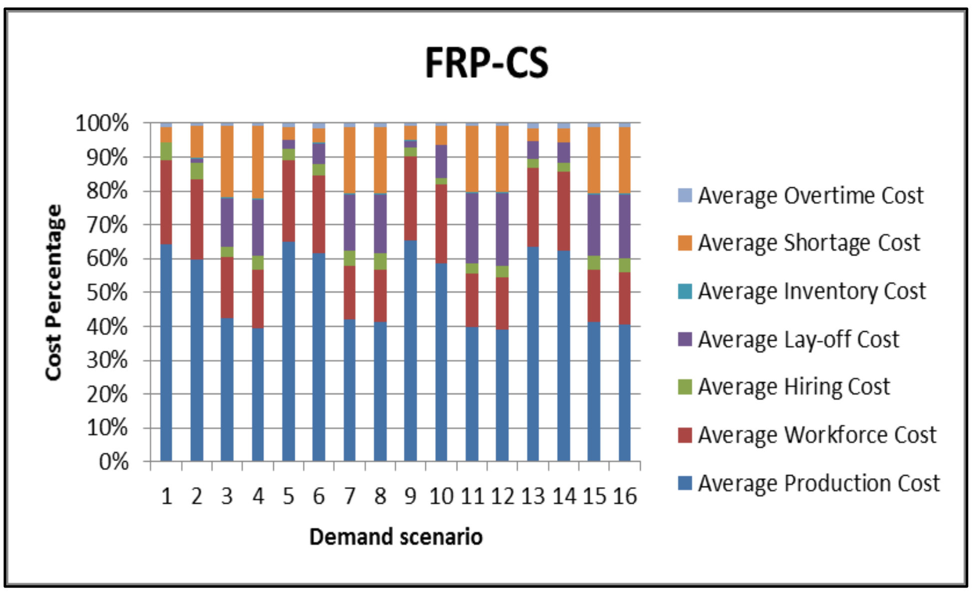


Figure 3.4 (Cont'd): Cost Graphs in Industry Type 2: FRP-AP vs. FRP-CS.

Cost components are highly pertinent to the industry scenarios. As discussed earlier, hiring and lay-off costs are significantly lower in the textile industry example, thus there are frequent changes in the workforce levels. On the other hand, automotive parts industry tries to avoid frequent changes in the workforce level as much as possible because of the high lay-off costs. In the automotive parts industry example, demand requirements are met through higher utilization of the workforce, and by allowing frequent changes in inventory levels. Figures 3.5 and 3.6 show the average operating costs for the automotive parts and textile industry examples, respectively. As reflected in Figure 3.5, three major cost drivers of the auto industry are the production, workforce, and shortage costs (54%, 22%, and 14% of the total costs, respectively). When FRP-AP is being implemented, high costs associated with hiring and lay-off workers prevent frequent changes of the workforce. However, FRP-CS approach frequently changes the workforce size to cope with demand variability, which increases the hiring/lay-off costs drastically, from 1% to 17% of the total costs to be precise. One noticeable observation for automotive parts industry is that the FRP-CS approach increases the shortage and overtime costs, especially when there is higher demand variability.



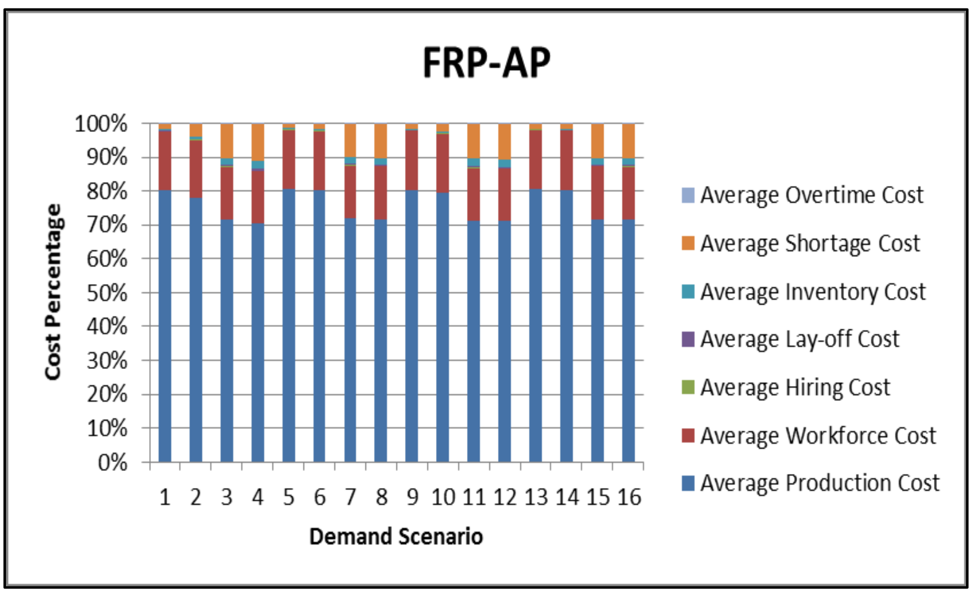
(a) Costs in Industry Type 2: FRP-AP.



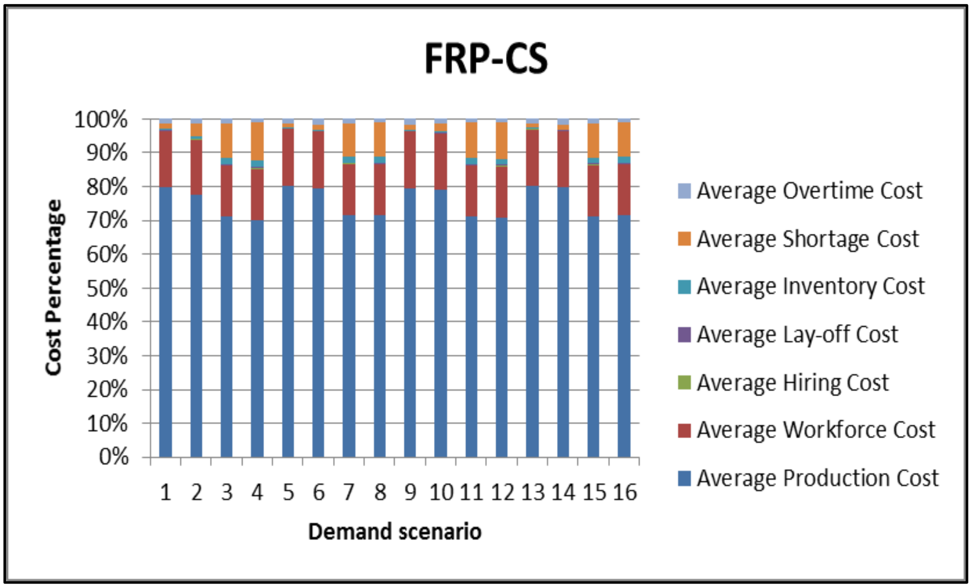
(b) Costs in Industry Type 2: FRP-CS.

Figure 3.5: Percentages of cost components in automotive parts industry.

Observe that the production and workforce are the main cost drivers in the textile industry. Production costs make up 76% of the costs in textile industry, workforce costs follow that with 16%. Overall, FRP-AP and FRP-CS approaches produce similar levels of costs for the textile industry, most likely reflecting the fact that changes in workforce levels are not the main cost drivers for the industry. The only significant difference between two approaches is that the overtime costs are higher in FRP-CS solution since the main emphasis in FRP-CS is to fulfill the demand, if possible, rather than to minimize cost. In both industries, we observe low inventory costs (i.e., less than 1% and 1% of the total costs for automotive parts and textile, respectively), and demand variability also causes significant changes in cost distributions, which can be observed from both Figures 3.5 and 3.6.



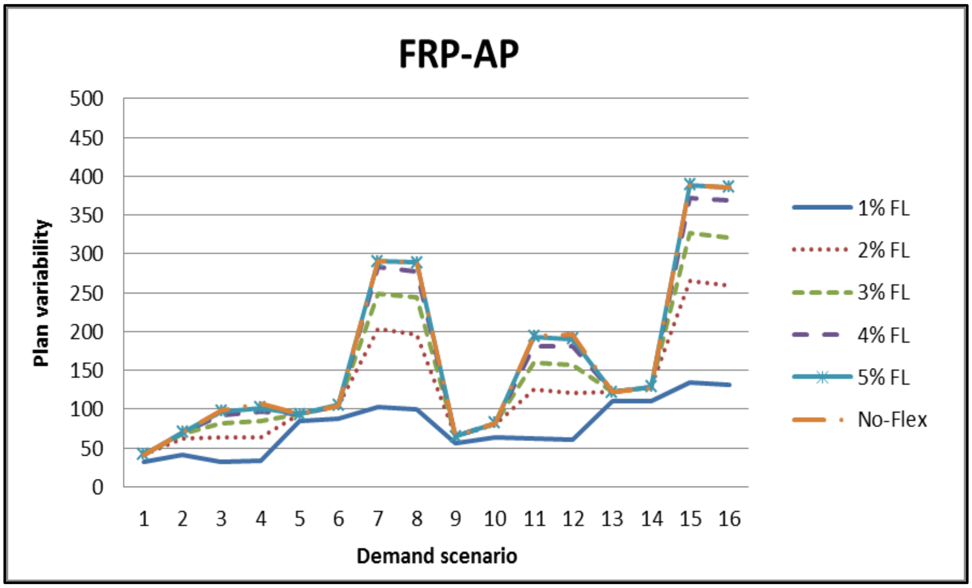
(a) Costs in Industry Type 1: FRP-AP.



(b) Costs in Industry Type 1: FRP-CS.

Figure 3.6: Percentages of cost components in textile industry.

The second performance measure, plan variability, is significantly impacted by the presence of flex-limits. As one can expect, the smaller flex-limits provide lower variability. Furthermore, using 5% flex-limits displays plan variability that is similar to that of no-flex limits for majority of the cases. This implies that production plan bounds with 5% flex-limits tends to be redundant, and the problem becomes the ordinary aggregate production planning. For Industry Type 1, in the FRP-AP approach, 3% flex-limits show 8% reduction on average in plan variability when compared to the no-flex-limits. This number increases to 42% with the implementation of 1% flex-limits (Figure 3.7).



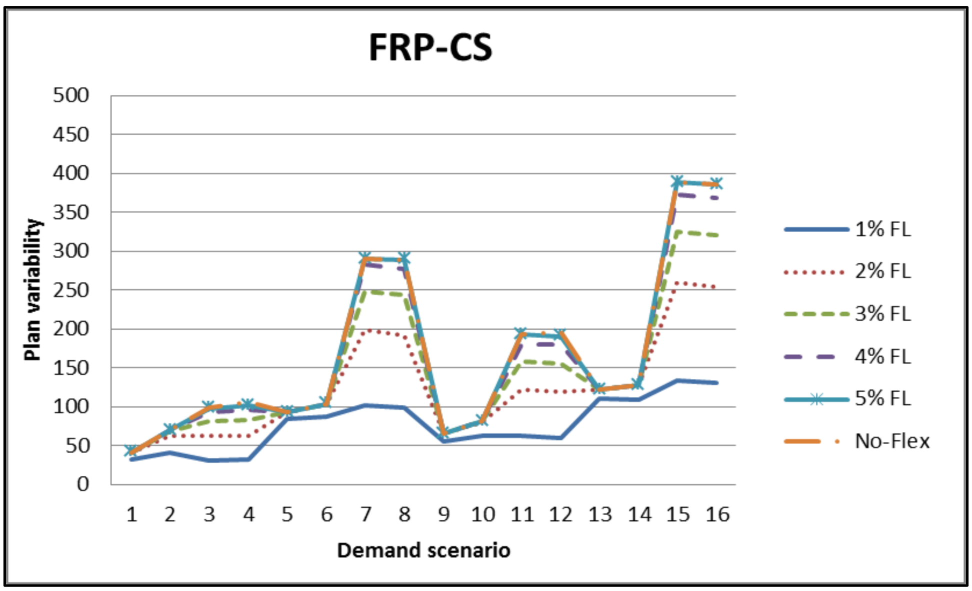


Figure 3.7: Stability Graphs in Industry Type 1: FRP-AP vs. FRP-CS.

For Industry Type 2, Both FRP-AP and FRP-CS approaches return very similar variability results. For example, in FRP-AP, 3% flex-limits show 12% reduction in plan variability on average when compared to the no-flex-limits. Similarly, FRP-CS shows 10% reduction for the same 3% flex-limits. This number increases to 47% and 43% respectively, with the implementation of 1% flex-limits. Traditional aggregate production planning without flex-limits constantly have the highest variability with an average value of 168 , which is twice as high as on average than FRP-AP with 1% flex-limits.

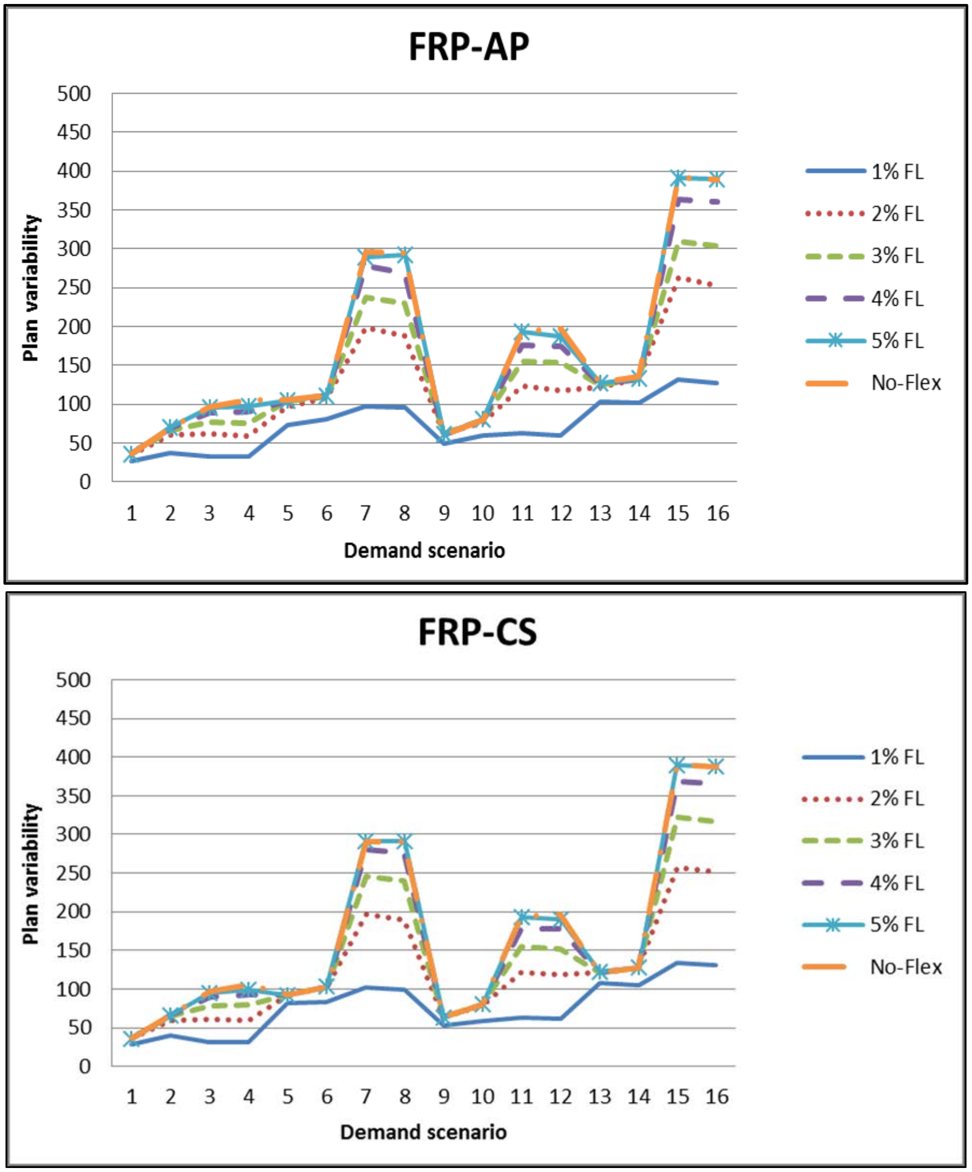


Figure 3.8: Stability Graphs in Industry Type 2: FRP-AP vs. FRP-CS.

When the behaviors among flex-limits are compared, it is observed that larger flex-limits yield higher plan variability, higher production costs, and smaller inventory levels. Highly uncertain demands result in higher variation in cost, plan variability, and actual production levels $\left(\text{i.e.}, P_{t,0}\right)$. Trend and seasonality are the major drivers of demand uncertainty. Scenarios 7-8 and 15-16 have high trend and seasonality patterns of demand, and flex-limits produce significant differences in stability performance for these scenarios. Scenarios 3-4 and 11-12 that have the low level of trend but the high level of seasonality also experience relatively large gaps between different flex-limits. On the other hand, when the high level trend but the low level of seasonality are present, as in scenarios 5-6 and 13-14, industry type 1 behaves similarly in both FRP-AP and FRP-CS. The only distinctive result is observed when 1% flex-limits are used (Figures 3.7 and 3.8).

3.7 Additional Industry Analyses

We conduct more analyses to gain more insight into the application of FRP in different industry settings. We consider the aggregate planning parameters given in Table 3.5, and create an experiment with 3 main factors each having 2 levels. Three main factors are the production/inventory costs, labor costs, and the production rates (Table 3.7). The high and low levels for each groups of factors are listed below (Table 3.8). Scenario 4 corresponds to the textile industry and scenario 7 results corresponds to automotive parts industry, whose results are previously shown. A center point is also added to our design, which is the average of two industries. A center point tell us whether the linear assumption that we use for the design is true.

Table 3.7: Factors and their corresponding levels.

Factors	Low Level	High Level
Production/Inventory Costs	Automotive Parts	Textile
Labor Costs	Textile	Automotive Parts
Production Rates	Textile	Automotive Parts

Table 3.8: Industry type scenarios.

Scenario No.	Production/Inventory Costs	Labor Costs	Production Rates
1	Low	Low	High
2	Low	Low	Low
3	Low	High	Low
4	High	Low	Low
5	High	High	High
6	High	High	Low
7	Low	High	High
8	High	Low	High
9	Center Point	Center Point	Center Point

There are several analyses we would like to do in this section. These include:

- comparing the overall cost and plan variability levels of industry type scenarios and identifying whether there are meaningful patterns exist between them,
- analyzing the impact of experimental factors and levels on our response variables,
- examining the main and interaction effects.

Figure 3.9 displays the average costs and plan variabilities of the industry type scenarios. As expected, the highest cost is observed in Scenario 6, where production/inventory and labor costs are high but the production rates are low. Scenario 6 is followed by Scenario 3, where labor costs are high but the rest of factors are set to low.

These two scenarios are also happen to have the lowest variability, which is another indicator of the trade-off between these two measures. The average plan variabilities are at similar levels with a single exception of Scenario 2, where all factors are set to the low levels. Scenario 1, where cost factors are low but production rate is high, returns the lowest cost per unit variability among all scenarios.

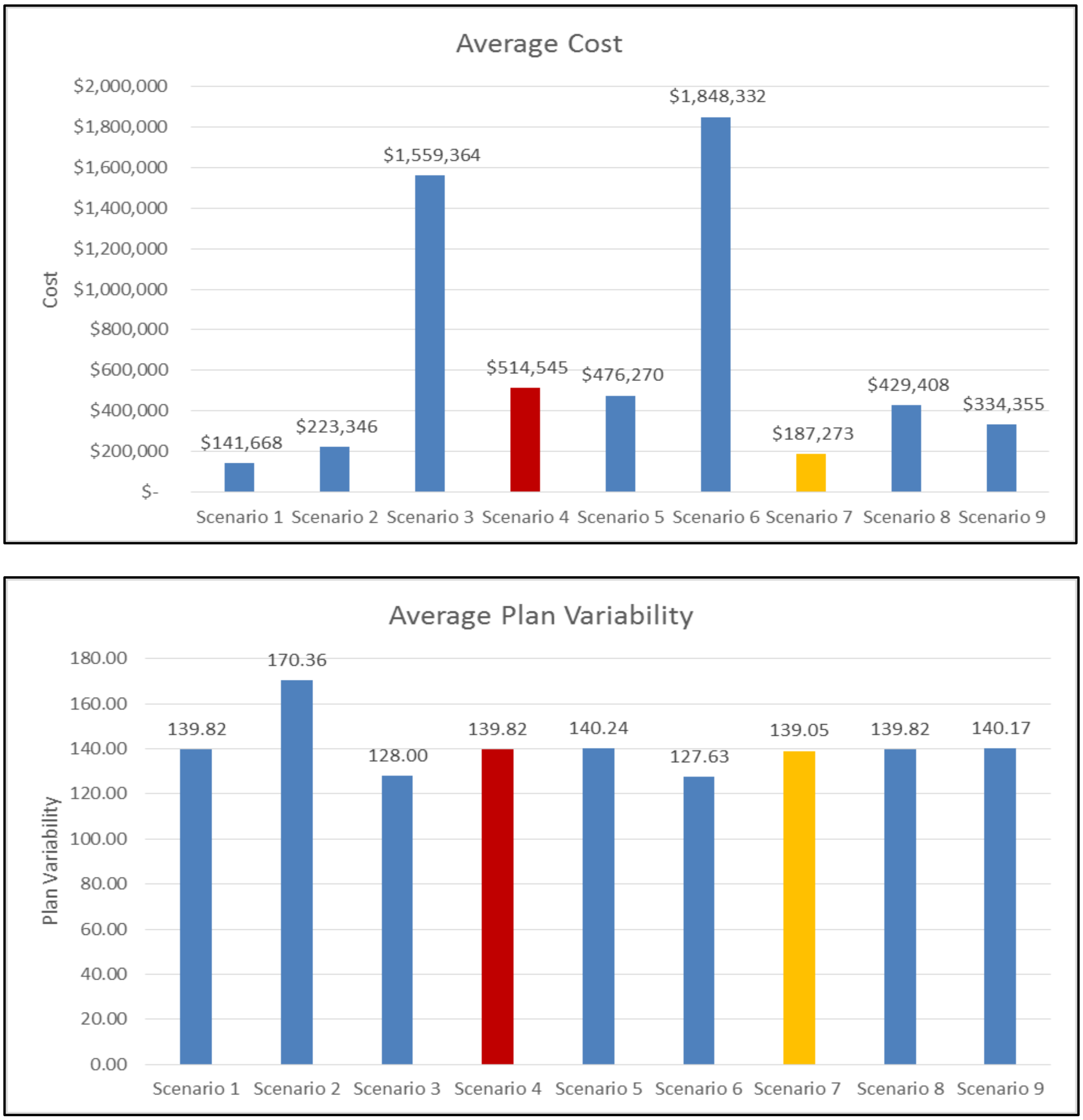


Figure 3.9: Cost and plan variability levels under different industry scenarios.

These cost and plan variability levels are then statistically compared using analysis of variance (ANOVA) via Minitab. Table 3.9 provides the ANOVA results, obtained using Minitab. Per the F and p-values, Production rates is the only main effect that is found to be not statistically significant.

Table 3.9: ANOVA results for industry factors.

	Cost		Plan Variability	
Source	**F-Value**	**P-Value**	**F-Value**	**P-Value**
Model	109597.55	0	8.23	0
Linear	204741.11	0	8.89	0
Production/Inventory Costs	47132.21	0	5.98	0.019
Labor Costs	268692.4	0	20.38	0
Production Rates	298398.71	0	0.32	0.575
2-Way Interactions	77973.11	0	11.16	0
Production/Inventory Costs*Labor Costs	0.03	0.856	6.65	0.014
Production/Inventory Costs*Production Rates	0.41	0.524	6.97	0.012
Labor Costs*Production Rates	233918.88	0	19.87	0
3-Way Interactions	0.43	0.517	5.68	0.023
Production/Inventory Costs*Labor Costs*Production Rates	0.43	0.517	5.68	0.023

The only significant interaction effect for cost variable is labor costs & production rates, which makes sense intuitively as the rates and labor costs comprise a majority portion of total costs. The interaction effects of production/inventory costs & labor costs and production/inventory costs & production rates show parallel lines in the plots, and hence are not found to be significant for the cost (Figure 3.10). On the other hand, interaction effects for plan variability show that there is no independence among variables (Figure 3.11). Plan variability also possesses a three-way interaction, which represents that the main effects that are found to be significant should also be treated carefully due to having highly dependent relationships between the experimental factors.

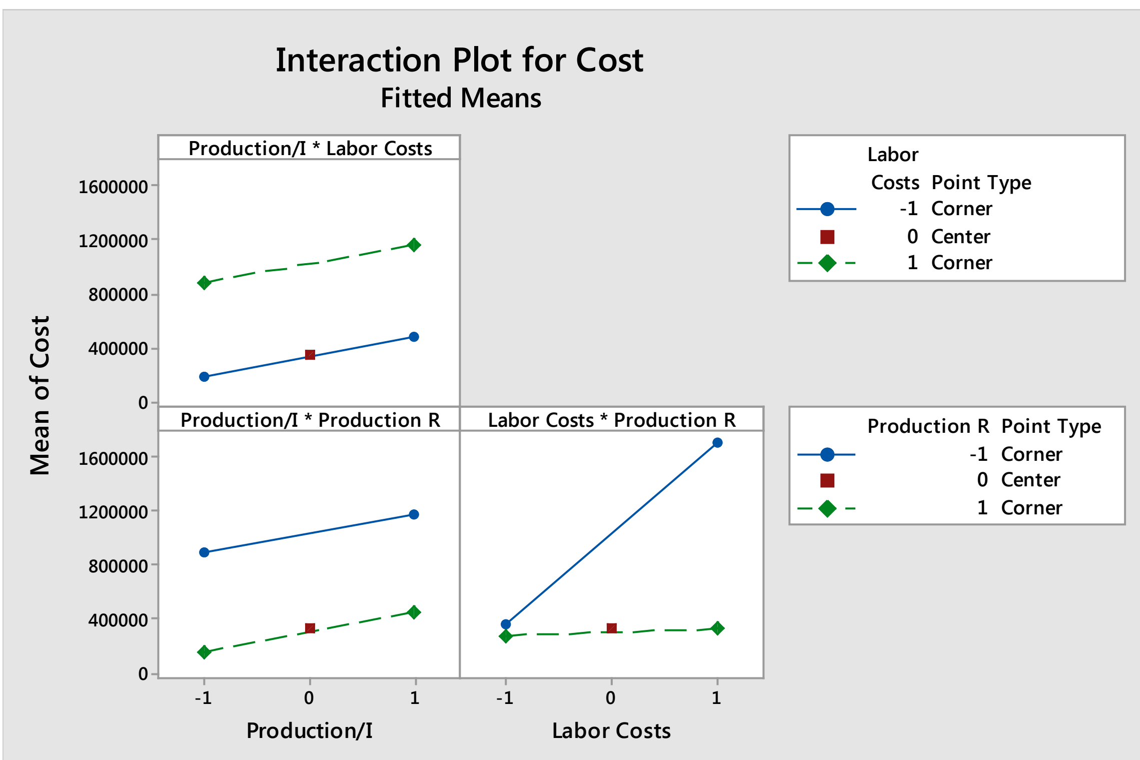
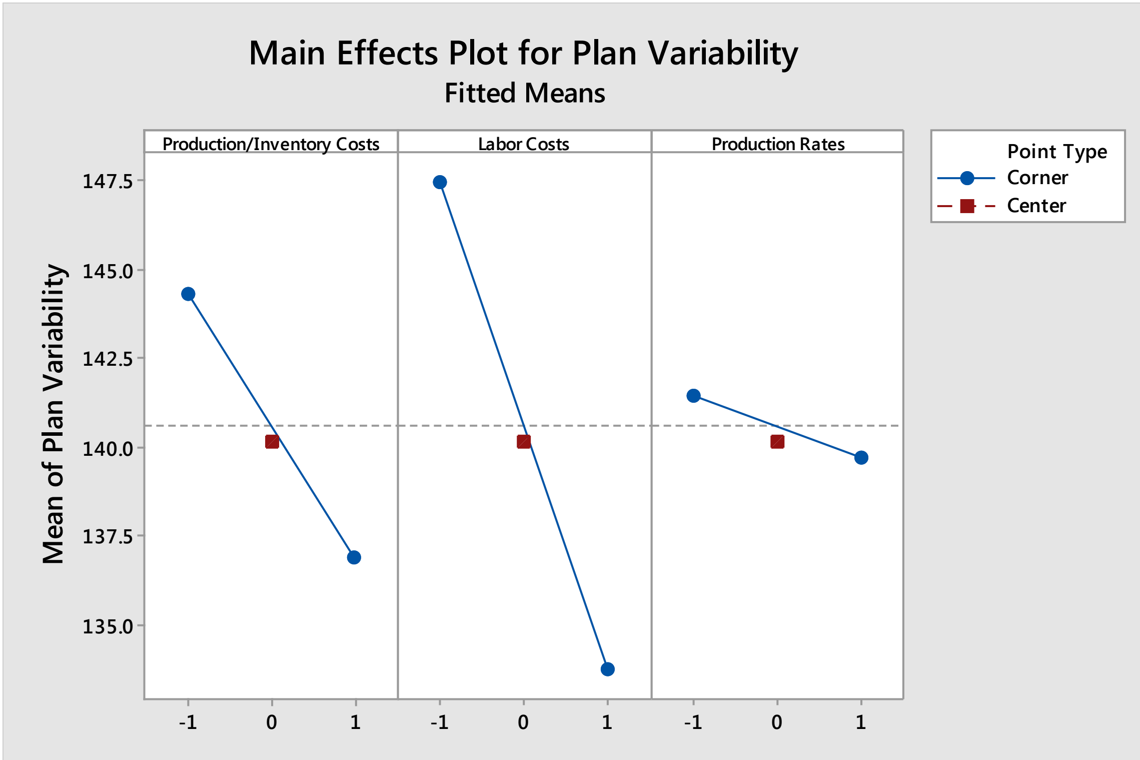


Figure 3.10: Main and interaction effects plots of cost for industry factors.



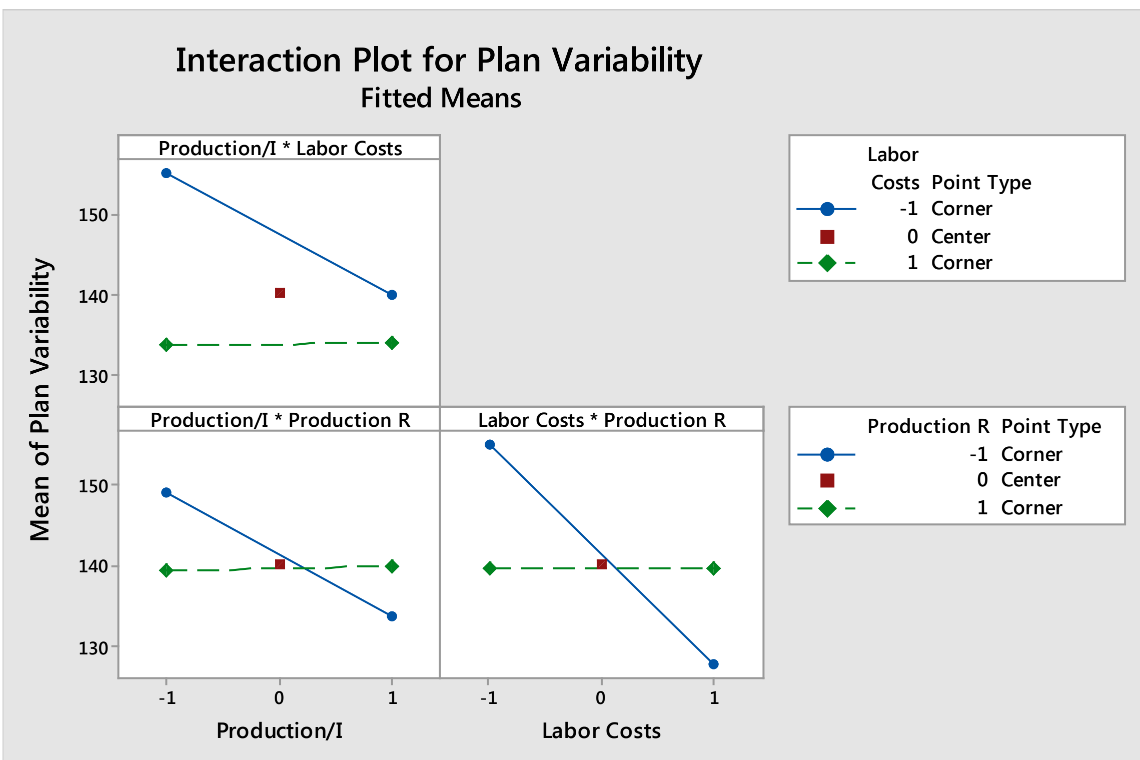
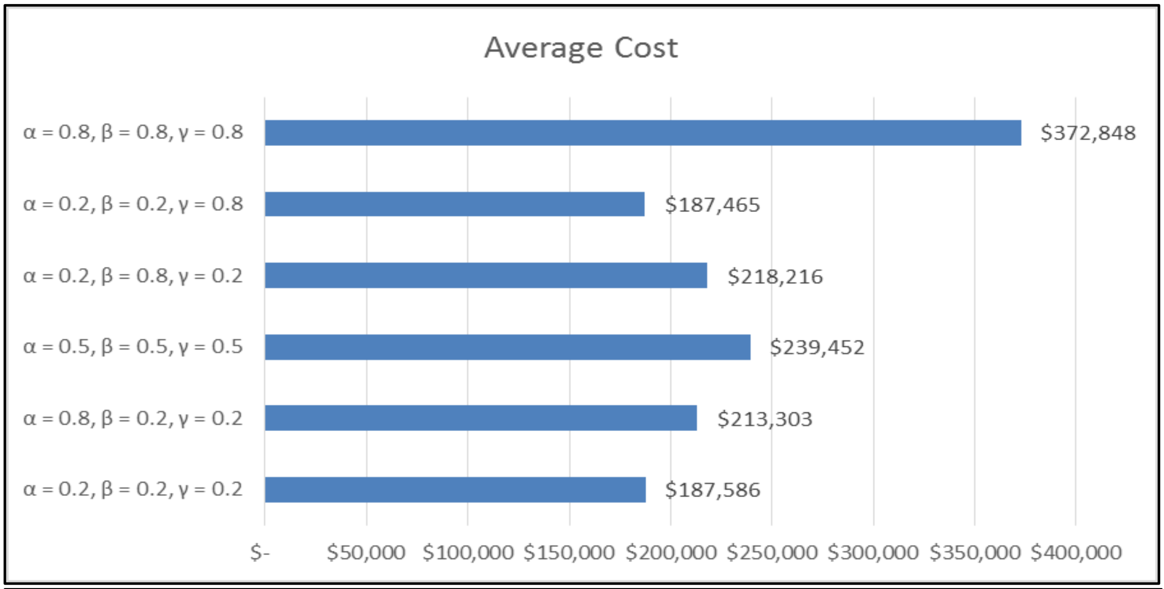


Figure 3.11: Main and interaction effects plots of plan variability for industry factors.

3.8 Effect of Forecasting Parameters

As we pointed out in Section 3.5.1, the Holt-Winters method is employed as the forecasting method in this study, where smoothing constants $\alpha, \beta,$ and γ are fixed at 0.2. Smoothing constants being close to 0 indicates that the forecasting model is less responsive to the changes in recent observations. In order to gain more insight how the smoothing parameters affect the overall results and conclusions, we conducted further analyses using the automotive parts industry data. Due to having a high number of demand runs, we chose to implement a fractional factorial design that consist of 2 levels and a center point. For each smoothing constant; 0.2 and 0.8 are set as low and high levels, respectively. In addition, 0.5 is used as the center point, which gives us a total of 5 runs. Figure 3.12 shows the average costs and plan variabilities for each of these runs along with our default parameters that are fixed at 0.2. When all constants are set at the low level (i.e., $\alpha = 0.2, \beta = 0.2,$ and $\gamma = 0.2$), the cost and stability levels are found \$187,465 and 139, respectively. A very close alternative was when $\alpha = 0.2, \beta = 0.2,$ and $\gamma = 0.8,$ which has attained the values \$187,465 and 139. These two similar cases have the lowest cost and highest stability results obtained in our runs but the variability per unit cost is smaller in the former case, when all smoothing constants are set at low levels. On the other hand, the highest variability was observed when all three smoothing parameters were at high levels (i.e., $\alpha = 0.8, \beta = 0.8,$ and $\gamma = 0.8$), which aligns with the literature recommending the use lower values for smoothing constants (Chatfield, 1978). When all constants are set high, we obtain the highest cost and variability values: \$372,848 and 706, which are significantly higher than the other runs. We would like to remark that in general, these smoothing constants can be selected based on the forecast error using historical data. However, since the objective here is investigation of the sensitivity of the proposed FRP model results and conclusions with respect to different forecasting parameters (rather than identification of the best forecasting model) an experimental design approach has been taken.



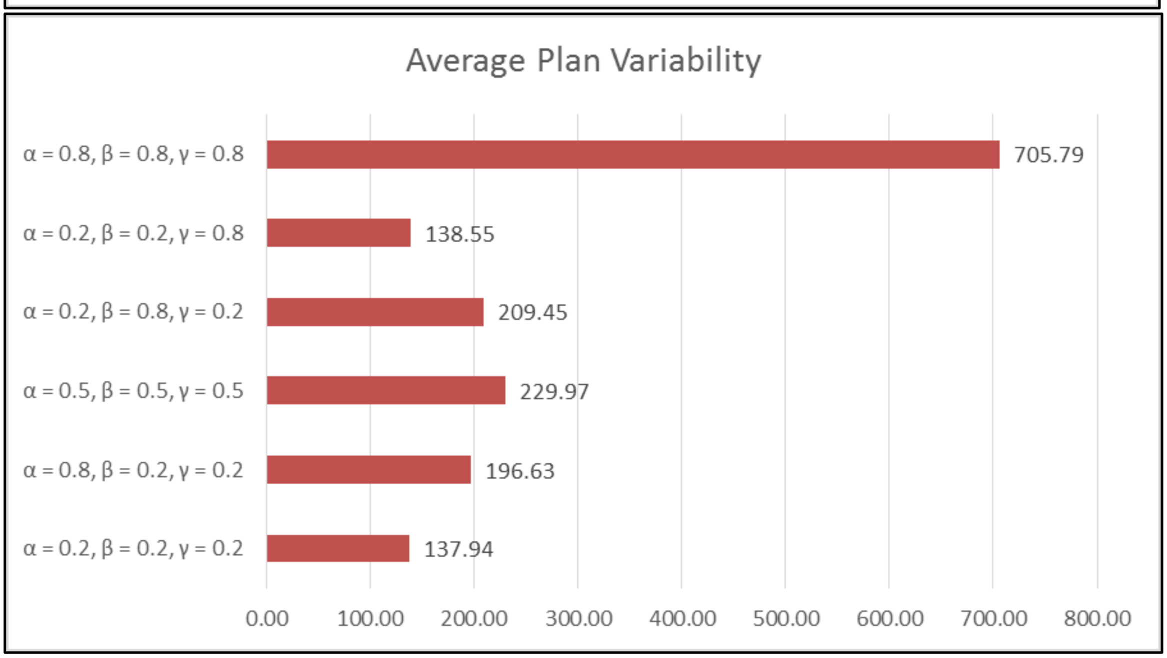


Figure 3.12: Cost and plan variability levels under different smoothing constants in FRP-AP approach.

When we look at these smoothing constant scenarios individually, we see a few new patterns that hasn't been observed in prior. As can be seen in Figures 3.13 and 3.14, the cost difference between flex-limits and no-flex limits increases when α or β are close to 1, which means favoring traditional aggregate planning without FRP. When α is high, the gap between different flex-limits also gets widened (Figure 3.13). In the two cases, where α and β values are the lowest, the behaviors of flex-limits are almost identical, which makes us conclude that the value of γ becomes insignificant in the final cost structure (See Appendix C).

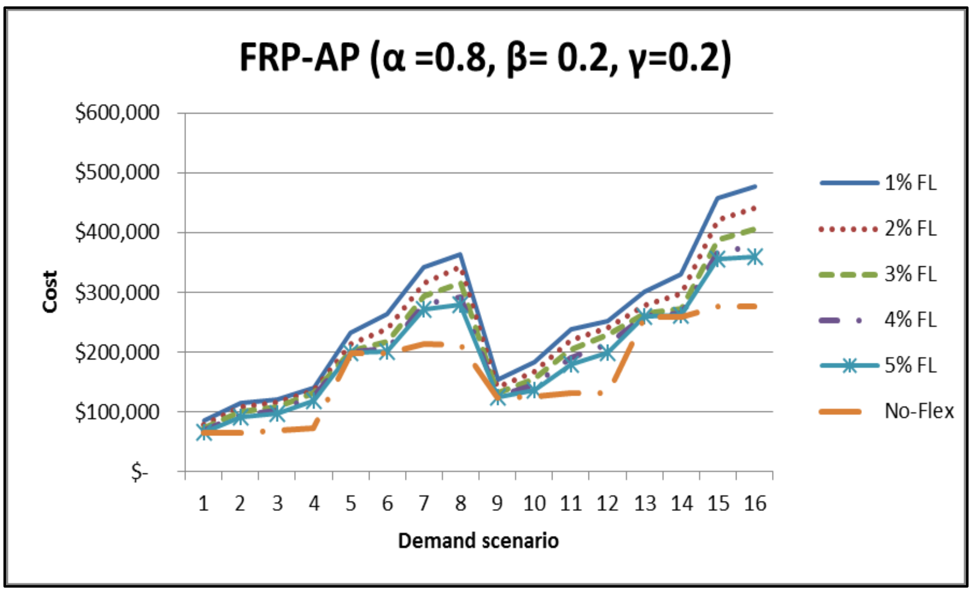


Figure 3.13: Cost graphs of FRP-AP when $(\alpha = 0.8, \beta = 0.2, \gamma = 0.2)$.

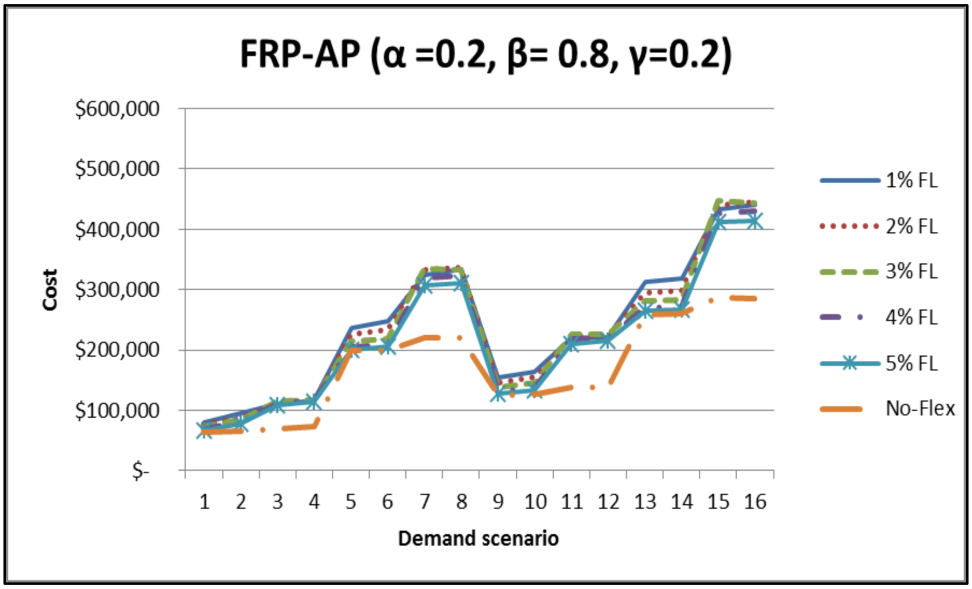


Figure 3.14: Cost graphs of FRP-AP when $(\alpha = 0.2, \beta = 0.8, \gamma = 0.2)$.

The amount of variability significantly increases when alpha and beta values are high (i.e., being more responsive to recent changes in the forecast). The highest variability is observed when all constants are set to 0.8. In that case, the comparison of no-flex limits vs. flex-limits reveal that flex-limits provide 62% less variability than the traditional aggregate planning without FRP (Figure 3.15). Another noticeable observation is that when all smoothing constants are set to 0.5, 3%, 4% and 5% return the same stability results. In all of the five runs, we see the same consistent pattern among flex-limits, where larger flex-limits yield higher plan variability (Figure 3.16).

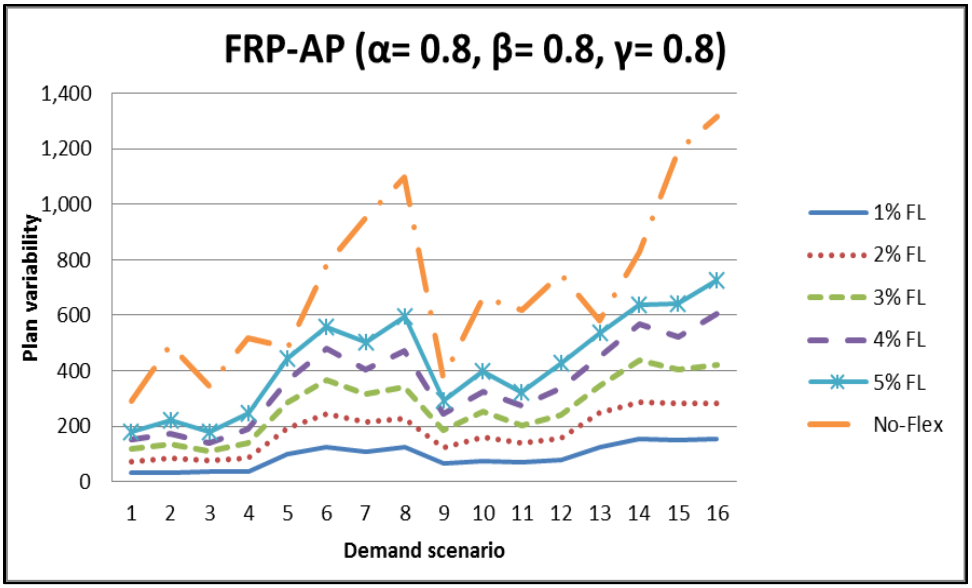


Figure 3.15: Stability graphs of FRP-AP when $\left(\alpha = 0.8, \beta = 0.8, \gamma = 0.8\right)$.

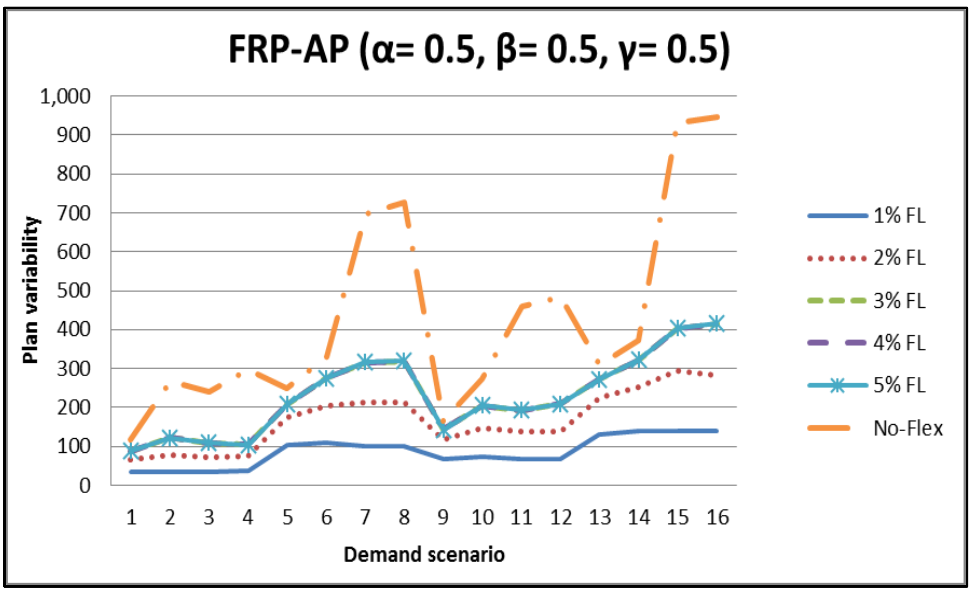


Figure 3. 16: Stability graphs of FRP-AP when $\left(\alpha = 0.5, \beta = 0.5, \gamma = 0.5\right)$.

Next, the output from the experimental design is examined by analysis of variance (ANOVA) using Minitab. For both response variables, smoothing constant for the level (baseline component), for the slope (trend component), and for the seasonal factor are found statistically significant. ANOVA results are presented in Tables 3.10 and 3.11. The p-value of curvature is extremely high, which suggests that there is no evidence of curvature.

Table 3.10: ANOVA results of smoothing constants for cost.

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	4	1.06724E+11	26681117056	33.43	0.000
Linear	3	1.06712E+11	35570541025	44.56	0.000
Alpha	1	40711430507	40711430507	51.00	0.000
Beta	1	45265405526	45265405526	56.71	0.000
Gamma	1	20734787043	20734787043	25.98	0.000
Curvature	1	12845148	12845148	0.02	0.901
Error	16	12771326768	798207923		
Total	20	1.19496E+11			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
28252.6	89.31%	86.64%	*

Table 3.11: ANOVA results of smoothing constants for plan variability.

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	4	108241	27060.2	117.75	0.000
Linear	3	107869	35956.3	156.46	0.000
Alpha	1	44254	44253.8	192.56	0.000
Beta	1	57135	57135.4	248.62	0.000
Gamma	1	6480	6479.6	28.19	0.000
Curvature	1	372	372.1	1.62	0.221
Error	16	3677	229.8		
Total	20	111918			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
15.1596	96.71%	95.89%	*

To gain more insight about statistical significance of the smoothing constants and to compare their magnitude, we plot the normal probability plot of the effects, which is shown in Figure 3.17. As per the results, all smoothing constants have significant positive effects on the response variables. Among the three, smoothing constant for the trend component $(\text{i.e.,}\beta)$, due to being located furthest from the fitted line, is the most significant effect for both cost and plan variability. Smoothing constant for the seasonal factor $(\text{i.e.,}\gamma)$, has the least significant impact on both, where its effect is slightly lesser for plan variability.

Figure 3.17: Normal probability plots of the standardized effects.

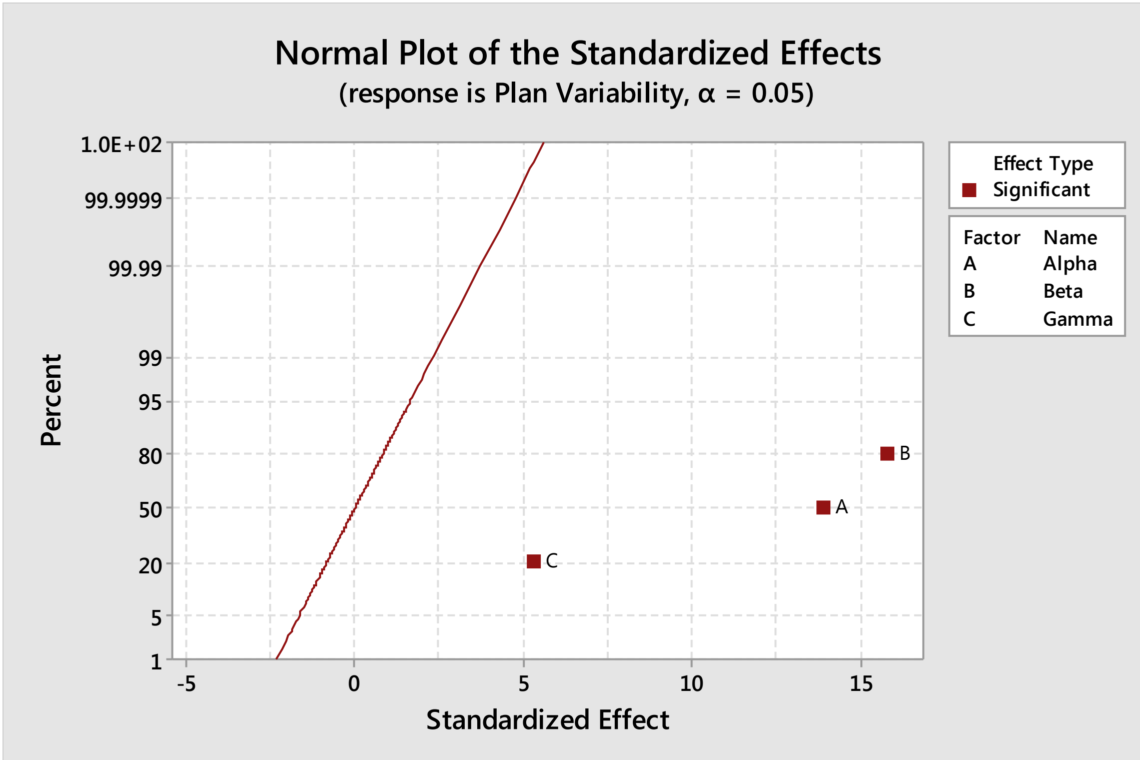


Figure 3.17 (Cont'd): Normal probability plots of the standardized effects.

3.9 Effect of Hiring and Layoff Costs in Textile Industry

As mentioned earlier, Industry type 1 is based on data obtained from automotive parts industry, whereas Industry Type 2 features textile industry, a Hong-Kong based specialty items manufacturer in particular, which observes higher turnover rates as a result of having lower hiring and lay-off costs. Below, we present a sensitivity analysis to demonstrate the impact of the turnover rates and show how cost savings change when the hiring and layoff costs parameters change in the problem settings. We solved our aggregate planning problem using both FRP-AP and FRP-CS approaches with alternative cost parameters to demonstrate how the savings change when the hiring and lay-off cost parameters change in the problem settings. We gradually increased the cost of hiring/lay-off from the base case, where they are set to 12.82 (\$/person) and 15.38 (\$/person), respectively, and the results have shown that when hiring and lay-off costs increase, the amount of savings increases as well. When hiring/lay-off costs are increased to 120 ($/person) and 200 ($/person), respectively, the amount of savings has reached up to $9,262, which is five times greater than the amount we obtained in the initial scenario. Table 3.11 provides the complete list of alternative scenarios and their respective savings for each flex-limit case under different cost settings in the textile industry.

Table 3.12: Average total savings for 16 demand scenarios with FRP-AP approach.

Hiring/ Lay-off Cost ($/person)	1%FL	2%FL	3%FL	4%FL	5%FL	No-FL	Average
Base Case	$3,001	$3,232	$720	$948	$2,062	$552	$1,752
$\boldsymbol{c^H = 30 / c^L = 50}$	$3,096	$2,877	$509	$754	$2,010	$(500)	$1,458
$\boldsymbol{c^H = 60 / c^L = 100}$	$3,654	$4,143	$2,598	$2,782	$4,197	$817	$3,032
$\boldsymbol{c^H = 120 / c^L = 200}$	$7,458	$8,374	$7,926	$9,241	$11,903	$10,670	$9,262

3.10 Assumptions and Limitations

The numerical study that we presented here only considers a single product. Thus, the demand forecasts are assumed to be independent and would not experience the correlated demand among multiple products, a case where demand of a particular product may depend on the inventory of other products (Baykal-Gursoy and Erkip, 2010). Another major assumption is the availability of resources to adjust the workforce levels due to changing demand. This is especially important for FRP-CS since the main emphasis on this approach is to fulfill the demand rather than minimize the cost. In real-world manufacturing environments though, this might not always be attainable due to the budget restrictions and regulations in hiring/lay-off processes. Another limitation is on the smoothing constants. Given the high number of scenarios generated and the respective run-time of each model, a fractional factorial experiment is considered in this study but performing a more detailed analysis on this subject would enhance our understanding of the relationship between the FRP and the forecast quality. As we underlined in Section 3.4, the results obtained reflect the industry specifics, and should not necessarily represent the industry as a whole. However, the results suggest strong room for growth in terms of plan stability and cost savings for both of these sample industry scenarios.

3.11 Summary and Conclusions

In this chapter, we discuss the application of flexibility requirements profile (FRP) in aggregate production planning (APP) problems to trade-off between cost and plan stability. A mixed-integer linear programming (MILP) model has been developed to solve the FRP-based APP (FRP-AP) problem in a rolling horizon setting, and the optimal production plans are determined. The model minimizes the overall costs related to production, workforce, inventory holding and backorder costs over the planning horizon, while incorporating additional constraints that reflect the FRP requirements. A computational study was carried out using experimental data corresponding to two industry types based on an automotive parts supplier case and a textile industry case. The conducted experimental designs and sensitivity analysis has shown how the change in certain parameters affect the efficacy of FRP.

The overall results suggest that the proposed FRP-AP method has given favorable results in production stability when flex-limits are enforced, without significantly sacrificing the cost production cost when compared with the traditional APP without FRP. The enforced flex-limits also acknowledge that the tight bounds provide better smoothing effect on production and inventory levels. In both industry cases, FRP-AP approach establishes high degrees of plan stability and provides higher cost-savings in comparison to the FRP-based chase strategy (FRP-CS). The results show that FRP-AP models may help the organizations to establish a certain degree of stability without jeopardizing their economic interests. Especially, industries with shorter product lifecycles and those which are exposed to heavy demand fluctuations may thoroughly benefit from the implementation of the proposed FRP-AP approach.

CHAPTER 4: BI-OBJECTIVE OPTIMIZATION FOR AGGREGATE PLANNING WITH FLEXIBILITY REQUIREMENTS PROFILE

4.1 Introduction

In this chapter, we extend our work in Chapter 3 and consider optimizing multiple conflicting objectives simultaneously. The proposed method employs multi-objective programming to FRP-based aggregate production planning. In the following sub-sections, first we present the compromise programming approach and the FRP-embedded bi-objective MILP model. Then, we compare the proposed model's results to those of the stand-alone bi-objective and the single objective FRP model. We wrap up the chapter with presenting the conclusions and the managerial benefits of stable production plans.

4.2 Multi-Objective Optimization

The goal of multi-objective optimization is to simultaneously optimize all the objectives (attributes) that are involved in the decision-making process and find an appropriate balance between them. These objectives are often conflicting and varying in nature; thus a unique feasible solution that optimizes all of them simultaneously often does not exist. Rather, there are multiple feasible solutions that are non-dominated with respect to each other. This is the notion of Pareto optimality. In Pareto optimality of real valued decision variables, there are infinitely many optimal solutions, where each of these solutions is superior in at least one of the objectives but inferior in the others. An optimal solution is established when there are no other feasible solutions that could improve at least one of the objectives without deteriorating the rest of them. This optimality condition can also be interpreted as the tradeoff between the solutions. The final solution to the multi-objective problem is the set of non-dominated solutions, also known as the Pareto front.

The classical multi-objective optimization problem can be described in the following form;

$$\text{Minimize } \left\{ f_1(x),\, f_2(x), \ldots.., f_Z(x) \right\} \tag{4.1}$$

$$\text{Subject to: } g_i(x) \geq 0, \qquad i = 1, 2, \ldots, \mathrm{j} \tag{4.2}$$

Where $\left\{ f_1(x),\, f_2(x), \ldots.., f_Z(x) \right\}$ represent the attributes that are involved the decision making process and j is total number of inequality constraints.

4.3 Bi-Objective Compromise Programming

Among the several methods for solving multi-objective optimization problems, *compromise programming* (CP) with additive utility functions is used in this study. CP is a distance-based technique to identify compromise solutions. It was first introduced by Zeleny (1973) and later used in various multi-objective programming problems. Compromise programming aims to obtain the set of solutions that are closest to an ideal point. The *utopia point* is considered as infeasible in the decision space because of the conflicting nature of the individual objectives and the *decision maker* (DM) has to find a compromise solution between the final solution and the utopia point. The utopia point (vector) contains the best possible values of each objective, and as opposed to goal programming, the utopia point in compromise programming is not a target established by the DM’s subjective preferences. L_p metrics is frequently used in CP as a distance measure and numerous applications can be found in the literature (Ozelkan et al., 2000; Ballestero, 2007).

$$L_p = \left(\sum_{j=1}^{N} w_j \left| \frac{f_j - B_j}{W_j - B_j} \right|^p \right)^{1/p}, \tag{4.3}$$

where f_j is the value of objective j, B_j is the best (i.e., utopia) value of objective j, W_j is the worst (i.e., nadir) value of objective j. B_j is called utopia point because this point is normally not feasible due to the conflicting nature of the individual objectives. The interval between nadir and utopia points locates all possible optimal values and avoids the bias generated by the different magnitude of each objective. w_j is the weight of the objective j, and p stands for the decision maker's compensation between deviations where $1 \leq p \leq \infty$. Additive utility functions are based on the utility theory: an approach used for quantifying the preferences of the DM. The idea is to develop a new scale to describe the relative values of different outcomes to avoid discrepancies caused by monetary values. To describe the relative values of different objectives, each objective in the decision space is assigned a utility and the goal is to achieve the highest expected utility with respect to all the objectives. Additive utility function combines these utilities and transform to a single utility function. The additive utility function assumes that there exists independence between the objectives, and thus the outcomes of one objective do not depend on the level of the other objective (Keeney and Raiffa, 1976). In this study, we use full compensation, i.e., $p = 1$, which results in an MILP formulation as presented in Section 4.4. L_1 can be considered as a weighted average of linear utility functions such that:

$$L_1 = \sum_{j=1}^{N} w_j U_j(f_j) \text{ where } U_j(f_j) = (f_j - B_j) \big/ (W_j - B_j) \tag{4.4}$$

4.4 Mixed-Integer Linear Programming Formulation

The objective of the proposed approach is to find the optimal production levels while considering cost and plan stability, simultaneously. At each time period *t*, the objective is to minimize the overall projected cost and the plan stability over the next *N* periods under given flex-limits. The first objective, cost, consists of the labor costs, hiring/layoff cost, material cost, backorder (shortage) cost, and inventory holding cost. The second objective, plan stability, considers the variability between forecasted (planned) production and the actual production. The parameters and decision variables that we introduced in Chapter 3 are also used in this bi-objective model.

The proposed bi-objective MILP problem to be solved at period *t* can be represented as follows:

$$\text{Minimize } wU_1\left[C\left(W,O,H,L,P,I^-,I^+\right)\right]+(1-w)U_2\left[S\left(P\right)\right] \tag{4.5}$$

Subject to:

$$\text{Inventory: } P_{t,i}=d_{t,i}+I^+_{t,i}-I^+_{t,i}-I^+_{t-1,i}+I^-_{t-1,i} \qquad i=0,1,...,N \tag{4.6}$$

$$\text{Workforce: } W_{t,i}=W_{t-1,i}+H_{t,i}-L_{t,i} \qquad i=0,1,...,N \tag{4.7}$$

$$\text{Capacity: } P_{t,i}\le m^R W_{t,i}+m^O O_{t,i} \qquad i=0,1,...,N \tag{4.8}$$

$$\text{FRP: } LB_{t-1,i+1}\le P_{t,i}\le UB_{t-1.i+1} \qquad i=0,1,...,N \tag{4.9}$$

$$P_{t,i},I^+_{t,i},I^-_{t,i},W_{t,i},O_{t,i},H_{t,i},L_{t,i}\ge 0 \qquad i=0,1,...,N \tag{4.10}$$

$$W_{t,i},H_{t,i},L_{t,i} \text{ are integers.} \tag{4.11}$$

Where W,O,H,P,I^-,I^+ are decision vectors and

$$C(W,O,H,L,P,I^-,I^+)=\left(\sum_{i=0}^{N}c^W W_{t,i}+\sum_{i=0}^{N}c^O O_{t,i}+\sum_{i=0}^{N}c^H H_{t,i}+c^L L_{t,i}+\sum_{i=0}^{N}c^P P_{t,i}+\sum_{i=0}^{N}h\,I_{t,i}^{+}+\sum_{i=0}^{N}b\,I_{t,i}^{-}\right) \tag{4.12}$$

$$\text{and } S(P)=\left(\sum_{i=0}^{N}\left|P_{t-1,i}-P_{t,i-1}\right|^{m}\right)^{1/m}. \tag{4.13}$$

Expression (4.13) can be considered as the L_m norm for production variability where m is the compensation parameter such that $1 \le m \le \infty$. $m=1$ implies full compensation, yielding the sum of absolute deviations from the planned production levels. w is between 0 and 1 determines the weights for the production cost and stability objectives. Solving for different w's yields different non-dominated solutions on the Pareto frontier. Workforce constraint (4.7) 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. Inventory Balance is provided through constraint (4.6), where the realized demand in period t plus the inventory (or backorder) at the end of period t, equals to the total production in period t plus the inventory (or backorder) from the previous period $(t-1)$. While Capacity constraint (4.8) ensures that the total production in period t will not exceed the available production capacity, FRP constraint (4.9) stipulates that production will stay within the pre-defined lower and upper production bounds, which are computed from (3.4) and (3.5) based on the FRP planning scheme. Since the proposed bi-objective problem already includes the stability metric in the objective function, one can consider a stand-alone bi-objective problem without those FRP constraints in (4.9). In our numerical study, we compare the performance of the proposed formulation with that of the stand-alone bi-objective problem in order to see the impact of the FRP constraints. The performance comparison also includes the conventional single objective problem that minimizes only the cost function (4.12).

The objective function (4.5) consists of two utility functions U_1 and U_2, which represent the cost utility (4.12) and the stability utility (4.13), respectively. As mentioned in Section 3.2, utility functions are used when the decision criteria have uncertain payoffs and they translate decision values into an equivalent scale to have meaningful comparisons between conflicting cost and stability objectives. Each of these utility functions has their respective decision spaces, where the worst and best outcomes are assigned the values of 0 and 1, respectively. *Worst (Nadir)* and *Best (Ideal)* values help us to determine the range of conceivable outcomes for each objective. In order to obtain the best and worst values, each objective in the problem should be minimized individually subject to the original constraints. To conceptualize this process, consider a multi-objective optimization problem as follows;

$$\begin{aligned} &\text{Minimize} \;\; \left\{ f_1(x),...., f_Z(x) \right\} \\ &\text{subject to} \quad x \in \Omega, \end{aligned} \tag{4.14}$$

where $f_i : \mathbb{R}^n \to \mathbb{R}$ are the conflicting objectives and $\Omega \subset \mathbb{R}^n$ is the feasible region. Based on this classic formulation:

$$f^{[i]} = \min_x \left\{ f_i\left(x\right) : x \in \Omega \right\} \quad \text{for } i = 1, 2, ..., \text{Z}, \tag{4.15}$$

will give us the Utopia point (the lower bounds of the Pareto optimal set) and,

$$g^{[i]} = \max\left(f_i(x^{[j]}) \right), \forall_i = 1, ..., k. \tag{4.16}$$

will be the Nadir Point, and act as the upper bounds of the Pareto optimal set. Next, these values are placed in the weighted average of utility functions. More specifically, In order to solve the bi-objective MILP model, at each period t in the planning horizon, the following steps are applied at each period in the evaluation horizon (i.e., $t = 1, 2, \ldots, T$).

Step 1: Solve the single-cost objective MILP problem with constraints (4.6), (4.7), (4.8), (4.9), (4.10), (4.11) to identify the *Best Cost* and *Worst Stability*.

$$\text{Minimize}\left(\sum_{i=0}^{N} c^W W_{t,i} + \sum_{i=0}^{N} c^O O_{t,i} + \sum_{i=0}^{N} c^H H_{t,i} + c^L L_{t,i} + \sum_{i=0}^{N} c^P P_{t,i} + \sum_{i=0}^{N} h\, I_{t,i}^{+} + \sum_{i=0}^{N} b\, I_{t,i}^{-} \right)$$

$$\text{Subject to:} \qquad x \in X \tag{4.17}$$

Step 2: Solve the single-cost objective MILP problem (4.17) with an additional constraint (4.18) to identify the *Worst Cost*. Note that the *Best Stability* is always zero, i.e., no change is made in the production plan.

$$\text{Subject to:} \qquad P_{t-1,\, i+1} = P_{t,i} \tag{4.18}$$

Step 3: Normalize both objectives by Equation 4.19, where the utopia and nadir values are found through Steps 1 and 2.

$$U_j(x) = \frac{f_j - B_j}{W_j - B_j}, \tag{4.19}$$

where $U_j\left(f_j\right) \in \left(0,1\right)$ and j is the corresponding utility.

Step 4: Solve the bi-objective model in (4.5-4.13)

The optimal plans are computed on a rolling horizon basis, and there is an optimal plan for each period in the planning horizon. Since both cost and stability objectives are being minimized smaller values are desired for each objective. We would like to remark that it is also possible to select the best and worst values subjectively by identifying meaningful upper and lower bounds for cost and stability based on decision maker’s subjective judgments.

4.5 Numerical Study

In this section, we present a numerical example to demonstrate the effectiveness of the proposed procedure. Our underlying idea is to create a dynamic optimization model under rolling horizon planning with presence of FRP. The production plans are computed on a rolling basis, and there is an optimal plan for each period in the planning horizon. In the production planning context, rolling horizon models entails periodical replanning activities and revision of MPS obtained in prior periods as more recent information become available. In this particular example, in each time period FRP-embedded bi-objective optimization model is solved over a prespecified planning horizon but only the initial period's decisions are implemented. The same procedure repeats the next decision period; the model is resolved considering new information and decisions are modified accordingly. Cost parameters for this study are selected from an Asian textile industry (Table 4.1). The original cost data is converted into American dollars with the following conversion rate; 1$=7.8HK. We generated 72 periods of demand data, where 48 of those are used as historical. In each time period, a planning horizon (funnel) of 8 periods is maintained. Triple-exponential smoothing is used as the forecasting procedure with smoothing constants fixed at 0.2. For our example, we use the following assumptions. There is an initial inventory of 100 units, and the initial workforce is set according to the first realized demand in the planning horizon. Each employee in the workforce is scheduled to work for 8 hours per day. The production capacity is determined by the size of the workforce. The inventory in the end of the planning horizon is set to 100 units.

4.5.1 Experimental Design

For conducting a numerical study, we constructed an experimental design using various demand scenarios with the following demand components; baseline, trend, seasonality, Gaussian error with each having two levels. The magnitude of flex-limits (F_i) and objective weights $((w)\,\&\,(1-w))$ are the other experimental factors included in the design. The objective weight pair $((w)\,\&\,(1-w))$ corresponds to production cost and plan stability weights, respectively. A full factorial design is used and each experimental scenario is replicated five times to reduce random effects. The complete list of experimental factors and their levels is displayed in Table 4.2.

Table 4.1: Cost data adapted from the textile industry (in $).

Production Cost ($/unit)	6.41
Inventory Cost per unit per week	1.92
Backorder Cost per unit per week	3.85
Labor Cost ($/person-hour)	0.80
Overtime Labor Cost ($/person-hour)	1.28
Hire Cost	12.82
Lay-off Cost	15.38

Source: Leung et al., 2003

Table 4.2: Experimental factors and levels.

Factors	***Number of levels***	***Values***
Demand-Baseline	2	Low (1000 units), High (3000 units)
Demand- Trend	2	Low (20), High (100)
Demand-Seasonality	2	Low +/- 0.1, High +/- 0.3
Demand- Magnitude of Error	2	Low (Std = 50), High (Std= 200)
Flex-Limits	2	1% Incremental, 5% Incremental
Objective Weights	5	0.9& 0.1, 0.7& 0.3, 0.5& 0.5, 0.3& 0.7, 0.2& 0.8

4.5.2 Computational Analysis

Comparisons between the single objective FRP, the stand alone bi-objective, and the bi-objective with FRP approaches are made within the context of planning costs and stabilities. In the full factorial design, there are a total of 800 experimental $(2\times2\times2\times2\times2\times5\times5)$ scenarios available that represent the six experimental factors with multiple levels. The first 12 periods in the horizon is used as a warming period, and the next 12 periods' results are analyzed. The resulting mathematical formulation is modelled in the AMPL programming language and solved by using CPLEX 12.0 solver.

Figure 4.1 displays the results of total cost for varying objective weights and flex-limits under these 16 demand scenarios. When flex-limits are set to 1% incremental and cost weight is high with w = 0.9, we observe that both single cost minimization and bi-objective model with FRP show similar cost results. The bi-objective formulation without FRP produces lower costs since there are no FRP bounds to maintain a certain degree of stability. The cost difference is higher in the scenarios 7-8 and 15-16, where demand has large trend and excessive seasonality. As more emphasis put on the stability (i.e., low w), it is observed that the cost gap between bi-objective approaches with and without FRP constraints is reduced. When the stability weight is 0.9 (i.e., w = 0.1), both bi-objective approaches produce identical results, whereas the single-objective cost minimization with FRP constraints displays the lowest cost among three approaches. However, although the single-objective model yields the lowest cost, the difference with other two approaches is relatively small. When flex-limits are wider (i.e., 5% incremental), the cost are significantly lower in the former case where the main emphasis is on cost (i.e., w = 0.9). The difference between bi-objective approaches (with and without FRP) is also significantly reduced compared to the 1% incremental. In the latter case (i.e., $w = 0.9$), the cost results of the bi-objective models are similar to what we observed in 1% incremental flex-limits, and the single objective approach distinctively becomes the cheapest approach.

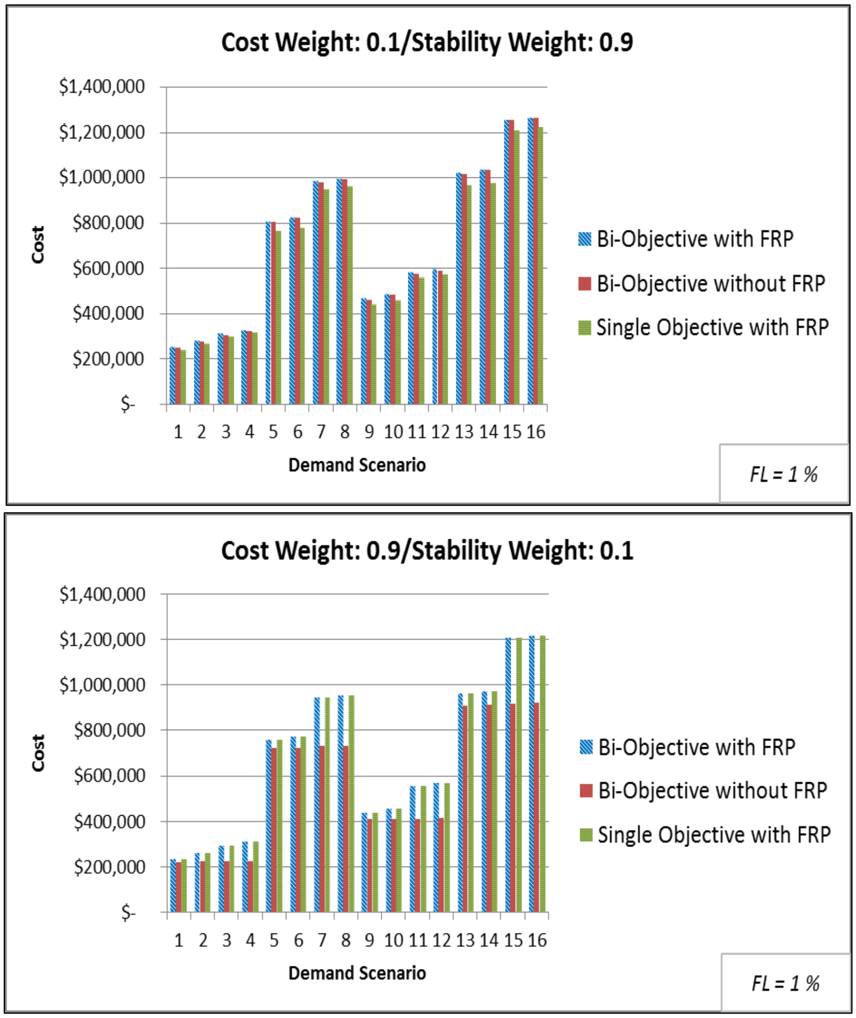


Figure 4.1: Cost comparison graphs (FL 1% incremental vs. FL 5% incremental).

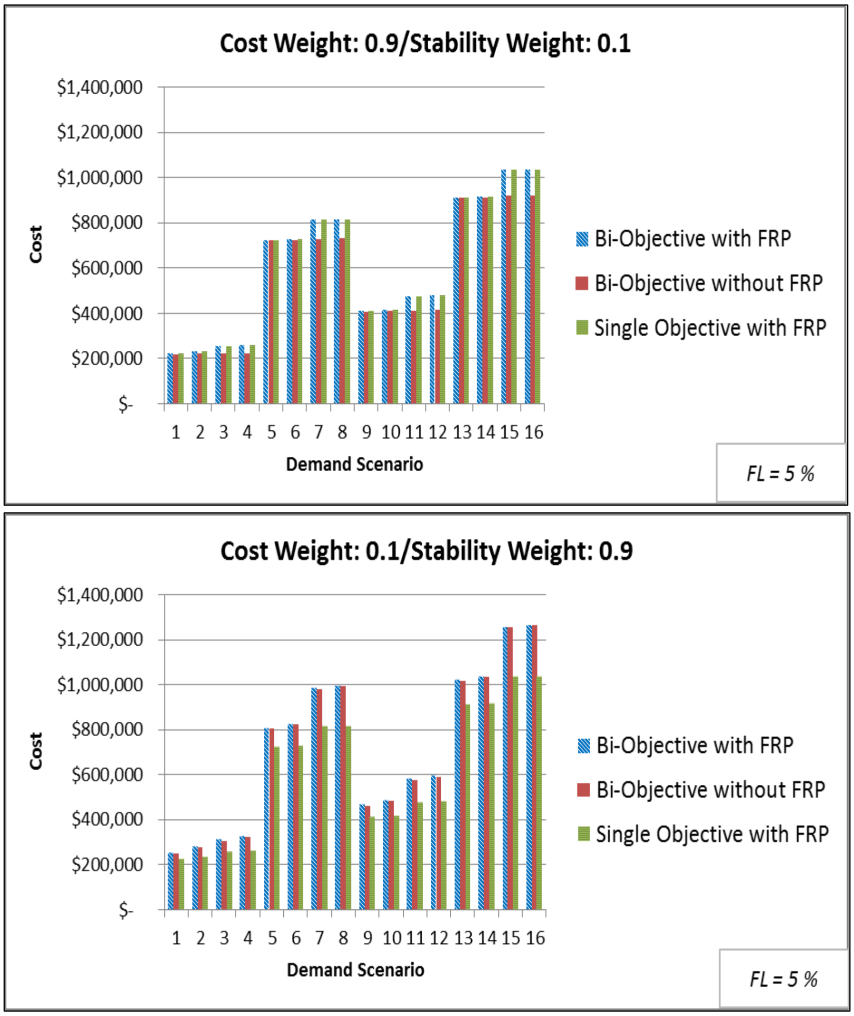


Figure 4.1 (Cont'd): Cost comparison graphs (FL 1% incremental vs. FL 5% incremental).

Production plan stability is significantly impacted as we move closer to higher state of stability. Figure 4.2 displays that the FRP embedded models produce high degrees of stability (i.e., low degrees of variability) when the emphasis on cost is high (i.e., w = 0.9).

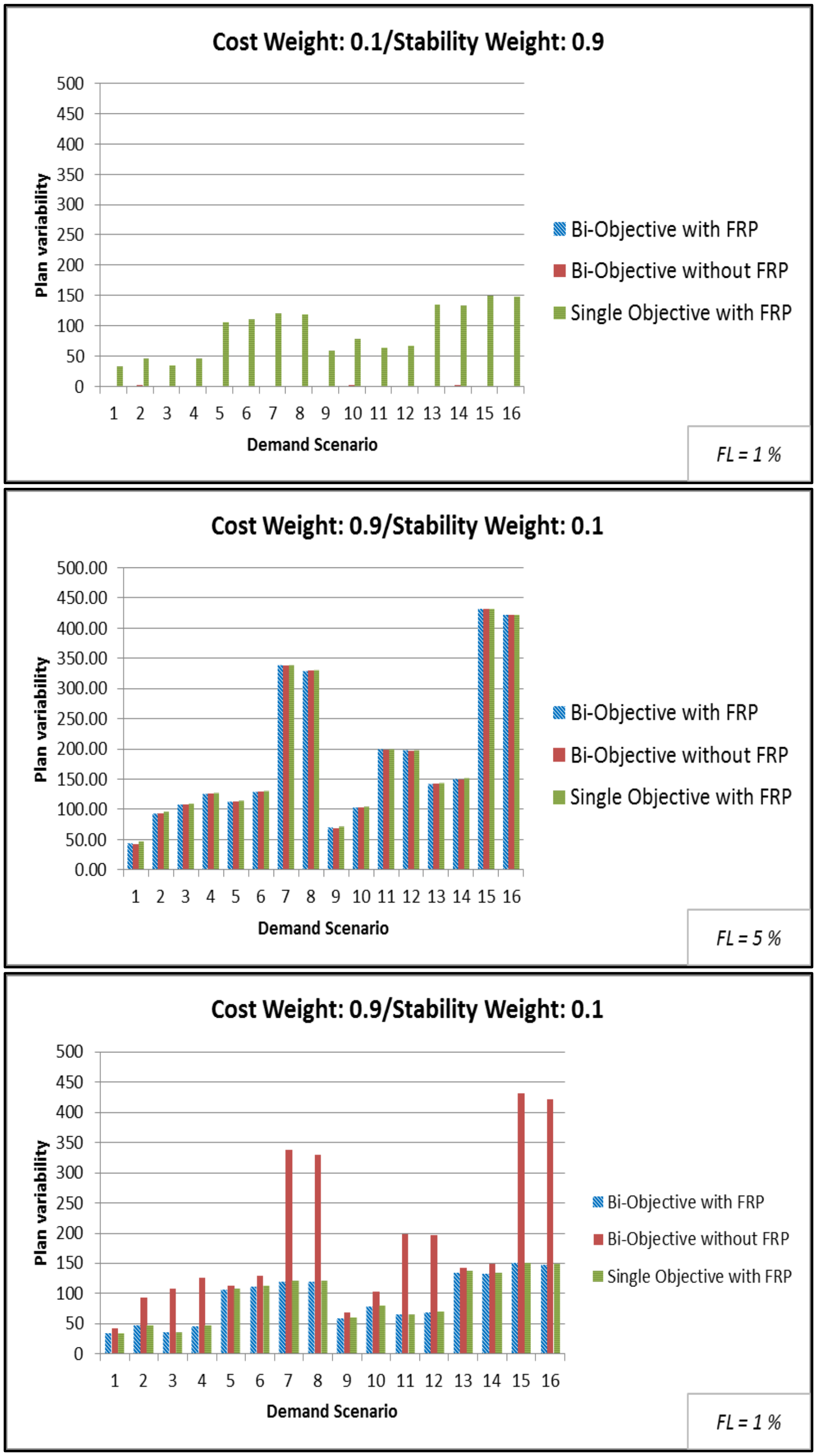


Figure 4.2: Planning variability comparison graphs (FL 1% incremental vs. FL 5% incremental).

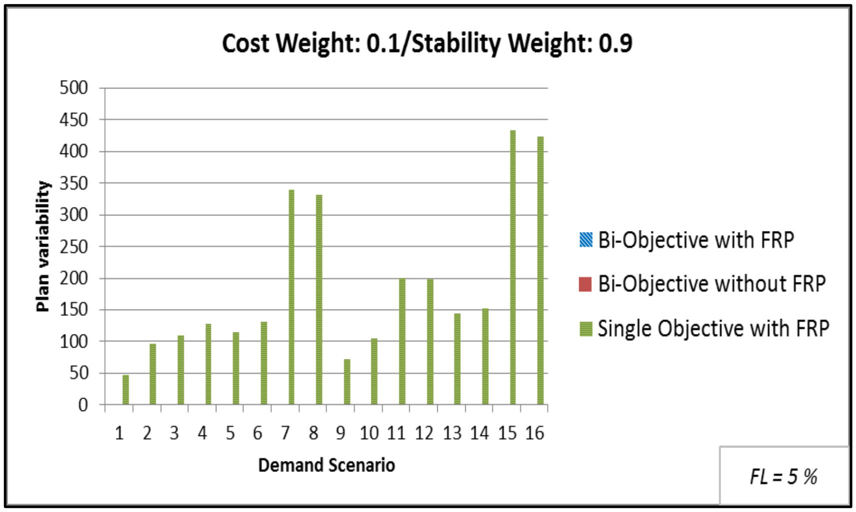


Figure 4.2 (Cont'd): Planning variability comparison graphs (FL 1% incremental vs. FL 5% incremental).

When 1% incremental flex-limits are implemented, we observe that while the bi-objective approach without FRP produces lower cost (see Figure 4.1), it is unable to keep a high degree of stability. The variability difference between the formulations with FRP and without FRP constraints is considerably lower in the scenarios where seasonality and trend are low (Scenarios 1-2 and 9-10), which indicates that FRP may be an effective tool when the variance in demand is higher. When stability weight is higher, both bi-objective approaches return better stability results, although the FRP-embedded model shows slightly better stability. Stability weight at 0.9 (i.e., w = 0.1) gives zero variability for both bi-objective approaches, which indicates that the FRP has no impact at that point of the Pareto set. A noticeable observation we made is that the bi-objective models with 5% incremental flex-limits result and cost weight at 0.9 return almost identical results, which means that the bounds enforced do not restrict the production levels. Nevertheless, the stability of these approaches is slightly higher than the single-objective approach due to the presence of a stability weight. The overall results show that, while the tighter flex-limits improve the stability, they also increase the total cost. This clearly demonstrates the trade-off between two conflicting objectives as well as underlines the importance of the magnitude of the flex-limits. Figure 4.3 shows a sample Pareto optimal frontier found under these conflicting objectives. The red line depicts the Pareto optimal set, which contains all potentially optimal solutions. The next step in our analysis is to test hypotheses regarding the impact of experimental design factors on the cost and stability measures.

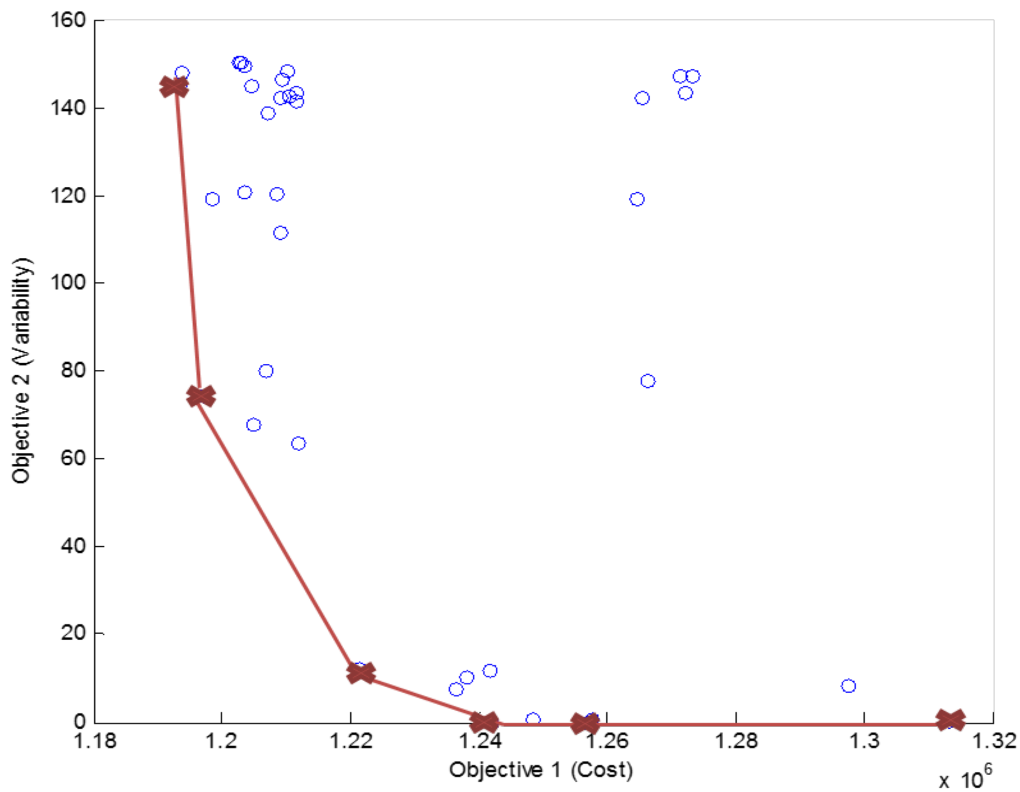


Figure 4.3: Sample Pareto frontier.

4.6 Research Hypotheses

We proposed and tested the following hypotheses in this study:

H1: Demand factors will influence the cost and plan stability levels.

H2: The magnitude of flex-limits will have a significant impact on the amount of plan variability.

H3: Varying objective weights will have significant influence on the cost and plan stability levels.

The hypotheses presented here are the alternative hypotheses. The first hypothesis investigates the impact of demand parameters on our proposed FRP-embedded bi-objective optimization model and determines their relative importance in terms of the impact they caused in cost and stability levels. The second hypothesis is concerned with the amount of flexibility permitted in production plans and it investigates whether the magnitude of the flex-limits influences the plan variability. Hypothesis 3 is concerned with the importance of objective weights and their impact on cost and stability performances. While the changes in response variables is directly related with the weights of each objective, the magnitude of the impact caused by changing these weights may give us a better interpretation of the trade-off between the objectives.

4.6.1 Results

We applied *analysis of variance* (ANOVA) procedure to test our hypotheses and to identify which factors have significant influence on the response variables. The values of the dependent variables are computed for each combination of independent variables. The data is analyzed using the *General Linear Model* (GLM) of Minitab software. Our main interest lies in the effect of the magnitude of flex-limits and the value of the assigned weights for teach objective. For that purpose, these factors were further grouped by using Tukey's procedure. The residual analysis from Minitab suggested that the plan variability data violates the assumption of normality and constant variance; hence, we applied a square root transformation. The analysis of the plan stability results was also restricted to the cases where plan variability is greater than zero.

Tables 4.3 and 4.4 provide the ANOVA results obtained using Minitab for cost plan stability, respectively. The results presented include the *degree of freedom* (DF), the *sum of squares* (SS), the *adjusted mean square* (MS), an *F-ratio*, and the significance level of the *p-value*. As can be seen, for both dependent variables, all main factors have *p*-values lower than 0.05 at 95% confidence level. Thus, all three null hypotheses can be rejected and it can be concluded that all experimental factors are statistically significant. Majority of the 2nd and 3rd degree interaction effects are also statistically significant impact for both cost and plan stability. However, some interaction factors showed no consensus. For example, interaction factors such as Baseline*Trend and Baseline*Error are found to have significant impact (*p*-value of 0.000) on plan variability but they have no impact on cost. Other higher degree interactions that are not listed have *p*-values significantly greater than 0.05 and thus concluded to be non-significant.

Table 4.3: Selected ANOVA results for cost.

Factors	DF	Seq SS	Adj SS	Adj MS	F	P
Baseline	1	9.99E+12	9.99E+12	9.99E+12	27086.22	0.000
Trend	1	6.57E+13	6.57E+13	6.57E+13	178057.4	0.000
Seasonality	1	2.98E+12	2.98E+12	2.98E+12	8072.74	0.000
Error	1	3.13E+10	3.13E+10	3.13E+10	84.82	0.000
Flex-Limits	1	6.70E+11	6.70E+11	6.70E+11	1816.25	0.000
Objective Weights	4	5.14E+11	5.14E+11	1.28E+11	348.24	0.000
Baseline*Seasonality	1	1.31E+11	1.31E+11	1.31E+11	355.7	0.000
Baseline*Flex-Limits	1	2.03E+10	2.03E+10	2.03E+10	55.08	0.000
Baseline*Objective Weights	4	1.49E+10	1.49E+10	3.72E+09	10.08	0.000
Trend*Seasonality	1	5.21E+11	5.21E+11	5.21E+11	1413.54	0.000
Trend*Error	1	1.57E+09	1.57E+09	1.57E+09	4.26	0.039
Trend*Flex-Limits	1	9.09E+10	9.09E+10	9.09E+10	246.48	0.000
Trend*Objective Weights	4	7.95E+10	7.95E+10	1.99E+10	53.92	0.000
Seasonality*Error	1	2.14E+09	2.14E+09	2.14E+09	5.81	0.016
Seasonality*Flex-Limits	1	1.25E+11	1.25E+11	1.25E+11	338.65	0.000
Seasonality*Objective Weights	4	2E+10	2E+10	5.01E+09	13.58	0.000
Error*Flex-Limits	1	2.47E+09	2.47E+09	2.47E+09	6.7	0.01
Flex-Limits*Objective Weights	4	1.27E+11	1.27E+11	3.18E+10	86.29	0.000
Baseline*Seasonality*Flex-Limits	1	4.79E+09	4.79E+09	4.79E+09	13	0.000
Trend*Seasonality*Flex-Limits	1	2.84E+10	2.84E+10	2.84E+10	77.08	0.000
Trend*Seasonality*Objective Weights	4	4.27E+09	4.27E+09	1.07E+09	2.89	0.022
Trend*Flex-Limits*Objective Weights	4	1.66E+10	1.66E+10	4.16E+09	11.28	0.000
Seasonality*Flex-Limits*Objective Weights	4	2.92E+10	2.92E+10	7.29E+09	19.77	0.000
Trend*Seasonality*Flex-Limits*Objective Weights	4	6.33E+09	6.33E+09	1.58E+09	4.29	0.002
Error	640	2.36E+11	2.36E+11	3.69E+08		
Total	799	8.13E+13				

Table 4.4: Selected ANOVA results for plan variability.

Factors	DF	Seq SS	Adj SS	Adj MS	F	P
Baseline	1	321.1	321.1	321.1	830.89	0.000
Trend	1	2115.08	2115.08	2115.08	5473.02	0.000
Seasonality	1	816.92	816.92	816.92	2113.88	0.000
Error	1	30.58	30.58	30.58	79.12	0.000
Flex-Limits	1	2325.5	2325.5	2325.5	6017.5	0.000
Objective Weights	4	11785.05	11785.05	2946.26	7623.81	0.000
Baseline*Trend	1	11.16	11.16	11.16	28.87	0.000
Baseline*Seasonality	1	12.22	12.22	12.22	31.62	0.000
Baseline*Error	1	2.45	2.45	2.45	6.33	0.012
Baseline*Flex-Limits	1	13.84	13.84	13.84	35.82	0.000
Baseline*Objective Weights	4	71.74	71.74	17.93	46.41	0.000
Trend*Seasonality	1	106.56	106.56	106.56	275.74	0.000
Trend*Error	1	13.4	13.4	13.4	34.67	0.000
Trend*Flex-Limits	1	54.2	54.2	54.2	140.24	0.000
Trend*Objective Weights	4	443.78	443.78	110.95	287.08	0.000
Seasonality*Error	1	16.86	16.86	16.86	43.63	0.000
Seasonality*Flex-Limits	1	846.95	846.95	846.95	2191.58	0.000
Seasonality*Objective Weights	4	341.25	341.25	85.31	220.76	0.000
Error*Flex-Limits	1	3.56	3.56	3.56	9.2	0.003
Error*Objective Weights	4	6.91	6.91	1.73	4.47	0.001
Flex-Limits*Objective Weights	4	216.03	216.03	54.01	139.75	0.000
Baseline*Trend*Seasonality	1	2.23	2.23	2.23	5.78	0.016
Baseline*Seasonality*Flex-Limits	1	20.04	20.04	20.04	51.86	0.000
Baseline*Seasonality*Objective Weights	4	8.93	8.93	2.23	5.78	0.000
Trend*Seasonality*Error	1	4.15	4.15	4.15	10.73	0.001
Trend*Seasonality*Flex-Limits	1	103.62	103.62	103.62	268.13	0.000
Trend*Seasonality*Objective Weights	4	54.26	54.26	13.56	35.1	0.000
Trend*Error*Flex-Limits	1	2.25	2.25	2.25	5.82	0.016
Trend*Error*Objective Weights	4	12.32	12.32	3.08	7.97	0.000
Trend*Flex-Limits*Objective Weights	4	9.69	9.69	2.42	6.27	0.000
Seasonality*Error*Flex-Limits	1	14.66	14.66	14.66	37.93	0.000
Seasonality*Error*Objective Weights	4	12.82	12.82	3.21	8.3	0.000
Seasonality*Flex-Limits*Objective Weights	4	122.21	122.21	30.55	79.06	0.000
Error	710	274.38	274.38	0.39		
Total	799	20207.06				

Tukey's test has indicated that objective weights are 0.2&0.8 and 0.3&0.7 are significantly different than the other weight combinations when cost is considered. For plan variability, 0.9&0.1 and 0.7&0.3 are the only combinations that are grouped together. The rest of the means are significantly different than each other. For each response variable, 1% incremental and 5% incremental flex-limits are also found to be significantly different (Table 4.5).

Table 4.5: Pairwise comparisons using Tukey's method (95.0% confidence level).

COST

Objective Weights	N	Mean	Grouping	Flex-Limits	N	Mean	Grouping
0.2&0.8	160	708814	A	1%	400	693239	A
0.3&0.7	160	676508	B	5%	400	635373	B
0.5&0.5	160	647737	C				
0.9&0.1	160	644290	C				
0.7&0.3	160	644180	C				

PLAN VARIABILITY

Objective Weights	N	Mean	Grouping	Flex-Limits	N	Mean	Grouping
0.9&0.1	160	11.116	A	5%	400	9.352	A
0.7&0.3	160	10.9	A	1%	400	5.942	B
0.5&0.5	160	9.684	B				
0.3&0.7	160	5.334	C				
0.2&0.8	160	1.202	D				

* Means that do not share a letter are significantly different.

Figures 4.4 and 4.5 present the main effects of the independent variables for each response variable. The line between the experimental levels reflects the statistical significance of the factors; when the line is less horizontal, different levels of the factor affect the response variable differently. In this case, cost response is impacted by baseline, trend and seasonality the most significantly. On the other hand, trend, flex-limits and objective weights are the most influential factors for plan variability. Error is the least influential effect in both categories. The impact of the flex-limits is also larger for plan variability.

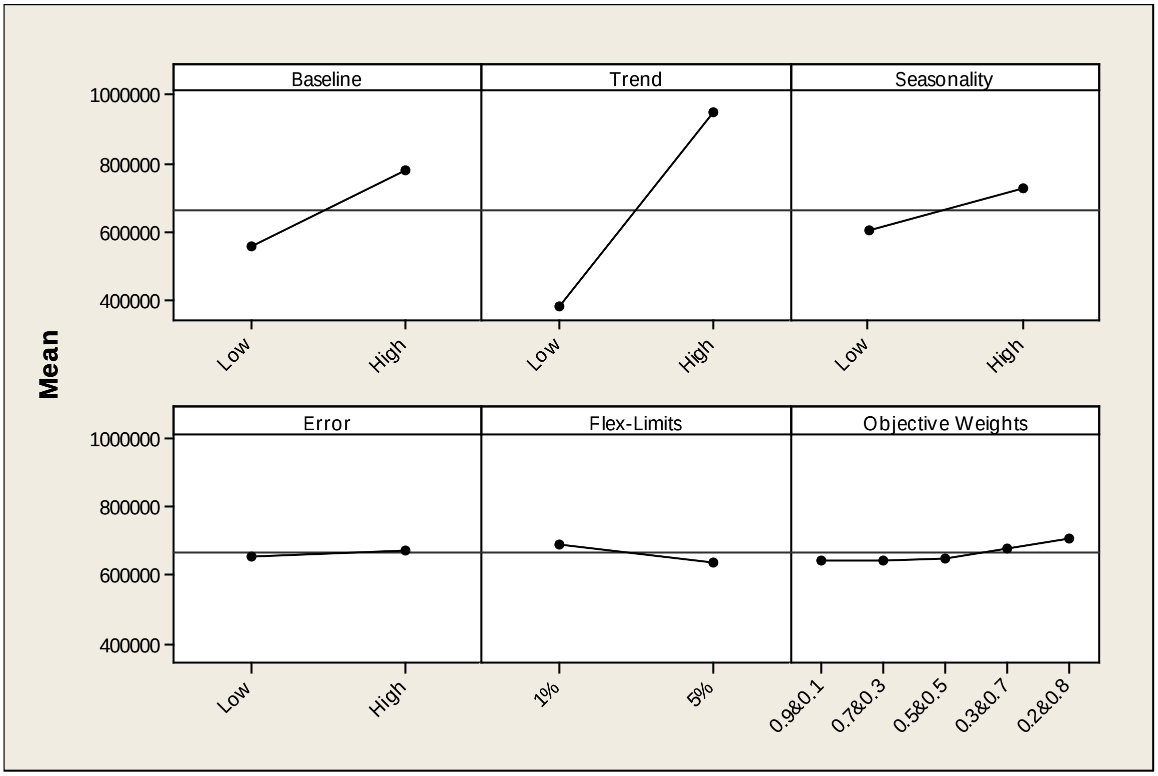


Figure 4.4: Main effects plot for cost.

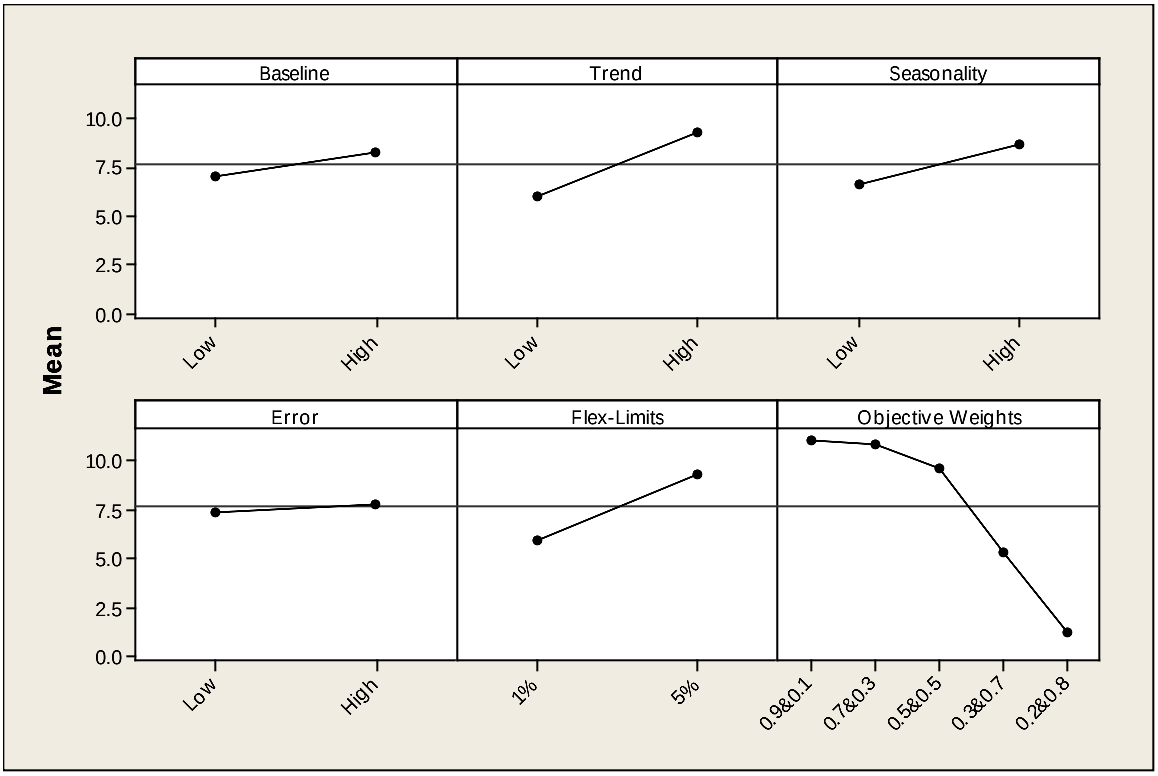


Figure 4.5: Main effects plot for plan variability.

4.7 Summary and Conclusions

Supply chain systems are required to be responsive to market needs while maintaining high degrees of cost efficiency and customer service. However, the increase in production variability due to increased responsiveness is costly and it is difficult to determine how much emphasis should be placed on production plan stability against cost. In this paper, we focus on this trade-off and present a mixed-integer linear programming (MILP) model with compromise programming (CP) approach to solve a rolling horizon aggregate production planning (APP) problem. The conflicting objectives that are considered: (1) minimization of total realized cost on the planning horizon, (2) minimization of production variability. The developed bi-objective MILP formulation in conjunction with flexibility requirements profile (FRP) analyzes the trade-off between two conflicting objectives namely, cost and plan variability.

Frozen horizon and other solution approaches attempt to provide insights on how to mitigate nervousness but most of the existing studies do not consider the flexibility aspect in production planning research. Instead of 0% flexibility in the case of a frozen period or 100% flexibility in the case of plan to order, the proposed model allows the trade-off of different levels of flexibility between conflicting planning objectives. The overall results show that the proposed FRP-based bi-objective aggregate planning is an effective way to analyze the trade-off between cost and stability objectives simultaneously and reduce the nervousness in organization by taking the plan stability into consideration. The comparisons among three approaches; the single objective FRP, the stand alone bi-objective, and the bi-objective with FRP have also revealed that enforcement of FRP constraints has further positive impacts on plan stability. The ANOVA results further reveal that all system parameters and operating factors have significant effects on both cost and plan stability. Most of the interactions among these demand and planning parameters are also significant. However, the impacts of these parameters and their interactions on the response variables are varying. Trend, seasonality, flex-limits, and objective weights have the most impact on production plan stability, whereas the most influential parameters for total cost are found to be baseline, trend and seasonality.

The proposed bi-objective formulation considers a wide range of solutions as objectives are traded-off against each other, and provides a great deal of flexibility to the decision makers. While the trade-off between these objectives is clearly significant, it should be noted that from the mathematical point of view every solution in the Pareto optimal set is equally acceptable, and the decision makers should be able to pick a point between different solutions using their insights, priorities and subjective judgments. Our method allows the decision maker to select from a set of mathematically feasible solutions.

CHAPTER 5: EFFECT OF PRODUCTION PLAN STABILITY ON LEAN SYSTEM OPERATIONS

5.1 Introduction

Chapter 5 will discuss stability in planning from the lean thinking perspective and investigate its role in eliminating non-value added activities such as overproduction, unnecessary inventory and over/under-utilization of resources through the utilization of FRP. FRP successfully integrates external market constraint and internal capacity constraint into the planning process; not only to establish stability in planning but also to identify the constraint that is expected to be the bottleneck in the future. In this chapter, we will demonstrate how stability in planning may help lean manufacturing and eliminate waste to establish leaner systems. We will specifically investigate how stability can contribute to leanness of a manufacturing operation and assess its sensitivity under different manufacturing conditions and environments.

5.2 Lean Production Principles

Lean methodology, pioneered by Toyota Motor Corporation, embraces the philosophy of eliminating all non-value added items and activities in the production operations as well as utilizing the employees' capabilities to its fullest extent (Monden 1998). The production system of Toyota led the development of key critical concepts in lean production such as *Value Stream Mapping, 5S, and Kanban- pull systems*, which are designed to increase the efficiency of systems and eliminate the *muda* (waste).

Leanness in production can be defined as creating production processes that deliver high quality products while using fewer resources and less time. In lean philosophy, any activity in a process, which does not add value to the customer, is called waste, which is classified into 8 categories (Table 5.1) (Rother and Shook, 1999).

Table 5.1: Eight Types of Waste: DOWNTIME (Rother and Shook, 1999).

Types of Waste	**Definition**
Defects	*Products or materials that contains errors or lacks the desired customer value*
Over-production	*Producing more than customer demand, a system employs push rather than pull*
Waiting	*Waiting or idle time caused by people, equipment or capacity related issues*
Non-utilized Resources/Talent	*Not, or under, utilization of resources/labor*
Transportation	*Unnecessary movement of product, materials or information*
Inventory	*Excess products/ materials on hand that are not needed by the customers or employees*
Motion	*Unnecessary movement of labor*
Excess Processing	*Extra work and effort that are not valued by the customer*

Lean thinking allows companies to build a value chain where the delivery of products to your customers follows a link in a chain while those 8 waste categories are being eliminated. This philosophy eventually created the five principles of lean thinking (Womack and Jones, 1996). One of these five main principles is to produce according to customer demand (Lean Enterprise Institute). According to this view, customer demand is the main driver in a production system and production should occur when there is demand from a downstream process. Customer-driven (pull) systems are highly preferred due to higher turnarounds in production levels and reductions in inventory levels. However, in reality most production planning systems operate under uncertainty. Customer demand may not be easily predictable as well as may possess high degrees of variability. Lean touches upon the plan stability issue mainly through the practice of

Heijunka, which intends to absorb fluctuations in customer demand by producing small batches of different types of products instead of large ones (Rother and Shook, 1999). Although lean philosophy utilizes stability through leveling techniques such as Heijunka, the studies concerning the relationship between stability in planning and lean systems could use further investigation. In this chapter, we focus on a sample set of the wastes listed in Table 5.1, namely inventory, overproduction, and non-utilized resources/talent and present how FRP-based production planning models can effectively eliminate them and contribute to the value chain. We utilize the mathematical optimization models presented in Chapter 3 in order analyze their performance in terms of leanness through a numerical study.

5.3 Numerical Study

In order to reduce plan variability, traditional aggregate planning systems apply a frozen horizon. A frozen horizon does not allow any changes within the frozen period whereas changes outside the frozen horizon are 100% flexible. Note that a slow reaction (lead) time creates high variations in the inventory, which in turn results in stock-outs and overstocks [6]. A main goal of FRP is to provide flexibility to respond quickly to true changes in the demand level, while preventing excessive changes in production plans.

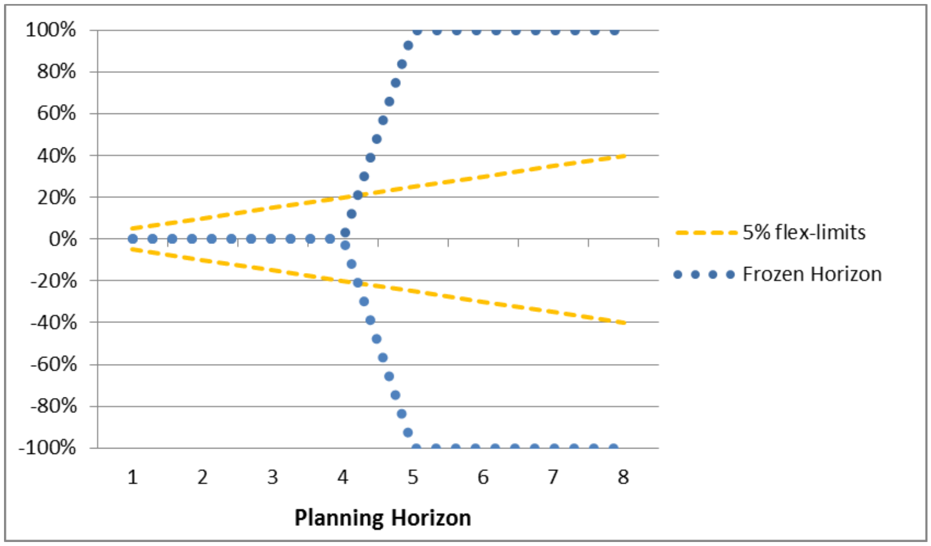
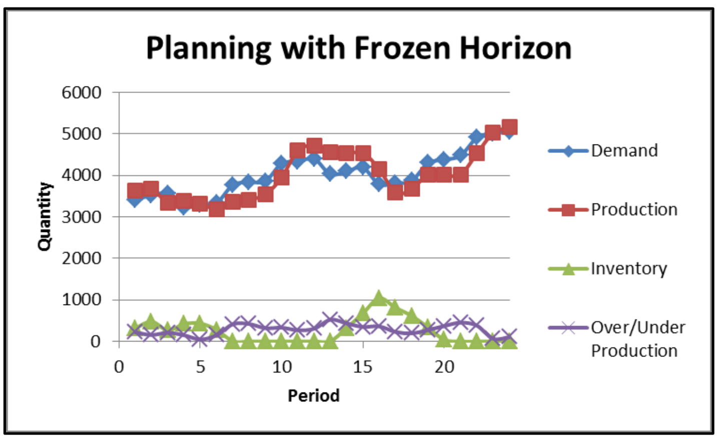


Figure 5.1: Illustrations of flex-limits and frozen horizon in the planning horizon.

Table 5.2: Demand cases.

Factors	Low Variance	High Variance
Baseline	1000 units	2000 units
Trend	50	100
Seasonality	+/- 0.1	+/- 0.3
Magnitude of Error	50	150

We provide an illustrative example that compares aggregate production planning utilizing FRP to a traditional frozen period approach under two demand cases. Considering customer demands that vary over time with a high degree of variability, we assume that the demand series are represented by a multiplicative seasonal model. Two demand scenarios, which are classified as low and high variance, are generated using the equation in 3.10. In this study we consider four measures in accordance with lean waste considerations; average production levels, average inventory levels, average over/under production levels, and capacity utilization. Figures 5.2 and 5.3 show the average demand, production, inventory, over/under production levels over the 24 period time frame for two approaches; APP with frozen horizon and FRP-based APP with 5% Incremental flex-limits. We observe that, for both demand cases, planning with flex-limits displays a better performance than the frozen horizon in all three measures. When the demand variance is low (Figure 5.2), the inventory and over production levels of the FRP approach are 10 and 24 units on average, respectively, whereas the frozen horizon approach yield 254 and 283, respectively. When the demand variance is high (Figure 5.3), the frozen horizon shows considerably worse performances displaying high degrees of inventory accumulation, 3679 units on average, between periods 14 and 20. On the other hand, FRP carries relatively lower inventory, 983 units on average, during the same period. The difference of overall inventories between frozen horizon and FRP are also significant as the averages inventories over the 24 periods are 1410 and 494 units, respectively.



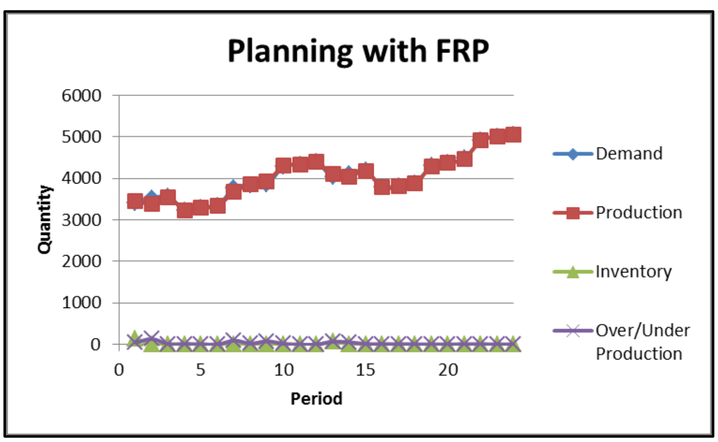
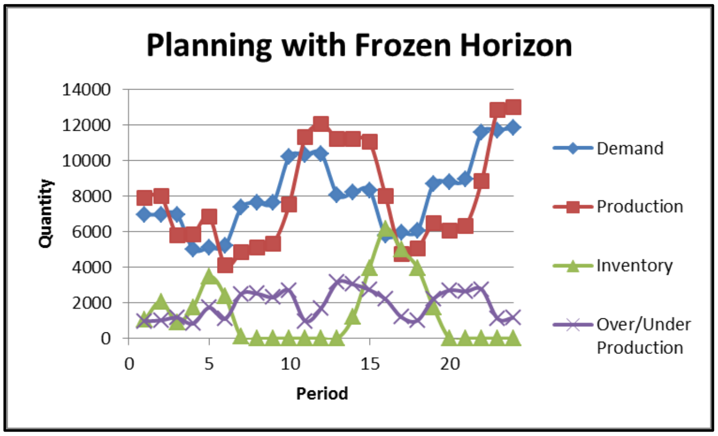


Figure 5.2: Comparison of performance measures for the low demand variance scenario.



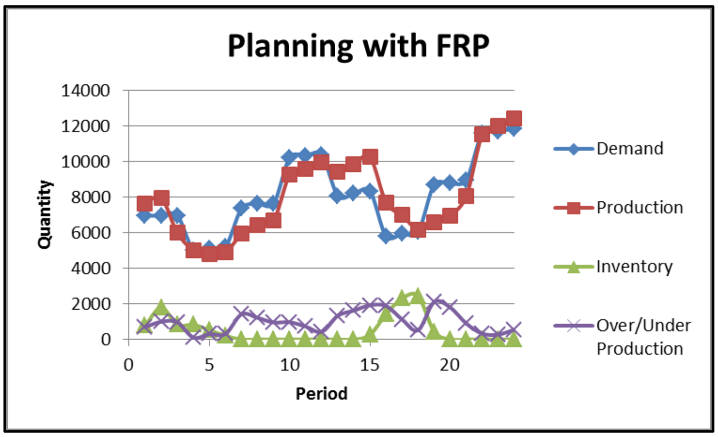
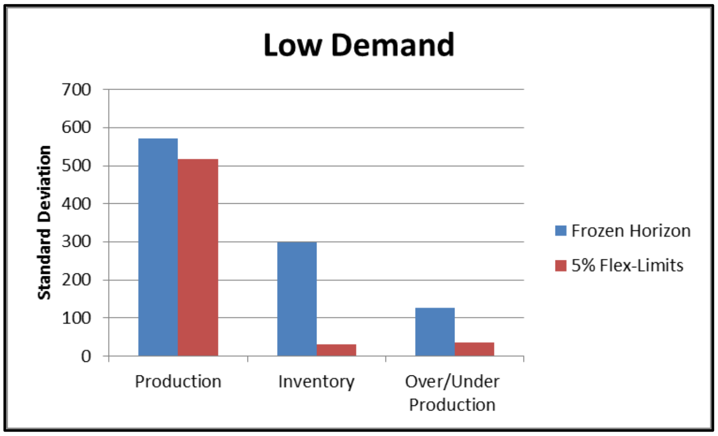


Figure 5.3: Comparison of performance measures for the high demand variance scenario.

Figure 5.4 displays the standard deviations of the performance measures for low and high demand variance scenarios, respectively. FRP approach produces considerably lower variation in comparison to frozen horizon, thus, makes us conclude that the production and inventory plans using FRP are much smoother than those made by the frozen period approach. The difference between two approaches is even more significant when the demand possesses higher variability. The capacity is well utilized for both approaches, but flex-limits return slightly better results by having 360 units of unused production capacity, whereas frozen horizon had 376 units of unused capacity in total (Figure 5.5).



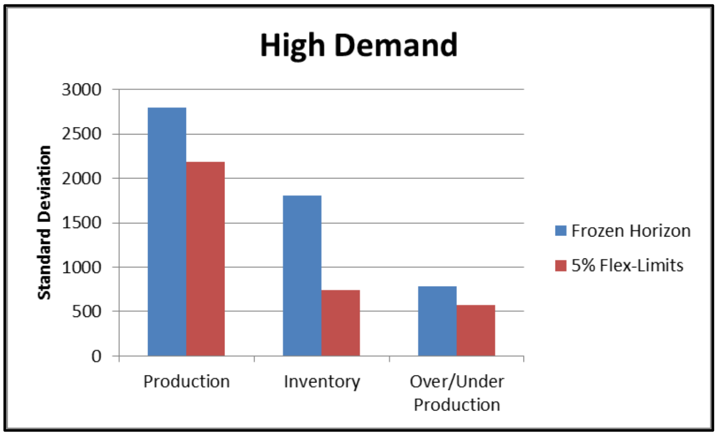


Figure 5.4: Standard deviations of leanness measures under low demand variance vs. high demand variance.

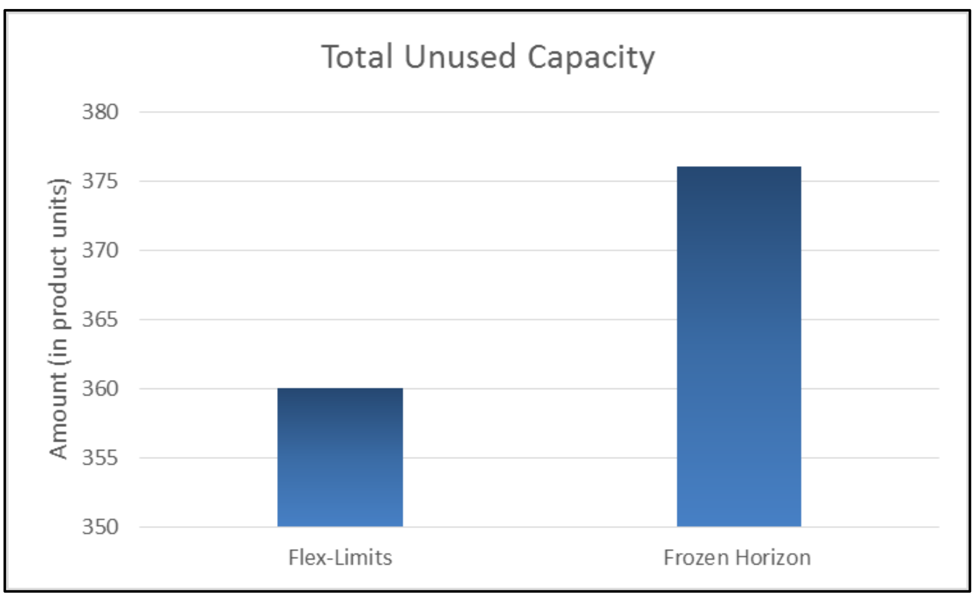


Figure 5.5: Comparison of flex-limits vs. frozen horizon in total unused capacity.

5.4 Managerial Insights

Nervousness has often been recognized as a major problem in the production environment, but many firms do not have not clear understanding of its effects on a greater scale. It is believed that a robust production plans that emphasizes stability will enhance not only organizations' performance but also the overall supply chain's performance due to a tighter collaboration (Van Landeghem and Vanmaele, 2002). As early support systems such as *manufacturing resource planning* (MRP) had evolved into more advanced systems such as *enterprise resource planning* (ERP), the importance of planning and the efficient utilization of internal resources became more important than ever before, which makes supply chain efficiency is vitally important for manufacturing firms (Olhager and Selldin, 2004). In order to create leaner supply chains, the efforts to reduce nervousness should be extended beyond the internal organization and involve other players such as suppliers and customers. All of these players should work jointly against uncertainties that restrict operational performance. This enhanced collaboration and reduction in plan variability should also eliminate the *bullwhip effect*.

5.5 Summary and Conclusions

Many companies pursue the lean thinking to improve the efficiency of their processes. The main objective of lean production is to eliminate non-value added items in a production process by minimizing variability related to demand, supply, lead times and processing times. In this chapter, we investigate the effect of production plan stability on lean systems. In specific, we compare the performance of FRP-embedded models in eliminating inventory and over/underproduction related wastes to those of a traditional aggregate planning model with frozen horizon under two separate demand scenarios. The

FRP-based aggregate planning and the enforced flex-limits have given favorable results in reducing average inventory and over/underproduction levels while providing smoothing effect on production levels. The results have validated that incorporating FRP as a part of the process planning would increase stability as well as contribute to leanness of a manufacturing operation. As a future research direction, different industry settings would be helpful to understand the sensitivity of the effect of plan stability. The components of the demand generation model can be altered to generate various demand patterns and extent of uncertainties to assess the relationship between the stability and lean systems. We also believe that the production system considered here and the corresponding mathematical formulations can be expanded to consider other lean waste items. Chapter 6 summarizes our findings in this dissertation and discusses related future research directions.

CHAPTER 6: CONCLUSIONS AND FUTURE DIRECTIONS

6.1 Conclusions

Managing supply chain operations has become increasingly difficult due to highly volatile and fiercely competitive markets. Customer needs are diverse, which cause shorter product life cycles and demands that are difficult to predict. Many companies have embodied new strategies that exploit flexibility and responsiveness to stay competitive in the marketplace. Although *Make to order* (build to order) strategy provides the necessary flexibility to accommodate the market demand it is not economically feasible especially in highly varied product portfolios or products that have short lifecycles.

In this dissertation, we discuss the application of flexibility requirements profile (FRP) in aggregate production planning problems. While FRP concept has been emphasized in the literature, mathematical optimization models for FRP-based production planning did not exist. As opposed to existing literature, which has shown limited interest at minimizing variability in production plans due to its high cost requirements, our findings have shown that establishing plan stability will not necessarily jeopardize the economic interests of manufacturing companies and can be a valuable tool against changing demand and market conditions.

The results indicate that FRP-embedded mathematical optimization models may help the organizations to establish a certain degree of stability in their production plans without necessarily sacrificing the economic interests.

Flexibility bounds increase the responsiveness to demand fluctuations, provide manufacturers and suppliers a better visibility in forecasting, and have a smoothing effect on production and inventory levels. Next, we extend the proposed optimization models to consider multiple conflicting criteria and to analyze the tradeoff between cost and plan stability under the presence of FRP. Specifically, we develop a bi-objective mixed-integer linear programming model using a compromise programming approach. Numerical experimentations reveal the trade-off between conflicting objectives and give the optimal cost and variability levels under changing weights. Our research also includes the ANOVA test of a selected set of planning parameters that would provide assistance to the decision maker in identifying parameters that are significantly impacting the production system and developing robust planning procedures and policies. Chapter 5 examines how planning stability can facilitate lean systems. Specifically, we provide insight about the relationship between stability in planning and the leanness of operations, and present a numerical study to assess the efficacy of FRP against the uncertainties in demand combined with rolling horizon planning.

6.2 Future Directions

The findings suggest several opportunities for further research. The proposed approach is generic in nature and can be considered for many types of APP problems. Especially industries with shorter product lifecycles and lead times and for those exposed to heavy demand fluctuations would thoroughly benefit from the application of flexibility bounds. In addition, the analysis and results should not only provide directions on better production planning policies and strategies but also can be extended to other planning problems such as distribution and transportation planning and to planning problems in service industries. As an extension of the analyses presented in Chapter 4, different multi-objective optimization approaches can be utilized to solve these APP problems and the results can be compared to those of compromise programming. This dissertation uses multiplicative seasonal model as the underlying demand model but these demand series may not be suitable for certain industries, hence investigating different demand patterns and forecasting techniques and comparing the responsiveness of FRP under those models would be a fruitful discussion topic.

The purpose of this research is to be applicable to a wide array of planning problems. Further research can investigate applications concerning periodical resource planning in the service industry. Plan stability can be incorporated as an additional objective to deal with fluctuations related to the uncertain service demand. For example, an application in healthcare can search for the optimal patient mix while considering flexibility in resource planning; instead of a 0% flexibility in the case of a frozen period or a 100% flexibility in the case of plan to order, the proposed model will enable the trade-off of different grades of flexibility with the traditional objectives of cost and service levels.

The flex-limits in this study were assumed to be increasing incrementally and have fixed magnitudes. However, in real-world production environments, the magnitude of flex limits may need to be altered depending on circumstances, and a study that utilizes flex-limits of varying magnitudes could be a useful addition to the literature.

As stated earlier, this research only accounts a single product and future efforts may concentrate on multiple products, especially on the cases, where demand correlation exist among them. A final possible research direction is to focus on models that could result in non-linear and large-scale optimization problems and to develop the appropriate solution algorithms to these problems.

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APPENDIX A: PSEUDO CODE FOR THE SIMULATION OF FRP-EMBEDDED APP

1: Realize the current demand and demand forecasts.

2: Compute the net production requirement via Equation 3.1

3: while $i < N$ do

4: if $P[i] - D[i] + I[i-1] - S[i-1] \geq 0$ then

5: $I[i] = P[i] - D[i] + I[i-1] - S[i-1]$ and $S[i] = 0$

6: else

7: $I[i] = 0$ and $S[i] = -(P[i] - D[i] + I[i-1] - S[i-1])$

8: end if

9: if $\text{Regular Production Capacity} * W[i-1] \geq P[i]$ then

10: $La[i] = \text{ floor }\left(\begin{array}{l} ((\text{Regular Production Capacity}*W[i\text{-}1]) - P[i]) / \\ (\text{Regular Production Capacity+ Overtime Production Capacity}) \end{array} \right)$

and $H[i] = 0$

11: else

12: if

$((\text{Regular Production Capacity+ Overtime Production Capacity}) * W[i-1]) \geq P[i]$

then

13: $O[i] = ((P[i] - m^R * W[i-1]) / m^O)$, Set $H[i] = 0$ and $La[i] = 0$

14: else

15:

$$H[i] = ceil\left(\begin{array}{l} P[i] - \left(\left(\begin{array}{l} \text{Regular Production Capacity+ Overtime} \\ \text{Production Capacity} \end{array} \right) * W[i\text{-}1] \right) \\ / \ (\text{Regular Production Capacity+ Overtime Production Capacity}) \end{array} \right)$$

and $La[i] = 0$

16: end if

17: Set $W[i] = W[i-1] + H[i] - La[i]$

18: end while

19: while $i = N$ do

20: $P[N] = \max\{-\infty, \min(+\infty, \operatorname{Re}q[N])\}$

21: Repeat steps 4-17.

22: end while

23: Set $W[input] = W[0]$ and $I[input] = I[0] - S[0]$

24: for $i = 0$ to $N-2$ do

25: $LB[i] = \max(LB[i+1], P[i+1]*(1-F[i]))$ and

$UB[i] = \min(UB[i+1], P[i+1]*(1+F[i]))$

26: end for

27: Set $LB[N-1] = P[N]*(1-F[N-1])$ and $UB[N-1] = P[N]*(1+F[N-1])$

28: Return performance measures.

APPENDIX B: AMPL .MOD AND .RUN FILES

MODEL FILE

Parameters

param cw; # the labor cost of a regular worker at regular time ($/ man-hour)

param co; # overtime production cost per hour

param ch; # hiring cost per worker

param cl; # layoff cost per worker

param cp; # material cost per unit product

param h; # unit inventory holding cost

param mr; # number of units produced by a regular employee per hour

param N ; # time period for which planning funnel is maintained $(N \leq T)$

param s; # target safety stock

param sc; # shortage cost

param th; # total weekly working hours for each worker

param F {i in 0..N} >=0, <=1; # i-step ahead flex limit

param D {i in 0..N} ; # demand at time t $(i = 0,1,2,...N)$

param Winput >=0 integer;

param Iinput >=0 integer;

param LowB {i in 0..N-1} >=0; # i-step ahead lower bound on planned production at time t $(i = 0,1,2,...N-1)$

param UpB {i in 0..N-1} >=0; # i-step ahead upper bound on planned production at time t $(i = 0,1,2,...N-1)$

param ph; # length of planning horizon

param ei; # demanded ending inventory

param hd; #end of historical (training) data

Variables

var W {i in 0..N} >=0 integer ; # i-step ahead workforce size at time t $(i = 0,1,2,...N)$

var H {i in 0..N} >=0 integer ; # i-step ahead number of employees hired at time t $(i = 0,1,2,...N)$

var La {i in 0..N} >=0 integer ; # i-step ahead number of employees laid off at time t $\left(i = 0,1,2,\ldots N\right)$

var I {i in 0..N} >=0 ; # i-step ahead inventory level at time t $\left(i = 0,1,2,\ldots N\right)$

var P {i in 0..N} >=0 ; # i-step ahead production level at time t $\left(i = 0,1,2,\ldots N\right)$

var O {i in 0..N} >=0; # i-step ahead overtime hours at time t $\left(i = 0,1,2,\ldots N\right)$

var S {i in 0..N} >=0 ; # i-step ahead shortage units at time t $\left(i = 0,1,2,\ldots N\right)$

Objective Function
minimize Cost: sum{i in 0..N} (cw*th*W[i] + ch*H[i] + cl*La[i] + h*I[i] + cp* P[i]+ co*O[i]+ sc*S[i]);

# Constraints #
subject to workforceinitial: W[0]=Winput+H[0]-La[0];

subject to workforce {i in 1..N}: W[i]= W[i-1]+H[i]-La[i];

subject to inventoryinitial: P[0]= D[0]+I[0]-Iinput-S[0];

subject to productioninitial: P[0] <= mr*th*W[0] + mr* O[0];

subject to inventory {i in 1..N} : P[i]= D[i]+ I[i]-S[i]-I[i-1]+ S[i-1];

subject to capacity {i in 1..N}: P[i] <= mr*th*W[i] + mr* O[i];

subject to ProductionBounds1 {i in 0..N-1}: LowB[i] <= P[i];

subject to ProductionBounds2 {i in 0..N-1}: P[i] <= UpB[i];

subject to overtimehours {i in 0..N}: O[i]<=W[i]*th*0.1;

subject to endinginventory: I[N]= ei;

subject to noshortage: S[N]= 0;

MODEL FILE

```
### RUN FILE ###
reset;
option solver cplexamp; # calling cplex solver
# LOAD DEMAND AND FORECAST GENERATION FILES #
model demand.mod;
data demand.dat;
# LOAD MODEL AND DATA FILES #
model modelfile.mod;
data datafile.dat;
# START EXPERIMENTING WITH DIFFERENT DEMAND SCENARIOS #
for {n in 1..L, j in 1..L, k in 1..L, e in 1..L, r in 1..R}
{
    let Winput:=round(demand[hd,n,j,k,e,r]/(mr*th));   #set initial workforce
    let Iinput:=100;    # set initial inventory
    for {i in 0..N-1}
    {
        let LowB[i]:= fore[1,1+i,n,j,k,e,r]*(1-F[i]) ;   #set initial lower bound
        let UpB[i]:= fore[1,1+i,n,j,k,e,r]*(1+F[i]) ;    #set initial upper bound
    }
    # LOAD PLANNING HORIZON #
    for {t in 1..T}
    {
        let D[0]:=demand[hd+t,n,j,k,e,r];    #assign the realized demand value
            for {i in 1..N}
            {
            let D[i]:=fore[t,i,n,j,k,e,r];   # assign forecast values for the next N
            period
            }
    solve;
```

```
        # SAVE THE CURRENT (REALIZED COSTS) #
        let obj_function[t]:=Cost;
        let currentcost[t]:= (cw*th*W[0] + co*O[0]+ ch*H[0] + cl*La[0] + h*I[0] + cp*
        P[0]+ sc*S[0]);
        let productioncost[t]:=cp*P[0];
        let workforcecost[t]:= cw*th*W[0];
        let hiringcost[t]:= ch*H[0];
        let layoffcost[t]:= cl*La[0];
        let inventorycost[t]:= h*I[0];
        let shortagecost[t]:= sc*S[0];
        let overtimecost[t]:=co*O[0];
        if (t==1) then
                {let delta := 0;}
                else
                {let delta := delta + sum{i in 1..N}(abs(pprev[i]-P[i-1]));}
        for {i in 1..N}
        {
                let pprev[i]:=P[i];
        }
        let Winput:= W[0]; #feeding input to next loop
        let Iinput:= I[0]-S[0]; #feeding input to next loop
        # UPDATING BOUNDS #
        for {i in 0..N-2}
        {
                let LowB[i]:= max (LowB[i+1], P[i+1]*(1-F[i])) ;
                let UpB[i]:= min (UpB[i+1], P[i+1]*(1+F[i])) ;
        }
        let LowB[N-1]:= P[N]*(1-F[N-1]);
        let UpB[N-1]:= P[N]*(1+F[N-1]);
}
```

```
# RESET COST OUTPUT #
let finalcost[n,j,k,e,r]:= 0;
let finalproductioncost[n,j,k,e,r]:=0;
let finalworkforcecost[n,j,k,e,r]:=0;
let finalhiringcost[n,j,k,e,r]:=0;
let finallayoffcost[n,j,k,e,r]:=0;
let finalinventorycost[n,j,k,e,r]:=0;
let finalshortagecost[n,j,k,e,r]:=0;
let finalovertimecost[n,j,k,e,r]:=0;
# FINALIZE COST OUTPUT #
for {t in 1..T}
{
let finalcost[n,j,k,e,r]:=finalcost[n,j,k,e,r] + currentcost[t];
let finalproductioncost[n,j,k,e,r]:=
finalproductioncost[n,j,k,e,r]+productioncost[t];
let finalworkforcecost[n,j,k,e,r]:= finalworkforcecost[n,j,k,e,r]+workforcecost[t];
let finalhiringcost[n,j,k,e,r]:= finalhiringcost[n,j,k,e,r]+ hiringcost[t];
let finallayoffcost[n,j,k,e,r]:= finallayoffcost[n,j,k,e,r]+layoffcost[t];
let finalinventorycost[n,j,k,e,r]:= finalinventorycost[n,j,k,e,r]+inventorycost[t];
let finalshortagecost[n,j,k,e,r]:= finalshortagecost[n,j,k,e,r]+shortagecost[t];
let finalovertimecost[n,j,k,e,r]:= finalovertimecost[n,j,k,e,r]+overtimecost[t];
}
#COMPUTING FINAL AVERAGE PRODUCTION STABILITY #
let finaldelta [n,j,k,e,r]:= delta/T*N;
}
### END OF RUN FILE ###
```

BI-OBJECTIVE MODEL FILE

Objective Functions
minimize CostObj: sum{i in 0..N} (cw*th*W[i] + ch*H[i] + cl*La[i] + h*I[i] + cp* P[i]+ co*O[i]+ sc*S[i]);

minimize StabObj: sum{i in 0..N} (cw*th*W[i] + ch*H[i] + cl*La[i] + h*I[i] + cp* P[i]+ co*O[i]+ sc*S[i]));

minimize Objective1 {t in 1..1}: ((cweight* (sum{i in 0..N} (cw*th*W[i] + ch*H[i] + cl*La[i] + h*I[i] + cp* P[i]+ co*O[i]+ sc*S[i])-CB[t]))/(CW[t]-CB[t])); _# Bi-objective function for the initial period where the plan stability component is omitted_

minimize Objective2: ((cweight* (sum{i in 0..N} (cw*th*W[i] + ch*H[i] + cl*La[i] + h*I[i] + cp* P[i]+ co*O[i]+ sc*S[i])-CostBest))/(CostWorst-CostBest))+ ((sweight*(sum {i in 1..N} (PA[i])-StabilityBest))/(StabilityWorst-StabilityBest)); _# Bi-Objective function (excluding initial period)_

# Constraints #
subject to workforceinitial: W[0]=Winput+H[0]-La[0];

subject to workforce {i in 1..N}: W[i]= W[i-1]+H[i]-La[i];

subject to inventoryinitial: P[0]= D[0]+I[0]-Iinput-S[0];

subject to productioninitial: P[0] <= mr*th*W[0]+ mr*O[0];

subject to inventory {i in 1..N} : P[i]= D[i]+ I[i]-S[i]-I[i-1]+ S[i-1];

subject to capacity {i in 1..N}: P[i] <= mr*th*W[i]+mr*O[i];

subject to overtimehours {i in 0..N}: O[i]<=W[i]*th*0.1;

subject to ProductionBounds1 {i in 0..N-1}: LowB[i] <= P[i];

subject to ProductionBounds2 {i in 0..N-1}: P[i] <= UpB[i];

subject to endinginventory: I[N]= 100;

subject to noshortage: S[N]=0;

subject to stabilityconstraint {i in 1..N}:pprev[i]=P[i-1]; _# additional constraint for stability minimization_

subject to absolutevalue1 {i in 1..N}: PA[i]>= (pprev[i]-P[i-1]); _# Modeling absolute values_

subject to absolutevalue2 {i in 1..N}: PA[i]>=-(pprev[i]-P[i-1]);

subject to WorstCostconstraint: sum{i in 0..N} (cw*th*W[i] + ch*H[i] + cl*La[i] + h*I[i] + cp* P[i]+ co*O[i]+ sc*S[i]) <= CostWorst; _#For Bi-objective Formulation_

END OF BI-OBJECTIVE MODEL FILE

```
### BI-OBJECTIVE RUN FILE ###

option presolve 0;

option cplex_options;

model modelfileindustry.mod;

data industry_data.dat;

param EVSP; #evaluation time frame starting period

param EVFP; #evaluation time frame ending period

# FINAL TABLE DECLARATIONS #

table output1 {w in 1..W} OUT "ODBC" "biobjectivetextile.xlsx"
("Final_CostandDelta"&w):

{n in 1..L,j in 1..L, k in 1..L, e in 1..L, r in 1..R}->[n~Baseline,j~Trend,k~Seasonality,
e~Error,r~Replications],finalcost,finaldelta;

table output2 {w in 1..W} OUT "ODBC" "biobjectivetextile.xlsx" ("Final_Costs"&w):

{n in 1..L,j in 1..L, k in 1..L, e in 1..L, r in 1..R}->[n~Baseline,j~Trend,k~Seasonality,
e~Error,r~Replications],finalproductioncost,finalworkforcecost,
finalhiringcost,finallayoffcost, finalinventorycost, #finalshortagecost,finalovertimecost;

table output3 {w in 1..W} OUT "ODBC" "biobjectivetextile.xlsx"
("CostandDelta_perperiod"&w):

{n in 1..L,j in 1..L, k in 1..L, e in 1..L, r in 1..R, t in EVSP..EVFP}-
>[n~Baseline,j~Trend,k~Seasonality, e~Error,r~Replications,
t~TimePeriod],costperperiod,deltaperperiod;

table output4 {w in 1..W} OUT "ODBC" "paretodiagrams.xlsx" ("Pareto"&w):

{n in 1..L,j in 1..L, k in 1..L, e in 1..L, r in 1..R, t in EVSP..EVFP }-
>[n~Baseline,j~Trend,k~Seasonality, e~Error,r~Replications, t~TimePeriod],obj1,obj2;

# PROBLEM DEFINITONS #

problem CostMinimization: O,I,S,P,W,H,La,CostObj,workforceinitial, workforce,
inventoryinitial, productioninitial, inventory, capacity, overtimehours,
ProductionBounds1, ProductionBounds2, endinginventory, noshortage;

problem StabilityMinimization : O,I,S,P,W,H,La,StabObj,workforceinitial, workforce,
inventoryinitial, productioninitial, inventory, capacity, overtimehours,
ProductionBounds1, ProductionBounds2, endinginventory, noshortage,
stabilityconstraint;
```

```
problem BiObjective1: O,I,S,P,W,H,La,Objective1,workforceinitial, workforce,
inventoryinitial, productioninitial, inventory, capacity, overtimehours,
ProductionBounds1, ProductionBounds2, endinginventory, noshortage;

problem BiObjective2: O,I,S,P,W,H,La,PA,Objective2,workforceinitial, workforce,
inventoryinitial, productioninitial, inventory, capacity, overtimehours,
ProductionBounds1, ProductionBounds2, endinginventory,
noshortage,absolutevalue1,absolutevalue2, a1;

# MAIN MODEL #

for {w in 1..W} {

        for {n in 1..L, j in 1..L, k in 1..L, e in 1..L, r in 1..R} {

        let Winput:=round(demand[48,n,j,k,e,r]/(mr*th)); # set initial workforce

        let Iinput:=100; #set initial inventory

        for {i in 0..N-1} {

        let LowB[i]:= round(fore[1,1+i,n,j,k,e,r]*(1-F[i])) ;   #set initial bounds

        let UpB[i]:= round(fore[1,1+i,n,j,k,e,r]*(1+F[i])) ;}

        #EVALUATION HORIZON #

        for {t in 1..24} {

                let D[0]:=round(demand[48+t,n,j,k,e,r]); #set demand values

                for {i in 1..8} {

                let D[i]:=round(fore[t,i,n,j,k,e,r]);} # set forecast values

                if (t==1) then {

                        for {i in 1..N} {

                                let pprev[i]:=0;

                                        }

                        solve CostMinimization;

                        let {i in 1..N} dPA[i]:=(abs(pprev[i]-P[i-1]));

                        let delta:=0;  #Final Delta Initialization

                        let CB[t]:= CostObj;

                        let CW[t]:=CB[t]*1.5;

                        # BI- OBJECTIVE PROBLEM 1 #

                        let cweight:=1;
```

```
        let sweight:=0;
        option cplex_options "absmipgap=0 mipgap=0 mipdisplay=2";
        solve BiObjective1;
        display BiObjective1.absmipgap;
        let currentcost[t]:= (cw*th*W[0] + co*O[0]+ ch*H[0] + cl*La[0] +
        h*I[0] + cp* P[0]+ sc*S[0]);
        let productioncost[t]:=cp*P[0];
        let workforcecost[t]:= cw*th*W[0];
        let hiringcost[t]:= ch*H[0];
        let layoffcost[t]:= cl*La[0];
        let inventorycost[t]:= h*I[0];
        let shortagecost[t]:= sc*S[0];
        let overtimecost[t]:=co*O[0];
        for {i in 1..N}
                {
                let pprev[i]:=P[i];
                }
        let Winput:= W[0]; #feeding input to next loop
        let Iinput:= I[0]-S[0]; #feeding input to next loop
        for {i in 0..N-2}
                {
                let LowB[i]:= max (LowB[i+1], P[i+1]*(1-F[i])) ;
                let UpB[i]:= min (UpB[i+1], P[i+1]*(1+F[i])) ;
                }
        let LowB[N-1]:= P[N]*(1-F[N-1]);
        let UpB[N-1]:= P[N]*(1+F[N-1]);
        }

if (t>=2) then {
        option presolve 0;
```

option cplex_options;

option cplex_options "absmipgap=0 mipgap=0 mipdisplay=2";

solve CostMinimization; # COST MINIMIZATION PROBLEM

let {i in 1..N} dPA[i]:=(abs(pprev[i]-P[i-1])); #Compute plan variability

let CB[t]:=CostObj; # Set the Best Cost

let SW[t]:= sum{i in 1..N}(abs(pprev[i]-P[i-1])); #Set the Worst Stability

VARIABILITY MINIMIZATION PROBLEM

display _varname, _var.astatus;

display _conname, _con.astatus;

option presolve 0;

option cplex_options;

solve StabilityMinimization;

BI- OBJECTIVE PROBLEM 2

let cweight:=weight[w];

let sweight:=1-cweight;

let CostBest:=CB[t];

let CostWorst:=CW[t];

let StabilityBest:=0;

let StabilityWorst:=SW[t];

option presolve 0;

if CostBest>=CostWorst then break;

option cplex_options;

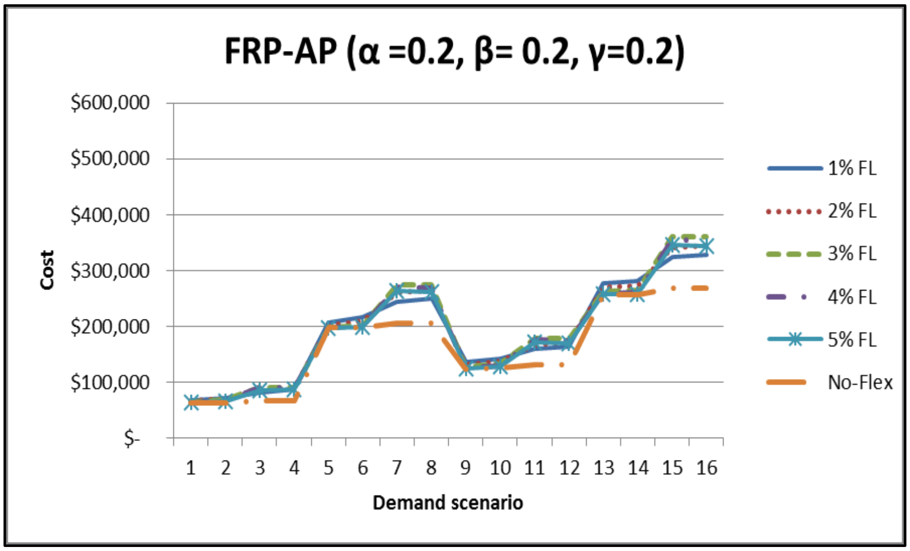
solve BiObjective2;

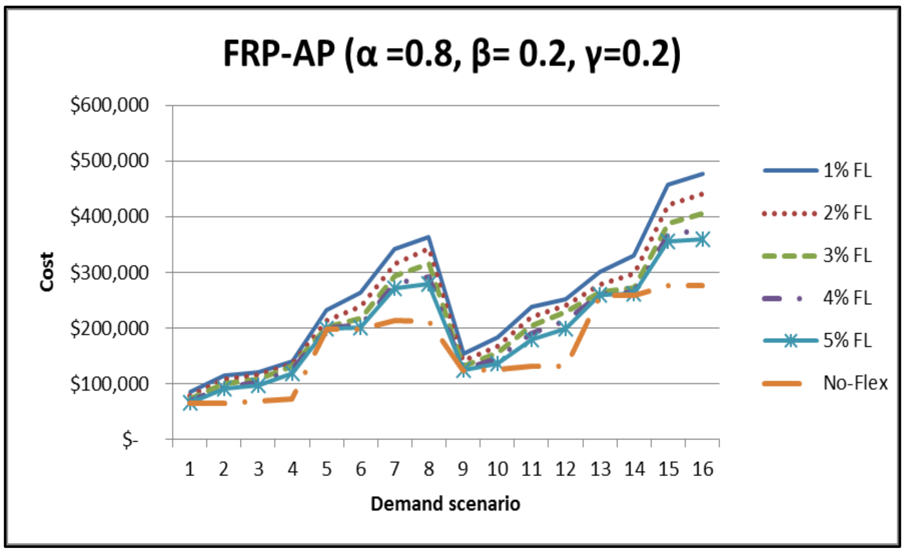
display BiObjective2.absmipgap;

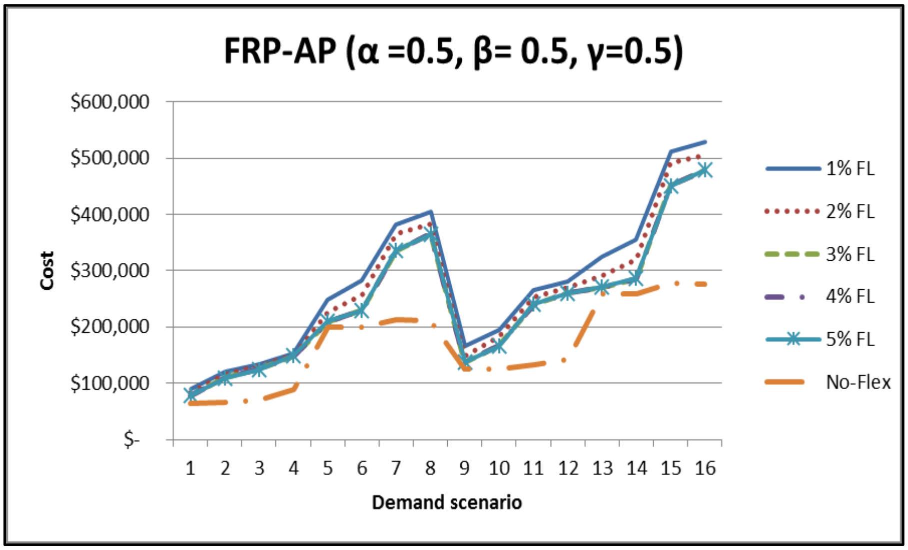
```
# OUTPUT VARIABLES #

let currentcost[t]:= (cw*th*W[0] + co*O[0]+ ch*H[0] + cl*La[0] + h*I[0] + cp* P[0]+
sc*S[0]);

let productioncost[t]:=cp*P[0];

let workforcecost[t]:= cw*th*W[0];

let hiringcost[t]:= ch*H[0];

let layoffcost[t]:= cl*La[0];

let inventorycost[t]:= h*I[0];

let shortagecost[t]:= sc*S[0];

let overtimecost[t]:=co*O[0];

let costperperiod[n,j,k,e,r,t]:=0;

let costperperiod[n,j,k,e,r,t]:= costperperiod[n,j,k,e,r,t]+ sum{i in 0..N}(cw*th*W[i] +
co*O[i]+ ch*H[i] + cl*La[i] + h*I[i] + cp* P[i]+ sc*S[i]);

let deltaperperiod[n,j,k,e,r,t]:= 0;

let deltaperperiod[n,j,k,e,r,t] := deltaperperiod[n,j,k,e,r,t] + sum{i in 1..N}(abs(pprev[i]-
P[i-1]));

let obj1[n,j,k,e,r,t]:=(((sum{i in 0..N} (cw*th*W[i] + ch*H[i] + cl*La[i] + h*I[i] + cp*
P[i]+ co*O[i]+ sc*S[i]))-(CB[t]-1))/(CW[t]-CB[t]));

let obj2[n,j,k,e,r,t]:=(((sum {i in 1..N} (PA[i]))-SB[t])/(SW[t]-SB[t]));

if (t>12) then {let delta:= delta+ sum{i in 1..N}(abs(pprev[i]-P[i-1]));


for {i in 1..N}{let pprev[i]:=P[i];}

        let Winput:= W[0]; #feeding input to next loop

        let Iinput:= I[0]-S[0]; #feeding input to next loop

for {i in 0..N-2} {

        let LowB[i]:= max (LowB[i+1], P[i+1]*(1-F[i])) ;

        let UpB[i]:= min (UpB[i+1], P[i+1]*(1+F[i])) ;}

let LowB[N-1]:= P[N]*(1-F[N-1]);

let UpB[N-1]:= P[N]*(1+F[N-1]); }}
```

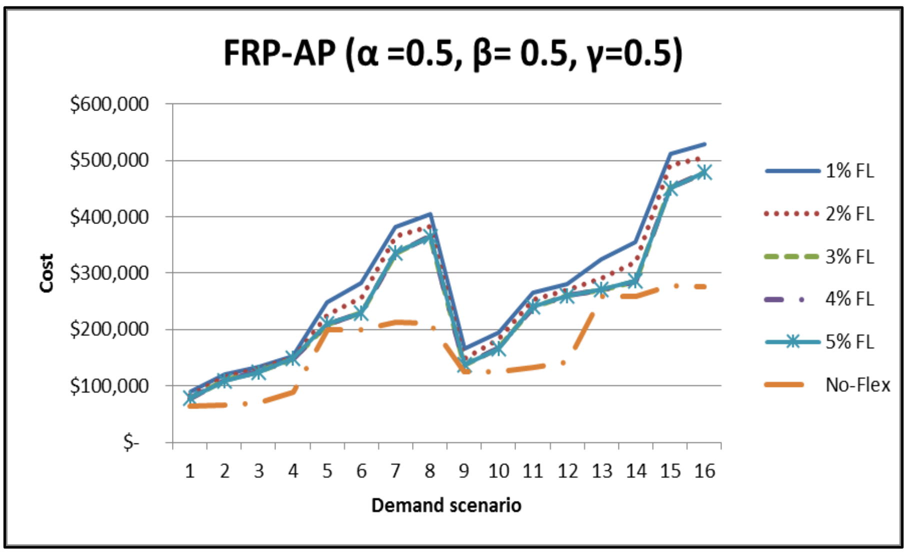
```
# WRITE OUTPUTS INTO EXCEL TABLE #
write table output1[w];
write table output2[w];
write table output3[w];
write table output4[w];
### END OF BI-OBJECTIVE RUN FILE ###
```

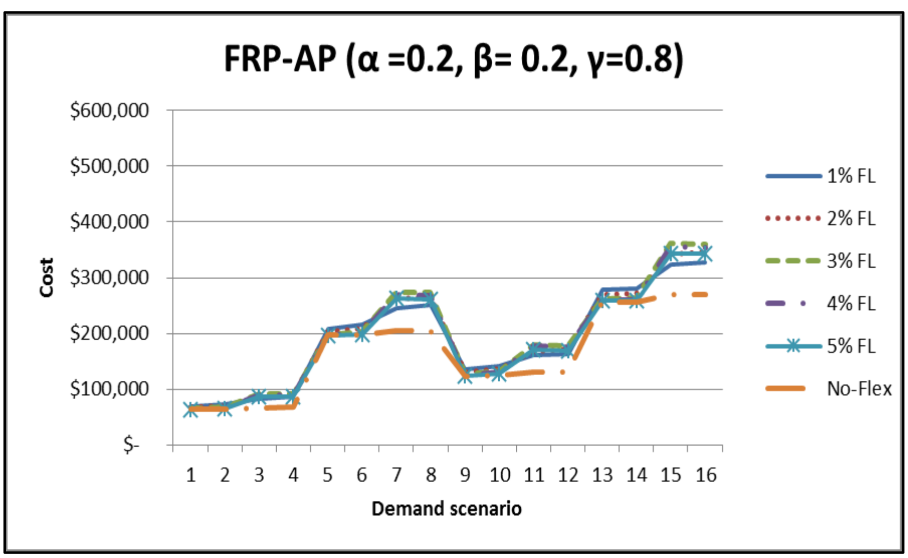
APPENDIX C: COST AND STABILITY GRAPHS

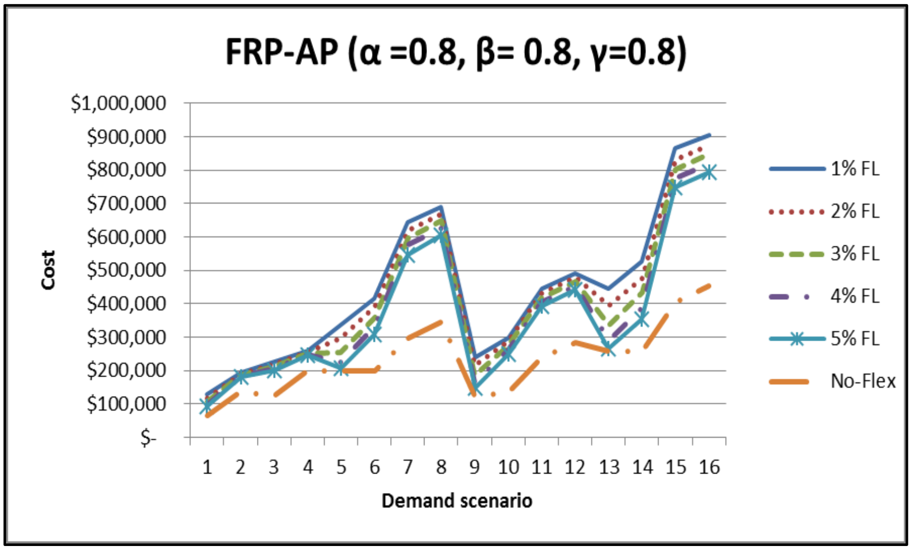


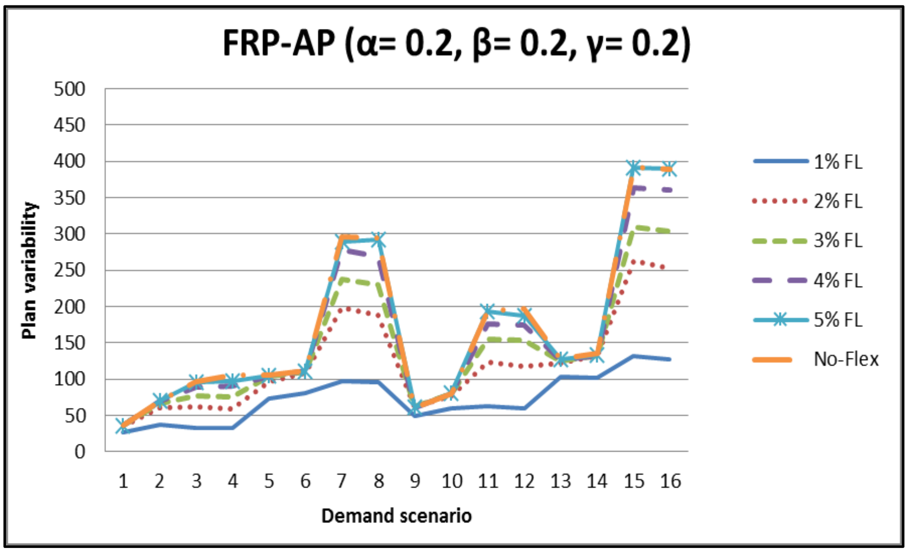


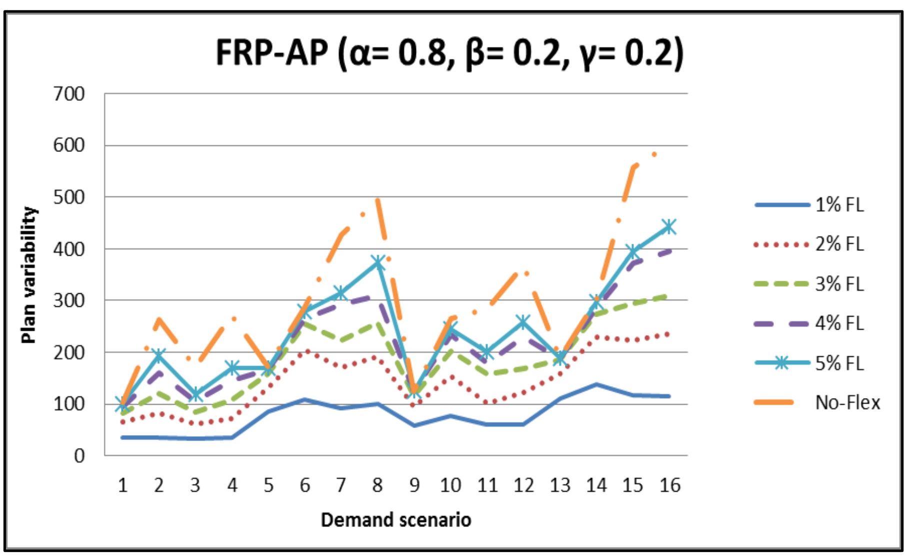

FRP-AP (α =0.5, β= 0.5, γ=0.5)
$600,000
$500,000
$400,000
$300,000
$200,000
$100,000
$-
Cost
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Demand scenario
1% FL
2% FL
3% FL
4% FL
5% FL
No-Flex

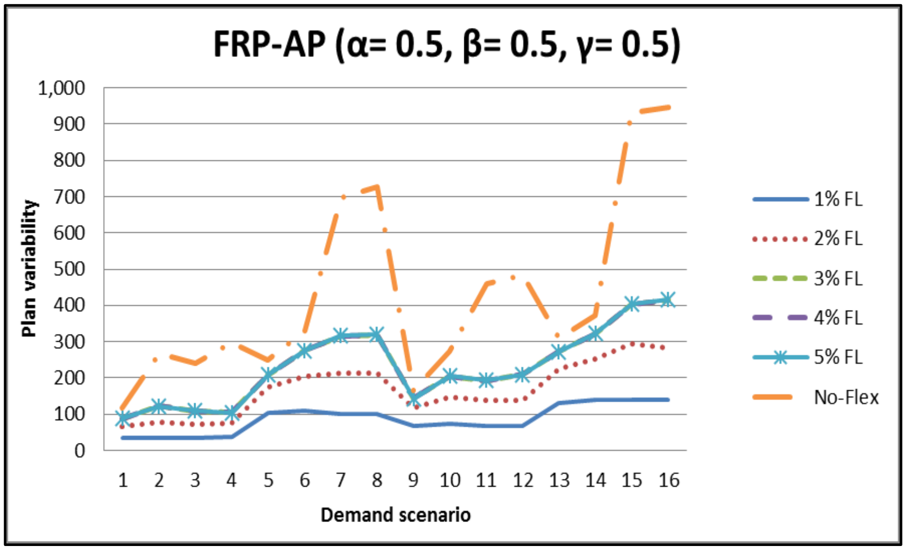

FRP-AP (α =0.5, β= 0.5, γ=0.5)
$600,000
$500,000
$400,000
$300,000
$200,000
$100,000
$-
Cost
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Demand scenario
1% FL
2% FL
3% FL
4% FL
5% FL
No-Flex

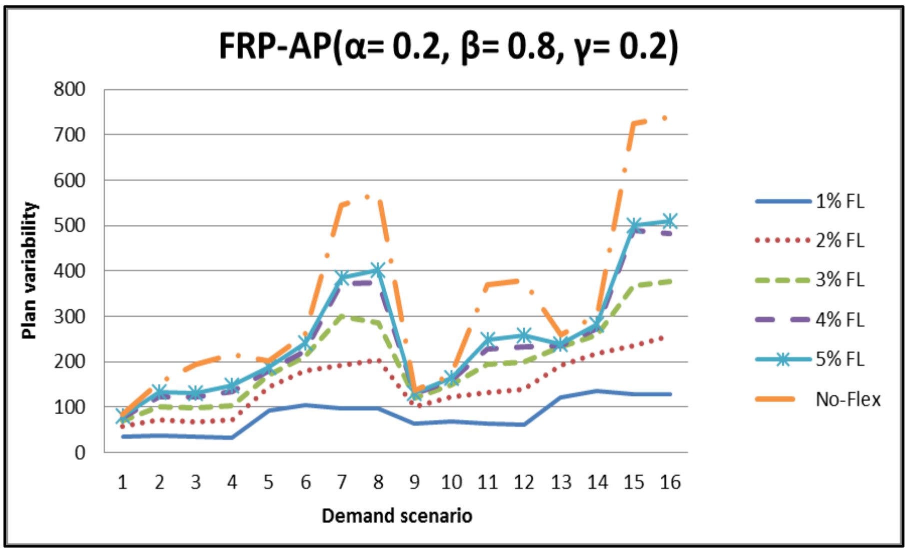

FRP-AP (α =0.2, β= 0.2, γ=0.8)
$600,000
$500,000
$400,000
$300,000
$200,000
$100,000
$-
Cost
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Demand scenario
1% FL
2% FL
3% FL
4% FL
5% FL
No-Flex

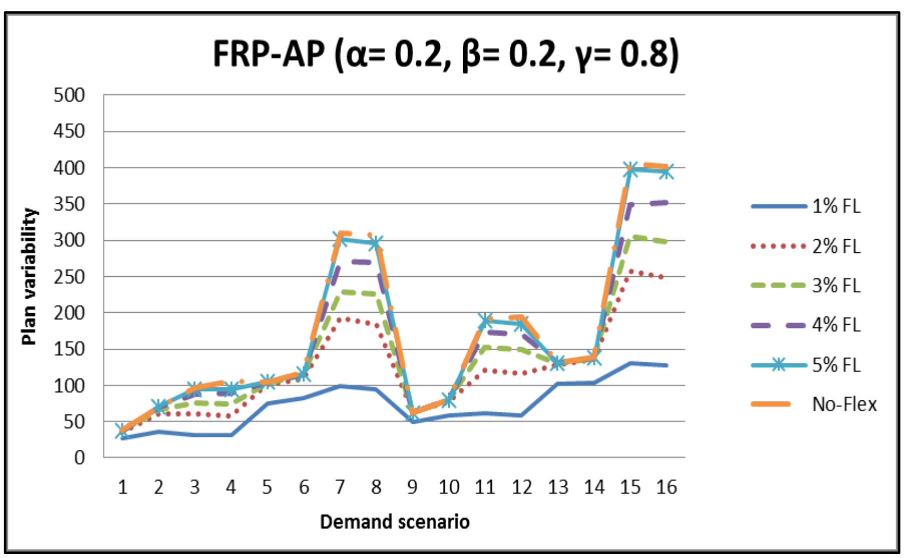

FRP-AP (α =0.8, β= 0.8, γ=0.8)
Cost
$1,000,000
$900,000
$800,000
$700,000
$600,000
$500,000
$400,000
$300,000
$200,000
$100,000
$-
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Demand scenario
1% FL
2% FL
3% FL
4% FL
5% FL
No-Flex

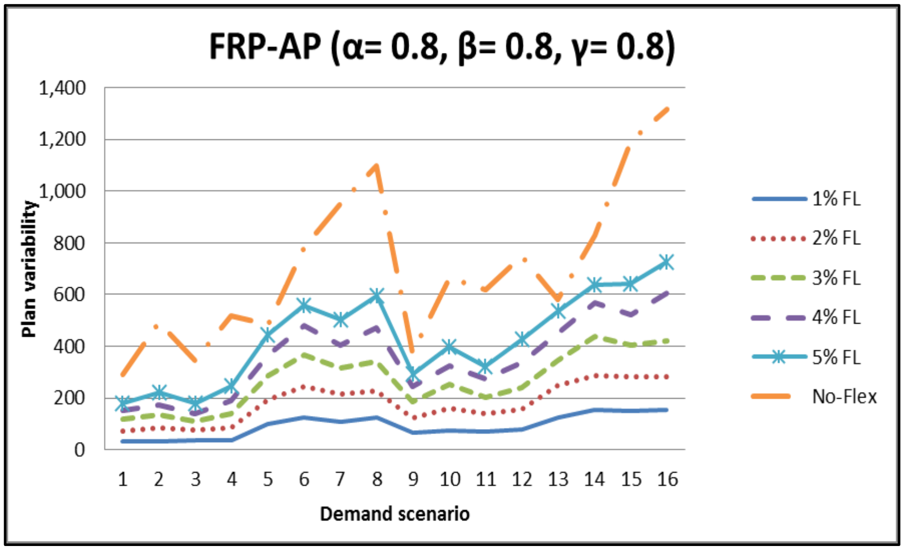

FRP-AP (α= 0.2, β= 0.2, γ= 0.2)
Plan variability
500
450
400
350
300
250
200
150
100
50
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Demand scenario
1% FL
2% FL
3% FL
4% FL
5% FL
No-Flex


FRP-AP (α= 0.8, β= 0.2, γ= 0.2)
Plan variability
700
600
500
400
300
200
100
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Demand scenario
1% FL
2% FL
3% FL
4% FL
5% FL
No-Flex


FRP-AP (α= 0.5, β= 0.5, γ= 0.5)
Plan variability
1,000
900
800
700
600
500
400
300
200
100
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Demand scenario
1% FL
2% FL
3% FL
4% FL
5% FL
No-Flex


FRP-AP(α= 0.2, β= 0.8, γ= 0.2)
Plan variability
800
700
600
500
400
300
200
100
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Demand scenario
1% FL
2% FL
3% FL
4% FL
5% FL
No-Flex


FRP-AP (α= 0.2, β= 0.2, γ= 0.8)
Plan variability
500
450
400
350
300
250
200
150
100
50
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Demand scenario
1% FL
2% FL
3% FL
4% FL
5% FL
No-Flex


FRP-AP (α= 0.8, β= 0.8, γ= 0.8)
Plan variability
1,400
1,200
1,000
800
600
400
200
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Demand scenario
1% FL
2% FL
3% FL
4% FL
5% FL
No-Flex