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**Multi-period, Multi-Platform Design and Lot-sizing for Hybrid Manufacturing
Considering Stochastic Demand and Processing Time**

By

Md Sadman Sakib

A Thesis

Submitted to the Faculty of Graduate Studies
through the Department of Mechanical, Automotive and Materials Engineering
in Partial Fulfillment of the Requirements for
the Degree of Master of Applied Science
at the University of Windsor

Windsor, Ontario, Canada

2023

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**Multi-period, Multi-Platform Design and Lot-sizing for Hybrid Manufacturing
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DECLARATION OF CO-AUTHORSHIP / PREVIOUS PUBLICATION

I. Co-Authorship

I hereby declare that this thesis incorporates materials that are the result of joint research of the author and his supervisors, Prof. Fazle Baki, Prof. Ahmed Azab, and Hany Osman. Chapter 3, 4 and 5 of this thesis were co-authored with Prof. Fazle Baki and Prof. Ahmed Azab. In all cases, the key ideas, primary contributions, experimental designs, data analysis, interpretation, and writing were performed by the author; Prof. Fazle Baki and Prof. Ahmed Azab provided feedback the on refinement of ideas, overall coordination, improvements and editing of the manuscript. Moreover, constructive feedback and review is also provided by H. Osman.

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II. Previous Publication

This thesis includes 1 conference paper that has been previously submitted, as follows:

Thesis Chapter	Publication title/full citation	Publication status*
Chapter 3, 4, and 5	Sakib, M. S., Osman, H., Azab, A., Baki, F., “Product-platform design and multi-period, multi-platform lot-sizing for hybrid manufacturing considering stochastic	<i>Accepted</i>

	demand and processing time” North American Manufacturing Research Conference (NAMRC) 51	
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ABSTRACT

During the era of digitalization, customer demand has become more customized than before. For this reason, the variety of products is increasing rapidly. Manufacturing industries are experiencing extraordinary challenges due to frequent updates of customer requirements. Now the manufacturers are focusing more on mass customization than mass production to keep pace with this situation, however, managing variety using the make-to-stock strategy increases holding costs, and the make-to-order strategy increases lead time. Moreover, uncertainty in demand is making mass customization more challenging. Though hybrid manufacturing is a promising concept for variety management, very few works consider stochastic demand. The concept of incorporating additive and subtractive manufacturing is known as hybrid manufacturing. Both the additive and the subtractive processes have some limitations when used separately; however, combining these methods can suppress the limitation and maximize the strength. Thus, this study aims to integrate the concept of product platform (considering delayed product differentiation technique) and hybrid manufacturing process to deal with product variety and stochastic demand. This research presents an optimal mixed integer programming (MIP) model to minimize manufacturing and holding costs. While developing the MIP model, multi-period stochastic demand is considered. According to the developed model, the platform consists of some common features, and a new variant will be produced by adding and/or removing features. This model's novelty is satisfying stochastic demand while maintaining a certain service level. The mathematical model is solved using the exact optimization solvers such as Gurobi through the AMPL programming language. Finally, four case studies are performed to showcase the strengths of the developed novel mathematical model.

DEDICATION

In the name of Allah, the most gracious, the most merciful

I dedicate this work to my parents, Shahera Khanum and Md. Sakender Ali and my life partner Syeda Marzia. I am grateful to my father-in-law Mohammad Shahid Hossain, mother-in-law Munira Hasnain, and my elder brother Harun-or-Rashid for their continuous support and encouragement.

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TABLE OF CONTENTS

DECLARATION OF CO-AUTHORSHIP / PREVIOUS PUBLICATION	iii
ABSTRACT.....	v
DEDICATION	vi
ACKNOWLEDGEMENTS	vii
LIST OF TABLES	x
LIST OF FIGURES	xi
LIST OF APPENDICES	xii
LIST OF ABBREVIATIONS/SYMBOLS	xiii
CHAPTER 1	
INTRODUCTION	1
1.1 Overview	1
1.1.1 Hybrid Manufacturing.....	1
1.1.2 Product Variety	2
1.1.3 Product Platform	2
1.1.4 Stochastic Environment	3
1.2 Problem Definition.....	4
1.3 Research Question	4
1.4 Contribution	4
1.5 Objective of the Research	4
1.6 Outline of the Thesis	5
CHAPTER 2	
LITERATURE REVIEW	6
2.1 Overview	6
2.2 Product Platform	6
2.3 Delayed Product Differentiation (DPD)	11
2.4 Hybrid Manufacturing	11

2.5 Inventory Management	12
2.6 Safety Stock	12
2.7 Summary and Research Gap.....	12
 CHAPTER 3	
PROBLEM DESCRIPTION AND MODEL FORMULATION.....	13
3.1 Problem Description	13
3.2 Model Formulation	13
3.2.1 Assumption	14
3.2.2 Notation.....	14
3.3 Mathematical Model	16
 CHAPTER 4	
COMPUTATIONAL EXPERIENCE.....	20
4.1 First Illustrative Case Study.....	20
4.2 Case Study of a Guiding Bush Family.....	27
4.3 Case Study of Gear Family	35
4.4 Fourth Illustrative Case Study	44
 CHAPTER 5	
CONCLUSION AND FUTURE WORK	54
5.1 Conclusion	54
5.2 Future Work.....	54
REFERENCES/BIBLIOGRAPHY.....	56
APPENDICES	63
Appendix A.....	63
Appendix B	64
VITA AUCTORIS	68

LIST OF TABLES

Table 2. 1: Research on Product Platform Development Summary	10
Table 4. 1: Variants and Features Relationship	20
Table 4. 2: Precedence Relation between Features	21
Table 4. 3: Demand and Holding Cost of a Variant for each period	21
Table 4. 4: Cost of Processing, Addition, and Removal of a Feature for each period	22
Table 4. 5: Solution of Case Study 1	23
Table 4. 6: Optimal platform for each period	24
Table 4. 7: Manufacturing 3 Variants from Platform one in period 1 & 2	24
Table 4. 8: Manufacturing 3 Variants from Platform two in period 3	25
Table 4. 9: Variants and Features Relationship	28
Table 4. 10: Precedence Relation between Features	29
Table 4. 11: Solution of Guiding Bush Family Case Study	30
Table 4. 12: Optimal platform for each period	31
Table 4. 13: Manufacturing 5 Variants from Optimal Platform 1	32
Table 4. 14: Manufacturing 5 Variants from Optimal Platform 2	32
Table 4. 15: Manufacturing 5 Variants from Optimal Platform 3	33
Table 4. 16: Optimal solution for variant 4	34
Table 4. 17: Variants and Features Relationship	37
Table 4. 18: Precedence Relation between Features	37
Table 4. 19: Solution of Case Study 3	38
Table 4. 20: Optimal platform for each period	41
Table 4. 21: Manufacturing 5 Variants from Optimal Platform 1	42
Table 4. 22: Manufacturing 5 Variants from Platform two	43
Table 4. 23: Variants and Features Relationship	46
Table 4. 24: Precedence Relation between Features	47
Table 4. 25: Solution of Case Study 4	48
Table 4. 26: Optimal platform for each period	51
Table 4. 27: Manufacturing 14 Variants from Optimal Platform 1	52

LIST OF FIGURES

Figure 1. 1: Subtractive manufacturing and Additive manufacturing	2
Figure 1. 2: Stochastic Demand	3
Figure 3. 1: Variable demand.....	18
Figure 3. 2: Inventory and Safety stock	18
Figure 4. 1: Platform 1 to variants processing	25
Figure 4. 2: Platform 1 to variants processing	26
Figure 4. 3: Cost Comparison	26
Figure 4. 4: Eight Features.....	27
Figure 4. 5: Five variants of guiding bush family.....	28
Figure 4. 6: Cost Comparison	33
Figure 4. 7: Twelve Features	35
Figure 4. 8: Four Variants of gear family	36
Figure 4. 9: Platform 1 and Platform 2	42
Figure 4. 10: Cost Comparison	43
Figure 4. 11: Eleven Features	44
Figure 4. 12: Fourteen Variants	45
Figure 4. 13: Cost comparison considering multiple platform	50
Figure 4. 14: Cost Comparison Considering Inventory	53

LIST OF APPENDICES

Appendix A	34
Appendix B	48

LIST OF ABBREVIATIONS/SYMBOLS

MIP:	Mixed Integer Programming
HM:	Hybrid Manufacturing
AM:	Additive Manufacturing
SM:	Subtractive Manufacturing
DPD:	Delayed Product Differentiation
RMS:	Reconfigurable Manufacturing System
PBF:	Powder Bed Fusion
DED:	Directed Energy Deposition
LMD:	Laser Metal Deposition
SLM:	Selective Laser Melting
PFA:	Product Family Architecture
GVI:	Generational Variety Index
CI:	Coupling Index
QFD:	Quality Function Development
DFV:	Design for Variety
DSM:	Design Structure Matrix
MDL:	Minimum Description Length
GA:	Genetic Algorithm
MOPSO:	Multi-Objective Particle Swarm Optimization
UGVs:	Unmanned Ground Vehicles
FDL:	Feature-based Decision-making Logic
MPCC:	Modular product Platform Configuration and Co-planning

CHAPTER 1

INTRODUCTION

1.1 Overview

During the era of digitalization, all the manufacturing industries have been experiencing a rapid transition from the traditional manufacturing process to the smart manufacturing process over the past few decades (Kusiak, 2018). Nowadays customer demand has become more customized than before. And day by day the variety of products is increasing. Manufacturing industries are experiencing extraordinary challenges due to frequent updates of customer requirements (ElMaraghy & Moussa, 2019). Managing variety using the make-to-stock strategy increases holding costs and the make-to-order strategy increases lead time (Gupta & Benjaafar, 2004). The integration of delayed product differentiation and hybrid manufacturing is an effective strategy to deal with product variety. Hybrid manufacturing is a part of smart manufacturing. A combination of additive and subtractive manufacturing methods is known as hybrid manufacturing. Both additive and subtractive processes have some limitations, however, the combination of these minimizes those limitations (Cortina et al., 2018). According to the demand characteristics, the demand for any product is not stable (Rădăşanu, 2016). Though hybrid manufacturing is a promising solution for this problem, there is hardly any model available in the literature that deals with the multi-period situation and stochastic demand and processing time. This research aims to develop a multi-period optimal model that can deal with demand and processing time uncertainty along with manufacturing cost minimization.

1.1.1 Hybrid Manufacturing

During this fourth industrial revolution, reducing cost and time of manufacturing through an efficient production process to increase quality and achieve competitiveness is the main objective for all the production industries. For this reason, use of hybrid machine tools is increasing though there are some limitations. Powder Bed Fusion (PBF), Directed Energy Deposition (DED), Laser Metal Deposition (LMD), Selective Laser Melting (SLM) are some of the additive operations and milling, turning, multitasking, grinding is some of the subtractive operations. By using hybrid machine tools different complex products can be manufactured whereas the traditional manufacturing process cannot. Increasing accuracy

and decreasing surface roughness in the main target of hybrid manufacturing system (Cortina et al., 2018). Hybrid manufacturing (HM) is the combination of two or more manufacturing processes (Zhu et al., 2013). However, combination of additive and subtractive manufacturing processes is known as hybrid manufacturing (Manogharan et al., 2016). Advantage of additive manufacturing (AM) is to form complex geometry and subtractive manufacturing (SM) is to gain high surface finishing. Though there are some limitations when AM and SM are used separately, the combination can maximize the strength of both manufacturing processes. HM makes the manufacturing process more flexible, and efficient (Zheng et al., 2020). HM is capable of dealing with product variety management (ElMaraghy & Moussa, 2019). AM and SM are illustrated in figure 1.1.

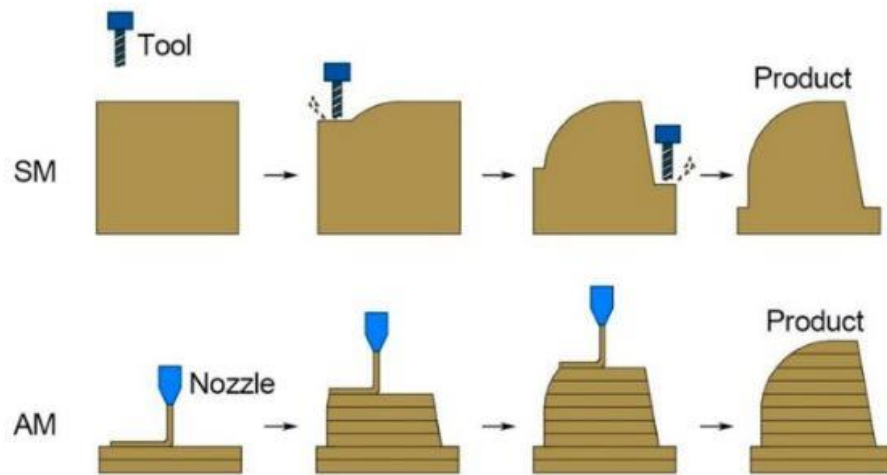


Figure 1. 1: Subtractive manufacturing and Additive manufacturing

1.1.2 Product Variety

Product variety refers to a number of different product variations that a manufacturer offers to the customer. Product variety helps the manufacturer to be competitive in the market and reach a wide range of customers. Recently, the variety of product is observed not only in small things like light bulb but also in complex products like automobile (ElMaraghy et al., 2013).

1.1.3 Product Platform

Product platform is a proven concept of product variety management (Andersen et al., 2022). When a group of product share some common parts, the group is known as product

platform and the common parts form the product platform (Gonzalez-Zugasti et al., 2000). Product platform offers the flexibility in manufacturing process and allows the manufacturers to offer bundle of products to the customers (Muffatto & Roveda, 2000). Product platform also allows the manufacturers to develop new products which reduce the cost and increase the productivity (Andersen et al., 2022). The proper use of delayed product differentiation (DPD) is properly utilized by product platform concept (Moussa & ElMaraghy, 2020a). Using the product platform concept the balance between make-to-stock and make-to-order can be perceived. Through this the extra holding cost and long delivery time problem can be minimized

1.1.4 Stochastic Environment

For product platform design, two types (exogenous and endogenous) of uncertainty are identified. Exogenous uncertainty is related to external uncertainty (e.g., demand, price etc.), and endogenous uncertainty is related to internal uncertainty. Stochastic demand is identified as exogenous uncertainty, and the stochastic processing time is identified as endogenous uncertainty. And both types of uncertainty have an impact on product platform design (J. R. Jiao, 2012).

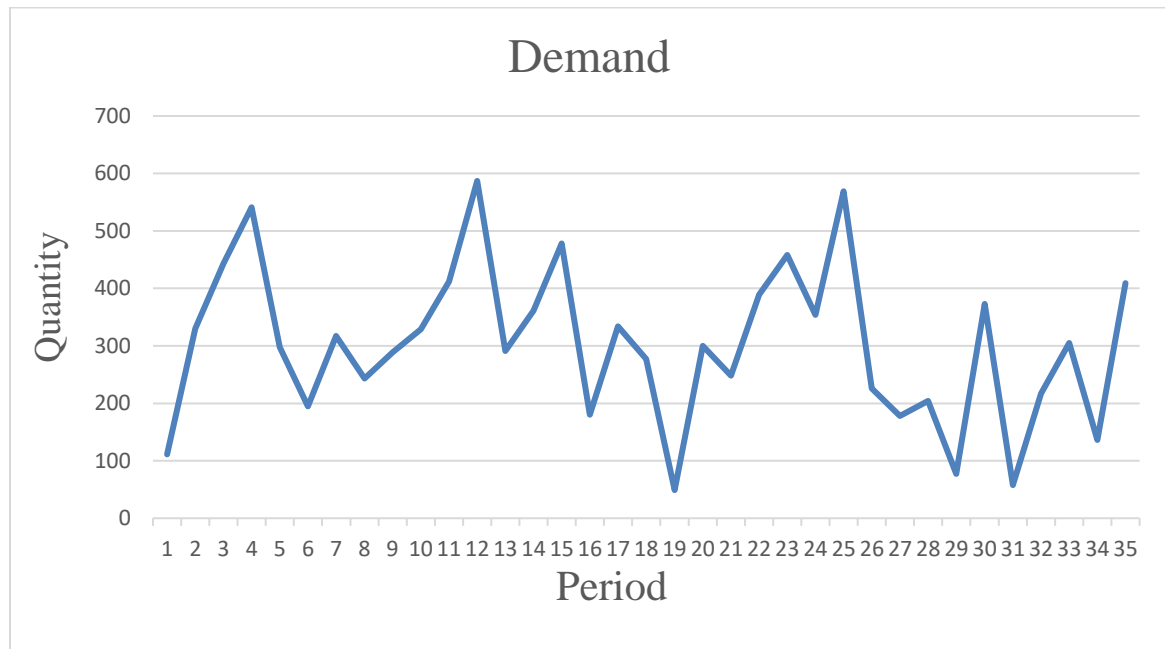


Figure 1. 2: Stochastic Demand

According to Wazed et al. (2010) uncertainties in the manufacturing environment can increase the total cost. Along with this, it has an impact on lot size. For additive manufacturing process the difference between designed and actual material addition time causes uncertainty in processing time (Poudel et al., 2023). As a result, the production environment becomes stochastic while considering demand and processing time uncertainties. Stochastic demand is illustrated in figure 1.2.

1.2 Problem Definition

Mass customization is one of the highlighted challenges that the manufacturing industries are facing nowadays (Stief et al., 2022). And, mass customization leads to product proliferation (Moussa & ElMaraghy, 2020b). The increasing fluctuation of demand for customized products from one period to another period leads to lower service-level for manufacturers (Rădășanu, 2016). To deal with this stochastic demand, the manufacturer either needs to follow the make-to-stock strategy which increases holding cost, or the make-to-order strategy which increases lead time to delivery which leads to demand loss.

1.3 Research Question

“How the stochastic demand for multiple periods can be managed while considering the product platform concept to ensure product variety management and a certain service level?”

1.4 Contribution

A new optimal mixed integer programming (MIP) model is developed considering the product platform concept, hybrid manufacturing, inventory, and safety stock to deal with stochastic demand and processing time to ensure a certain service level for multiple periods. With this developed model the real-world demand situation can be dealt with. And the developed model will be able to maintain a specific service level. The developed model is able to satisfy all the customer demand either from the production or from inventory and safety stock.

1.5 Objective of the Research

The proposed research plan's long-term goal is to assist the manufacturing industry to deal with stochastic demand along with minimizing manufacturing costs. This research aims to

develop a reliable cost-minimization model. This developed model will help to decide on production quantity, safety stock quantity for each period, and each variant. The objectives of this research are as follows:

1. Classification of available literature on the developed model for hybrid manufacturing: There is a lack of literature surveys that efficiently develop a model for hybrid manufacturing considering multi-period, demand and processing time uncertainty. The surveys will help to provide research routes and available models for hybrid manufacturing.
2. Developing an optimal model: A mathematical optimization model will be developed to minimize the cost of production. and it will help to determine the production and safety stock quantity for each period. Some constraints will be developed considering multi-period variable demand, processing time, service level, and variety of products.
3. Developing an optimization technique: To solve the developed MIP model, AMPL will be used for programming. Gurobi will be used for optimization considering computational time and complexity.
4. Case study: Using the developed model, four case studies will be conducted to evaluate the feasibility and efficiency of the model.

1.6 Outline of the Thesis

In this thesis, there are five chapters in total, which are organized as follows. In chapter 1, we provide an overview of the hybrid manufacturing, product-platform, product variety considering stochastic demand and processing time, possible application areas of our developed MIP model and overall objective of the proposed work. Chapter 2 consists of literature review, analysis of the existing modelling approaches for product-platform development, inventory management, hybrid manufacturing and research gaps. Chapter 3 explains the model formulation process. Also, illustrates the developed Mixed Integer Programming model integrating hybrid manufacturing and product-platform development to deal with stochastic demand and processing time. Chapter 4 depicts the case studies result for an illustrative example-1, guiding bush family, gear family, and illustrative example-2. In Chapter 5 conclusions and the discussion is illustrated and a brief direction of future work is discussed at the end of the chapter.

CHAPTER 2

LITERATURE REVIEW

In this chapter, the most relevant articles are reviewed for product platform design considering hybrid manufacturing. While designing platform how the other factors (e.g., Stochastic demand, and processing time) can be considered is identified through the literature review. After proper analysis of the selected article, the research gap is identified in context of considering stochastic demand and processing time for product platform design problem.

2.1 Overview

Product platform has become a promising concept for dealing with mass customization (Ben-Arieh et al., 2009; ElMaraghy et al., 2013). Researchers have published several research papers focusing on the principle, challenges, opportunities, and development of product platforms (Dilberoglu et al., n.d.; Facin et al., 2016; J. Jiao et al., 2007; Muffatto & Roveda, 2000; Otto et al., 2016; Robertson & Ulrich, 1998; Simpson, 2004; Van Den Broeke et al., 2015).

2.2 Product Platform

Most of the researchers consider only the assembly or/and disassembly manufacturing process while developing a product platform. After observing several product platform development methods, Jose & Tollenaere (2005) classified them into three categories (Clustering method, Graph and matrix partitioning method, and Mathematical programming method). Moreover, the importance and efficiency of modular design for variety management was illustrated using a motorcycle example. Aydin & Ulutas (2016) combined clustering algorithm and clonal selection algorithm using commonality index and design structure matrix for modular product design. A refrigerator product family consisting of 3 versions of data was used for the assessment of the proposed algorithm to minimize planning complexity. Jiao & Tseng (1999) developed a systematic approach to generating Product Family Architecture (PFA) considering technical, physical, and functional views for mass customization. While developing the PFA three challenges are identified (Commonality, Product Platform Development, and Integrated Product

Development) For feasibility analysis a case study was conducted in a power supply company.

Martin & Ishii (2002) proposed a decoupled Product Platform Architecture (PPA) by combining the generational variety index (GVI) and Coupling Index (CI). Using some external drivers, a QFD is developed, and using this QFD, the calculation of GVI is performed. For a proper illustration of design for variety (DFV), an example of a water cooler was used. The redesigning process becomes more efficient using this DFV. Jiao et al. (2007) illustrated a decision framework for platform-based product development considering both front-end and back-end issues. Modularity, commonality, variety, cost, profit, and platform related matrix are identified as product family design metrics. Uncertainty consideration is identified as a gap of product platform design. Yu et al. (2007) developed the building block for product module identification using design structure matrix (DSM). Moreover, using this DSM architecture, minimum description length (MDL), and genetic algorithm (GA), a new clustering method is developed to produce common platform. The real-world complex products example is used to demonstrate the efficiency of the clustering method. Zhang et al. (2008) suggested a mixed integer model for simultaneous configuration of platform products and supply chains (SCPPSC). In this model deterministic demand, no back log, no capacity constraint, fixed lead time, and no stock out condition are incorporated. A three-level iteration process is followed to find out the optimal solution. However, a more sophisticated algorithm is required when the complexity of the model increases. Ben-Arieh et al. (2009) proposed a mixed integer optimal model for multiple platforms to minimize overall production cost. Only manual assembly and/or manual removing features are considered. Genetic algorithm is used for optimization process. However, the model fails to perform when any variant has excessive demand than others. Demand uncertainty, stochastic programming is identified as future research work.

Jiao (2012) developed a hybrid real option analysis framework which consider product-related and project-related flexibility for product platform flexibility planning. Endogenous uncertainty and demand uncertainty is considered while developing the model. Six scenario of demand uncertainty is considered. Genetic algorithm along with Non-Dominated

Sorting GA II (NSGA2), the Strength Pareto Evolutionary Algorithm II (SPEA2), and the Multi-Objective Particle Swarm Optimization (MOPSO) The effectiveness of the developed framework was illustrated using a vibration motor platform planning example. Simpson et al. (2012) introduced a novel approach by integrating the market segmentation grid, Generational Variety Index (GVI), Design Structure Matrix (DSM), commonality indices, mathematical modeling and optimization, and multidimensional data visualization. The main objective of this approach is to identify the common and unique features and their parameter setting. The advantages and limitations of this approach is illustrated using a family of unmanned ground vehicles (UGVs) example. Kumar & Chatterjee (2013) formulated a MILP model for Product Platform Development (PPD), sourcing, maximizing profit and production planning. Multi-period, certain demand, zero lead time, no capacity constraints are considered while developing the model. A heuristic process is used to identify the optimal solution (ILOG CPLEX 10.2). Dealing with uncertain demand is not covered in this research.

Zhu et al. (2014) developed a feature-based decision-making logic (FDL) for hybrid and remanufacturing process. Interchangeable use of additive, subtractive, and inspection procedure is reflected in the research. Using iAtractive process 3 identical parts are produced from 3 different existing parts. This developed logic is unable to deal with sculptured free-form surface. Moreover, a paradigm shift is observed with the increasing demand. Van Den Broeke et al. (2015) depicted the effect of cost of platform and cost of transforming platform over optimal product platform design. Fixed demand, development cost, purchasing and ordering cost, inventory related cost, and platform transformation cost are considered while developing the model. To solve the developed model simulated annealing algorithm is used. The developed model is used in a medical screen manufacturing industry to develop 12 platforms for 12 different products. Aydin & Ulutas (2016) illustrated a clonal selection-based clustering algorithm using design structure matrix and similarity matrix to minimize the planning complexity for managing product variety. For efficiency analysis data from a refrigerator manufacture company is used and proofs that it helps to minimize the release time of new variant. Miao et al. (2017) introduced a bi-level mixed non-linear programming model for platform-based production line planning. This model maximizes the profit along with identifies the optimal multiple

platforms. A bi-level GA is developed for the solution process. The developed model is applied in an automobile industry.

Hanafy & ElMaraghy (2017) proposed a Modular product Platform Configuration and Co-planning (MPCC) mixed integer mathematical model. This model can reduce the cycle time and required number of manual assembly stations. AMPL is used for programming and CPLEX12.6 is used for solution. Data from the mobile phone (7 variants, 20 components) manufacturing company is used for testing the MPCC model. ElMaraghy & Moussa (2019) presented a mixed integer linear programming model for optimal single platform design to minimize manufacturing cost. This model considers a single period of additive and subtractive manufacturing interchangeably. AMPL programming language is used for coding and Gurobi Optimizer 8.1 is for solution. The model is applied for a guiding bush family for fixed demand of five different variants. An extension of this model is developed using GA to deal with a large number of products and features (Moussa & ElMaraghy, 2020a). An example of a product family (14 variants, 12 features) is used for analyzing the GA based model. Colombo et al. (2020) developed a methodology of value analysis using customers' opinion. This methodology is used for comparing different product platforms. Using this method, a ranking is generated for modular smart phone of Google ARA's Spiral-2.

Song et al. (2021) introduced a non-linear mixed integer programming model which deals with uncertainty. After identifying the customer requirements and sequence of assembly the model is applied to reduce the total cost. The model is linearized and solved by CPLEX 12.8. A mobile phone company found that the modular platform is more effective than redundancy strategy. Moussa & ElMaraghy (2021) illustrated a model for identifying multiple optimal platforms for variety management. While developing the process plan customer demand, commonality index, and cost of manufacturing are considered. GA is used for optimal solutions. Multiple additive and subtractive processes are utilized for process planning. This developed model is applied on a guiding bush family (five variants) and a gear shaft family (eight variants). Moussa & ElMaraghy (2022) proposed a holistic non-linear optimal model for multi-period platform design and inventory management. This model is applicable only when the demand is certain for each period and when there

is no backlog. AMPL programming language is used for coding and Gurobi Optimizer is used for solution. The model is illustrated using an example of a gear shaft family (4 variants and 12 features).

Table 2. 1: Research on Product Platform Development Summary

Sl. No.	Author & Year	Mathematical Model	Product Variety Management	Stochastic Demand	Safety stock	Hybrid		Assembly	Single Platform	Multiple Platform	Single Period	Multi Period	Inventory Management
						Additive	Subtractive						
1	Zhang et al. (2008)	×	×								×		
2	Ben-Arieh et al. (2009)	×						×		×	×		
3	Jiao (2012)	×	×	×				×	×		×		
4	Simpson et al. (2012)		×					×	×		×		
5	Kumar & Chatterjee (2013)	×							×			×	×
6	Zhu et al. (2014)					×	×		×				
7	Van Den Broeke et al. (2015)	×	×							×	×		×
8	Aydin & Ulutas (2016)		×					×			×		
9	Hanafy & ElMaraghy (2017)	×	×					×		×	×		
10	Miao et al. (2017)	×						×	×		×		
11	ElMaraghy & Moussa (2019)	×	×			×	×		×		×		
12	Colombo et al. (2020)	×	×						×		×		
13	Redeker et al. (2020)		×			×	×						
14	Song et al. (2021)	×	×					×		×	×		
15	Moussa & ElMaraghy (2021)	×	×			×	×			×	×		
16	Moussa & ElMaraghy (2022)	×	×			×	×			×		×	×

2.3 Delayed Product Differentiation (DPD)

Gupta & Benjaafar (2004) introduce Delayed Product Differentiation (DPD) as a strategy to manage mass customization along with the low lead time. The cost-benefit analysis is evaluated considering the make-to-stock of the platform and make-to-order for variants. Algeddawy & Elmaraghy (2010a) and Hanafy & Elmaraghy (2015) present an assembly-line layout considering DPD (form postponement). The Cladistics tool is used to analyze the commonality among variants. After that, the assembly line balancing is performed utilizing the DPD concept (Algeddawy & Elmaraghy, 2010b). A case study of an automobile engine assembly is illustrated using the developed strategy. Moussa & ElMaraghy (2020a) and Moussa & ElMaraghy (2021a) introduced the integration of the product platform concept, DPD, and hybrid manufacturing. Though DPD is applied by several industries (Sony, Kodak, Black & Decker, etc.), there is a limited number of research considering DPD and hybrid manufacturing (Galizia et al., 2020).

2.4 Hybrid Manufacturing

During this fourth industrial revolution, reducing cost and time of manufacturing through an efficient production process to increase quality and achieve competitiveness is the main objective for all the production industries. For this reason, use of hybrid machine tools is increasing though there are some limitations. Powder Bed Fusion (PBF), Directed Energy Deposition (DED), Laser Metal Deposition (LMD), Selective Laser Melting (SLM) are some of the additive operations and milling, turning, multitasking, grinding is some of the subtractive operations. By using hybrid machine tools different complex products can be manufactured whereas the traditional manufacturing process cannot. Increasing accuracy and decreasing surface roughness in the main target of hybrid manufacturing system (Cortina et al., 2018).

Though hybrid manufacturing is a promising solution to variety management, there is hardly any model in the literature that deals with both multi-period situations and stochastic situations for both demand and processing time for HM systems (E. Kim & Min, 2021; H. Kim & Kim, 2022; Moussa & ElMaraghy, 2021b)

2.5 Inventory Management

From the previous section, it is visible that a limited number of researchers consider the multiperiod situation for product platform development. As a result, a limited number of researchers focus on integrating product platforms and inventory management. Zhang et al. (2008) and Van Den Broeke et al. (2015) consider inventory cost by focusing on the supply-chain perspective while developing a product platform. Kumar & Chatterjee (2013) considers inventory cost (holding common parts) while developing the MILP model for Product Platform Development; however, the hybrid manufacturing concept is not considered. Moussa & ElMaraghy (2022) introduce the integration of inventory management and product platform considering a hybrid manufacturing perspective.

2.6 Safety Stock

Ghadimi & Aouam (2021) consider a safety stock strategy to deal with stochastic demand to achieve the predetermined service level. Bhavsar & Sinha (2019) and Eppen & Martin (1988) also consider the stochastic situation and use safety stock to satisfy the demand to ensure a certain service level. However, safety stock is not considered for product platform development.

2.7 Summary and Research Gap

In conclusion of this section, it is identified that for product platform design-

- There is a limited number of research that focuses on multi-period models.
- There is hardly any article that considers safety stock while inventory management.
- There are limited numbers of articles that deal with stochastic demand.

Thus, this paper introduces a new optimal mixed integer programming model integrating the product platform concept, hybrid manufacturing, and inventory to deal with the stochastic demand and processing time for multiple periods.

By combining these factors the model will be able to deal with more realistic problems. Inventory and safety stock will help to manage stock out situation and a certain service level will be ensured. Multi-period consideration helps to deal with different trends in demand. And consideration of multiple platforms helps to reduce the feature addition and subtraction cost. Through this the manufacturing cost will be minimized.

CHAPTER 3

PROBLEM DESCRIPTION AND MODEL FORMULATION

In this chapter, the problem is defined for product platform design to manage product variety considering stochastic environment. After that the MIP is developed considering some assumption. The equations development strategy is explained, and the explanation of the constraints are also provided.

3.1 Problem Description

The increasing fluctuation of demand for customized products from one period to another leads to lower service levels for manufacturers. Customer retention will be difficult without the availability of the offered variants. Different variants create a stochastic situation for both demand and processing time. To deal with this stochastic situation, the manufacturer either needs to follow the make-to-stock strategy, which increases holding cost, or the make-to-order strategy, which increases lead time to delivery, leading to demand loss which has a direct impact on profit. Some researchers propose the integration of both strategies to deal with product variety management (ElMaraghy & Moussa, 2019; Moussa & ElMaraghy, 2022). However, these models ignore the stochastic situation.

A new model has to be formulated so as to satisfy the stochastic situation of demand and processing time. The overall objective of the new model is to deal with stochastic demand and processing time to fulfil the demand with a predetermined service level. The new model minimizes the total manufacturing and holding cost.

3.2 Model Formulation

A MIP model is developed for minimizing manufacturing and holding costs along with product variety management over multiple periods. The concept behind this model is initially the platforms are manufactured using the mass production concept. After that, using the mass customization concept, the variants will be produced using additive (e.g., DMD, FFF) and/or subtractive (e.g., CNC) manufacturing techniques.

A variety of parts is considered in the proposed model, where each variant contains a unique set of features. Required feature j for each variant k is given through the V_{jk} matrix. The precedence relation among features is provided by the F_{jlk} matrix. Other technological

constraints on the features, such as features in an inclusion relationship, B_{jl} and features in a seclusion relationship, S_{jl} are considered in the proposed model. The cost of processing any feature on the platform stage, the cost of adding any feature to a platform in a variant stage, and the cost of removing any feature from a platform in a variant stage are given through Cp_{jt} , Ca_{jkt} , and Cr_{jkt} , respectively. The demand is considered a normally distributed random variable. The mean value, μd_{kt} , and standard deviation, σd_{kt} , of demand for each period is given. The processing time is also considered as a normally distributed random variable. The mean value, μp_{kt} , and standard deviation, σp_{kt} , of processing time of the variant for each period is given.

3.2.1 Assumption

The following assumptions are considered while developing the model.

- This model does not address operational concerns. Hence, at this tactical stage, the model ensures that features related to tight tolerances are included as a part of either the platform or the variant stage.

Through this assumption the sequence of adding features is not considered

- Known cost components and deterministic parameters.
- The features of each variant are predefined.
- One week is considered one period.
- Demand and processing time are considered normally distributed random variables.

3.2.2 Notation

Indices, parameters, and decision variables of the proposed model are defined below:

Indices:

j : 1, 2... J , set of features.

k : 1, 2... K , set of product variants.

t : 1, 2, ... T , set of production periods.

Parameters:

Cp_{jt} : cost of processing feature j on the platform of period t .

Ca_{jkt} : cost of adding feature j to the platform to form a variant k for period t .

Cr_{jkt} : cost of removing feature j from the platform to form a variant k for period t .

Ch_{kt} : cost of holding variant k in period t .

V_{jk} : binary parameter to indicate whether feature j is required in variant k .

F_{jlk} : binary parameter to indicate whether feature j precedes feature l in variant k .

B_{jl} : binary parameter to indicate whether features j and l should be processed together either at the platform stage or at the variant stage.

S_{jl} : binary parameter to indicate whether features j and l should be secluded from each other.

A_t : total production capacity at period t .

Sl_{kt} : Required service level for product k of period t .

μd_{kt} : Mean demand for item k of period t

σd_{kt} : Standard deviation of demand for item k of period t .

μp_{kt} : Mean production time for item k of period t

σp_{kt} : Standard deviation of production time for item k of period t .

σ_{kt} : Standard deviation of production time and demand for item k of period t .

Random Variable:

D_{kt} : Demand of variant k for period t . The demand varies with the mean (μd_{kt}) and standard deviation (σd_{kt}).

Decision variables:

x_{jt} : binary variable that is equal to 1 if feature j is processed in the platform.

a_{jkt} : binary variable that is equal to 1 if feature j is added to the platform to form variant k .

r_{jkt} : binary variable that is equal to 1 if feature j is removed from the platform to form variant k .

p_{kt} : amount produced from variant k in period t .

I_{kt} : inventory amount from variant k in period t .

z_{kt} : Safety factor for product k of period t .

ss_{kt} : Safety Stock for product k of period t .

Here, the platform stage is defined as processing the features ($j \in J$) to develop a platform, and the variant stage is defined as adding (e.g., DMD/FFF) or subtracting (e.g., CNC) any features ($j \in J$) to form a variant ($k \in K$).

For dealing with the stochastic situation for both demand and processing time, the normal distribution is used as an efficient way to represent the underlying variability in these two random variables (Osman & Demirli, 2012; J. Zhang et al., 2020). Based on the literature review the normal distribution is used to deal with demand uncertainty (Bhavsar & Sinha, 2019; Eppen & Martin, 1988; Ghadimi & Aouam, 2021; Rădăşanu, 2016). Moreover, to deal with the uncertainty of processing time, it is considered as a random normal distribution with a known mean and standard deviation value (Bentaha et al., 2015, 2018; Joo et al., 2018; Xia et al., 2008). For this study, the demand is considered as normally distributed using a mean (μd_{kt}) and standard deviation (σd_{kt}) value. And processing time also follows normal distribution ($\mu p_{kt}, \sigma p_{kt}^2$). For this model, the following equation (1) is used to have a combined effect for the standard deviation of demand and processing time (Bhavsar & Sinha, 2019; Eppen & Martin, 1988; Ghadimi & Aouam, 2021; Osman & Demirli, 2012; Rădăşanu, 2016). The equation is derived from variable demand and lead-time situations (Tersine, 1988). For this case, the processing time is considered instead of the lead time.

$$\sigma_{kt} = \sqrt{(\mu p_{kt} \times \sigma d_{kt}^2) + (\mu d_{kt}^2 \times \sigma p_{kt}^2)} \quad \forall k \in K, \forall t \in T \quad (1)$$

3.3 Mathematical Model

The model proposed for providing optimal lot-sizing plans and platform design in hybrid manufacturing systems facing variability in production time and customer demand is composed of the following objective function and set of constraints.

$$\begin{aligned} \text{Min } Z = & \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T C p_{jt} p_{kt} x_{jt} + \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T C a_{jkt} p_{kt} a_{jkt} \\ & + \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T C r_{jkt} p_{kt} r_{jkt} + \sum_{k=1}^K \sum_{t=1}^T C h_{kt} (I_{kt} + ss_{kt}) \end{aligned} \quad (2)$$

Subject to:

$$a_{jkt} + x_{jt} \leq 1 \quad \forall j \in J, k \in K, t \in T \quad (3)$$

$$a_{jkt} + x_{jt} \geq V_{jk} \quad \forall j \in J, k \in K, t \in T \quad (4)$$

$$V_{jk} \geq a_{jkt} \quad \forall j \in J, k \in K, t \in T \quad (5)$$

$$r_{jkt} - x_{jt} + V_{jk} \geq 0 \quad \forall j \in J, k \in K, t \in T \quad (6)$$

$$1 + x_{jt} \geq F_{jlk} + x_{lt} \quad \forall j \in J, l \in J, k \in K : l \neq j, t \in T \quad (7)$$

$$B_{jl}(x_{jt} - x_{lt}) = 0 \quad \forall j \in J, l \in J : l > j, t \in T \quad (8)$$

$$S_{jl}(x_{jt} + x_{lt}) \leq 1 \quad \forall j \in J, l \in J : l > j, t \in T \quad (9)$$

$$I_{kt} = I_{kt-1} + p_{kt} - Sl_{kt}D_{kt} - ss_{kt} + ss_{kt-1} \quad \forall k \in K, t \in T \quad (8)$$

$$p_{kt} + I_{k(t-1)} + ss_{kt} \geq Sl_{kt}D_{kt} \quad \forall k \in K, t \in T \quad (9)$$

$$z_{kt} = \alpha \times Sl_{kt} - \beta \quad \forall k \in K, t \in T \quad (10)$$

$$ss_{kt} \geq z_{kt}\sigma_{kt} \quad \forall k \in K, t \in T \quad (11)$$

$$ss_{kt} \leq z_{kt}\sigma_{kt} + 1 \quad \forall k \in K, t \in T \quad (12)$$

$$a_{jkt}, r_{jkt}, x_{jt} \text{ is binary} \quad \forall j \in J, k \in K, t \in T \quad (13)$$

$$p_{kt}, I_{kt}, z_{kt}, ss_{kt} \geq 0 \quad \forall k \in K, t \in T \quad (14)$$

There are four terms in the objective function (2). The first term indicates the mass production cost of the platform, and the second and third terms indicate the additive cost of any feature and the subtractive cost of any feature in the variant stages, respectively. The last term indicates the inventory holding cost, including the cost of the safety stock needed to cope with variability in customer demand and production time.

Constraints (3)-(5) ensure the addition of feature j if variant k requires feature j , and the feature is not included in the platform of that period. Constraint (3) confirms that feature j is not added twice to form variant k . Constraint (4) confirms the addition (e.g., DMD/FFF) of feature j on the platform only if feature j is not available on the platform and it is required to form variant k . Constraint (5) satisfies the situation when feature j is not required to form variant k ; it will not be added. Constraint (6) ensures the subtraction (e.g., CNC) of any feature j if variant k does not require feature j in case the feature is included in the platform of that period. Constraint (7) respects the precedence relationship among features while assigning features to the platform. If feature j precedes feature l , the constraint avoids processing feature l in the platform and feature j in the variant stages. Instead, the two features are either processed in the platform or not, and if not constraint (4) ensures processing both features in the variant stages. Constraint (8) ensures that same feature j is not added and subtracted at the same time to form variant k . Constraints (9) and (10) indicate the inclusion and seclusion of two features in the same platform. Constraint (11)

indicates the relation among inventory, safety stock and production quantity. It ensures that the demand is satisfied from production, inventory, or safety stock. Constraints (12) indicates that the production quantity, inventory, and safety stock ensure the defined service level for the demand of period t .

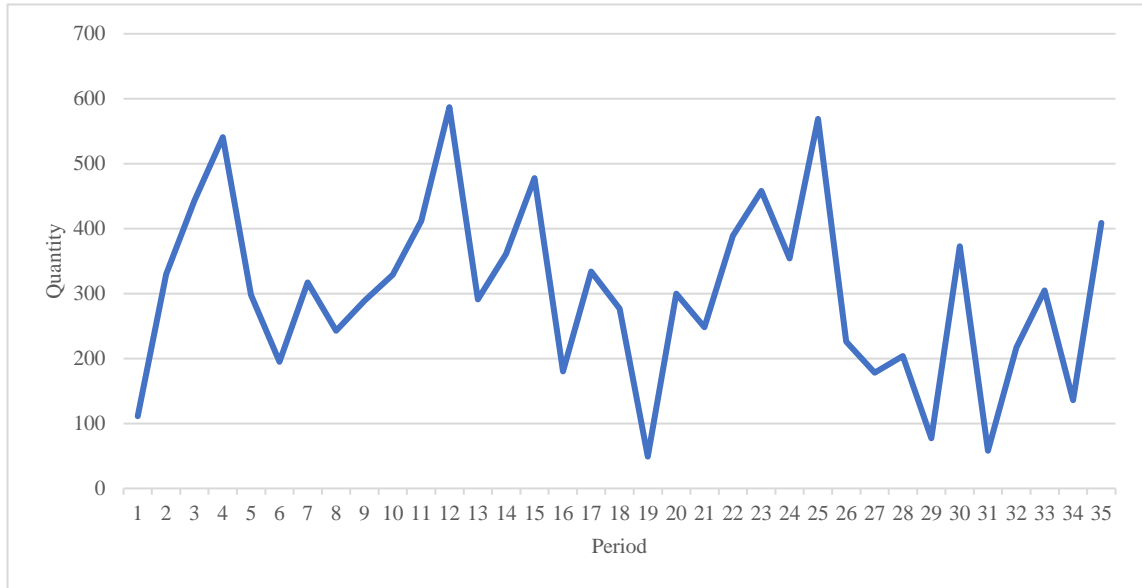


Figure 3. 1: Variable demand

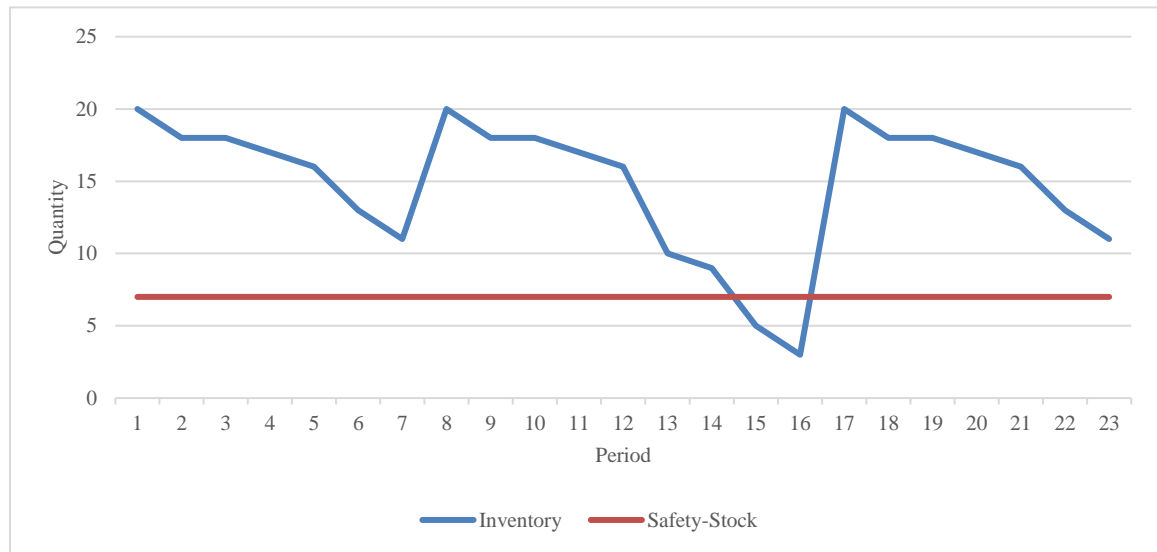


Figure 3. 2: Inventory and Safety stock

From constraint (13), the safety factor will be determined. Using these linear constraints, the safety factors can be found without the factor table using the predefined value of service

level. These constraints are derived from linear regression between safety factors and service level ($z_{kt} = \alpha Sl_{kt} + \beta$). This constraint ensures high accuracy of safety factor, in between the range of 50%-99.99% of service level. Initially, using the normal distribution table, safety factors are identified according to the service level. After that, the linear regression process is conducted to identify the slope (α) and constant value (β).

Constraints (14) and (15) specify the safety stock level needed to ensure a certain service level. In figure 3.1, random variable demand is illustrated. Here, the demand varies randomly within the range of 49-587, with a mean value of 322 and a standard deviation of 130. And in figure 3.2, inventory levels and safety stock are illustrated. Here the maximum level of inventory is 20, and the minimum level of inventory is 7. When the demand is more than the production quantity and the available minimum level of inventory, the safety stock can be used to satisfy that demand (Tersine, 1988). Constraint (16) indicates the binary decision variables. And constraint (17) ensures non-negativity of production quantity, inventory amounts, and safety stock.

The developed model has nonlinearity only in objective function; however all the constraints are linear. Gurobi 9.5.2 is able to deal with this situation and for the developed model it is able to provide the optimal solution.

CHAPTER 4

COMPUTATIONAL EXPERIENCE

In this chapter, the solution procedure is explained, and different case studies are illustrated to analyze the effectiveness of the developed mathematical model. The first case study is an illustrative example of a product family. The second case study is for a guiding bush family. The third case study is on a gear family. And the fourth case study is another illustrative example for testing large instances of a product family.

4.1 First Illustrative Case Study

A manufacturing company offers 3 variants of a product. The relation between variants and features, precedence relation between feature is illustrated in table 4.1 and table 4.2 respectively. (Data collected from (Jin & Chen, 2008)).

The parameter V_{jk} (variant and feature relation) is a binary parameter which represents the features required for any variant, represented in table 4.1. In this case, for variant 1, F1, F2, and F4 are required. So, the V_{jk} value is 1 for these three features, and for the rest of the features, the V_{jk} value is 0. For variant 2, F1, F2, and F3 are required. So, the V_{jk} value is 1 for these three features, and for the rest of the features, the V_{jk} value is 0. For variant 3, F1, and F2 are required. So, the V_{jk} value is 1 for these two features, and for the features F3, and F4, the V_{jk} value is 0.

Table 4. 1: Variants and Features Relationship

Variant/Feature	1	2	3	4
1	1	1	0	1
2	1	1	1	0
3	1	1	0	0

The parameter f_{jlk} (precedence relation between features) is a binary parameter represented in table 4.2. For this case, F2, and F3 are preceded by F1. So, the f_{jlk} value is 1 for these relations. And F4 is preceded by F2. So, the f_{24k} value is 1 for this relation. Moreover, F3,

and F4 do not precede other features. For this reason, all the f_{jik} values are 0 in column 4, and 5 of table 4.2.

Table 4. 2: Precedence Relation between Features

Feature/Feature	1	2	3	4
1	0	0	0	0
2	1	0	0	0
3	1	0	0	0
4	0	1	0	0

Table 4. 3: Demand and Holding Cost of a Variant for each period

Variant	Period	Demand	Ch
1	1	52	1
1	2	130	1
1	3	107	1
2	1	96	1
2	2	247	1
2	3	85	1
3	1	154	1
3	2	157	1
3	3	87	1

For this case study, demand is normally distributed. The mean value of demand is 112 and standard deviation is 75. Jin & Chen (2008) considers deterministic demand within the range of 50-200 per period. With the mean value and standard deviation of the demand the stochastic demand is fabricated within the range of 52-247. Demand and cost of holding, Ch for each variant and each period is presented in table 4.3.

From table 4.3, it is also visible that the demand for a variant is not deterministic. For example, variant 1, in period 1, its demand is 52, whereas, in period two, it becomes 130. Variant 1 and Variant 2 experience a cyclic trend in demand. For variant 3 demand is initially steady for the first two periods; after that there is a sudden decrease in demand in period 3.

Table 4. 4: Cost of Processing, Addition, and Removal of a Feature for each period

Feature	Period	Cp	Ca	Cr
1	1	3	4	1
1	2	2	3	1
1	3	3	3	1
2	1	3	4	2
2	2	2	3	2
2	3	3	3	2
3	1	3	4	1
3	2	2	4	1
3	3	2	4	2
4	1	2	3	1
4	2	3	3	1
4	3	3	4	2

The cost of processing any feature on the platform, C_p is in the range of \$(2-3)\$, the cost of adding (e.g., DMD/FFF) any feature, C_a is in the range of \$(3-4)\$, and the cost of removing (e.g., CNC) any feature, C_r is in the range of \$(1-2)\$ which is illustrated in table 4.4.

The developed model is coded by using AMPL, while the solver used to find optimal solutions of the developed model is Gurobi 9.5.2. The optimal solution is found within approximately 0.82 sec on a PC with Intel® X®(R) 3.07GHz processor and 12 GB RAM. Whereas the source use OPL and CPLEX 11.0 and it took more than 40 hours to solve.

A comparison of the total cost with and without considering inventory is illustrated in table 4.5. When the inventory and safety stock is considered, production is not required for each period. When inventory is not considered, demand must be satisfied by the production quantity. The total cost for three periods considering inventory (\$10,513) is less than without considering inventory (\$10,721). The average cost per period is \$3,504.33.

Table 4. 5: Solution of Case Study 1

Variant	Period	Demand	Production	Inventory	Safety stock	Cost with Inventory	Cost without Inventory
1	1	52	62	0	10	10513	10721
1	2	130	236	107	9		
1	3	107	0	0	9		
2	1	96	107	0	11		
2	2	247	330	84	10		
2	3	85	0	0	9		
3	1	154	162	0	8		
3	2	157	245	88	8		
3	3	87	0	0	9		

Moreover, in Table 4.5, it is illustrated that for each variant, period 1 and 2's demand is satisfied from production and for each variant, period 3's demand is satisfied from inventory and safety-stock.

The number of platforms and which features ($j \in J$) are available on the platform is an outcome of the developed model. From the outcome of variable x_{jt} , the number of platforms and which features ($j \in J$) are processed on the platform of any period is identified. The outcome of x_{jt} for the case study is illustrated in Table 4.6.

Table 4. 6: Optimal platform for each period

Feature/period	1	2	3
1	1	1	1
2	1	1	1
3	1	1	0
4	0	0	0

The optimal platform for each period is illustrated in table 4.6. For period one and period two, platform one is used. For period three platform two is used based on the demand. In platform one F1, F2, and F3 are included. On the other hand, platform two consists of only F1 and F2.

Table 4. 7: Manufacturing 3 Variants from Platform one in period 1 & 2

Platform 1	Variants
F1, F2, F3	Variant 1: Remove F3 + Add F4
	Variant 2: No addition + No removal
	Variant 3: Remove F3

From the solution it is identified that platform one consists of feature 1, feature 2 and feature 3. How all the variants are processed from platform 1 is illustrated in figure 4.1 and in table 4.7. From platform one variant 1 can be produced by removing feature 3 and adding feature 4. As variant 2 is made of feature 1, 2, and 3, no operation is required for producing variant 2. variant 3 can be produced by only removing feature 3.

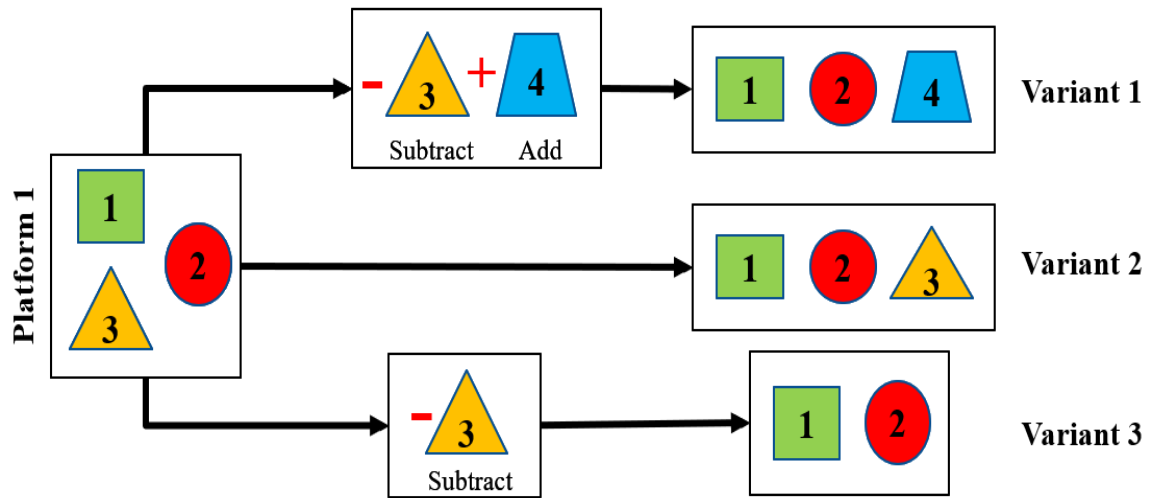


Figure 4. 1: Platform 1 to variants processing

Table 4. 8: Manufacturing 3 Variants from Platform two in period 3

Platform 2	Variants
F1, F2	Variant 1: Add F4
	Variant 2: Add F3
	Variant 3: No addition + No removal

From the solution it is identified that platform two consists of feature 1 and feature 2. How all the variants are processed from platform 2 is illustrated in figure 4.2 and in table 4.8. From platform two variant 1 can be produced by adding feature 4 and variant 2 can be produced by adding feature 3. As variant 3 is made of feature 1 and 2, no operation is required for producing variant 3.

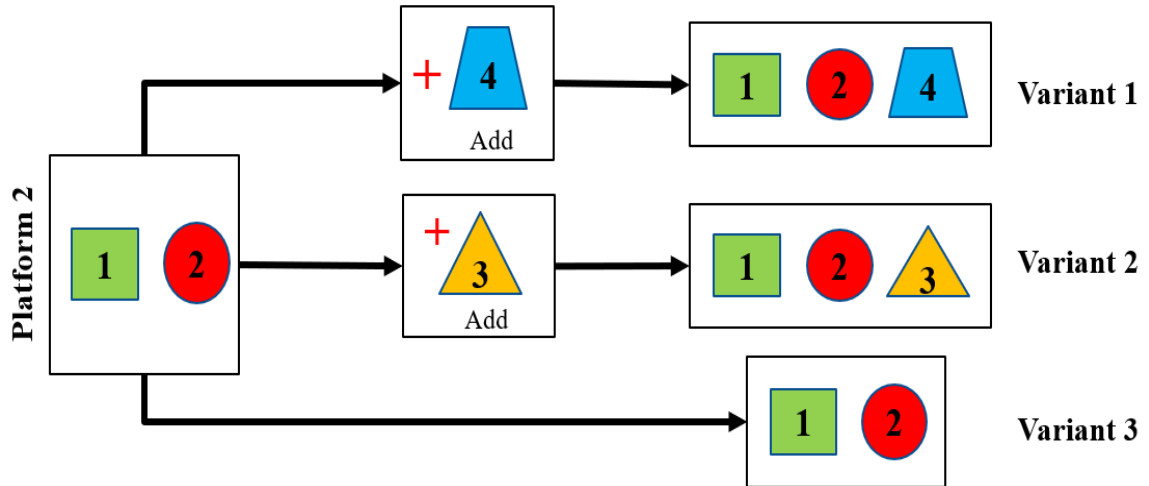


Figure 4. 2: Platform 1 to variants processing

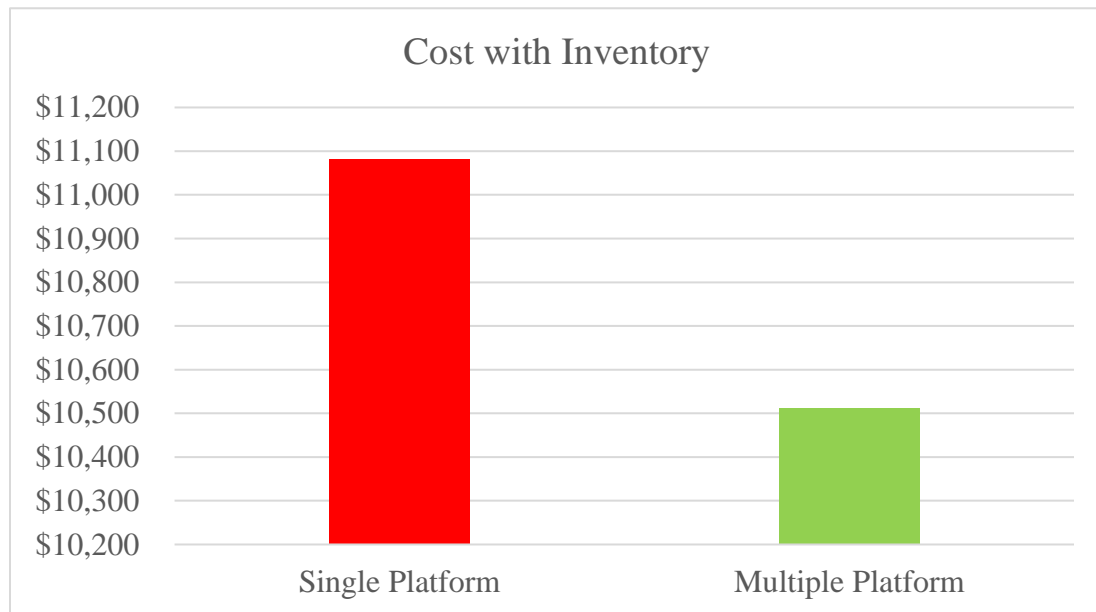


Figure 4. 3: Cost Comparison

Another cost comparison of using multiple platforms and a single platform for all periods is illustrated in figure 4.1. When a single platform is used for all periods, the total cost becomes \$11,083, whereas using different platforms for different periods according to the order becomes \$10,513 (5% less than using the single platform).

4.2 Case Study of a Guiding Bush Family

The case study considers five variants and eight features of a guiding bush family. For this case study, the data is collected from (ElMaraghy & Moussa, 2019). The relation between variants and features precedence relation between features is illustrated in table 4.9 and table 4.10 respectively. The parameter V_{jk} (variant and feature relation) is a binary parameter which represents the features required for any variant, represented in table 4.9. In this case, for variant 1, F1, F2, and F3 are required. So, the V_{jk} value is 1 for these three features, and for the rest of the features, the V_{jk} value is 0.

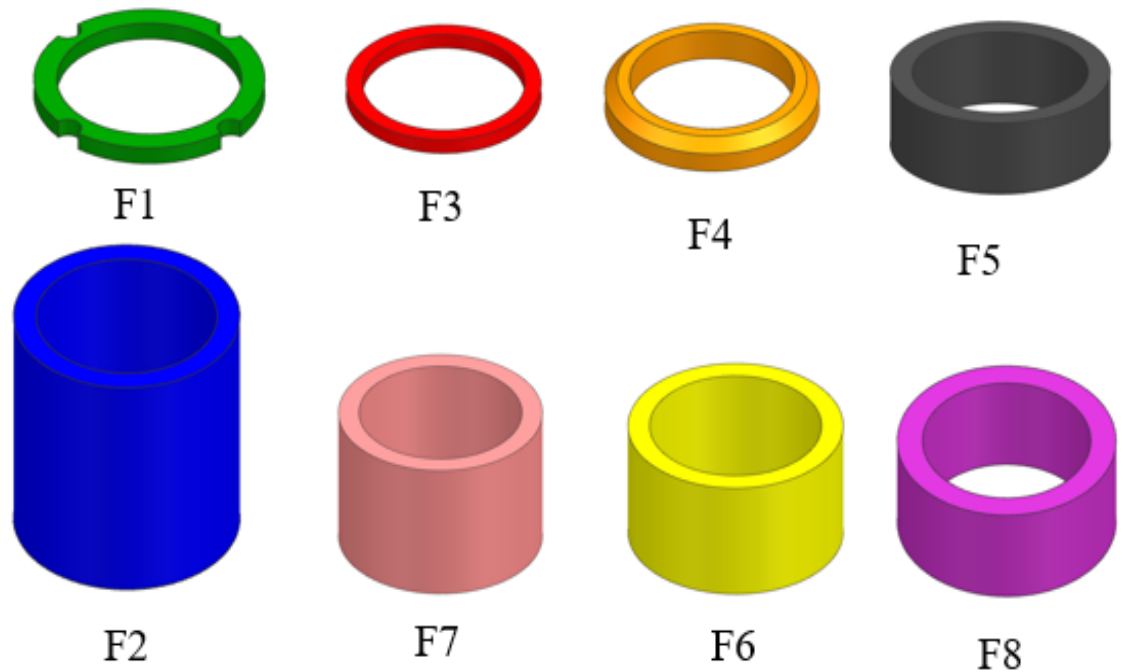


Figure 4. 4: Eight Features

In figure 4.4 all eight features are illustrated. Using these features, the variants are produced, which is illustrated in figure 4.5 The 3D model of the features and the variants are created using NX. Guiding bush family can be used in the automotive and manufacturing industry. A guiding bush can be used for the alignment of the conveyor.

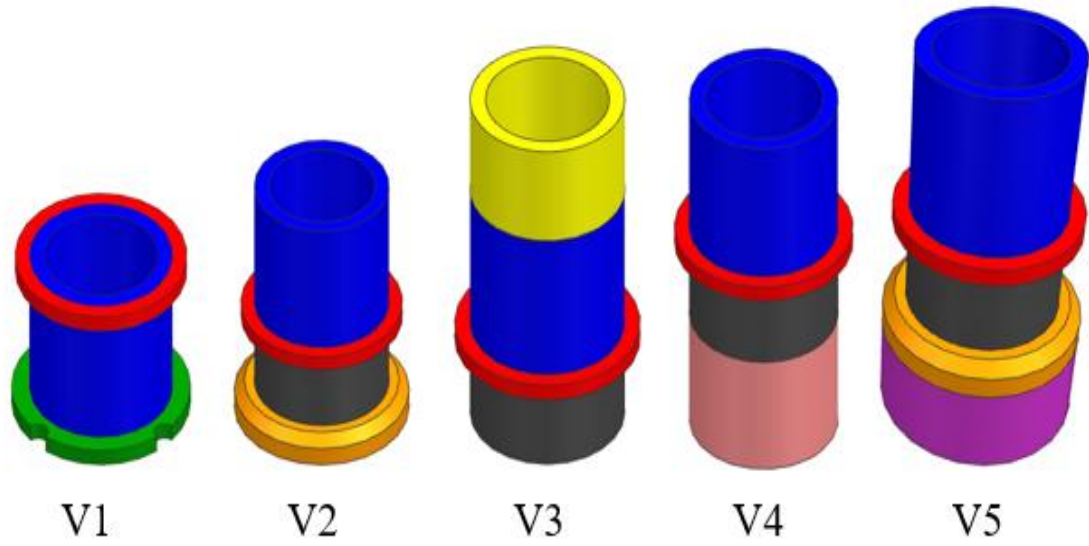


Figure 4. 5: Five variants of guiding bush family

The parameter f_{jlk} (precedence relation between features) is a binary parameter represented in table 4.10. For this case, F1, F5, F6 are preceded by F2. So, the f_{jlk} value is 1 for these relations. Moreover, F1, F3, F4, F6, and F8 do not precede other features. For this reason, all the f_{jlk} values are 0 in column 2, 4, 5, and 7 of table 4.10.

Table 4. 9: Variants and Features Relationship

Variant/ Feature	F1	F2	F3	F4	F5	F6	F7	F8
V1	1	1	1	0	0	0	0	0
V2	0	1	1	1	1	0	0	0
V3	0	1	1	0	1	1	0	0
V4	0	1	1	0	1	0	1	0
V5	0	1	1	1	1	0	1	1

Table 4. 10: Precedence Relation between Features

Feature/ Feature	1	2	3	4	5	6	7	8
1	0	1	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0
3	0	1	0	0	0	0	0	0
4	0	0	0	0	1	0	0	0
5	0	1	0	0	0	0	0	0
6	0	1	0	0	0	0	0	0
7	0	0	0	0	1	0	0	0
8	0	0	0	0	1	0	1	0

For this case study, normally distributed demand and production time are considered. The mean value of demand is 322, and the standard deviation is 130 for this case study. ElMaraghy & Moussa (2019) considers deterministic demand within the range of 50-750. With the mean value and standard deviation of the demand, the stochastic demand is fabricated within the range of 49-587. And it satisfies almost all the demand scenarios. The cost of adding (e.g., DMD/FFF) any feature is in the range of \$(5-12). The cost of removing (e.g., CNC) any feature is in the range between \$(2-4). The cost of processing any feature on the platform is in the range of \$(0.5-2). The developed model is coded by using AMPL, while the solver used to find optimal solutions of the developed model is Gurobi 9.5.2. The optimal solution is found within approximately 0.93 sec on a PC with Intel® X®(R) 3.07GHz processor and 12 GB RAM.

A comparison of the total cost with and without considering inventory is illustrated in table 4.11. When the inventory and safety stock is considered, production is not required for each period. When inventory is not considered, demand must be satisfied by the production

quantity. The total cost for seven periods considering inventory (\$125,159) is less than without considering inventory (\$183,453). The average cost per period is \$17,880. In this case study, three optimal platforms are identified for seven periods considering the demand of each variant. From table 4.11, it is also visible that the demand for a variant is not deterministic. For example, variant 3, in period 1, its demand is 478, whereas, in period five, it has only 49-unit demand. Variant 2 experiences a gradual increase in demand up to period 5; after that, there is a sudden decrease in demand. Moreover, variant five is dealing with a cyclic trend in demand.

Table 4. 11: Solution of Guiding Bush Family Case Study

Period	Variants	Cost	
	V1, V2, V3, V4, V5	With Inventory	Without Inventory
1	111, 243, 478, 389, 77	\$125,159	\$183,453
2	330, 289, 180, 458, 373		
3	443, 329, 334, 354, 58		
4	541, 412, 277, 569, 217		
5	298, 587, 49, 226, 305		
6	195, 291, 300, 178, 136		
7	317, 361, 248, 204, 409		

The optimal platform for each period is illustrated in table 4.12. For period one and period 6, platform one is used. For period two and period 5, platform two is used. For period 3, period 4, and period 7, platform three is used based on the demand.

The number of platforms and which features ($j \in J$) are available on the platform is an outcome of the developed model. From the outcome of variable x_{jt} , the number of platforms and which features ($j \in J$) are processed on the platform of any period is

identified. The outcome of x_{jt} for the case study is illustrated in table 6. For period 2, there are F1, F2, F4, F5, F7, and F8 processed on platform-two (P2). Which is similar to period 5. For periods 1 and 6 same platform-one (P1) is used, and for periods 3, 4, and 7, platform-three (P3) is used.

Table 4. 12: Optimal platform for each period

Platform	P1	P2	P3	P3	P2	P1	P3
Period	1	2	3	4	5	6	7
F1	0	1	0	0	1	0	0
F2	1	1	1	1	1	1	1
F3	1	0	1	1	0	1	1
F4	1	1	0	0	1	1	0
F5	1	1	1	1	1	1	1
F6	1	0	1	1	0	1	1
F7	1	1	1	1	1	1	1
F8	1	1	0	0	1	1	0

From Platform one, Variant 1 can be produced by adding F1 and removing F4, F5, F6, F7, and F8. Variant 2 can be produced by only removing F6, F7, and F8. Variant 3 can be produced by removing F4, F7, and F8. Variant 4 can be produced by removing F4, F6, and F8. Finally, Variant 5 can be produced by removing F6.

From Platform two, Variant 1 can be manufactured by adding F3 and by removing F4, F5, F7, and F8. Variant 2 can be produced by adding F3 and by removing F1, F7, and F8. Variant 3 can be produced by adding F3 and F6 and by removing F1, F4, F7, and F8.

Variant 4 can be produced by adding F3 and by removing F1, F4, and F8. Finally, variant five can be produced by adding F3 and by removing F1.

Table 4. 13: Manufacturing 5 Variants from Optimal Platform 1

Platform 1	Variants
F2, F3, F4, F5, F6, F7, F8	Variant 1: Add F1 and Remove F4, F5, F6, F7, F8
	Variant 2: Remove F6, F7, F8
	Variant 3: Remove F4, F7, F8
	Variant 4: Remove F4, F6, F8
	Variant 5: Remove F6

From Platform three, Variant 1 can be manufactured by adding F1 and by removing F5, F6, and F7. Variant 2 can be produced by adding F4 and by removing F6 and F7. Variant 3 can be produced by removing F7. Variant 4 can be produced by removing F6. Finally, variant five can be produced by adding F1 and F8 and by removing F6. This situation is given in table 4.13.

Table 4. 14: Manufacturing 5 Variants from Optimal Platform 2

Platform 2	Variants
F1, F2, F4, F5, F7, F8	Variant 1: Add F3 and Remove F4, F5, F7, F8
	Variant 2: Add F3 and Remove F1, F7, F8
	Variant 3: Add F3, F6 and Remove F1, F4, F7, F8
	Variant 4: Add F3 and Remove F1, F4, F8
	Variant 5: Add F3 and Remove F1

Table 4. 15: Manufacturing 5 Variants from Optimal Platform 3

Platform 3	Variants
F2, F3, F5, F6, F7	Variant 1: Add F1 and Remove F5, F6, F7
	Variant 2: Add F4 and Remove F6, F7
	Variant 3: Remove F7
	Variant 4: Remove F6
	Variant 5: Add F1, F8 and Remove F6

Another cost comparison of using multiple platforms and a single platform for all periods is illustrated in figure 4.6. When a single platform is used for all periods, the total cost becomes \$187,494, whereas using different platforms for different periods according to the order becomes \$125,159 (33% less than using the single platform).

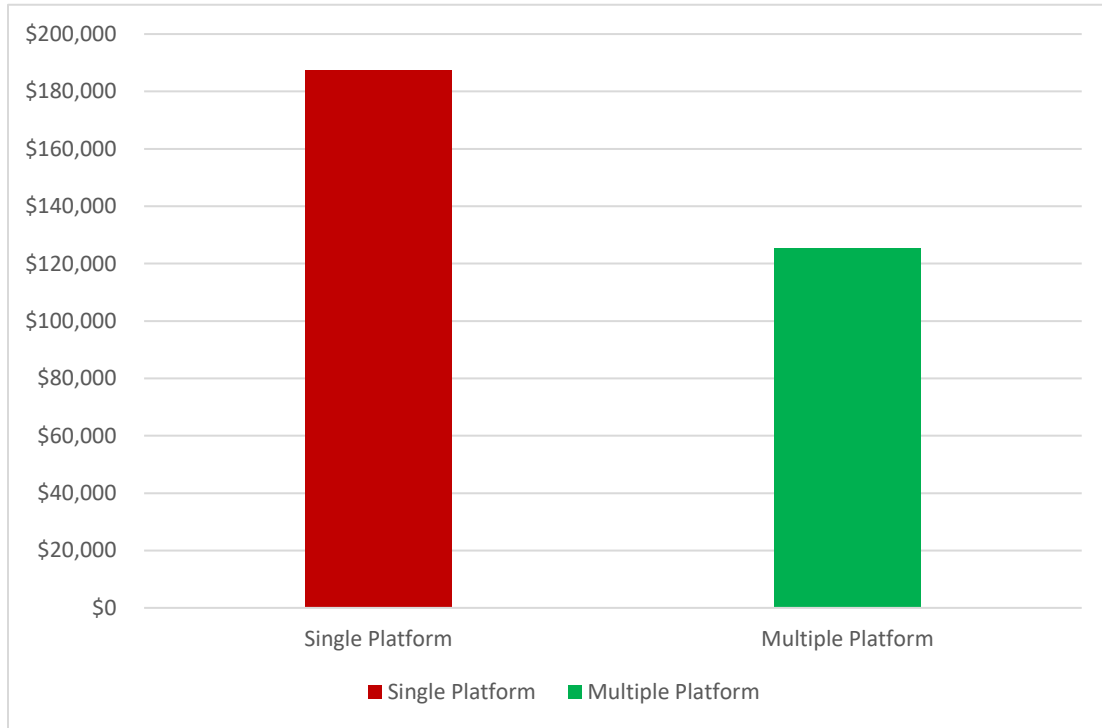


Figure 4. 6: Cost Comparison

Detailed results of variant 4, as an example, are given in table 4.16. The demand for this variant in periods 3 and 7 is more than the production quantity and inventory amount of these two periods. Therefore, the extra demand is satisfied by the safety stock. This shows the importance of ensuring adequate safety stock amounts to cope with stochastic demand and production time and minimize the demand loss. A solution for all the variants is available in appendix A.

Table 4. 16: Optimal solution for variant 4

Period	Demand	Production	Inventory	Safety stock
1	389	857	458	10
2	458	0	0	10
3	354	352	0	8
4	569	974	403	10
5	226	0	179	8
6	178	0	0	9
7	204	203	0	8

4.3 Case Study of Gear Family

This case study considers four variants and twelve features of a gear shaft family. For this case study the data is collected from (Moussa & ElMaraghy, 2022). The relation between variants and features, precedence relation between feature is illustrated in table 4.17 and table 4.18 respectively.

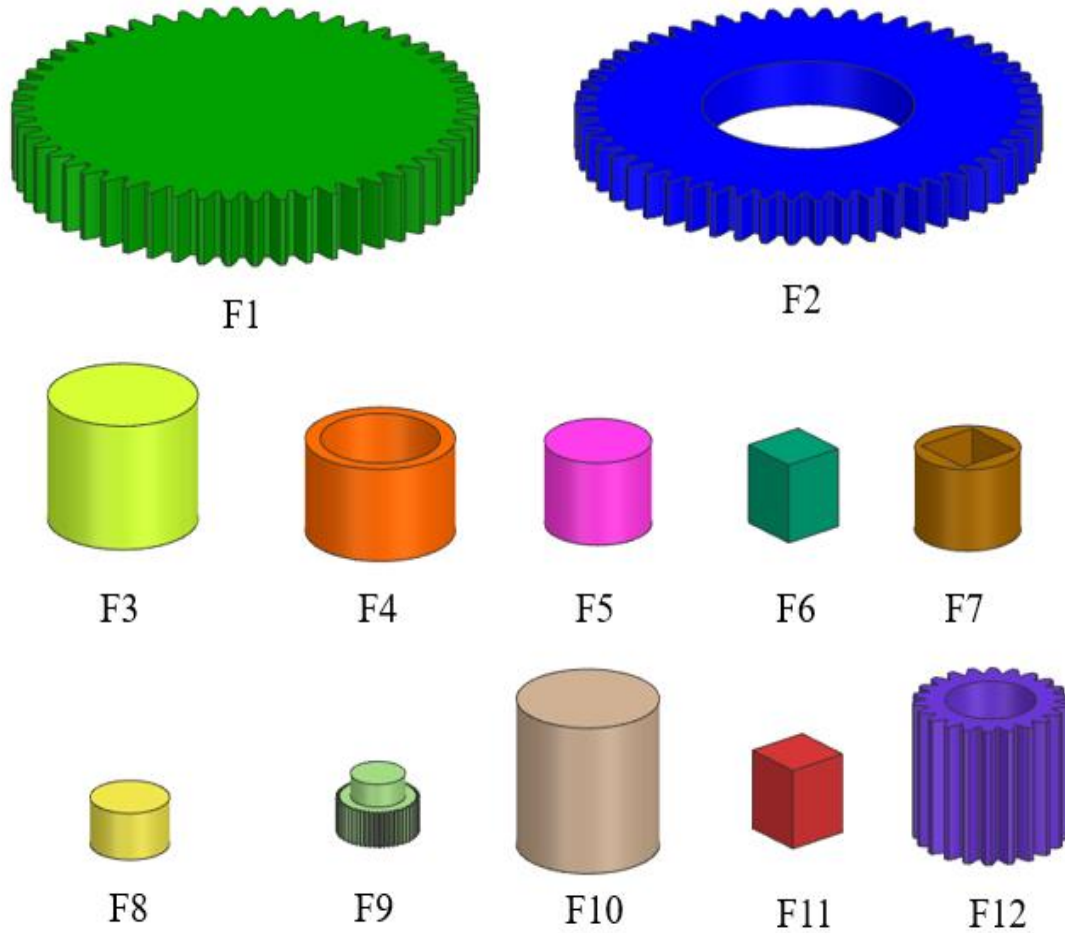


Figure 4. 7: Twelve Features

The parameter V_{jk} (variant and feature relation) is a binary parameter which represents the features required for any variant, represented in table 4.17. In this case, for variant 1, F1, and F3 are required. So, the V_{jk} value is 1 for these two features, and for the rest of the features, the V_{jk} value is 0. For variant 2, F1, F3, F5, F6, F7, F8, and F9 are required. So, the V_{jk} value is 1 for these seven features, and for the rest of the features, the V_{jk} value is 0.

For variant 3, F1, F2, F3, F4, F5, F6, F10, and F11 are required. So, the V_{jk} value is 1 for these eight features, and for the rest of the features, the V_{jk} value is 0. For variant 4, F1, F3, F4, F5, F6, F7, F8 and F12 are required. So, the V_{jk} value is 1 for these eight features, and for the rest of the features, the V_{jk} value is 0.

In figure 4.7 all twelve features are illustrated. Using these features, the variants are produced, which is illustrated in figure 4.8 The 3D model of the features and the variants are created using NX. The gear family can be used in the automotive and manufacturing industry. Gear can be used for the power transmission of automobiles, and manufacturing machinery.

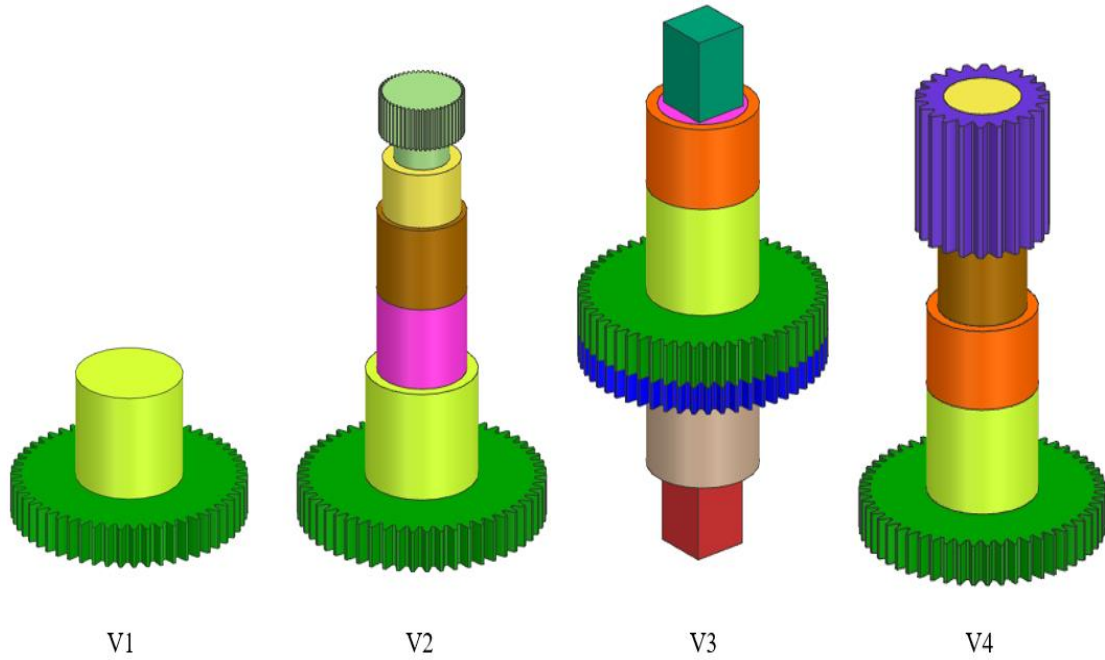


Figure 4. 8: Four Variants of gear family

The parameter f_{jlk} (precedence relation between features) is a binary parameter represented in table 4.18. For this case, F2, F3, and F10 are preceded by F1. So, the f_{jlk} value is 1 for these relations. Moreover, F2, F4, F7, F9, F11, and F12 do not precede other features. For this reason, all the f_{jlk} value is 0 in column 3, 5, 7, 10, 12, and 13 of table 4.16.

Table 4. 17: Variants and Features Relationship

Variants/Features	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
V1	1	0	1	0	0	0	0	0	0	0	0	0
V2	1	0	1	0	1	1	1	1	1	0	0	0
V3	1	1	1	1	1	1	0	0	0	1	1	0
V4	1	0	1	1	1	1	1	1	0	0	0	1

Table 4. 18: Precedence Relation between Features

Features/Features	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
F1	0	0	0	0	0	0	0	0	0	0	0	0
F2	1	0	0	0	0	0	0	0	0	1	0	0
F3	1	0	0	0	0	0	0	0	0	0	0	0
F4	0	0	1	0	1	0	0	0	0	0	0	0
F5	0	0	1	0	0	0	0	0	0	0	0	0
F6	0	0	0	0	1	0	0	0	0	0	0	0
F7	0	0	0	0	0	1	0	0	0	0	0	0
F8	0	0	0	0	0	1	0	0	0	0	0	0
F9	0	0	0	0	0	0	0	1	0	0	0	0
F10	1	0	0	0	0	0	0	0	0	0	0	0
F11	0	0	0	0	0	0	0	0	0	1	0	0
F12	0	0	0	0	0	0	1	0	1	0	0	0

From table 4.18, it is observed that F4, and F5 are preceded by F3. So, the f_{ijk} value is 1 for these relations. F4 preceded by two features F3 and F5. Similarly F12 is also preceded by two features (F7 and F9). Feature 5 precedes Feature 6 and Feature 6 precedes Feature 7 and Feature 8. Feature 9 is preceded by Feature 8 and Feature 11 is preceded by Feature 10.

For this case study, demand is normally distributed. The mean value of demand is 390 and standard deviation is 195. Moussa & ElMaraghy (2022) consider deterministic demand within the range of 0-700. With the mean value and standard deviation of the demand the stochastic demand is fabricated within the range of 03-703. And it satisfies almost all the demand scenarios. The cost of adding (e.g., DMD/FFF) any feature is in the range of \$(16.6-53.9). The cost of removing (e.g., CNC) any feature is in the range between \$(4.8-12.2). The cost of processing any feature on the platform is in the range of \$(3.26-11.19).

Table 4. 19: Solution of Case Study 3

Variant	Period	Demand	Production	Inventory	Safety stock	Cost with Inventory	Cost without Inventory
1	1	463	474	0	11	\$980,927	\$1,104,138
1	2	3	0	0	8		
1	3	504	1721	1217	8		
1	4	562	0	657	6		
1	5	406	0	250	7		
1	6	251	0	0	6		
1	7	303	305	0	8		
2	1	703	711	0	8		
2	2	413	1213	802	6		

2	3	203	0	599	6		
2	4	318	0	281	6		
2	5	281	0	0	6		
2	6	306	448	141	7		
2	7	141	0	0	7		
3	1	185	629	438	6		
3	2	267	0	170	7		
3	3	170	0	0	7		
3	4	482	482	0	7		
3	5	39	341	303	6		
3	6	292	0	10	7		
3	7	10	0	0	7		
4	1	275	799	517	7		
4	2	134	0	382	8		
4	3	384	0	0	6		
4	4	628	629	0	7		
4	5	548	1568	1020	7		
4	6	665	0	356	6		
4	7	356	0	0	6		

The developed model is used to find the optimal solution using AMPL. Using Gurobi 9.5.2 optimizer, the optimal solution is found within approximately 1.33 sec on a PC with Intel® X®(R) 3.07GHz processor and 12 GB RAM. The solution is presented in table 4.19.

A comparison of the total cost with and without considering inventory is illustrated in table 4.19. When the inventory and safety stock is considered, production is not required for each period. When inventory is not considered, demand must be satisfied by the production quantity. The total cost for seven periods considering inventory (\$980,927) is less than without considering inventory (\$1,104,138). The average cost per period is \$140,132.43. In this case study, two optimal platforms are identified for seven periods considering the demand of each variant. From table 4.17, it is also visible that the demand for a variant is not deterministic. For example, variant 1, in period 1, its demand is 463, whereas, in period two, it has only 3-unit demand. So, variant 1 experienced a sudden drop of demand from period 1 to period 2. Variant 2 experiences a cyclic trend from period 2 to period 7. Variant 3 illustrates pure cyclic trend in demand. Moreover, variant four deals with steady increasing and decreasing trend of demand.

Moreover, for variant 1 period 4, variant 1 period 6, variant 4 period 3 when the demand is more than production quantity then demand is satisfied by the inventory and safety stock. From here it is visible that safety stock is a useful technique to deal with stochastic demand.

The number of platforms and which features ($j \in J$) are available on the platform is an outcome of the developed model. From the outcome of variable x_{jt} , the number of platforms and which features ($j \in J$) are processed on the platform of any period is identified. The outcome of x_{jt} for the case study is illustrated in table 4.20. For period 1, period 3, period 4, and period 7, feature F1, F3, F5, F6, F10, and F11 are processed on platform-one. For period 2, period 5, and period 6 the same platform is used. Feature F1, F3, F5, F6, F7, F8, F9, and F12 are processed on this platform

Table 4. 20: Optimal platform for each period

Feature/ Period	1	2	3	4	5	6	7
1	1	1	1	1	1	1	1
2	0	0	0	0	0	0	0
3	1	1	1	1	1	1	1
4	0	0	0	0	0	0	0
5	1	1	1	1	1	1	1
6	1	1	1	1	1	1	1
7	0	1	0	0	1	1	0
8	0	1	0	0	1	1	0
9	0	1	0	0	1	1	0
10	1	0	1	1	0	0	1
11	1	0	1	1	0	0	1
12	0	1	0	0	1	1	0

From Platform one, Variant 1 can be produced by removing F5, F6, F10 and F11. Variant 2 can be produced by adding F7, F8, and F9, and by removing F10 and F11. Variant 3 can be produced by adding F2 and F4. Variant 4 can be produced by adding F4, F7, F8 and F12, and by removing F10, and F11.

Table 4. 21: Manufacturing 5 Variants from Optimal Platform 1

Optimal Platform	Variant
F1, F3, F5, F6, F10, F11	Variant 1: Remove F5, F6, F10, F11
	Variant 2: Add F7, F8, F9 – Remove F10, F11
	Variant 3: Add F2, F4
	Variant 4: Add F4, F7, F8, F12 – Remove F10, F11

From Platform two, Variant 1 can be produced by removing F5, F6, F7, F8, F9 and F12. Variant 2 can be produced by only removing F12. Variant 3 can be produced by adding F2 and F4, and by removing F7, F8, F9, and F12. Variant 4 can be produced by adding F4 and by removing F9.

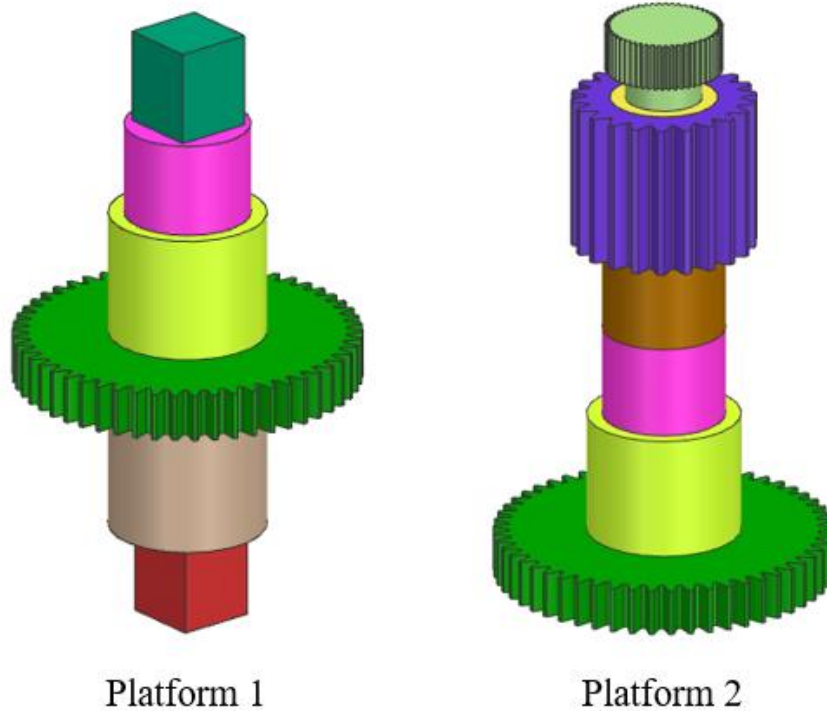


Figure 4. 9: Platform 1 and Platform 2

Table 4. 22: Manufacturing 5 Variants from Platform two

Optimal Platform	Variant
F1, F3, F5, F6, F7, F8, F9, F12	Variant 1: Remove F5, F6, F7, F8, F9, F12
	Variant 2: Remove F12
	Variant 3: Add F2, F4 – Remove F7, F8, F9, F12
	Variant 4: Add F4 – Remove F9

Another cost comparison of using multiple platforms and a single platform for all periods is illustrated in figure 4.10. When a single platform is used for all periods, the total cost becomes \$1,082,241, whereas using different platforms for different periods according to the order becomes \$980,927 (10.3% less than using the single platform).

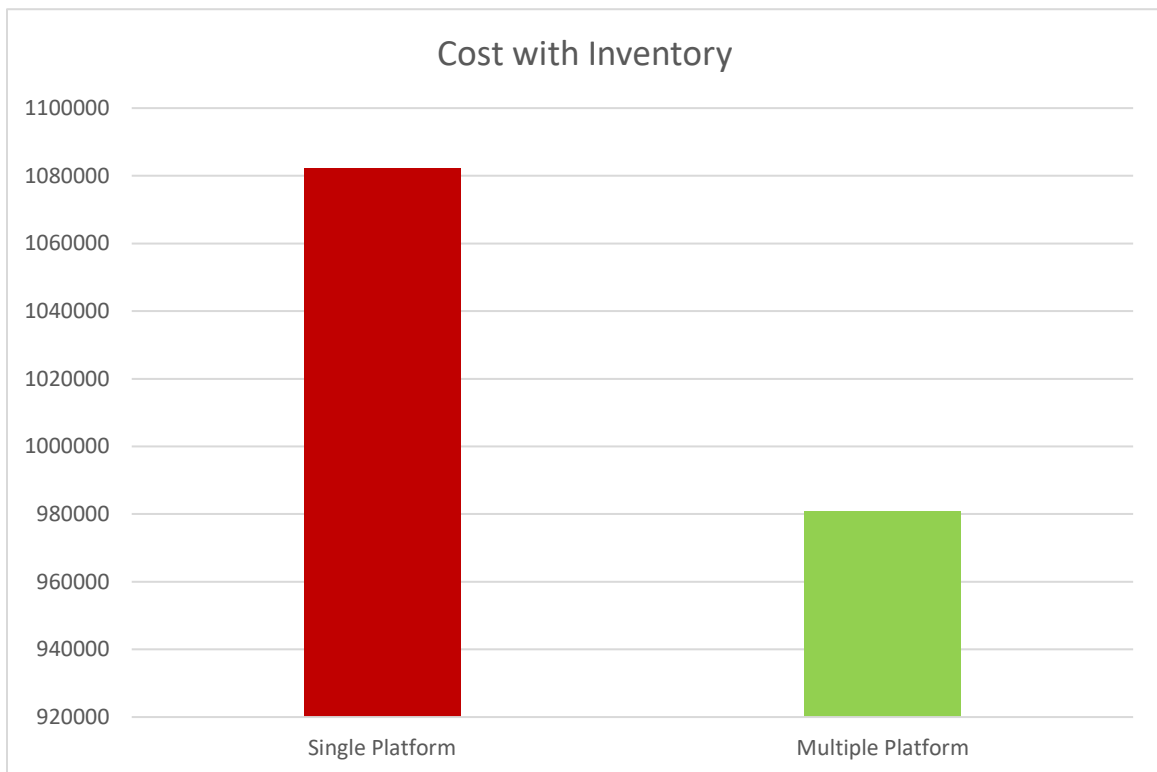


Figure 4. 10: Cost Comparison

4.4 Fourth Illustrative Case Study

In this illustrative case study a family of fourteen variants and eleven features is considered. For this case study the data is collected form (Moussa & ElMaraghy, 2020b). The relation between variants and features, precedence relation between feature is illustrated in table 4.23 and table 4.24 respectively.

In figure 4.11 all eleven features are illustrated. Using these features, the variants are produced, which is illustrated in figure 4.12. The 3D model of the features and the variants are created using NX.

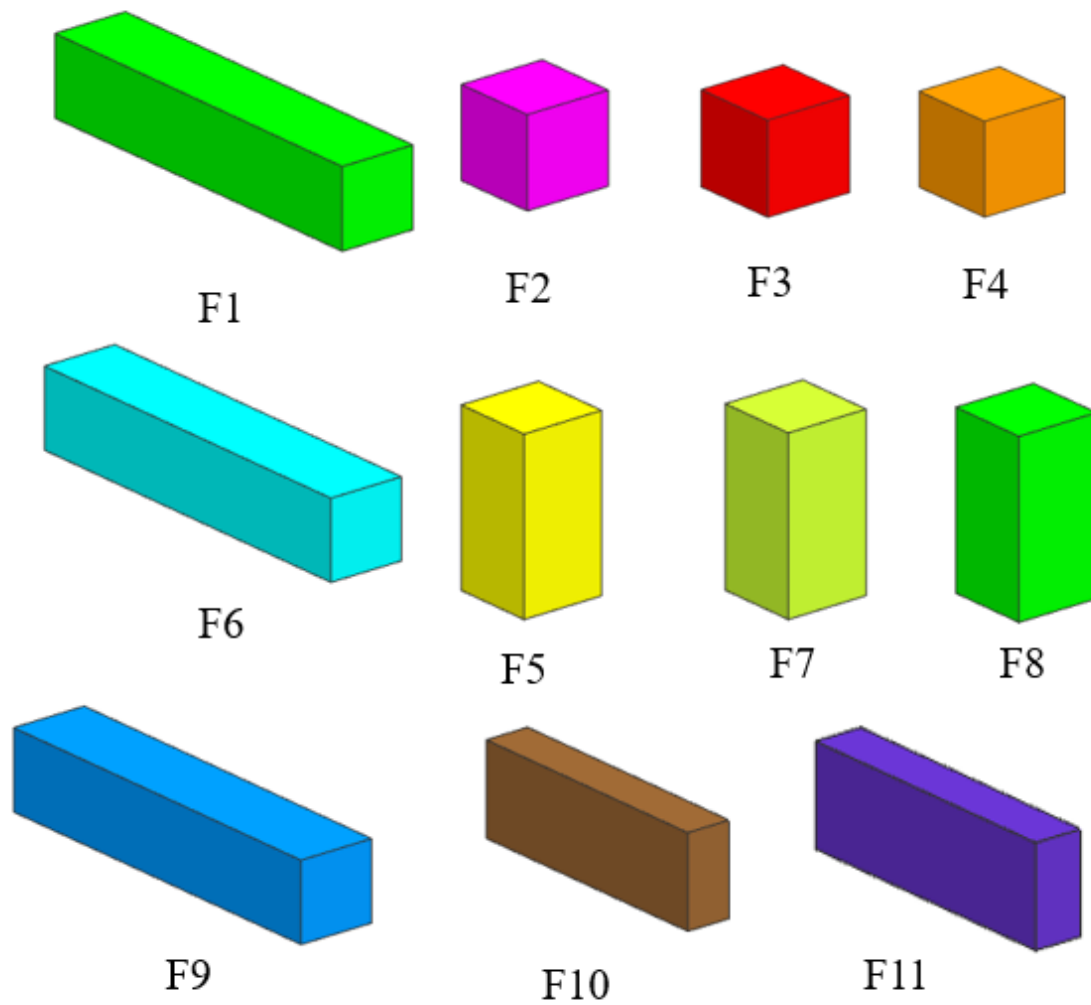


Figure 4. 11: Eleven Features

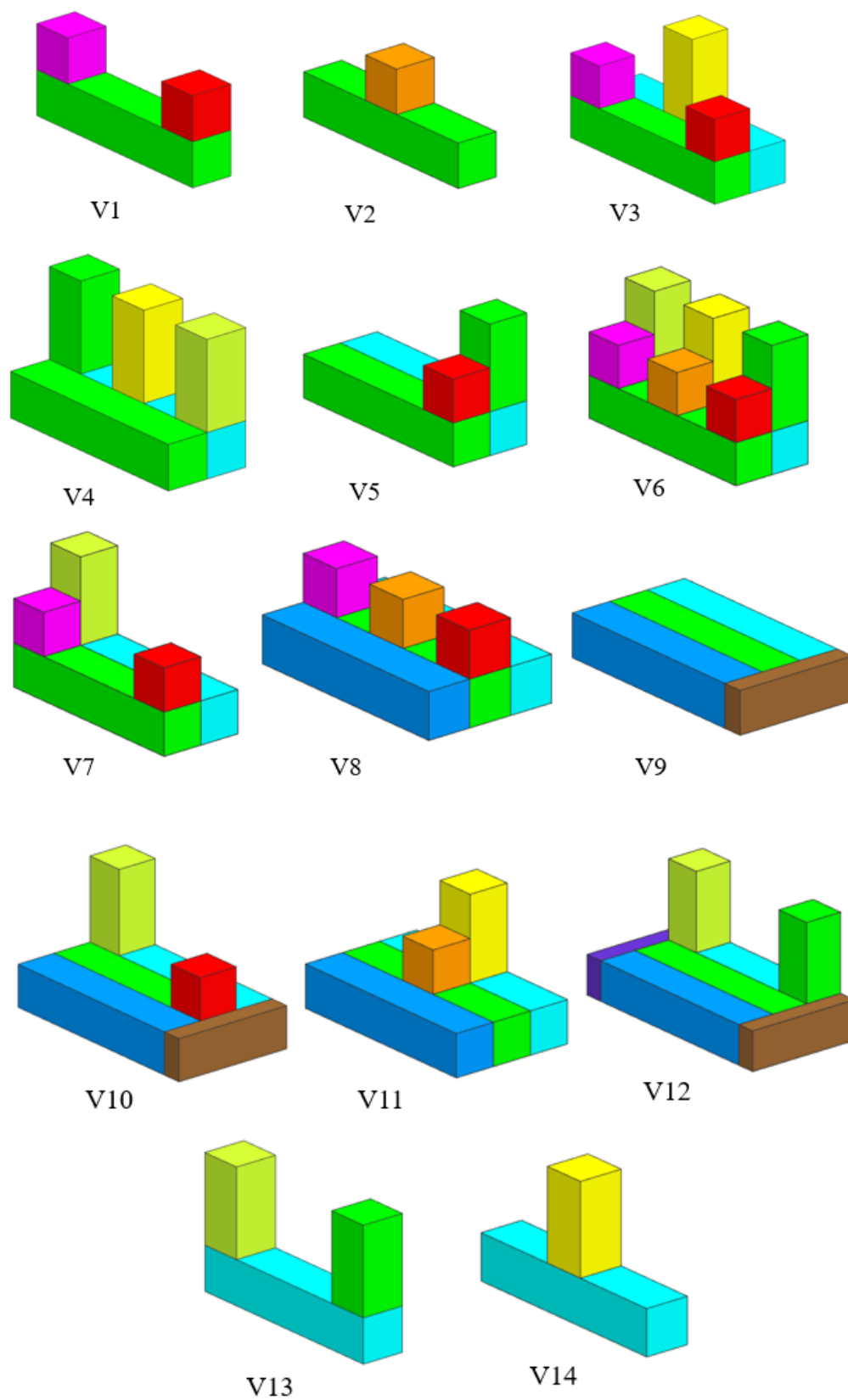


Figure 4. 12: Fourteen Variants

Table 4. 23: Variants and Features Relationship

Variants/Features	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
V1	1	1	1	0	0	0	0	0	0	0	0
V2	1	0	1	0	0	0	0	0	0	0	0
V3	1	1	1	0	1	1	0	0	0	0	0
V4	1	0	0	0	1	1	1	1	0	0	0
V5	1	0	1	0	0	1	0	1	0	0	0
V6	1	1	1	1	1	1	1	1	0	0	0
V7	1	1	1	0	0	1	1	0	0	0	0
V8	1	1	1	1	0	1	0	0	1	0	0
V9	1	0	0	0	0	1	0	0	1	1	0
V10	1	0	1	0	0	1	1	0	1	1	0
V11	1	0	0	1	1	1	0	0	1	0	0
V12	1	0	0	0	0	1	1	1	1	1	1
V13	0	0	0	0	0	1	1	1	0	0	0
V14	0	0	0	0	1	1	0	0	0	0	0

The parameter V_{jk} (variant and feature relation) is a binary parameter which represents the features required for any variant, represented in table 4.23. In this case, for variant 1, F1, F2, and F3 are required. So, the V_{jk} value is 1 for these three features, and for the rest of the features, the V_{jk} value is 0.

The parameter f_{jlk} (precedence relation between features) is a binary parameter represented in table 4.24. For this case, F2, F3, F10 are preceded by F1. So, the f_{jlk} value is 1 for these relations. Moreover, F2, F4, F7, F9, and F11 do not precede other features. For this reason, all the f_{jlk} value is 0 in column 3, 5, 8, 10, and 12 of table 4.24. Feature 2 is preceded by two features F1 and F10. Similar to this feature 4 is also preceded by F3 and F5.

Table 4. 24: Precedence Relation between Features

Features/Features	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
F1	0	0	0	0	0	0	0	0	0	0	0
F2	1	0	0	0	0	0	0	0	0	1	0
F3	1	0	0	0	0	0	0	0	0	0	0
F4	0	0	1	0	1	0	0	0	0	0	0
F5	0	0	1	0	0	0	0	0	0	0	0
F6	0	0	0	0	1	0	0	0	0	0	0
F7	0	0	0	0	0	1	0	0	0	0	0
F8	0	0	0	0	0	1	0	0	0	0	0
F9	0	0	0	0	0	0	0	1	0	0	0
F10	1	0	0	0	0	0	0	0	0	0	0
F11	0	0	0	0	0	0	0	0	0	1	0

For this case study, demand is normally distributed. The mean value of demand is 322 and standard deviation is 100. Moussa & ElMaraghy (2020b) consider deterministic demand within the range of 15-500. With the mean value and standard deviation of the demand the stochastic demand is fabricated within the range of 18-564. And it satisfies almost all the

demand scenarios. The cost of adding (e.g., DMD/FFF) any feature is in the range of \$(2.25-5). The cost of removing (e.g., CNC) any feature is in the range between \$(0.5-1.1). The cost of processing any feature on the platform is in the range of \$(0.45-1). The developed model is coded by using AMPL, while the solver used to find optimal solutions of the developed model is Gurobi 9.5.2. The optimal solution is found within approximately 120 sec on a PC with Intel® X®(R) 3.07GHz processor and 12 GB RAM. The solution for variant 1, variant 2, variant 9, and variant 10 is presented in table 4.25. The complete solution is presented in appendix B.

Table 4. 25: Solution of Case Study 4

Variant	Period	Demand	Production	Inventory	Safety stock
1	1	305	312	0	7
1	2	299	299	0	7
1	3	330	852	522	7
1	4	320	0	202	7
1	5	202	0	0	7
1	6	394	393	0	6
1	7	405	405	0	6
2	1	560	567	0	7
2	2	293	1234	940	8
2	3	127	0	813	8
2	4	564	0	251	6

2	5	250	0	0	7
2	6	449	890	440	8
2	7	442	0	0	6
9	1	483	490	0	7
9	2	242	259	16	8
9	3	18	0	0	6
9	4	399	400	0	7
9	5	251	1164	912	8
9	6	502	0	410	8
9	7	410	0	0	8
10	1	390	398	0	8
10	2	404	635	231	8
10	3	233	0	0	6
10	4	505	505	0	6
10	5	381	844	462	7
10	6	188	0	275	6
10	7	274	0	0	7

A comparison of the total cost with and without considering inventory is illustrated in figure 4. 13. When the inventory and safety stock is considered, production is not required for each period. When inventory is not considered, demand must be satisfied by the

production quantity. The total cost for seven periods considering inventory (\$503,171) is less than without considering inventory (\$535,825). The average cost per period is \$71,881.57. In this case study, four optimal platforms are identified for seven periods considering the demand of each variant. From appendix B, it is also visible that the demand for a variant is not deterministic. For example, a steady rate of demand is observed for variant 1. variant 9 experiences the maximum fluctuation of demand in the range between 502-18. Moreover, Variant 2, variant 3, variant 4 are experiencing the cyclic trend of demand.

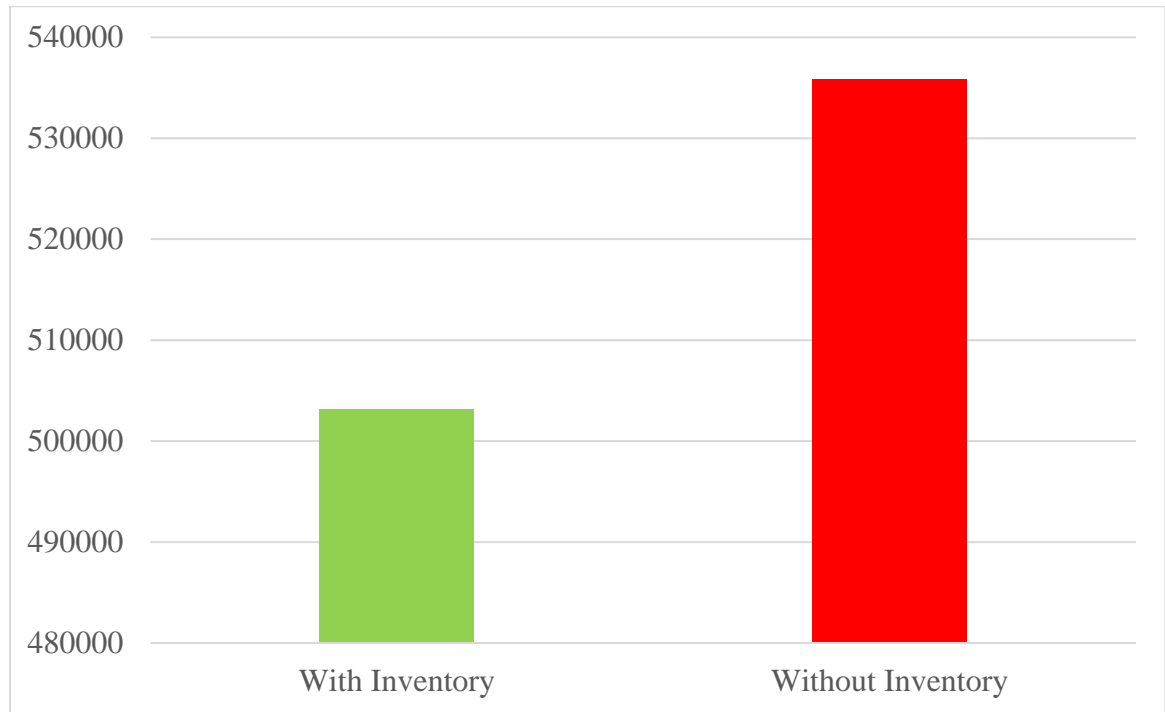


Figure 4. 13: Cost comparison considering multiple platform

The number of platforms and which features ($j \in J$) are available on the platform is an outcome of the developed model. From the outcome of variable x_{jt} , the number of platforms and which features ($j \in J$) are processed on the platform of any period is identified. The outcome of x_{jt} for the case study is illustrated in table 4.26. For period 1, there are F1, F3, F6, F7, and F9 processed on platform one. Which is similar to period 2 and period 7. For periods 3 and period 6 same platform two is used, and for period 4 and period 5 platform three and platform four are used.

Table 4. 26: Optimal platform for each period

Feature/Period	1	2	3	4	5	6	7
F1	1	1	1	1	1	1	1
F2	0	0	1	0	0	1	0
F3	1	1	1	1	1	1	1
F4	0	0	0	0	0	0	0
F5	0	0	1	0	1	1	0
F6	1	1	1	1	1	1	1
F7	1	1	1	1	1	1	1
F8	0	0	1	1	0	1	0
F9	1	1	1	1	0	1	1
F10	0	0	0	0	0	0	0
F11	0	0	0	0	0	0	0

From Platform one, Variant 1 can be manufactured by adding F2 and by removing F6, F7, and F9. Variant 2 can be produced by adding F4 and by removing F3, F6, F7, and F9. Variant 3 can be produced by adding F2, and F5 and by removing F7, and F9. Variant 4 can be produced by adding F5, and F8, and by removing F3, and F9. Variant five can be produced by adding F8 and by removing F7, and F9. Variant 6 can be manufactured by adding F2, F4, F5, F8, and by removing F9. Variant 7 can be manufactured by adding F2 and by removing F9. Variant 8 can be manufactured by adding F2, F4 and by removing F7. Variant 9 can be manufactured by adding F10 and by removing F3, F7. Variant 10 can be manufactured by adding F10. Variant 11 can be manufactured by adding F4 and F5 and by removing F3, and F7. Variant 12 can be manufactured by adding F8, F10, and F11 and

by removing F3. Variant 13 can be manufactured by adding F8 and by removing F1, F3, and F9. Variant 14 can be manufactured by adding F5 and by removing F1, F3, F7, and F9. This situation is given in table 4.27.

Table 4. 27: Manufacturing 14 Variants from Optimal Platform 1

Platform	Variants
F1, F3, F6, F7, F9	Variant 1: Add F2 – Remove F6, F7, F9
	Variant 2: Add F4 – Remove F3, F6, F7, F9
	Variant 3: Add F2, F5 – Remove F7, F9
	Variant 4: Add F5, F8 – Remove F3, F9
	Variant 5: Add F8 – Remove F7, F9
	Variant 6: Add F2, F4, F5, F8 – Remove F9
	Variant 7: Add F2 – Remove F9
	Variant 8: Add F2, F4 – Remove F7
	Variant 9: Add F10 – Remove F3, F7
	Variant 10: Add F10
	Variant 11: Add F4, F5 – Remove F3, F7
	Variant 12: Add F8, F10, F11 – Remove F3
	Variant 13: Add F8 – Remove F1, F3, F9
	Variant 14: Add F5 – Remove F1, F3, F7, F9

Another cost comparison of using multiple platforms and a single platform for all periods is illustrated in figure 4.14. When a single platform is used for all periods, the total cost becomes \$ 547,620, whereas using different platforms for different periods according to the order becomes \$ 503,171 (8.83% less than using the single platform).

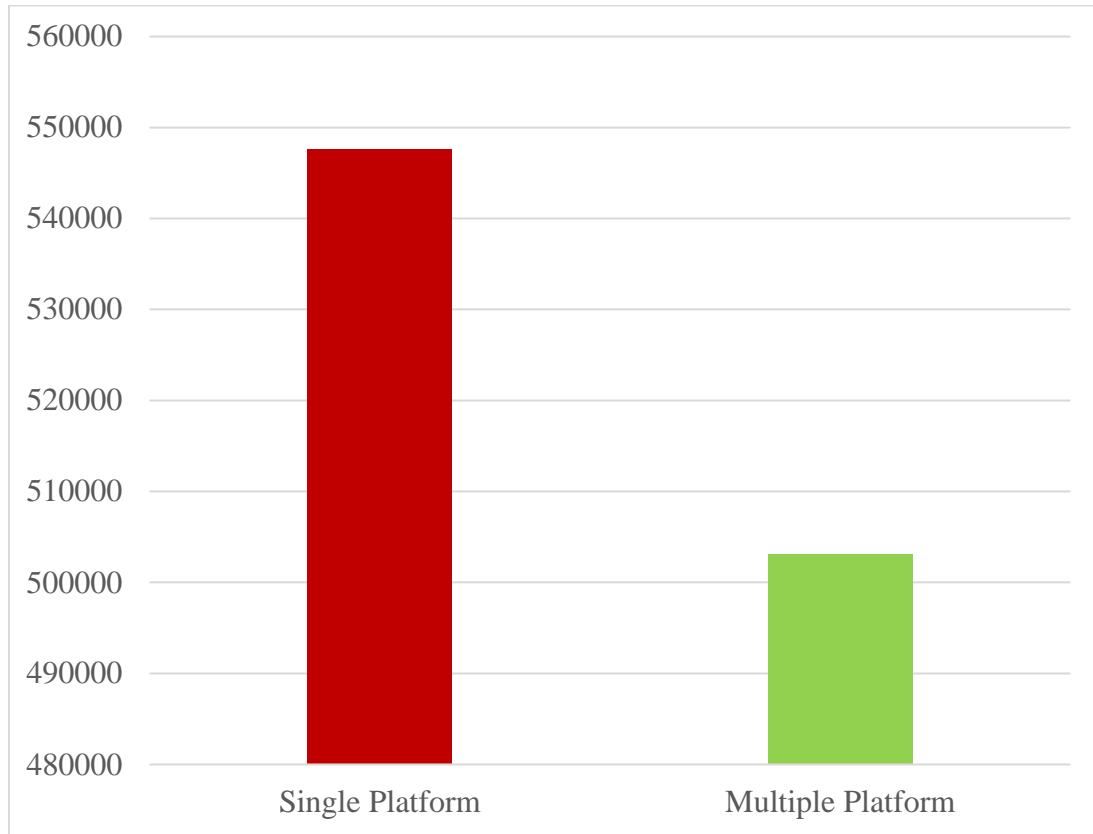


Figure 4. 14: Cost Comparison Considering Inventory

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

The aim of this research is to deal with stochastic demand and processing time along with managing product variety by evaluating optimal platforms for multiple periods. Inventory and safety stock are used to deal with stochastic demand. Based on the stochastic demand of each variant, the platforms are processed using the mass production concept. Afterwards, according to the variant's requirement, features are added to or removed from the platform using a hybrid manufacturing concept. Thus, the model ensures product variety management along with minimizing manufacturing and holding costs.

An existing gap of ignoring stochastic demand and production time for platform design is addressed through the developed MIP model. The model is capable of dealing with different real-world demand values and processing time. The model proves that when the demand exceeds the production quantity and inventory, the demand is satisfied from the safety-stock. The model minimizes demand loss which also minimizes loss of potential profit and avoids losing the customer goodwill. The model also realizes a pre-defined service level using inventory and safety-stock.

The case studies illustrate the efficiency of the developed model. It justifies that the model can be used for any real-world product family. Different types of demand scenarios are illustrated using the normal distribution. Also normally distributed processing time is used for production. The model is capable of minimizing the manufacturing cost and inventory holding cost. It can provide a specific inventory and safety-stock level to deal with stochastic demand. The model also integrates the delayed product differentiation strategy and hybrid (additive and subtractive) manufacturing concept.

5.2 Future Work

Product platform design considering hybrid manufacturing is a rapidly evolving field. The proper utilization of hybrid manufacturing can increase the flexibility and efficiency of manufacturing. Some of the future scopes is discussed in this chapter.

Combination of hybrid manufacturing and assembly can enhance the flexibility as well as the capability of the manufacturing process. With this combination a novel production process can be introduced for the integration of hybrid manufacturing and traditional manufacturing processes. Using hybrid manufacturing multiple operations can be performed in a single station which reduce the time of manufacturing as well as the cost of manufacturing. This unique combination can produce complex geometry and product which is not possible to produce using only traditional manufacturing processes.

A multi-level reconfigurable manufacturing system (RMS) can be developed with the combination of hybrid manufacturing and assembly. In this system hybrid manufacturing, product platform development, and assembly system will be integrated to increase the flexibility and capability of manufacturing system. A more realistic model can be developed, and it can be implemented in a manufacturing industry (e.g., automotive, aerospace, medical device etc.) where complex parts/products are required.

Overall, the future scope for product platform design, hybrid manufacturing and assembly system is broad and diverse. And this integration has a huge potential to be utilized in a wide range of industries.

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APPENDICES

Appendix A

Complete solution for case study of guiding bush family:

Variant	Period	Demand	Production	Inventory	Safety stock
1	1	111	1435	1315	9
1	2	330	0	984	10
1	3	443	0	542	9
1	4	541	0	0	10
1	5	298	296	0	8
1	6	195	195	0	8
1	7	317	318	0	9
2	1	243	1283	1030	10
2	2	289	0	742	9
2	3	329	0	414	8
2	4	412	0	0	10
2	5	587	586	0	9
2	6	291	290	0	8
2	7	361	363	0	10
3	1	478	667	179	10
3	2	180	0	0	9
3	3	334	336	0	11
3	4	277	872	597	9
3	5	49	0	548	9
3	6	300	0	248	9
3	7	248	0	0	9
4	1	389	857	458	10
4	2	458	0	0	10
4	3	354	352	0	8
4	4	569	1177	606	10

4	5	226	0	382	8
4	6	178	0	203	9
4	7	204	0	0	8
5	1	77	459	373	9
5	2	373	0	0	9
5	3	58	58	0	9
5	4	217	657	441	8
5	5	305	0	136	8
5	6	136	0	0	8
5	7	409	410	0	9

Appendix B

Complete solution for fourth case study:

Variant	Period	Demand	Production	Inventory	Safety stock
1	1	305	312	0	7
1	2	299	299	0	7
1	3	330	852	522	7
1	4	320	0	202	7
1	5	202	0	0	7
1	6	394	393	0	6
1	7	405	405	0	6
2	1	560	567	0	7
2	2	293	1234	940	8
2	3	127	0	813	8
2	4	564	0	251	6
2	5	250	0	0	7
2	6	449	890	440	8
2	7	442	0	0	6
3	1	384	630	240	6

3	2	239	0	0	7
3	3	322	811	490	6
3	4	159	0	330	7
3	5	331	0	0	6
3	6	399	782	382	7
3	7	383	0	0	6
4	1	194	666	465	7
4	2	464	0	0	8
4	3	340	339	0	7
4	4	251	468	218	6
4	5	217	0	0	7
4	6	134	489	356	6
4	7	356	0	0	6
5	1	485	493	0	8
5	2	326	324	0	6
5	3	396	881	484	7
5	4	198	0	285	8
5	5	287	0	0	6
5	6	507	687	178	8
5	7	178	0	0	8
6	1	258	575	310	7
6	2	310	0	0	7
6	3	350	812	461	8
6	4	324	0	138	7
6	5	138	0	0	7
6	6	515	943	427	8
6	7	429	0	0	6
7	1	336	703	359	8
7	2	361	0	0	6
7	3	374	374	0	6

7	4	259	671	412	6
7	5	411	0	0	7
7	6	192	389	197	7
7	7	197	0	0	7
8	1	350	356	0	6
8	2	429	1190	761	6
8	3	214	0	547	6
8	4	354	0	191	8
8	5	191	0	0	8
8	6	311	557	248	6
8	7	247	0	0	7
9	1	483	490	0	7
9	2	242	259	16	8
9	3	18	0	0	6
9	4	399	400	0	7
9	5	251	1164	912	8
9	6	502	0	410	8
9	7	410	0	0	8
10	1	390	398	0	8
10	2	404	635	231	8
10	3	233	0	0	6
10	4	505	505	0	6
10	5	381	844	462	7
10	6	188	0	275	6
10	7	274	0	0	7
11	1	326	685	352	7
11	2	351	0	0	8
11	3	310	308	0	6
11	4	524	899	373	8
11	5	373	0	0	8

11	6	306	757	452	7
11	7	451	0	0	8
12	1	336	972	628	8
12	2	317	0	312	7
12	3	312	0	0	7
12	4	396	1651	1254	8
12	5	342	0	913	7
12	6	511	0	403	6
12	7	401	0	0	8
13	1	421	741	314	6
13	2	313	0	0	7
13	3	189	188	0	6
13	4	310	648	337	7
13	5	338	0	0	6
13	6	378	629	250	7
13	7	250	0	0	7
14	1	360	366	0	6
14	2	419	420	0	7
14	3	342	771	429	7
14	4	342	0	88	6
14	5	87	0	0	7
14	6	454	747	293	7
14	7	292	0	0	8

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