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Process Planning for Assembly and Hybrid Manufacturing in Smart Environments

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DECLARATION OF CO-AUTHORSHIP / PREVIOUS PUBLICATION

I. Co-Authorship

I hereby declare that this thesis incorporates material that is result of joint research, as follows: Chapters 3, 4, 5 and 6 of the thesis were under the supervision of Professor Hoda ElMaraghy. In all cases, the key ideas, primary contributions, experimental designs, data analysis, interpretation, and writing were performed by the author, and the contribution of Professor Hoda ElMaraghy was primarily through providing feedback on refinement of ideas, funding acquisition and editing of the manuscript. This joint research has been submitted to Journals and Conferences that are listed below.

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I certify that, with the above qualification, this thesis, and the research to which it refers, is the product of my own work.

II. Previous Publication

This thesis includes six original papers that have been previously published/submitted for publication in peer-reviewed journals and conferences, as follows:

Thesis Chapter	Publication title/full citation	Publication status*
3	Mostafa Moussa and Hoda ElMaraghy. "Master assembly network for alternative assembly sequences." Journal of Manufacturing Systems 51 (2019): 17-28.	Journal (Published)
3	Mostafa Moussa and Hoda ElMaraghy. "Master Assembly Network Generation." Procedia CIRP 72 (2018): 756-761.	Conference proceeding (Published)

4	Hoda ElMaraghy, and Mostafa Moussa. "Optimal platform design and process plan for managing variety using hybrid manufacturing." CIRP Annals 68(1) (2019): 443-446.	Journal (Published)
5	Mostafa Moussa and Hoda ElMaraghy. "Delayed Product Differentiation utilizing additive and subtractive manufacturing using Phylogenetic Networks "	Journal (To be submitted)
6	Mostafa Moussa and Hoda ElMaraghy. " Multi-Product Platform design and Process Planning for Hybrid Manufacturing"	Journal (To be submitted)
6	Mostafa Moussa and Hoda ElMaraghy. "A Genetic Algorithm-Based Model for Product Platform Design for Hybrid Manufacturing" CIRP-CMS2020	Conference proceeding (Accepted)

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ABSTRACT

Manufacturers strive for efficiently managing the consequences arising from the product proliferation during the entire product life cycle. New manufacturing trends such as smart manufacturing (Industry 4.0) present a substantial opportunity for managing variety. The main objective of this research is to help the manufacturers with handling the challenges arising from the product variety by utilizing the technological advances of the new manufacturing trends. This research focuses mainly on the process planning phase. This research aims at developing novel process planning methods for utilizing the technological advances accompanied by the new manufacturing trends such as smart manufacturing (Industry 4.0) in order to manage the product variety. The research has successfully addressed the macro process planning of a product family for two manufacturing domains: assembly and hybrid manufacturing.

A new approach was introduced for assembly sequencing based on the notion of soft-wired galled networks used in evolutionary studies in Biological and phylogenetic sciences. A knowledge discovery model was presented by exploiting the assembly sequence data records of the legacy products in order to extract the embedded knowledge in such data and use it to speed up the assembly sequence planning. The new approach has the capability to overcome the critical limitation of assembly sequence retrieval methods that are not able to capture more than one assembly sequence for a given product. A novel genetic algorithm-based model was developed for that purpose. The extracted assembly sequence network is representing alternative assembly sequences. These alternative assembly sequences can be used by a smart system in which its components are connected together through a wireless sensor network to allow a smart material handling system to change its routing in case any disruptions happened.

A novel concept in the field of product variety management by generating product family platforms and process plans for customization into different product variants utilizing additive and subtractive processes is introduced for the first time. A new mathematical programming optimization model is proposed. The model objective is to provide the optimum selection of features that can form a single product platform and the processes needed to customize this platform into different product variants that fall within the same product family, taking into consideration combining additive and subtractive manufacturing. For multi-platform and their associated process plans, a phylogenetic median-joining network algorithm based model is used that can be utilized in case of the demand and the costs are unknown. Furthermore, a novel genetic algorithm-based model is developed for generating multi-platform, and their associated process plans in case of the demand and the costs are known. The model's objective is to minimize the total manufacturing cost.

The developed models were applied on examples of real products for demonstration and validation. Moreover, comparisons with related existing methods were conducted to demonstrate the superiority of the developed models. The outcomes of this research provide efficient and easy to implement process planning for managing product variety benefiting from the advances in the technology of the new manufacturing trends. The developed models and methods present a package of variety management solutions that can significantly support manufacturers at the process planning stage.

DEDICATION

To Allah

For the privilege of giving me this life

'I only intend reform as much as I am able. And my success is not but through Allah. Upon him I have relied, and to Him I return.' [11:88]

To my Dad and Mom

For their infinite love and support through my life

To my Brother, my Sister and my Nephews

For their love and endless joy that they have brought to my life

To my Wife and my Children

I have no idea who you are, but I love you already

To my Supervisor

For her guidance during this journey

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LIST OF ABBREVIATIONS

AGV	Automated Guided Vehicle
AMPL	A Mathematical Programming Language
CAD	Computer-Aided Design
CAPP	Computer-Aided Process Planning
CNC	Computer Numerical Control
DAG	Direct Acyclic Graph
DED	Direct Energy Deposition
DFM	Design for Manufacturing
DMD	Direct Metal Deposition
DPD	Delayed Product Differentiation
EBM	Electron Beam Melting
EOL	End of Life
FFF	Fused Filament Fabrication
GA	Genetic Algorithm
I 4.0	The fourth industrial revolution
IDEF0	A compound acronym which stands for "Icam DEFinition for Function Modeling", where ICAM is an acronym for "Integrated Computer-Aided Manufacturing."
IoT	Internet of Things
MILP	Mixed Integer Linear Programming
MJPN	Median Joining Phylogenetic Network
MRF	Modified Robinson Foulds
MTS	Make-To-Stock
NP	Non-deterministic Polynomial time

NPS	Nominal Pipe Size
PBF	Powder Bed Fusion
PPF	Product Platform Features
SLM	Selective Laser Melting

NOMENCLATURE

K the set of product variants in the product family, $k \in K$.

J the features set $j \in J$.

I represents the platforms, $i \in I$.

Cs the setup cost of one platform.

VC_k the manufacturing cost of variant k

SC the total setup cost of manufacturing multiple platforms

D_k the demand of the kth product variant (units).

Cp_j the cost of mass production of the j_{th} feature using a platform.

Ca_j the cost of adding the j_{th} feature/material to form a product variant ($Ca_j>Cp_j$)

Cr_j the cost of removing the j_{th} feature/material ($Cr_j > Cp_j$) from the platform to form a product variant

V the product matrix with

$$v_{jk} = \begin{cases} 1 \text{ if product k requires feature j} \\ 0 \text{ otherwise} \end{cases}$$

f_{jlk} elements in the features precedence

$$f_{jlk} = \begin{cases} 1 \text{ if feature j preceds feature l} \\ 0 \text{ otherwise} \end{cases}$$

The binary decision variables are:

x_j to indicate that feature j is included in the platform;

$$x_j = \begin{cases} 1 \text{ if the platform contains feature j} \\ 0 \text{ otherwise} \end{cases}$$

a_{jk} to denote that feature j is added to the platform to customize it to form product k;

$$a_{jk} = \begin{cases} 1 \text{ if feature j is added to the platform to form product k} \\ 0 \text{ otherwise} \end{cases}$$

r_{jk} to show that feature k is removed from the platform to customize to form product k.

$$r_{jk} = \begin{cases} \quad 1 \text{ if featurej is removed from the platform to form product k} \\ 0 \text{ otherwise} \end{cases}$$

Z_i to indicate that feature j is included in the platform i;

$$Z_i = \begin{cases} 1 \text{ if the platform i is used to produce at least one variant} \\ 0 \text{ otherwise} \end{cases}$$

GLOSSARY

Term	Definition
Additive Manufacturing	As per ISO/ASTM standard, additive manufacturing is defined as a "process of joining materials to make parts from 3D model data, usually layer upon layer as opposed to subtractive manufacturing and formative manufacturing methodologies" (Rashid 2019).
Hybrid Manufacturing	The International Academy for Production Engineering (CIRP) has suggested an open and a narrow definition of Hybrid Manufacturing: (1) Open definition: a hybrid manufacturing process combines two or more established manufacturing processes into a new combined set-up whereby the advantages of each discrete process can be exploited synergistically; (2) Narrow definition: Hybrid processes comprise a simultaneous acting of different (chemical, physical, controlled) processing principles on the same processing zone (Zhu et al. 2013b). In this dissertation, hybrid manufacturing refers to combining additive and subtractive manufacturing.
Master Assembly Network	A master assembly network is generic multiple alternative assembly sequences for a group of product variants belonging to a family where they share some parts and have common product structure (Moussa and ElMaraghy 2019).
Median Joining Phylogenetic Network (MJPN)	The MJPN is a branch of unrooted phylogenetic networks used to trace and classify DNA sequences, according to their relationship to hypothetical ancestral nodes (Bandelt et al. 1999).

Multi-Platform	Product platforms are a collection of modules or parts that are common to a number of product variants. Using more than one platform is a means to reduce costs and obtain access to multiple market segments by developing different product variants. (Harland et al. 2020)
Process Planning	Process planning, in the manufacturing context, is the determination of processes and resources needed for completing any of the manufacturing processes required for converting raw materials into a final product to satisfy the design requirements and intent and respect the geometric and technological constraints. At the "macro" process planning level, the sequence of operations and the selection of appropriate resources are the main concerns, whereas at the "micro" process planning level, the focus is on defining parameters of each operation, determining the time it takes to perform that operation, and selecting tools and fixtures as needed. (ElMaraghy and Nassehi 2019) This dissertation focuses on the macro process planning level.
Product Platform	Product platform is defined as a set of sub-systems and interfaces that form a common structure from which a stream of derivative products can be efficiently produced and developed (Meyer and Lehnerd 1997).
Product Variant	A product variant represents a specific item for purchase, and is contained within a parent Product. At least one Product Variant is required for each Product. The variants are different from each other in either the components or features that formed them.
Reticulation	A node in a rooted phylogenetic network that has more than one in-edge

Smart Manufacturing	Smart manufacturing, also sometimes referred to as IIoT or Industry 4.0, marries physical production and operations with smart digital technology, machine learning, and big data to create a more holistic and better connected ecosystem for companies that focus on manufacturing and supply chain management (Davis et al. 2012).
Soft-Wired Galled Network	The soft-wired galled network is a network that represents all of the clusters in a given set of trees. The cluster represents a group of closely related species, which share a trait, or suite of traits. The clusters are represented by links in the network, each of which represents one or more clusters depending on which reticulation links are "on" and "off" (Huson et al. 2010).
Subtractive Manufacturing	Subtractive manufacturing processes are the processes that involve removing particles of material in the form of the chips from a solid block of starting raw material or from an unfinished part by the cutting edges of a tool to create or modify shapes (Toenshoff 2014).

CHAPTER 1. INTRODUCTION

1.1 Motivation

Nowadays, manufacturers are facing many challenges as the result of changing demands, global competition, customer requirements, regional legislation and environmental issues (ElMaraghy et al. 2013). Failure to meet these market demands responsively and efficiently will lead to potential loss of manufacturers' market share to their competitors. In light of that, manufacturers strive to produce an entire spectrum of products in order to survive in the competitive market and satisfy different market segments. This product proliferation will result in high costs for manufacturers if it is not managed well. Mass customization is the main manufacturing strategy that manufacturers use to attain the competitive edge of decreasing the costs while keeping the quality and prevent loss of functionality of the products. Mass customization aims to produce a wide range of product variants to satisfy different market segments with efficiency approaching mass production by focusing on the commonality within the product/part family.

Process planning is a crucial intermediate and integrating phase between the design and manufacturing of a product (Jain and Jain 2001) as it is responsible for the efficiency of the production (Denkena and Mörke 2017). It comprises the selection and sequencing of processes and operations to transform a chosen raw material into a finished product (Scallan 2003). Product variety has a significant effect on the complexity of planning in general. Thus, well-designed strategies and models are needed to handle the variety observed in parts, products and families as well as changes in manufacturing resources utilization and inventory. The efficient generation of process plans plays a crucial role as an enabler of manufacturing systems needed to successfully manage variety (ElMaraghy 1993, ElMaraghy and Wiendahl 2009, ElMaraghy 2009).

Meanwhile, new manufacturing trends/initiatives such as smart manufacturing (Industry 4.0), and Made in China 2025 arise. These manufacturing trends aim at driving solutions to manufacturing challenges. They have huge potential for meeting customer requirements and increasing flexibility and resource productivity and efficiency (Kagermann et al. 2013). Figure 1-1 shows the four main characteristics of industry 4. Among these characteristics is the impact of exponential technologies as an accelerant or catalyst that allows individualized solutions, flexibility and cost savings in industrial processes (Schläpfer et al. 2015). Additive manufacturing and sensor technology are among the examples of these exponentially growing technologies, as shown in Figure 1-2. Sensor technology has the potential to increase autonomy and to speed up individualization and flexibilization (Lu 2017, Li et al. 2017), while additive manufacturing allows new manufacturing solutions (Dilberoglu et al. 2017, Vaidya et al. 2018, Cotteleer and Joyce 2014). Although many of these technologies are not very new and available from 2 or 3 decades, utilizing these technologies was limited due to their unsuitability of industrial use. Recently, there is a breakthrough in computing power (Moore's law) and the reduction in cost for acquiring and use these technologies makes them capable of industrial use (Hagel III et al. 2015, Schläpfer et al. 2015, Xu et al. 2018). These technologies will open the way for radically changing industrial processes, accelerating them and making them more flexible.

The new trends will not only pose an exclusively technological or IT-related challenge to the manufacturers. It will have far-reaching implications on the entire product lifecycle from inception, through engineering design, process planning and manufacture, to service and disposal of manufactured products (Kagermann et al. 2013, Tohmatsu 2018).

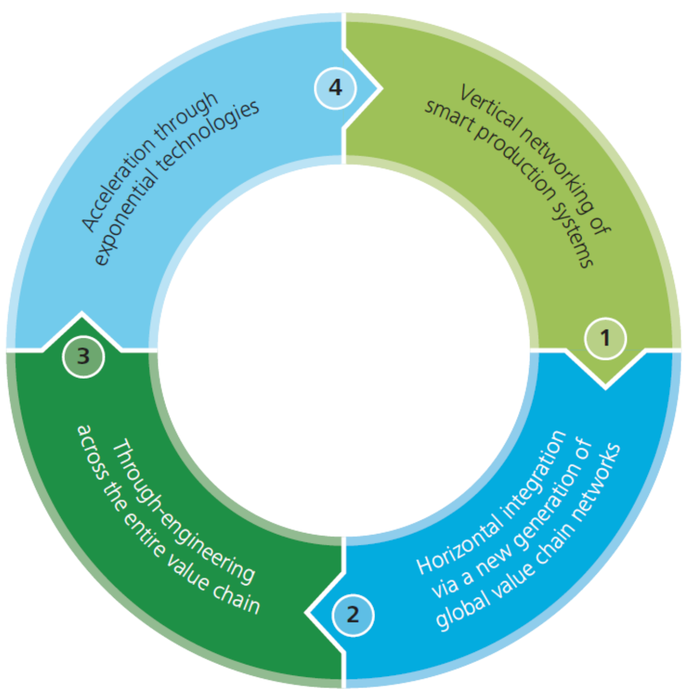


Figure 1-1 The four characteristics of Industry 4.0 (Schläpfer et al. 2015)

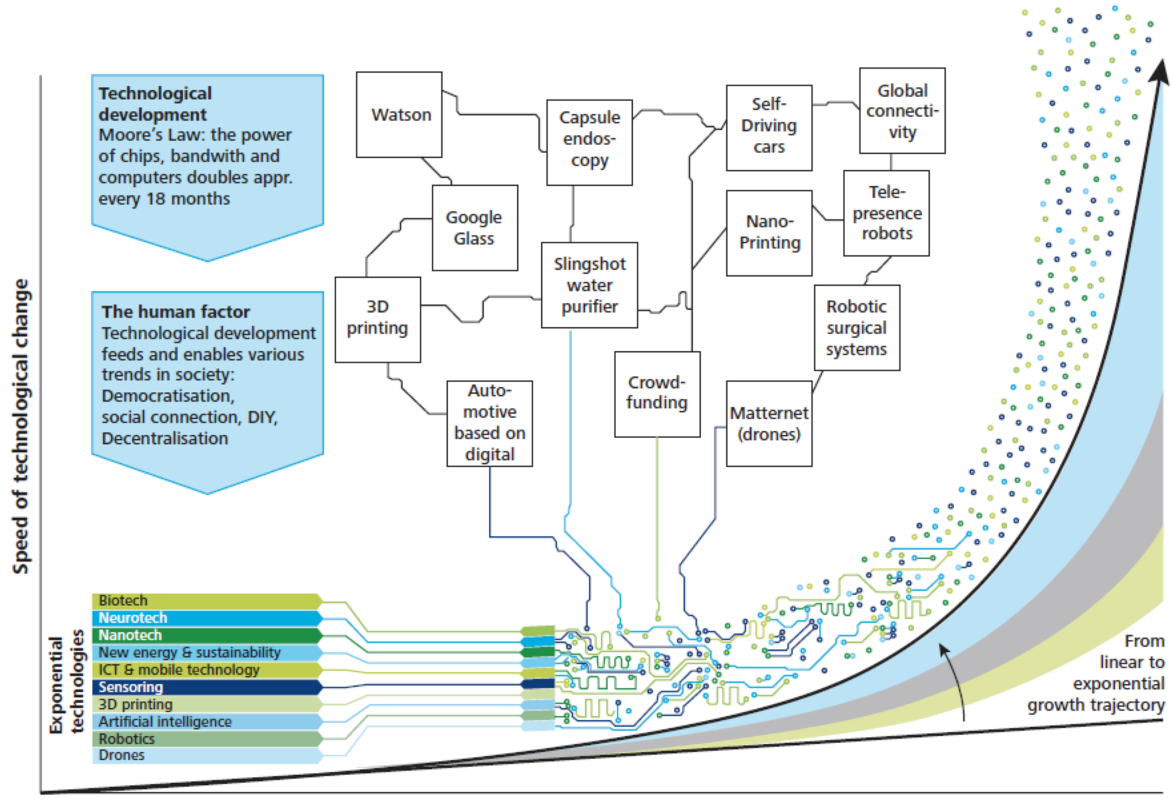


Figure 1-2 Exponential technologies (Schläpfer et al. 2015)

Accordingly, this research is motivated by the product proliferation as the result of the aforementioned reasons, the exponential advances in technologies accompanied by the new manufacturing trends and the role of the process planning in managing variety. This motivation leads to a growing need for more efficient process planning methods that could help manufacturers in managing the product variety responsively by utilizing technological advances such as hybrid manufacturing and the wireless sensor network.

This research exploits the existing process planning methods and builds on the new technological advances to provide novel methods that could help manufacturers in managing the product variety responsively.

1.2 Engineering problem statement

The increasing product variety and the dynamic fluctuation in the production volumes constitute a financial burden on manufacturing companies and could deteriorate manufacturing performance. Process planning methods have a significant effect on the cost and efficiency of managing variety. Advances in technologies open new avenues to handle the variety. Thus, process planning methods that benefit from the advances in technologies to overcome the complexities arise from variety is required.

1.2.1. Assembly Domain

The assembly sequence is one of the crucial aspects of process planning. The assembly sequence is the sequence in which product parts are to be assembled together to form a product. During production, the planned assembly sequence may need to be changed due to various shop-floor changes as a result of machine breakdown, tool failure, machine overload, etc. Hence, there is a need for planning alternative assembly sequences for the same product for use in adaptive manufacturing systems, which include smart AGVs that can deal with the introduction of different product variants as well as allow product-station re-assignment if a workstation is down. These smart AGVs have built-in intelligence to act on requests for changing operations sequence, parts workstation assignments and routes received digitally or via distributed sensors, and change the processing routes according to pre-planned flow sequence alternatives.

1.2.2. Hybrid Manufacturing Domain

Over the last decade, 3D printing has evolved from prototyping with basic materials and equipment to produce low tolerance components with limited use, to what we know of today as additive manufacturing. Additive manufacturing can provide industrial components composed of advanced materials and meeting today's stringent quality requirements. This additive manufacturing evolution will lead to a change in the way of manufacturing. Combining additive manufacturing with subtractive manufacturing may introduce new solutions for manufacturing problems, including product variety management. Hence, process planning for hybrid manufacturing in order to efficiently manage the product variety is needed.

1.3 Objectives

Based on the engineering problem statement, the research objective is to develop models/tools/methods for the macro process planning of product families, taking into consideration the current advances in technologies. This research is accomplished within two main manufacturing domains, the assembly and hybrid manufacturing domains.

1.3.1. Assembly Domain

The objective of the assembly domain is to develop a novel knowledge-based approach. This approach is capable of determining alternative assembly sequences for product families that can be utilized in any manufacturing system that allows alternative assembly sequences including but not limited to those utilizing Smart AGVs in Industry 4.0 environment.

1.3.2. Hybrid Manufacturing Domain

The objective of the hybrid manufacturing domain is to develop novel approaches that are capable of determining the product platform(s) and the process plans of product families, taking into consideration the additive and subtractive manufacturing processes.

1.4 Research Scope

This research focuses on macro process plans. The macro process planning addressed in this dissertation is concerned with the family of products. A family of products consists of either single part variants with features (e.g. guiding bushes), or multi-part variants (e.g. valves) is considered. Each variant shares some common and similar features and/or parts with other variants that fall within the same considered product family. The research scope focuses on families of mechanical products/parts such as families of valves, guiding bushes, flanges and gear shafts.

Different types of manufacturing processes are required to produce the considered product families that include hybrid manufacturing processes (Additive manufacturing and Subtractive manufacturing) and assembly processes. This research focuses on mass customization. The demand for the product falls within medium to low volume with medium variety. The considered manufacturing system types are flexible manufacturing system, and reconfigurable manufacturing system that utilizes advances technology, and smart manufacturing systems. The considered manufacturing system components include machine tools for additive and subtractive manufacturing and assembly machines (e.g. CNC machines, Laser deposition welding machines, 3D hybrid machines, industrial robots,…etc.). Material handling units that allow change of assembly sequence in case of shop floor disruption or introducing a new product such as smart AGVs are taken into consideration.

1.5 Dissertation Structure

The models and methods presented in this research are a package of product variety management solutions that can significantly help manufacturers in saving a lot of effort and time at the process planning stage. Figure 1-3 shows the structure and flow of the research carried out in this proposal report. The report is presented in seven chapters, where the literature review is presented in chapter 2. Chapter 3 presents the knowledge-based assembly sequence method based on the soft-wired galled network method used in Biological Sciences. The Integer Programming model for single-platform design and process planning for hybrid manufacturing of product family are presented in Chapter 4. Chapter 5 and Chapter 6 are addressing the multi-platform generation and product family process plan for hybrid manufacturing problem using the median-joining phylogenetic network and genetic algorithm-based model respectively. Finally, Chapter 7 includes the summary and conclusions as well as the future work of this research.

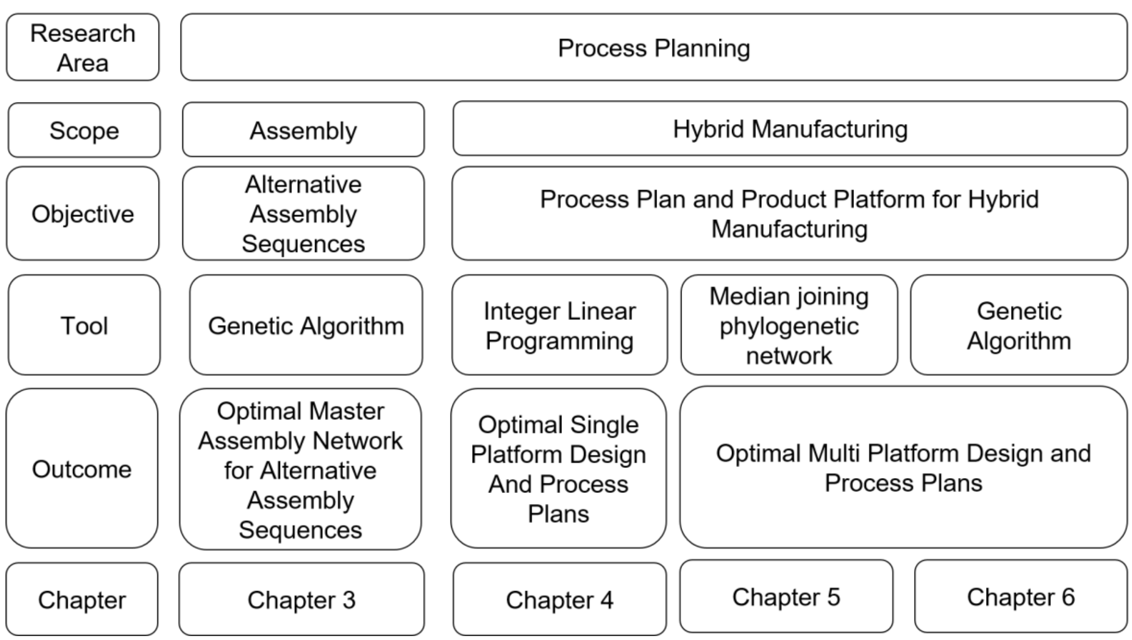


Figure 1-3 Research map.

1.6 Research Hypothesis

This research is based on the hypothesis that:

> *"Managing product variety by process planning of product family while utilizing the benefits of the technological advances such as additive could overcome the complexities arising from variety, enhance the effectiveness of mass customization; and decrease manufacturing costs."*

CHAPTER 2. LITERATURE REVIEW

2.1 Overview

This chapter provides a detailed summary and explanation of the state of knowledge on the most relevant topics within this dissertation. The process planning has gained considerable attention from industry and academia over decades. Thus, a considerable amount of research has been carried out in that field. This is why several authors have published literature review papers that offer an overview of key observations, principles and developments regarding the process planning, such as (Niebel 1965, Weill et al. 1982, Alting and Zhang 1989, ElMaraghy 1993, Xu et al. 2011). The literature review of process planning, covered in this chapter, is limited to the literature related to assembly sequence and process planning of hybrid manufacturing. The first section reviews the previous research work in the area of assembly sequence, especially the retrieval methods. The next sections are concerned with the literature in the topics process planning for hybrid manufacturing, product platform and product delayed differentiation, respectively. Finally, these sections are followed by discussions that highlight the research gaps in the literature that result in the origination of this research.

2.2 Assembly Sequence

Since the eighties, a large amount of research was carried out in the area of automating or semi-automating assembly sequence planning. ElMaraghy (1993) classified the approaches used for assembly sequence planning into three main categories; generic, generative, retrieval and hybrid. In the generative approach, a new assembly sequence and process plan are generated from scratch based on planning knowledge rules and mathematical models as well as interpretation of the component/product model/drawing in terms of assembly features and requirements (Sadaiah et al. 2002). Rashid et al. (2012) presented a review on soft computing approaches to optimize assembly sequence planning and assembly line balancing problems. Genetic Algorithm, Ant Colony Optimization and Particle Swarm Optimization were the most frequent approaches utilized to solve the considered problems.

Wang and Liu (2010) proposed a method to generate optimal or near-optimal assembly sequence of products by combining chaos method with particle swarm optimization model. Kardos et al. (2017) decomposed feature-based assembly planning into a macro level master problem and a micro-level sub-problem. The macro-level master problem determines optimal sequencing and resource assignment while the micro-level sub-problem checks for the plan feasibility regarding technology, fixturing, tooling and collision. A case study for a medium-sized mechanical assembly from the automotive industry was used to demonstrate the efficiency of the proposed algorithms. Pintzos et al. (2016) presented an algorithm for generating assembly precedence diagrams of products directly from its design CAD files. They introduced the assembly tiers concept in which parts to be assembled were separated into groups based on their geometric characteristics. This algorithm generated all the possible sequences that can be used rather than the optimum one. The algorithm was applied as a software extension to a commercial CAD software. Several industrial case studies were used for illustration. The difficulty in the generative planning is the identification of useable assembly features and in representing, managing, and utilizing relevant human expertise (Yusof and Latif 2014). Su (2007) proposed a geometric constraint analysis method that was capable of generating geometric feasible assembly sequence. A software system was developed based on this method and integrated with a CAD system. Wang et al. (2005) presented an ant colony algorithm-based approach to assembly sequence generation where parallel assembly operations are not allowed.

The retrieval approach is one in which a new assembly plan is generated based on the similarity between the new and existing product variants with respect to the common product parts and/or assembly structure (Dong et al. 2005). The assembly plan of the most similar existing product variant is used as the starting plan for the new product variant. Some researchers focus on the similarity between products based on the bill of material. Hegge and Wortmann (1991) introduced the concept of generic bill of material. The generic bill of material compromises the product structure of all variants within a product family. Thus, it could be used to search for similar parts. Romanowski and Nagi (2004) developed text and tree mining approach to generate the generic bill of material to facilitate the search for a similar design. A case study from a manufacturer of nurse call devices was used for illustration. Based on the generic bill of material concept, Shu et al. (2014) evaluated the disruption risk and uncertainty of production in supply chain construction. Shih (2011) proposed an orthogonal Procrustes approach to measure the product similarity in order to match product structures (Bills of Material) of different product variants and data for the variant similar to the new one can be utilized to generate the new variant assembly sequence. The drawback of this method that the new variant may have a combination of parts that exist in more than one existing variants.

To avoid this drawback, some researchers developed a method to generate a master assembly sequence for products that have similar parts or forming a family, then retrieve the data for the new product variant from the master assembly sequence. Kashkoush and ElMaraghy (2014) proposed a retrieval method for assembly planning. A genetic algorithm was developed to generate a binary consensus tree that represents the set of all assembly sequence trees with minimum total dissimilarity distance. The generated consensus tree represented the master assembly sequence of a given product family. The Robinson-Foulds distance, which is one of the most common methods to measure the dissimilarity distance, was used. The objective function was to minimize the total dissimilarity distance between all assembly sequence trees of the considered product family. A family of three control valves was used as a case study for demonstration.

In order to guarantee the optimality of the results, Kashkoush and ElMaraghy (2015) extended their previous work by developing a knowledge-based mixed-integer programming model for generating the master (consensus) assembly sequence tree for a product family. The developed mathematical model guaranteed finding the optimal consensus tree. The assembly sequence for a new product family variant can be generated from the master assembly sequence tree. The developed method was demonstrated using a family of pilot valves. However, the developed method generates only one assembly sequence for the new variant. Navaei and ElMaraghy (2018) developed two mixed integer programming (MIP) models for generating master operation/assembly sequence with the objective of minimizing the total dissimilarity distance between the existing variants of a considered product family. The first MIP model dealt with variants that have a serial operation/assembly sequence. The second MIP model is a generalization of the first model and can handle variants with serial and/or networked operation/assembly sequence. The mathematical model was efficient in solving small and medium-size problems. Its efficiency decreases for the large-size problem as the number of operations increase; however, a heuristic algorithm was developed to handle the large-size problem efficiently. Two case studies, pilot control valves assembly, and ejecting and coupling parts/components machining, were presented for demonstration.

2.3 Discussion of the Studied Literature for the Assembly Domain

Extensive research has been conducted in the field of assembly sequence generation; however, there is no work considers the generation of a master assembly network composed of multiple assembly sequences. A generic master assembly network is composed of multiple alternative assembly sequences for a group of product variants belonging to a family in which they share common parts and product structure. This master assembly network can be used for constructing an assembly sequence network for a new product variant belonging to the considered product family. The critical limitation of the assembly sequence retrieval methods in the literature is that only one assembly sequence can be retrieved for a product variant. Table 2-1 shows the research gaps regarding the assembly sequence in the literature.

Table 2-1 Research in the assembly sequence summary

Author	Approach	Output	Retrieved Assembly sequence	
			Single	Multiple
Navaei and ElMaraghy (2018)	Mathematical model, Heuristic model	Master assembly sequence	X	
Kashkoush and ElMaraghy (2015)	Mathematical model	Master assembly sequence	X	
Shu et al. (2014)	Simulation and neural network	Generic bill of material	X	
Kashkoush and ElMaraghy (2014)	Genetic Algorithm	Master assembly sequence	X	
Shih (2011)	Orthogonal Procrustes approach	Bill of material	X	
Romanowski and Nagi (2004)	Text and tree mining	Generic bill of material	X	

2.4 Process Planning for Hybrid Manufacturing

There is a growing number of manufacturers across multiple industries use 3D printing (aka additive manufacturing) for more than creating prototypes (Gao et al. 2015, Cortina et al. 2018). There are many reasons for the additive manufacturing/ 3D printing hype. Now, additive manufacturing is capable of producing parts with better quality than before to the extent of producing ready to use parts (Wimpenny et al. 2017, Khorram Niaki and Nonino 2017). The time of the printing/processing has been significantly reduced to an acceptable point (Kumar et al. 2019). The printable materials have evolved from a limited number of plastic types to metals and plastics that are commonly used in industrial parts manufacturing. Almost every year has seen an exponential rise in available systems, technologies, and materials for additive manufacturing (Hashmi 2014, Sahasrabudhe et al. 2018).

Although this significant increase in utilizing additive manufacturing in manufacturing, additive manufacturing, in some cases, is still more expensive and takes more time per part than subtractive manufacturing. Additive manufacturing is proven to be cost-effective in product customization (Goodridge and Ziegelmeier 2017). Thus, additive manufacturing is not going to replace the traditional (subtractive) manufacturing (Stewart 2019). In contrast, additive and subtractive manufacturing can complement each other in order to benefit from the combined advantages of both and overcome their individual drawbacks. This is known as hybrid manufacturing. Hybrid manufacturing can be defined as the combinations of two or more manufacturing operations, each of which is from different manufacturing technologies such as joining, subtractive, transformative and additive manufacturing, and has interactions with and influences on each other (Zhu et al. 2013b).

The research in the area of hybrid manufacturing can be categorized into four major categories based on the different combinations/incorporation of manufacturing technologies. These areas are hybrid additive and subtractive (e.g. Laser cladding and mechanical machining), hybrid joining and subtractive (e.g. CNC milling and welding technology), hybrid additive and transformative (e.g. selective laser melting (SLM) and laser erosion process) and hybrid subtractive and transformative (e.g. Turning and rolling). UK government reported in one of its white paper on the future of manufacturing that hybrid manufacturing can shorten or simplify value chains and/or enable novel processing (O'Sullivan and Mitchell 2013). Combining additive and subtractive manufacturing is among the most common hybrid manufacturing and is expected to shape the future of manufacturing. Hybrid manufacturing extends the application areas and achieves a higher performance of the combined manufacturing technologies (Zhu et al. 2013b) and has the opportunity to develop new solutions for the manufacturing challenges such as product proliferation.

Hybrid manufacturing technologies have been subject of extensive research and implementation in academia and industry for the last decade; however, research concerning process planning for hybrid manufacturing has been limited. There are three main categories of process planning for hybrid manufacturing in the literature. ElMaraghy (1993) classified the methodologies used for process planning into: generative, retrieval and combination of both generative and retrieval.

Methods for generic process planning and manufacturability evaluation for subtractive or additive manufacturing processes have been developed (e.g. (Kerbrat et al. 2011, Behandish et al. 2018)). ElMaraghy (1993) defined generic process planning as the highest level of planning in which the selection of the most suitable technology for producing a feature, a part or a product takes place. Kerbrat et al. (2011) extended the Design for Manufacturing (DFM) approaches in order to consider more than one manufacturing process within CAD software. Kerbrat et al. (2010) proposed a methodology to estimate manufacturing complexity for subtractive and additive manufacturing. Manufacturing indices values were proposed to assess in determining the features that are to be machined or fabricated by layers. Behandish et al. (2018) presented a computational framework for manufacturability analysis and generic process planning of Hybrid manufacturing. The manufacturability analysis and process planning were decomposed into purely symbolic reasoning through a finite Boolean algebra (FBA) that enumerates the entire search space for planning. The work in this approach focus on the selection of the process type based on technological constraints.

Another group of researchers (e.g. (Ren et al. 2010, Basinger et al. 2018)) developed process planning methodologies for hybrid manufacturing of a single part in two separate steps where a near-net shape part is built by additive manufacturing followed by subtractive machining for finishing. Ren et al. (2010) introduced an integrated process planning framework for 3D laser-aided deposition and five-axis surface finish machining. The paper focused on automating components of the process planning, including decomposition of the computer-aided design (CAD) model, improvement of the toolpath generation pattern, and collision detection algorithms. Basinger et al. (2018) developed a feature-based planning method for hybrid manufacturing of pockets, holes, and flat surfaces. A heuristic model was developed to minimize tool and orientation changes to improve process times.

Finally, several studies have focused on developing process planning methodologies in which both additive and subtractive technologies are used alternatively to remanufacture a single part. Newman et al. (2015) introduced a Re-Plan process planning system based on a hybrid process framework named iAtractive, proposed by (Zhu et al. 2013a, Zhu et al. 2014), in which different plans to re-incarnate existing/legacy plastic products into new products were generated. The iAttractive framework is a combination of subtractive (i.e. CNC machining), additive (i.e. fused filament fabrication, FFF) and inspection processes for manufacturing plastic parts. Zhu et al. (2017) developed a feature-based decision-making logic to restrict the number of process plans generated by the Re-Plan system based on the geometry and dimensions of features of both existing and final parts. (Le et al. 2017b, Le et al. 2018a) proposed a similar direct material reuse approach but for metallic parts. End of Life (EOL) metallic parts or existing parts were recovered by combining metal-based additive such as powder bed fusion (PBF) and directed energy deposition (DED) with subtractive processes.

2.5 Product Platform and Delayed Differentiation

Postponement strategy is an effective strategy for variety management (ElMaraghy et al. 2013, Ferreira et al. 2018). It can be described as that manufacturing the final product is deferred as much as possible. The postponement strategy is categorized into time postponement and form postponement (Lee and Billington 1994). The time postponement is described as reallocating the differentiation tasks/process from the central plant to regional distribution centers for reacting to localization needs (Su et al. 2005, Shao and Ji 2008). The time postponement is commonly used for high-technology products, and many companies such as Dell and Gateway adapted this strategy. For instance, Fujitsu opened a configuration center in Tennessee to perform the final assembly (Hsu and Wang 2004).

On the other hand, the form postponement is based on standardizing the upstream stages as much as possible and deferring the product differentiation at the downstream stages. It can be described as that various product variants share some common processes, features, and/or parts that can be manufactured in the upstream manufacturing stages to produce generic products (Harrison and Skipworth 2008, Skipworth and Harrison 2006). Then, at some point in the manufacturing process known as the point of product differentiation, differentiating processes are utilized to customize the generic product, up to that point, into different product variants. The form postponement centers upon redesigning the process to delay the point of differentiation as much as possible. As an example, Compaq adapted the form postponement and redesigned its process. It achieved 98% of customer service level and 3 days of order fulfillment as a result of utilizing form postponement (Hsu and Wang 2004). The delayed product differentiation strategy falls under the form postponement category.

During the last decades, the product platform design has gained much attention from the industry and academia. Thus, there has been a significant amount of research conducted in that area. This was the reason that derived many authors to publish literature review papers that gives an overview of key findings, concepts and developments concerning the product platform such as (Simpson 2004), (Jose and Tollenaere 2005), (Jiao et al. 2007), (Pirmoradi and Wang 2011), (Zhang 2015), (Otto et al. 2016), (Facin et al. 2016) and (Han et al. 2019).

Jiao and Tseng (1999) proposed a methodology for designing product platform architecture. The customer requirement was mapped to the facility capabilities based on three consecutive views: functional, technical and physical views. The proposed methodology was applied to a family of power supplies for the demonstration. Martin and Ishii (2002) developed a method to design a decoupled product platform architecture based on two indices, namely; the generational variety index (GVI) and the coupling index (CI). The GVI was used to assess the redesign effort needed for future designs of the product while the CI assessed the coupling among the product components. A case study of a family of water cooler was used to demonstrate the developed method.

Jose and Tollenaere (2005) reviewed various product platform development methods. The methods used to produce specific platforms for a group of products were categorized into groups: Clustering methods (e.g. MADROC, Production Flow Line, Rank Order Clustering, etc.), Graph and matrix partitioning methods and Mathematical Programming methods. Besides, the paper showed the high impact of developing product platforms on the easiness of managing variety and product life cycle savings. Jiao et al. (2007) presented a comprehensive review of the state-of-the-art research in the areas of product family design optimization, product family configuration, modular architectures, and product portfolio planning. Moreover, they provided a decision framework for a holistic view of product family design and platform-based product development, comprising both front-end and back-end issues.

Yu et al. (2007) developed a clustering method to produce common platforms for complex products based on the design structure matrix (DSM). The developed method used a simple genetic algorithm (GA) with the minimum description length (MDL) principle-based objective function to cluster DSMs. Three real-world case studies (turbofan engine at Pratt and Whitney (P&W), engine at GM and gas turbine-driven electrical generator set (GAS)) were used for demonstration of the method and show its effectiveness. Ben-Arieh et al. (2009) introduced the notion of assembling and disassembling components to and from platforms to customize products. A multiple platforms configuration problem was formulated as a mixed-integer program. The model requires specifying the expected number of platforms a priori. It suffers from instability and nonlinearity and is not able to form platforms and families in cases where the demand of one of the products is zero. A family of cordless drills was employed to demonstrate the proposed approach.

Rojas Arciniegas and Kim (2011) presented a framework to identify the optimal set of components to be shared among a group of products based on the architectural information contained in the product Design Structure Matrix (DSM) and the Functional-Component Matrix (FCM). A genetic algorithm was implemented based on the framework. The objective function includes the minimum description length representation of the product, which provides a global score of how compact the structure and the impact metric (IM) score of the selected components for sharing. The framework was applied to a family of digital cameras for illustration. Jiao (2012) proposed a hybrid real options analysis framework for product platform flexibility planning. The framework integrated the financial and technical analyses of product platforms, taking into consideration the product-related and project-related flexibility. A bi-level optimization problem was formulated in order to support optimal product platform planning. The first level focuses on maximizing the expected profits of possible configurations of platform options for a particular target market segment, while the second level focuses on satisfying the equilibrium constraints related to the market and manufacturing concerns of platform planning. The rationale of the proposed hybrid approach for supporting optimal product platform planning was manifested using an example of vibration motor platform planning.

Simpson et al. (2012) proposed a framework in order to translate user needs and requirements into commonality specifications during product family design. The framework integrated different platform-based product development tools: market segmentation grid, Generational Variety Index (GVI), Design Structure Matrix (DSM), commonality indices, mathematical modelling and optimization, and multi-dimensional data visualization. The framework aimed at determining the unique and common components and their best parameter settings in the product family. The proposed approach was illustrated through the design of a family of unmanned ground vehicles (UGVs). AlGeddawy and ElMaraghy (2013) proposed a reactive design methodology for the product platform. The methodology was based on physical commonality rather than the commonality index. Cladistics was used to design a core platform by hierarchically clustering common components as well as combine the common parts into integral parts and modules, if possible. The model was capable of balancing between the Design for Manufacturing and Assembly (DFMA) and product modularity. The proposed model was applied to household kettles family.

ElMaraghy and Abbas (2015) introduced for the first time, the concept of co-platforming in which the product feature platform is mapped with the corresponding manufacturing system machines platform. For the demonstration, the fabrication of automobile cylinder blocks was used as a case study. Abbas and ElMaraghy (2017) developed a mixed integer linear programing (MILP) model to synthesize manufacturing systems based on the co-platforming methodology , which maps the platform and non-platform features of the product to the platform and non-platform features of its manufacturing system. It takes into consideration machine level changes including addition or removal of machine axes and changing setup as well as system level changes such as addition or removal of machines. The objective is to minimize the cost of change needed for transition between product families and production periods by maintaining the core/platform machines and only changing the non-core machines or machine components. An illustrative numerical example and an industrial case study from tier I automotive supplier are used for verification. Abbas and ElMaraghy (2018) extended their work to assembly domain. An integrated methodology for synthesizing assembly systems for customized products through mapping between products platform and the assembly system platform was presented. A matrix-based formulation and mixed integer linear programming optimization models were developed. For illustration, the methodology was applied to a case study for an automotive cylinder head assembly line.

Hanafy and ElMaraghy (2015a) used median-joining phylogenetic networks (MJPN) to generate delayed product differentiation (DPD) platform network taking into consideration the concept of assembly/disassembly modular platforms. Hanafy and ElMaraghy (2015b) developed a mathematical model for modular product multi-platform configuration. The model takes into consideration both assembly and disassembly of components to customize platforms into product variants. A family of touch screen tablets was used as a case study to demonstrate the model application.

Schuh et al. (2018) proposed a methodology for function-oriented design of the modular product platforms for mechatronic systems. The proposed approach was illustrated through a case study of an electric vehicle. Zhang et al. (2019) presented a product platform planning method by utilizing the existing product data in the product lifecycle management (PLM) database. Galizia et al. (2019) presented a decision support system for multiple product platforms design in high-variety manufacturing. The median-joining phylogenetic networks (MJPN) was used in order to generate platforms that can further assemble and/or disassemble the derived final products. This decision support system was applied to a case study of a large family of plastic valves.

2.6 Discussion of the studied literature for the Hybrid Manufacturing Domain

Although hybrid manufacturing has gained much attention in the literature as it benefits from combining additive and subtractive processes in recent years, no research work considers the utilization of hybrid manufacturing to produce a family of product.

Table 2-2 Research in Product Platform and delayed product differentiation summary

Author	Generic process planning	Processes performed		Purpose	Product (Part)	
		Two separate steps	Interchangeably		Single	Multiple (Family)
Kerbrat et al. (2010)	X			Process selection	X	
Ren et al. (2010)		X		Manufacturing	X	
Kerbrat et al. (2011)	X			Process selection	X	
Newman et al. (2015)			X	Remanufacturing	X	
Zhu et al. (2017)			X	Remanufacturing	X	
Le et al. (2017b)			X	Remanufacturing	X	
Basinger et al. (2018)		X		Manufacturing	X	
Behandish et al. (2018)	X			Process selection	X	
Le et al. (2018a)			X	Remanufacturing	X	

The conducted research in the field of process planning for hybrid manufacturing was limited to process selection, manufacturing of a single item, or remanufacturing of an old part. Table 2-2 shows the research gaps regarding the process planning for hybrid manufacturing in the literature.

Besides, most of the literature in the area of the product platform focuses on the assembly domain. For the hybrid manufacturing domain, the researchers consider only subtractive manufacturing while designing the product platform. In other words, only successive machining of features of the product platform is considered to produce product variants. Table 2-3 shows the research gaps regarding the product platform in the literature.

Table 2-3 Research in Product Platform and delayed product differentiation summary

Author	**Problem Formulation**	**Platform**		**Market demand**	**Costs**	**Domain**
		Single	Multiple			
Galizia et al. (2019)	Phylogentic Median Joining Algorithm		X	X		Assembly
Schuh et al. (2018)	Systemic evaluation methodolgy	X			X	Assembly
Abbas and ElMaraghy (2018)	Mathematical Model	X		X	X	Assembly
ElMaraghy and Abbas (2015)	Mathemtical model	X		X	X	Subtractive Manufacturing Only
Hanafy and ElMaraghy (2015a)	Phylogentic Median Joining Algorithm		X			Assembly
Hanafy and ElMaraghy (2015b)	Mathematical model	X	X	X	X	Assembly
Simpson et al. (2012)	Mathematical model	X		X		Assembly
Rojas Arciniegas and Kim (2011)	Genetic algorithm	X				Assembly
Ben-Arieh et al. (2009)	Mathematical model, Genetic Algorithm		X	X	X	Assembly

CHAPTER 3. MASTER ASSEMBLY NETWORK FOR ALTERNATIVE ASSEMBLY SEQUENCES

3.1 Overview

The fourth industrial revolution (I 4.0) is paving the way for change in manufacturing systems. A logical enabler for dynamic and adaptive manufacturing systems, including smart automated guided vehicles (AGVs), is presented. It can respond to requests for changing operations sequences received digitally or via distributed sensors and change the processing route according to pre-planned flow sequences and pre-determined alternatives. A novel method for generating a master assembly network with alternative sequences based on legacy assembly data for a product family is developed. A master assembly network is generic multiple alternative assembly sequences for a group of product variants belonging to a family where they share some parts and have common product structure. The assembly network with alternative sequences for a new variant is extracted from the master assembly network. These alternative sequences increase the flexibility and adaptability of the assembly system to handle workshop disruptions such as change orders, machine breakdowns and tool failures. The developed method is inspired by the phylogenetic networks used in biology, namely the soft-wired galled network. A Genetic Algorithm based model is developed to generate the master assembly network that summarizes a set of conflicting rooted assembly sequence trees. A family of three control valves is used as a case study. The proposed method can be utilized in any manufacturing system that uses alternative assembly sequences including those utilizing smart AGVs in and Industry 4.0 dynamic environment. The developed method decreases the time and cost of introducing a new product variant as well as increases the responsiveness of the manufacturing system.

3.2 Introduction

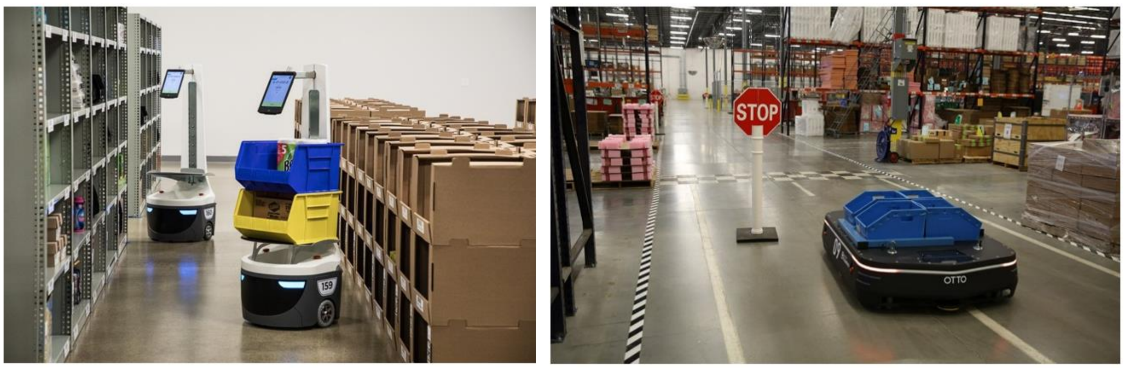
The wide scope of product variants driven by customers' preferences, regional requirements, certification specifications and dynamic fluctuation in the annual demands per variant introduces manufacturing challenges (ElMaraghy et al. 2013, ElMaraghy et al. 2017). These challenges have a direct impact on manufacturing systems design and operation to cope with products and markets changes efficiently and cost-effectively. Thus, the manufacturers are facing an urgent need to make changes to their manufacturing/assembly systems to increase production and implement the required product changes.

Industry 4.0 aims at creating a smart manufacturing environment that can cope with manufacturing challenges (Lee et al. 2015, Lasi et al. 2014). It focuses on making manufacturing/assembly systems more modular, reconfigurable, adaptable and more intelligent. It utilizes the recent innovations in sensing technology and the Internet of Things (IoT) (Lu 2017, Lee et al. 2014). In contrast to conventional manufacturing systems, the application of sensing technology and the Internet of Things (IoT) in the manufacturing system results in a significant increase in the degree of automation and autonomy where intelligent machines can collect real-time information needed for dynamic and synchronized behaviour (Fu et al. 2018). Such a smart manufacturing system can provide unprecedented opportunities for improving productivity and adaptability.

The assembly sequence is the most crucial part of an assembly plan (Zhou et al. 2011). It represents the feasible assembly sequence of different parts and sub-assemblies in the product and has a significant impact on operation time, cost and the system control complexity. The difficulty of assembly steps, need for fixturing, potential for parts damage during assembly, ability to do in-process testing, and rework are also affected by the assembly sequence choices (De Fazio and Whitney 1987).

Powered conveyors and traditional racks with free rollers conveyor have been used for decades to move pallets, parts, products and sub-assemblies between stations and are sequenced and operated synchronously or asynchronously to maintain the desired cycle time. Traditional Automated Guided Vehicles, used in more modern assembly lines, offer more automation but limited flexibility. They still follow a pre-determined path using moving chains embedded in the floor, painted floor stipes or frequency-controlled zones.

During production, the planned assembly sequence may need to be changed, as mentioned earlier. Hence, the way parts and sub-assemblies flow in the assembly systems must also change without violating the assembly precedence constraints. Industry 4.0 shows considerable promise to change the rigid, structured transport paradigm not only by using Automatic Guided Vehicles (AGVs) but also by embedding intelligence into the product transport system, including the AGVs, to allow more flexibility and adaptability. The Smart AGVs represent a new transportation system based on industry 4.0 principles. They have built-in intelligence to act on requests for changing operations sequence, parts-workstation assignments and routes received digitally or via distributed sensors, and change the processing routes according to pre-planned flow sequence alternatives. This smart system would add flexibility to the assembly system to deal with the introduction of different product variants as well as allow product-station re-assignment if a workstation is down, hence, preventing blocking and starving stations, delays and costly downtime. Figure 3-1 shows two examples of smart AGVs by Locus Robotics (Locus Robotics 2018) and Otto Motors (Otto Motors 2018).



(a) (b)

Figure 3-1(a) Smart AGV produced by Locus Robotics (Locus Robotics 2018) (b) Smart AGV produced by Otto Motors (Otto Motors 2018)

This research focuses on developing generic assembly networks for generating alternative assembly sequences for a given product for use in adaptive manufacturing systems, which include smart AGVs. Adaptable, flexible and reconfigurable alternate routing is a logical enabler of the new smarter transportation system for moving parts, sub-assemblies and products between stations that is capable of changing assembly routes as needed without stopping for reprogramming. The multiple assembly sequence alternatives to assemble a product are generated in the form of an assembly network. All sequences represented by the assembly network lead to the same final assembled product family.

Extensive research has been conducted in the field of assembly sequence generation; however, there is no work considering the generation of a master assembly network composed of multiple assembly sequences. A generic master assembly network is composed of multiple alternative assembly sequences for a group of product variants belonging to a family in which they share common parts and product structure. This master assembly network can be used for constructing an assembly sequence network for a new product variant belonging to the considered product family.

A novel master assembly network generation method is presented. It is inspired by problems studied in phylogenetics to construct a network that summarizes a set of conflicting rooted phylogenetic trees. Conflicting data is not uncommon; it is part of the legacy products assembly sequence plans reality that should be dealt with (Kashkoush and ElMaraghy 2015, Navaei and ElMaraghy 2017). The proposed method utilizes conflict found in assembly sequences of different variants in the product family in order to find alternative assembly sequences for the same product. The generated network is called soft-wired galled network and represents the master assembly network of a given product family. A new soft-wired galled network generation method based on the genetic algorithm has been developed to deal with the specific characteristics of products' assembly sequences. The generated assembly network, used to extract and generate a network for a new product variant, capitalizes on the existing similarity between new and legacy product variants, which decreases the time and cost needed for assembly sequence planning. The new variant assembly sequence is extracted from the master assembly network by removing the parts which do not exist in the new variant from the generated master assembly sequence. If new parts introduced in the new variant which do not exist in the previous variants, a planner will decide its position within the extracted network. A real case study for a family of back flushing control valves is used to illustrate the use of the developed method and compare its results with other methods found in the literature.

This research targets product families which consist of different product variants (instances), all of which are perfectly valid and feasible products regardless of differences in geometry or other attributes which make them different variants of the same product family. The assembly sequence problem and its precedence constraints should not be confused with technological assembly issues such as tools and fixtures to be used in assembly.

3.3 Master Assembly Network Generation

3.3.1. Problem Description

For a given set of N assembly sequences for N variants of a product family with a total number of n different parts, it is required to find multiple alternative assembly sequences for all the n parts. These multiple alternative assembly sequences are achieved by minimizing a modified Robinson Foulds distance, which represents the difference between the generated master assembly network and the given trees, as detailed in section 3.4.4.

The following assumptions are made:

- Non-linear assembly with parallel operations is allowed.
- Assembly operations are sequential, with one part added at a time.
- Assembly sequences data for existing product variants are available.
- The same name or part number is used for various versions or variants of the same part in the product family.

3.3.2. Soft-Wired Galled Network as Assembly Network

Many elegant solutions to engineering problems have been inspired by biological phenomena (Shu et al. 2011). The proposed method for constructing the master assembly network is inspired by a method for constructing a soft-wired galled network that is used in biological and phylogenetic contexts. A non-traditional approach for assembly sequence generation is proposed. Each individual assembly sequence for a product variant of a given product family that shares a number of parts and has a common product structure is represented as a partial assembly tree (Miller and Hoffman 1989). The partial assembly tree which is an unordered rooted binary tree used in literature to represent the assembly sequence. These assembly trees are merged together into one master assembly network. Then, the master assembly network is used to extract the assembly network of a new variant that lies within the boundary of the considered product family. The master assembly network is a network that represents a combination of assembly sequence trees. Each tree represents a complete product assembly sequence. Thus, the network represents alternate assembly sequences for the same product.

Traditionally, the galled network is a directed acyclic graph that models evolutionary histories with reticulation events (Huson et al. 2010). It is a rooted phylogenetic network in which each reticulation has a tree cycle. The evolutionary histories trace the processes by which living and fossil organisms by indicating the presence of a common ancestor from which species have diverged. Reticulation events happen when the origination of an ancestry is the result of a partial merging of two ancestor lineages leading to relationships better described by a phylogenetic network than a tree. Examples of reticulation events are hybridization, horizontal gene transfer, recombination, or gene duplication and loss. These phylogenetic networks are richly linked networks where hybrid nodes (nodes with two parents or more) exist instead of only tree nodes (a hierarchy of nodes, each with only one parent) that exist in phylogenetic trees. The phylogenetic trees are a subset of the phylogenetic networks. The galled network has become very popular due to its biological significance (Cardona et al. 2011). These networks can be represented in a soft-wired network form. The soft-wired galled network is a network that represents all of the clusters in a given set of trees. The cluster represents a group of closely related species, which share a trait, or suite of traits. The clusters are represented by links in the network, each of which represents one or more clusters depending on which reticulation links are "on" and "off" (Huson et al. 2010). A soft-wired network is a rooted phylogenetic network interpreted in the soft-wired sense in which reticulate edges can be switched on or off while hard-wired network is a rooted phylogenetic network interpreted in the hardwired sense in which all reticulate edges are considered to be on. Figure 3-2 shows an example of a soft-wired network of five leaves. Leaves 3 and 4 are included in the cluster represented by the link labelled "a" if the x link is switched on, and y link is thus switched off, and it is not included if y link is switched on, and x link is thus switched off. In the assembly network, the "on" and "off" feature of the soft-wired network can be used to represent assembly sequence alternatives, as discussed in the following paragraphs.

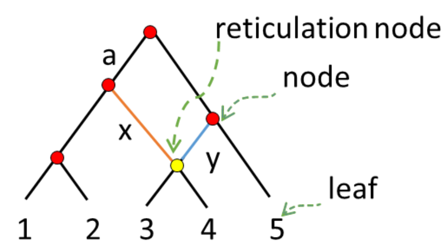


Figure 3-2 A soft-wired network

In this chapter, these assembly trees are combined to form a network based on the features of the soft-wired galled network. A special soft-wired galled network, in which the network can have hybrid (reticulation) nodes with only two parents, is proposed based on the stated assumption to represent the assembly network. These reticulation nodes are utilized to represent the different alternative sequences.

This paragraph illustrates the representation of an assembly network with multiple alternative sequences by the soft-wired galled network. The root of the network represents the final product (complete assembly), and the leaves represent individual parts. Two types of intermediate nodes can exist. The first type is a hierarchy of nodes; each with only one parent represents the subassembly resulting from adding its two sub-nodes while the second type is reticulation (hybrid) nodes with two parents in the case of alternative (reticulation) links. Figure 3-3a shows the assembly network representing the multiple alternative assembly sequences for a product consisting of five parts. Two alternative assembly sequences are available depending on which reticulation links are "on" and "off." The first assembly sequence is shown in Figure 3-3b, and its precedence graph is shown in Figure 3-3d. Four assembly operations are done. Assembly operation (A1) in which part 1 and part 2 are assembled forming sub-assembly (1-2), before or after assembly operations (A3) and (A4) are performed. Assembly operation (A3) of parts 4 and 5 to form sub-assembly (4-5) while assembly operation (A4) of part 3 to the sub-assembly (4-5) forms sub-assembly (3-4-5). The final assembly operation is A5 in which the two sub-assemblies (1-2) and (3-4-5) are assembled together. The second assembly sequence is shown in Figure 3-3c, and its precedence diagram is shown in Figure 3-3e. It includes assembly operations (A1) and (A3) in addition to two new assembly operations (A2) and (A6). Assembly operation (A2) is assembling part 3 to the sub-assembly (1-2) to form sub-assembly (1-2-3). Assembly operation (A6) produces the final product by assembling the two sub-assemblies (1-2-3) and (4-5).

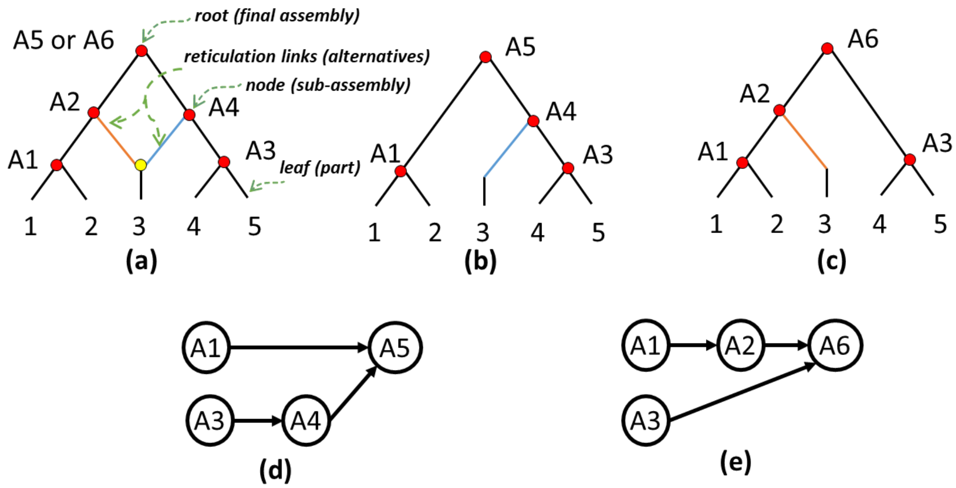


Figure 3-3 (a) Multiple alternative assembly network; (b) First assembly sequence alternative; (c) Second assembly sequence alternative; (d) First alternative precedence diagram; (e) Second alternative precedence diagram

3.4 Generation of Master Assembly Network using Genetic Algorithm

This section presents the developed method for constructing the master assembly network (soft-wired galled network) for a given set of assembly sequence trees. Constructing the soft-wired galled network is an NP-hard problem (Van Iersel and Kelk 2011). Many algorithms and methods have been developed in the biology and phylogenetics literature for constructing soft-wired Galled networks (Gusfield 2015, Van Iersel et al. 2010, Wang et al. 2013, Huson et al. 2009). However, the master assembly network is considered as a special case of the soft-wired galled network in which the maximum number of links coming out directly from any node is limited to two links. This constraint is needed to prevent any confusion that may happen in the order of the assembly operations within any generated assembly sequence. None of the algorithms and methods found in the literature deals with this special case. In addition, they did not consider trees with a different number of leaves.

A Genetic Algorithm (GA) based model was developed for this purpose and is presented in this section. GA is an evolutionary optimization meta-heuristic originally introduced by (Holland 1992), inspired by the process of natural selection. The GA-based model is developed to construct the master assembly sequence network for a given set of individual partial assembly sequence trees. This set of assembly trees represents the assembly sequence of different variants in a specific product family. The number and type of parts in each variant may be different. The master assembly network is equivalent to the soft-wired galled network for the given set of individual assembly trees. The developed model is implemented using the MATLAB® numerical computing environment and proprietary programming language.

3.4.1. Methodology

Each of the available assembly trees is encoded into a m x m square matrix form where m is the number of leaves (parts) in each tree. This matrix captures the same information about the sequence of parts and the tree topology (assembly processes) provided by the trees. Hence, the tree corresponding to any encoded matrix can be easily restored. The master assembly network is represented by a n x n square matrix where n is the total number of different parts. The developed genetic algorithm-based model is used to derive the matrix that represents the master assembly network. The resulting network must consist of all the parts that appear in the considered set of assembly trees. A set of n x n matrices (initial population) representing the initial set of assembly networks (solutions) is randomly generated. A detailed explanation for the encoding/decoding scheme is covered in the next subsections. In other words, the diagonals of these matrices are formed of the n parts with random order and the upper triangles are filled with ones randomly. The GA is applied to this set to find the optimal assembly network matrix that has the minimum fitness function. Figure 3-4 shows an IDEF0 model of the proposed genetic algorithm illustrating its main activities as well as inputs, outputs, controls and mechanisms for each activity.

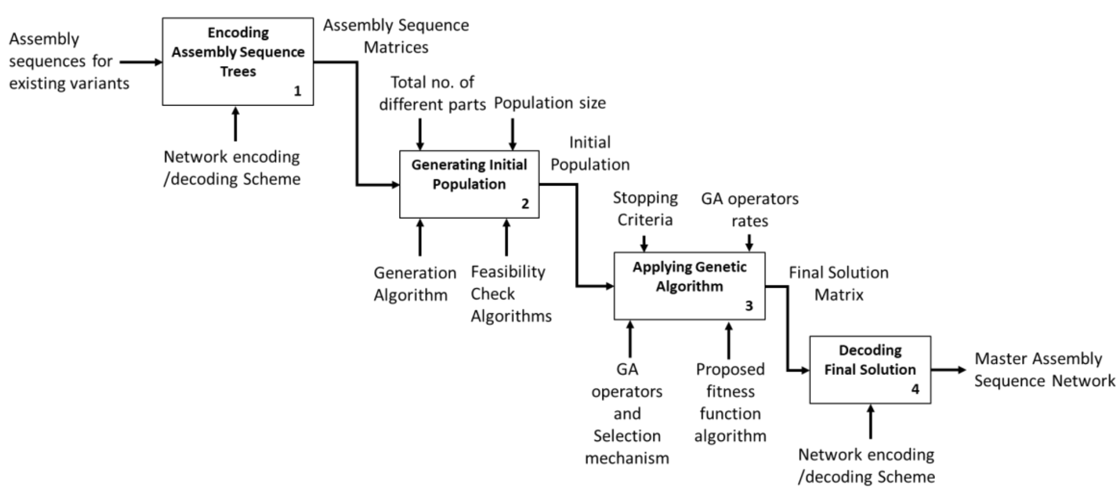


Figure 3-4 IDEF0 model of the GA for finding the master assembly network

3.4.2. Network Encoding/Decoding Scheme

The performance of the GA is profoundly affected by the chromosome (individual) representation. A matrix-based representation is chosen for the network. A new encoding/decoding scheme is developed to convert the network and the given set of trees (the trees are a special case of the network) into a matrix. This encoding matrix captures two types of network information: network topology or structure and the sequence of leaves (parts). It is a m x m square matrix where m is the number of leaves (parts) of the network. The topology of the network is encoded in the form of binary values (0-1) in the upper triangular of the matrix, and the diagonal elements of the matrix encode the assembly parts. The developed network encoding/decoding scheme is capable of representing the soft-wired galled networks, unlike other encoding/decoding schemes such as those found in references (Kashkoush and ElMaraghy 2015, Kashkoush and ElMaraghy 2014, ElMaraghy and AlGeddawy 2012).

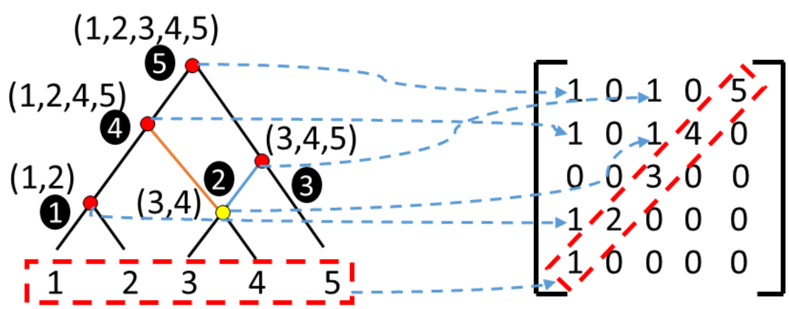


Figure 3-5 Proposed network-to-matrix encoding/decoding scheme

Figure 3-5 illustrates the encoding/decoding scheme. The network shown in Figure 3-5 includes five (5) nodes. Each node is represented by 1 in the upper triangular of the encoding matrix. Thus, the sum of the 1s in the upper triangular of the encoding matrix is the node count. The location of the 1s in the matrix represents the location of the nodes in the network. In order to encode the network in figure 5 into a matrix, the leaves (parts) are placed on the diagonal of the encoded matrix maintaining their sequence. Then the 1s on the upper triangular of the matrix are allocated. First, the nodes that contain clusters of two leaves (parts) are allocated, followed by nodes of clusters of three leaves and so on until reaching the final node that contains all the leaves (parts). Thus, nodes 1 and 2 are the first ones to locate their 1s. For node 1 that represents the parts 1 and 2, the 1 is located in the matrix at the intersection of the vertical line from 1 on the diagonal (representing part 1) and the horizontal line from the 2 on the diagonal (representing part 2). This is the 1 at the fourth row and the first column cell in the matrix.

Similarly, the 1 for node 2 is located in the second row and third column cell. Then, node 3 to which the three leaves (parts) 3, 4 and 5 belong in the network is represented by locating 1 at the first row and third column cell. This location of the 1 for node 3 is the intersection of the vertical line from the 1 in the second row and third column cell (representing the cluster of parts 3 and 4 node 2) and the horizontal line from 5 on the diagonal (representing part 5). The same process is done for the rest of the nodes until node 5 that contains all the parts is reached. Hence, the encoded matrix maintains the hierarchy and grouping relationships among parts and the sub-assemblies. For all encoded matrices, the cell at the intersection of the first row and the first column (left) must be equal to one as it represents the network (final assembly) root node to which all leaves (parts) belong.

3.4.3. Generating the Initial Population of the Master Assembly Network

The developed GA starts with an initial population, which is an initial set of solutions randomly generated from the search space contains all the possible (feasible) solutions. The initial population is a set of n x n square matrices where n is the total number of different parts. To generate the initial population from 1 to n is generated in the diagonal cells, and a random number of 1s are located in different cells above the diagonal. The main challenge in using this approach is that the resulting matrices may represent infeasible assembly sequence networks (solutions). Thus, checking the feasibility of the resulting matrices and converting infeasible ones into valid matrices is needed. The permutations of the matrix diagonal and the random number of 1s located in the different cells above the diagonal both help in exploring more points that fall the solution space.

Turning unfeasible matrix into a feasible matrix is done on two steps. The first step is checking that all n parts in the network are included in the encoded matrix by ensuring that each element on the diagonal has at least a 1 in the cell on its left or the cell above it. If not, then a 1 is added either to a cell on its left or above it. The 1 is selected to be filled left or above in a random way. Figure 3-6a & c show an infeasible matrix and its corresponding network, respectively, and Figure 3-6b & d show the matrix after adding 1 to include part 2 and its corresponding network, respectively.

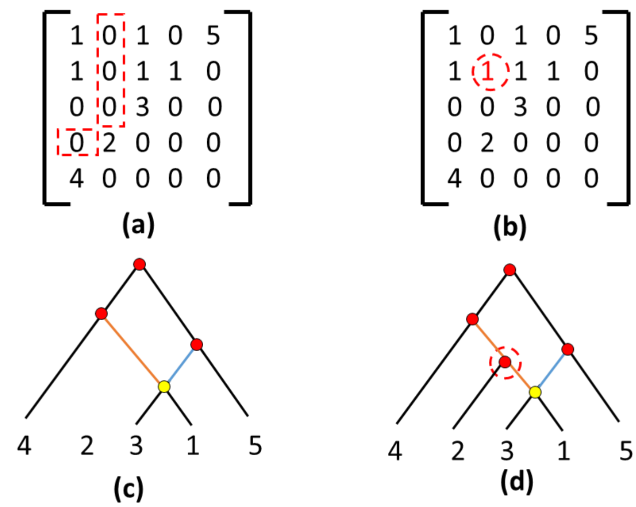


Figure 3-6 First feasibility checks

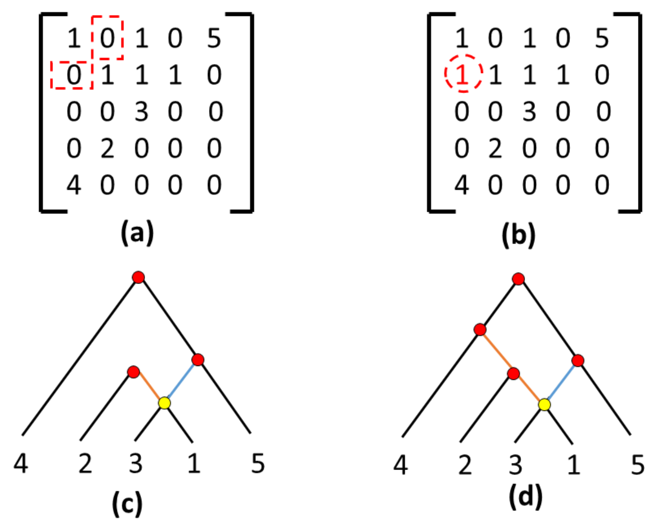


Figure 3-7 Second feasibility check

The second step is to ensure that all the nodes (1s) are connected to at least one parent node (one in cells on its left or cells above it). A check is performed by ensuring that each 1 in the upper triangular of the matrix has at least a 1 on the cells on its left or the cells above it. In case that check fails, a 1 is randomly added to a cell on its left or the cells above it that has a 1 on its left and the cells above it. Figure 3-7 graphically shows this step for further illustration. Figure 3-7a & c show an infeasible matrix and its corresponding network, respectively, and Figure 3-7b & d show the matrix after adding 1 to include part 2 and its corresponding network, respectively.

3.4.4. Modified Robinsons-Foulds Distance and Fitness Function

The Robinson-Foulds distance (Robinson and Foulds 1981) is the most widely used metric for comparing phylogenetic trees (Pattengale et al. 2007). It can be defined as a normalized count of the nodes (i.e. clusters of leaves) not shared by two trees.

In this research, a modification of the Robinson-Foulds distance is proposed to compare phylogenetic trees representing the assembly sequence trees, and the network representing the master assembly network. This Robinson-Foulds modification assigns a higher weight to the nodes (clusters) which exist only in a given assembly tree compared to those that are only found in the master assembly network. This modification ensures that the resulting network has all the clusters (nodes) in the existing assembly trees with reticulation nodes. The modified Robinson-Foulds is considered as a difference measure and is no longer a distance function according the distance function definition, since the difference between network 1 and 2 is not the same as the difference between network 2 and 1.

Given two networks NT1 and NT2, both having m number of leaves, then C1 is a set that includes subsets of NT1 (each node of NT1), and each subset includes the leaves (parts) belonging to the node represented by this subset. Similarly, C2 contains subsets representing the nodes of NT2. The modified Robinson-Foulds distance (MRF) is given by equation (3.1), where 'w' is the weight to be given for the difference between the sets of the C1 and C2 and '\' refers to set difference operation. As the objective is to minimize the MRF, the assumption of the weight 'w' value should be large enough to force the algorithm to minimize the first term of equation (3.1) then the second term. The first term in the equation (w $|C1\backslash C2)|$ represents the number of nodes in the first network and not in the second network while the second term ($|C1\backslash C2|$) represents the opposite. The first term's role is to ensure that the network will contain as many of the nodes in the given trees while the second term prevents the addition of extra nodes to the network.

$$\text{MRF (N1,N2)} = w \,|C1\backslash C2| + |C2\backslash C1| \tag{3.1}$$

A reasonable assumption for the weight is to be equal to the maximum number of nodes for an assembly network, which is defined by the following equation (3.2):

$$w = \frac{n\,(n-1)}{2} \tag{3.2}$$

where n is the total number of different parts.

For instance, the two networks NT1 and NT2 shown in Figure 3-8 each has five leaves (parts). NT1 is representing a tree which is a special case of a network. For NT1, C1 = {{4, 5, 1, 2, 3}Le et al. (2017a), {5, 1, 2, 3}, {1, 2, 3}, {2, 3}} and for NT2, C2 = {{5, 4, 1, 2, 3}, {4, 1, 2, 3}, {4, 2, 3}, {1, 2, 3}, {2, 3}}. The order of sets within C1 and C2 or order of leaves (parts) within any of their subsets have no significance. By substituting in equations 3.1 and 3.2, MRF (NT1, NT2) = 28 (1)+(2)= 30.

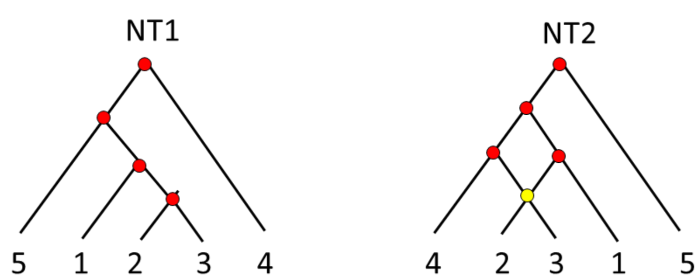


Figure 3-8 Two Networks NT1 and NT2 with MRF (NT1, NT2) = 30

An algorithm using the encoded matrix representation is developed to calculate the MRF. Based on the proposed encoding/decoding scheme, getting the C set for any given network is straightforward. The parts that are included in any subset of the set C can be determined by checking the values to the right and below the 1 representing the considered node till the diagonal values are reached. For example, in Figure 3-9, the subset of the C set that represents node A of the shown network includes part 4 as there are no 1s below the 1 of the considered node till we reach the diagonal at the value of 4. In addition, the subset includes parts 1 and 3 as the 1 to the right of the considered 1 includes the cluster of parts 1 and 3. Thus, the subset of node A is {1,3,4}, identified by the location of the cell representing A in the corresponding matrix.

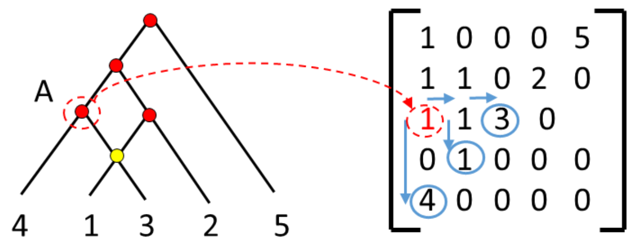


Figure 3-9 Obtaining the subsets of the C set for a given network

Throughout the developed GA iterations, a fitness function is applied for evaluating the fitness of each candidate master assembly network (solution). For a given set of existing assembly sequence trees N, with a total of n different parts, and a candidate master network MNT, the fitness function is the average of the modified Robinson-Foulds (MRF) distances between every individual tree T out of the N available trees and the candidate master network MNT. The fitness function is given by equation 3.3. The objective is to minimize the fitness function.

$$Fitness = \frac{\sum_{i=1}^{i=N} MRF(MNT, T_i)}{N} \tag{3.3}$$

MNT has more parts than T in the majority of cases. Hence, in calculating Modified Robinson-Foulds distance between a candidate master network MNT and any individual tree T, only the parts that exist in T are considered. In other words, only the parts that exist in MNT but not in T are ignored and temporarily removed from the C set of MNT.

3.4.5. Selection

Selection simulates the natural law of survival of the fittest in the population evolutionary process (El Hassani et al. 2015). It is the process of selecting parents for forming the new generation. Tournament selection is applied where the two individuals are chosen at random, and the better of the two is selected with fixed probability (Goldberg and Deb 1991).

3.4.6. Genetic Algorithm Operators

3.4.6.1 Crossover

The crossover operator plays a vital role in searching for better solutions from generation to generation. Two special matrix-based crossover operators were developed to ensure generating feasible offspring solution matrix. The crossover mechanism is based on combining/mating two randomly selected parents (matrices from the current generation) to form a new matrix (offspring) representing a new solution in the next generation. The first crossover procedure is that the upper triangular of the offspring matrix, which is responsible for the network topology is taken (inherited) from one of the parent matrices, and the diagonal of the offspring matrix, which is responsible for the sequence is taken (inherited) from the other parent. The second crossover procedure is that the upper triangular of the offspring is taken (inherited) from one of the parent matrices as in the previous crossover operation. The diagonal of the offspring matrix is considered as a string as well as the diagonal of the two parent matrices and the popular Position-based crossover by Syswerda (1991) is applied. It is applied to the diagonal of the offspring by selecting a random set of positions in one of the parent diagonals, and it imposes the values in the selected positions on the corresponding positions of the other parent diagonal. Using these two crossover operators guarantees producing feasible offspring matrices. The developed crossovers are presented graphically in the matrix and network forms in Figure 3-10 and Figure 3-11 for illustration.

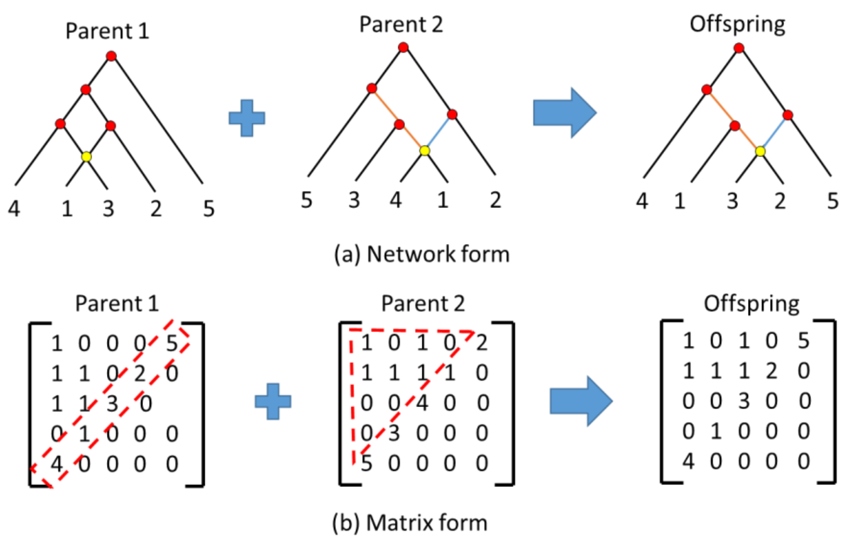


Figure 3-10 First proposed crossover operator

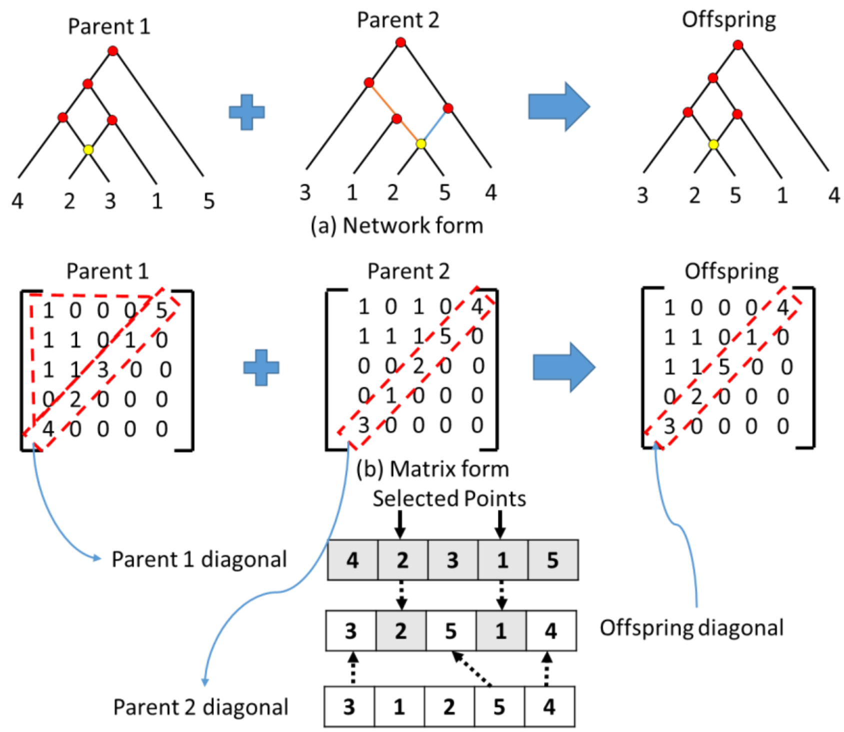


Figure 3-11 Second proposed crossover operator

3.4.6.2 Mutation

The mutation is another crucial GA operator that helps in searching for better solutions. A well-designed mutation eases the convergence towards a local optimum solution. Three special matrix-based mutation operators were developed. The first two mutation operators deal with the topology while the third operator deals with the sequence. The first mutation procedure is that a 1 is added in a random location in the upper triangular of the parent matrix to form the upper triangular of the offspring matrix. The two-feasibility checks, applied to the initial population, are applied to ensure the feasibility of the offspring matrix. For the first mutation, the diagonal of the offspring is similar to the diagonal of the parent. The second mutation procedure is similar to the first mutation operator except a 1 is removed from a random location in the upper triangular of the parent matrix instead of added to form the upper triangular of the offspring matrix. The third mutation procedure is that the well-known swapping mutation, proposed by Oliver et al. (1987), is applied to the parent matrix diagonal to produce the offspring diagonal while the upper triangular of the matrix of the offspring remains the same as the parent matrix. The swapping mutation is applied to the parent matrix diagonal by considering it as a string, then selecting two random positions and exchanging them to produce the offspring matrix diagonal. The matrix form and network form of the developed mutation operators are presented in Figure 3-12, Figure 3-13 and Figure 3-14.

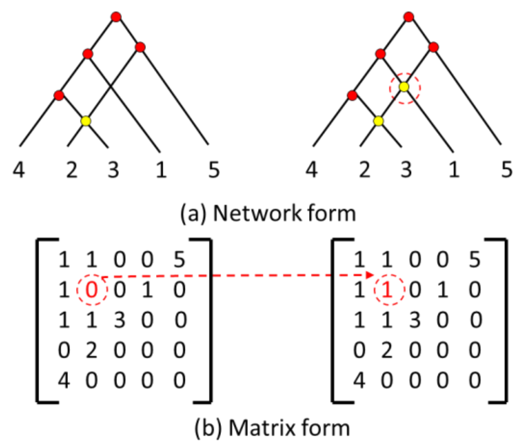


Figure 3-12 First proposed mutation operator

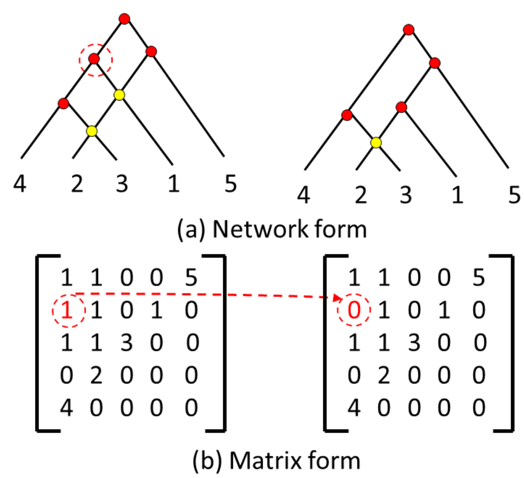


Figure 3-13 Second proposed mutation operator

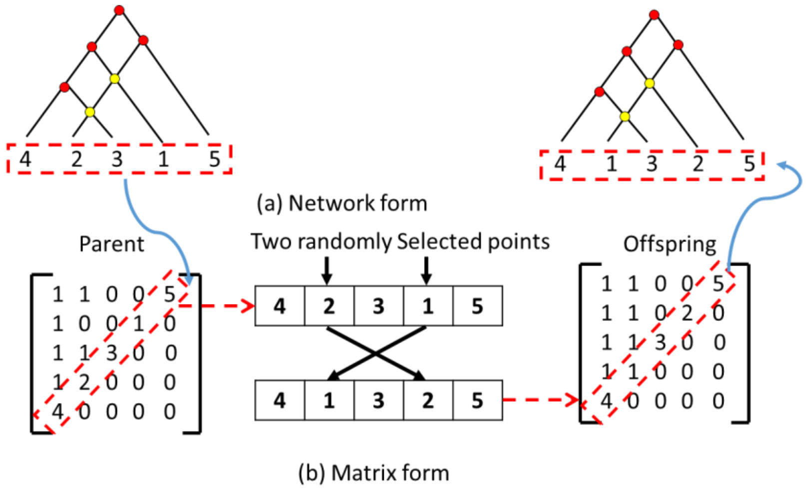


Figure 3-14 Third proposed mutation operator

3.4.7. Stopping Criteria

The stopping criteria specify when to terminate the genetic search according to pre-defined stopping conditions. In the developed GA, the stopping conditions are reaching either a previously determined number of generations or no change in the value of the objective function of the best solution during a fixed number of successive generations.

3.5 Illustrative Example

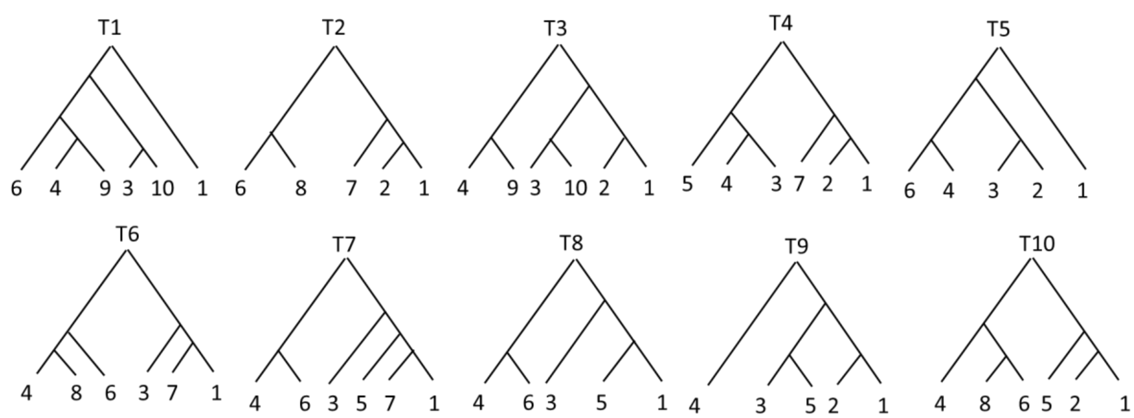


Figure 3-15 Assembly sequence trees for a family of ten variants.

A simple hypothetical example is presented to demonstrate the generation of the master assembly network and its utilization to obtain the assembly network for a new product family variant. The example is for a product family consisting of ten variants. The assembly sequence for each variant of the given product family, involving a total of ten different parts, is represented as a partial assembly tree, as shown in Figure 3-15. The ten trees are encoded in the matrix form, and the developed GA is applied. The following GA parameters: 0.35 for each crossover operator, 0.1 for each mutation operator, and population size of 100 are used. The stopping condition was reaching 500 generations (iterations) or no change in the best solution for 100 generations. The weight is calculated based on equation 2 and is equal to 45. This weight forces the algorithm to generate a network that includes as many of the nodes in the given trees while taking the constraints into account. The optimal master assembly network for the product family (Figure 3-16a) with 11.9 average Modified Robinson-Foulds distance from any of the ten trees was obtained in 84 seconds on a PC of Intel Core i7 3.40 GHz processor and 16 GB Ram.

Assume that a new variant consists of the following parts: 1, 2, 4, 5, 6, 8 and 10 is introduced. The new variant has a new combination of parts that does not exist in the ten existing variants. Thus, the assembly network for the new variant is extracted from the master assembly network. The assembly network for the new variant is shown in Figure 3-16b. This network is extracted from the master network shown in Figure 3-16a by removing any parts that are not present in the new variant.

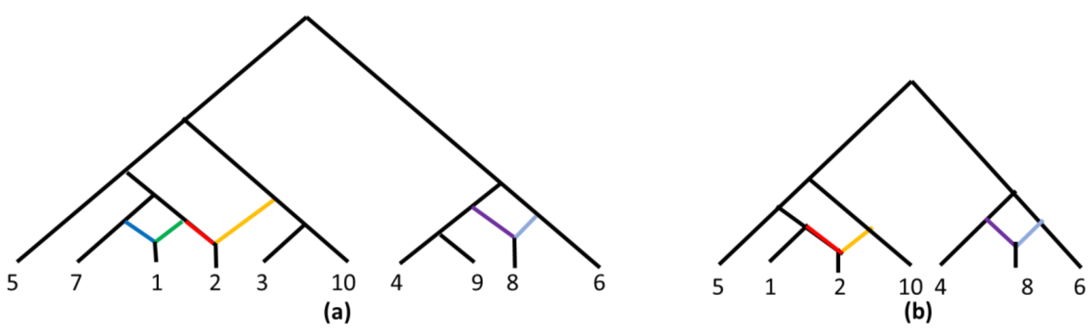


Figure 3-16 (a) Generated Master Assembly network; (b) Extracted Assembly network.

The assembly network for the new variant could be decomposed into four alternative assembly trees. For the first sequence (Figure 3-17a), parts 1 and 2 are assembled together to form sub-assembly [1-2], then part 5 is assembled to the sub-assembly [1-2]. Afterwards, part 10 is assembled to sub-assembly [1-2-5]. At the same time, before or after, part 8 and 4 are assembled together to form subassembly [4-8], then part 6 is assembled to the sub-assembly [4-8]. Finally, the two sub-assemblies [1-2-5-10] and [4-8-6] are assembled to form the new variant. For the second sequence (Figure 3-17b), part 8 is assembled to part 6 to form the sub-assembly [6-8]. Then, part 4 is assembled to the sub-assembly [6-8] to form sub-assembly [4-6-8]. The rest of the parts (1, 2, 5 and 10) are assembled similar to the first sequence. For the third sequence (Figure 3-17c), part 2 is assembled to part 10 to form sub-assembly [2-10]. At the same time or before or later, parts 1 and 5, as well as parts 4 and 8, are assembled to form sub-assemblies [1-5] and [4-8], respectively. Part 6 is assembled to sub-assembly [4-8]. The two sub-assemblies [1-5] and [2-10] are assembled. The final step is the two sub-assemblies [1 2 5 10] and [4 6 8] are assembled to form the final assembly. The fourth sequence is shown in Figure 3-17d, which is the same as the third sequence except that part 8 is assembled to part 6, then sub-assembly [6-8] is assembled with part 4.

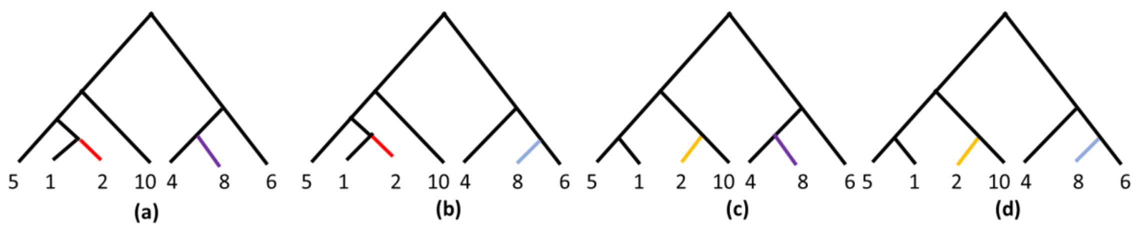


Figure 3-17 (a) First assembly sequence alternative; (b) Second assembly sequence alternative; (c) Third assembly sequence alternative; (d) Fourth assembly sequence alternative

3.6 Family of Control Valves Case Study

A family of back-flushing valves, adapted from (Kashkoush and ElMaraghy 2014), is used as a case study to illustrate the benefits of generating a master assembly network. Figure 3-18 shows the family of valves, which consists of three (3) product variants with thirteen (13) different parts. The considered family is a family of a modular product. The parts' names and numbers are representing modules, and some modules have more than one instance. The assembly sequence tree for each variant shown in Figure 3-19 was encoded into a matrix. The matrices of the product variants are the input to the developed GA. The output is a network that represents the master assembly network showing the alternative assembly sequences that may be used.

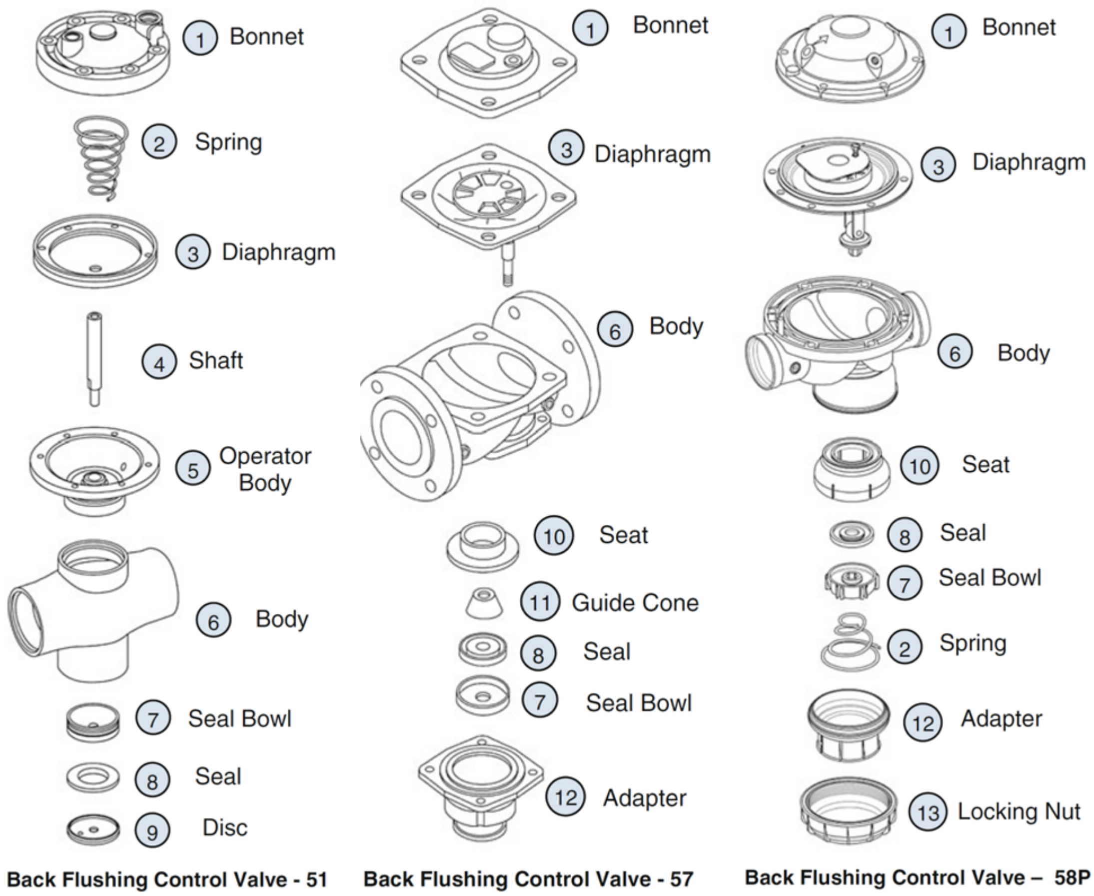


Figure 3-18 Exploded views for the family of control valves (Kashkoush and ElMaraghy 2014)

The master assembly network with average MRF = 78.5 was obtained in less than 4 minutes on the same PC used in the illustrative example using the same values of the algorithm parameters. Figure 3-20a shows the obtained master assembly network for the considered family of valves.

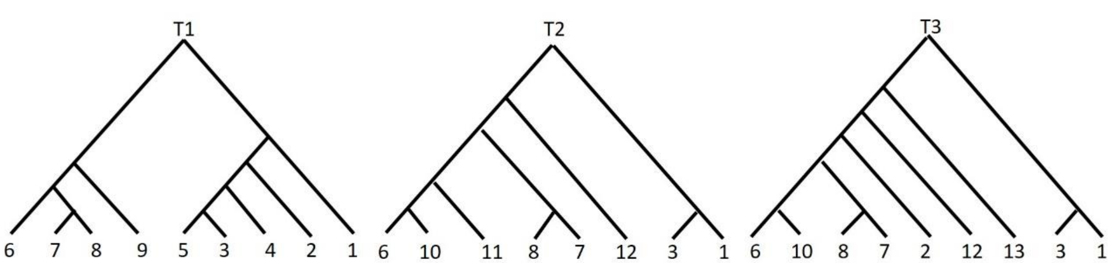


Figure 3-19 Assembly sequence trees for a family of three back-flushing control valves (Kashkoush and ElMaraghy 2014)

It is informative to compare the results obtained using the proposed method and the consensus tree method developed by (Kashkoush and ElMaraghy 2014) for the same case study. The consensus tree method formed a master assembly tree (Figure 3-20b) that includes only one assembly operation for each part or sub-assembly even if alternate assembly operations exist across the different product variants' tree. On the other hand, the soft-wired galled network method formed a network that includes as many of the assembly operation alternatives for each part or sub-assembly while taking into consideration the defined assembly constraints.

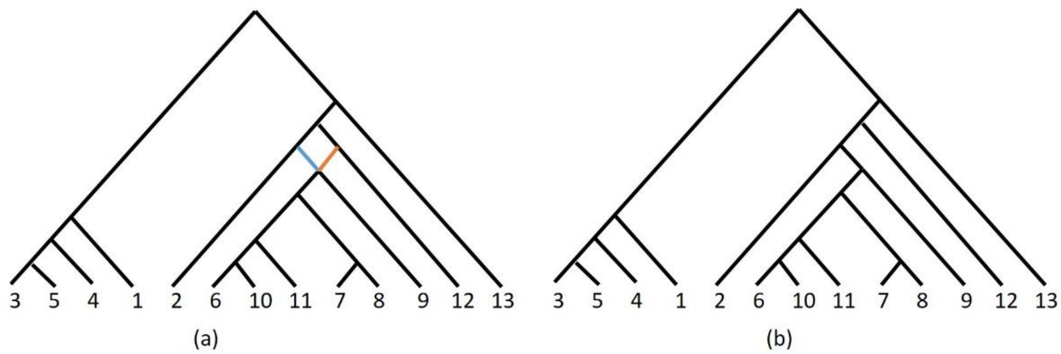


Figure 3-20 (a) Generated Master Assembly network (soft-wired galled network-based method), and (b) Generated Master Assembly tree (consensus tree-based method)

To illustrate the advantage of the proposed method over the consensus tree-based method, consider retrieval of an assembly sequence for a new back-flushing valve variant. The new variant (back-flushing control valve—62) consists of eight parts: bonnet (1), diaphragm (3), chamber (14), spring (2), shaft (4), body (6), seat (10), and adapter (12). The assembly sequence for the new variant is extracted from the master assembly network produced by the soft-wired galled network method is shown in Figure 3-21a, and the master assembly tree produced by the consensus tree method is shown in Figure 3-21b. Two assembly sequences were identified from the network extracted from the master assembly network. For the first sequence (Figure 3-21c), the subassembly [6-10] is assembled to part 2 then subassembly [6-10-2] is assembled to part 12. In the second sequence (Figure 3-21d), the subassembly [6-10] is assembled to part 12 then the subassembly [6-10-12] is assembled to part 2.

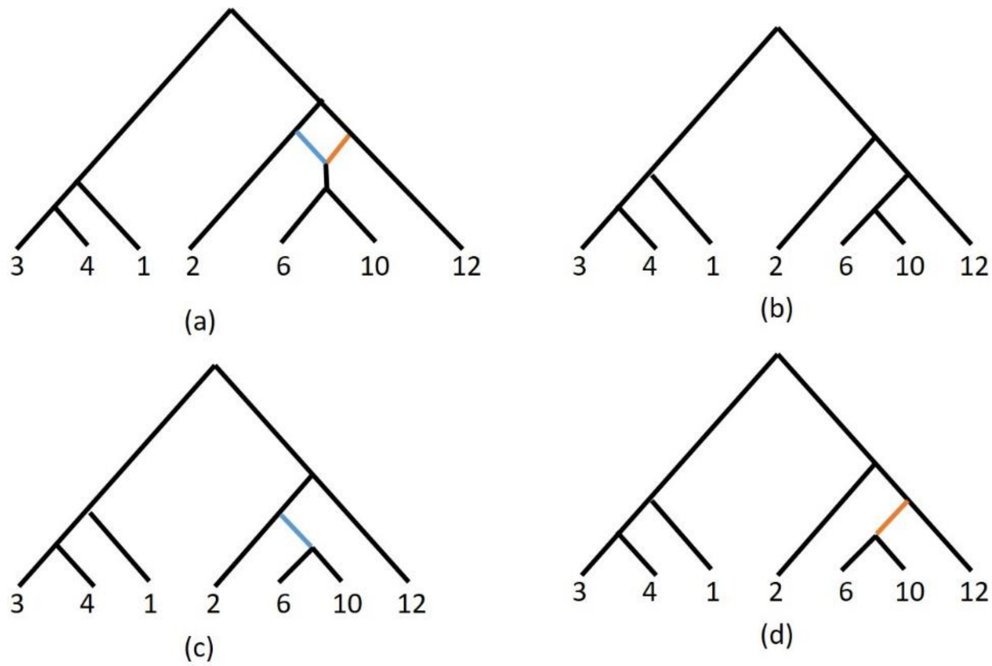


Figure 3-21 (a) Assembly network extracted from the Master assembly network for the new variant; (b) Assembly tree extracted from the Master Assembly tree for the new variant; (c) First assembly sequence alternative; (d) Second assembly sequence alternative

The tree extracted from the consensus tree-based method is one of the two alternative trees embedded in the network extracted using the soft-wired galled network-based method. Based on this case study, the soft-wired galled network-based method produced more alternative sequences than the consensus tree method. These alternative sequences increase the flexibility and adaptability of the system to handle workshop disruptions such as machine breakdowns and tool failure. For both methods, a planner will decide the position of the chamber (14) within the extracted assembly sequence, as this new part does not exist in the previous variants

3.7 Summary and Conclusions

This study presents a logical enabler (i.e. soft support function) for smart AGVs to allow them to change their routes to handle any real-time workshop disruptions in Industry 4.0 type of assembly systems. A novel method is developed for generating a master assembly network with multiple alternative assembly sequences. The master assembly network is constructed based on legacy data of the given assembly sequences for the set of variants of a product family. An assembly sequence for any new variant that falls within, or significantly overlaps with, the scope of the considered family of products can be extracted from the developed master assembly network. The proposed method is inspired by generating soft-wired galled networks used in biology and phylogenetic contexts. A Genetic Algorithm is developed for building the master assembly network. The developed method is a retrieval type assembly sequence generator.

Using retrieval process sequence planning, as in the presented method, avoids re-generating new assembly sequence every time a new product variant is considered, hence, contributes to reducing the overall process planning time and cost. Moreover, the extracted assembly network has multiple alternative assembly sequences that increase the flexibility and adaptability of the system to deal with real-time workshop disruptions. These disruptions may include, but are not limited to, new process-machine assignments, machines breakdown, tool failure and machine overload.

Compared with the traditional assembly sequence retrieval methods in the literature (e.g. the works presented in (Kashkoush and ElMaraghy 2015, Navaei and ElMaraghy 2018, Kashkoush and ElMaraghy 2014), the proposed method is capable of retrieving multiple alternative assembly sequences for the product variants. In contrast, the other methods were limited to only one assembly sequence. In comparison with the heuristic approach (Dendroscope) applied in (Moussa and ElMaraghy 2018), the proposed Genetic Algorithm approach generates near-optimal master assembly networks, while the Dendroscope program used in (Moussa and ElMaraghy 2018) provides a feasible solution but optimality or near optimality is not guaranteed.

It is worth mentioning that the quality of the generated master assembly network and the subsequently extracted sequences depend on the quality of the assembly sequences of the product family. The proposed method can be utilized in any manufacturing system that allows alternative assembly sequences including but not limited to Smart AGVs in Industry 4.0 environment.

Finally, the future work may include applying the concept of the soft-wired galled network to machining (metal cutting) operations. In the proposed method, if a new part is introduced in the new variant, a planner assigns the new part location within the network manually. Developing a method for autonomously allocating the new part in the network can be a possible subject for future research. Another direction for research work is developing a mathematical optimization model to guarantee the optimality of the solution. Assigning higher weights to the existing sequences of the product variants with higher demand can be studied for future research. The proposed method can be extended by adding a pre-defined set of precedence and technological constraints to ensure the feasibility of the generated sequences. A merit-based ranking of alternative process sequences to select the best candidate in case of disruptions is potential future research.

CHAPTER 4. OPTIMAL PLATFORM DESIGN AND PROCESS PLAN USING HYBRID MANUFACTURING

4.1 Overview

A novel generic process planning concept is introduced to manage the variety of product families produced by hybrid manufacturing. An optimal product family platform containing the core features of all variants is first developed. A combination of additive and subtractive processes of a product variant differentiating features determines its optimal process plan and minimizes manufacturing cost. The developed mixed-integer linear programming model and a case study used for demonstration are presented. This novel planning approach is adaptable to changes in product design and demands. It will impact the use of additive manufacturing to produce a family of product and its manufacturing cost.

4.2 Introduction

Product variety management is one of the most severe challenges manufacturing companies face nowadays (ElMaraghy et al. 2013). New manufacturing paradigms such as Smart Manufacturing (Industry 4.0), and Made in China 2025 consider additive manufacturing to be a key enabler. Combining additive and subtractive manufacturing technologies, known as hybrid manufacturing, has the potential to change the methods of realizing products. It can overcome some technological constraints while benefiting from the advantages of both techniques. The product platform concept is one of the most effective methods to deal with challenges arising from product variety (ElMaraghy et al. 2013).

This research introduces a novel approach for product variety management by utilizing the product platform concept and hybrid manufacturing for producing product variants by customizing the product platform. A macro process planning methodology capable of adapting to design and demand changes within a considered product family, and minimizing the total manufacturing cost is proposed.

4.3 Variety Management Utilizing Hybrid Manufacturing

A novel variety management concept utilizing hybrid additive and subtractive technologies is introduced. The product variants are produced by customizing the product family platform. The proposed concept is based on combining additive manufacturing processes such as direct metal deposition (DMD) or fused filament fabrication (FFF)) and subtractive manufacturing processes such as CNC machining in the same manufacturing system. The DMD and FFF are capable of building new features onto existing parts (Le et al. 2017b, Newman et al. 2015).

A product platform for the considered product family is produced in large quantity (i.e. mass production) to reduce cost and time, and then it is customized into individual variants as needed. The product platform is defined as a set of features (sub-parts) that forms a common structure from which a stream of derivative products can be efficiently produced and developed (Meyer and Lehnerd 1997). This product platform is further manufactured using additive and/or subtractive processes by which it can be transformed into different product variants. The product platform features (PPFs) may or may not all be required by a given product variant. The PPFs may be preserved or processed further by adding and/or subtracting material if they are not required in the considered product variant.

The philosophy behind this concept is depicted in Figure 4-1, where the product platform can be further manufactured into each product variant (1, 2 or 3) using either additive or subtractive processes. This approach can change the existing ways of manufacturing product families. The variants thus produced are near-net-shape that may require some finishing for the critical features only not the whole geometry.

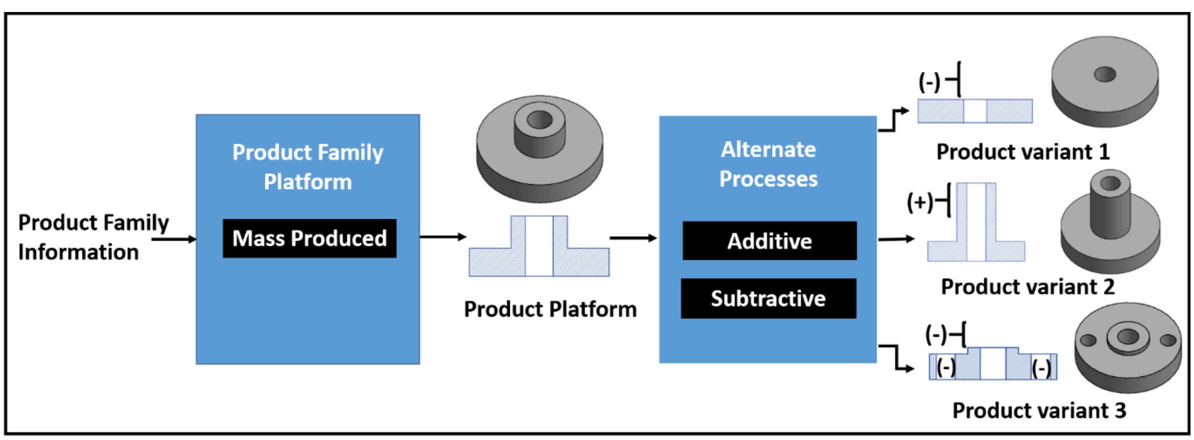


Figure 4-1 The philosophy of the proposed Variety Management concept

4.4 Hybrid Manufacturing and Process Planning for Variety

Hybrid Manufacturing Process Planning for Variety, named HMPPV, is proposed. It determines the product platform from which the product variants are derived as well as the types of processes required (additive or subtractive) in order to produce the different product variants at a minimum cost. The workflow of the HMPPV methodology consists of three steps outlined as follows:

4.4.1. Feature Extraction and Identification of the Relationship between Features

The product variants are decomposed into features (sub-parts). These features are defined as geometric shapes that can be built and/or machined without tool collisions. The features are identified and extracted based on the available information and drawings of all the variants within the considered family. A detailed explanation of the extraction procedure is covered in the next section.

4.4.2. Product Platform Design

A mixed-integer linear programming (MILP) model is used to build the platform with minimum cost based on the extracted features, relationships between features, associated manufacturing cost for each feature and the demand for each variant. The mathematical model identifies the features that form the product platform.

4.4.3. Determining Process Type

The MILP identifies the features to be added and/or removed (if needed) from the platform to produce each variant. This is the basis of the process planning approach for determining the subsequent process. The MILP used for designing the product platform design and determining the process type is explained in detail in section 4.6.

An IDEF-0 representation of the proposed HMPPV methodology is shown in Figure 4-2. The inputs are the product mix, which is determined by the demand for each product variant (i.e. the required units of each variant over a single production period), features within each product variant and features precedence as well as manufacturing costs for mass-producing the platform, adding feature by additive manufacturing and removing it by subtractive technologies. The constraints are the additive and the subtractive processes capabilities, which determine whether a feature can be manufactured by an additive process (e.g. DMD, FFF), subtractive process (e.g. CNC) or both. The mechanism is the MILP model. The output is the product family platform, as well as the type and sequence of processes to realize each product variant starting with the product family platform.

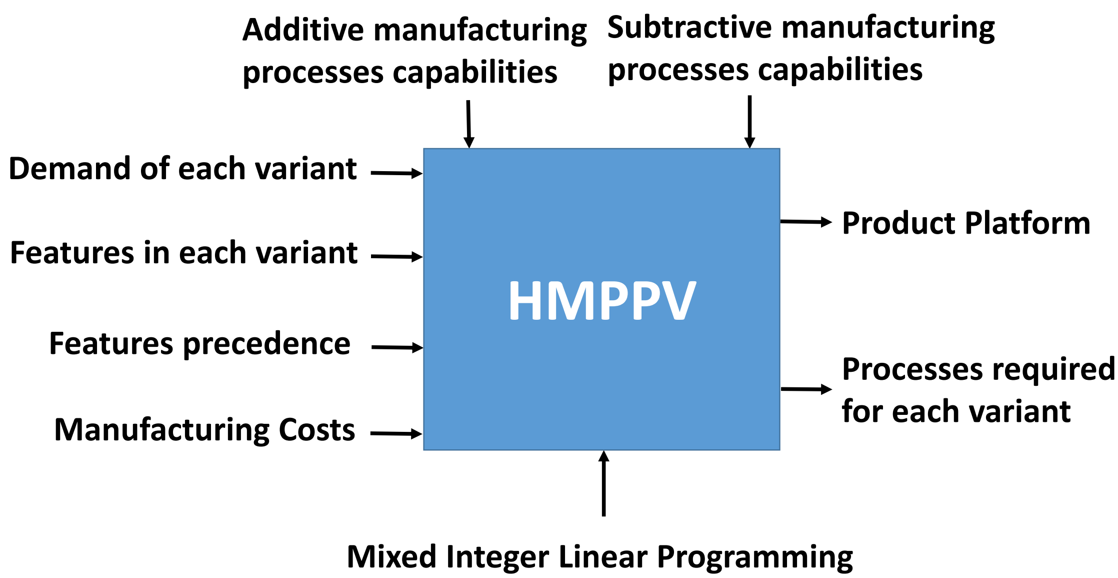


Figure 4-2 IDEF0 representation of HMPPV

4.5 Feature Extraction Procedure

Even though extensive research work has been conducted in the area of feature extraction in the context of CAPP (computer-aided process planning), as reported in ((Madurai and Lin 1992, Liu et al. 1996, Perng et al. 1990, Pal et al. 2005, Aslan et al. 1999, Holland et al. 2002, Sivakumar et al. 2019, Sateesh and Mahesh 2017, Kumar et al. 2017)), the majority of the feature extraction methods are limited to the extraction of the machining features only and do not consider the additive features. The subtractive (machining) feature can be defined as a geometrical shape and a set of specifications for which at least a subtractive manufacturing (machining) process is known (Terrazas et al. 2014) while the additive feature is defined as a geometrical shape and associated technological attributes for which at least an additive manufacturing process is known (Le et al. 2017a). Extracting feature for both additive and subtractive manufacturing was only considered in (Le et al. 2018b, Le et al. 2017a). Le et al. (2018b) and proposed a feature extraction procedure that extracts both subtractive and additive features between a legacy part and a final product. On the contrary, in this chapter, product platforms are formed from the majority common features within a considered product family and then additive, and subtractive manufacturing processes are performed on the platforms to produce different product variants. This work is different from (Le et al. 2018b, Le et al. 2017a). Consequently, a new feature extraction procedure is proposed to identify and extract subtractive and additive features for a considered family of product. Hence, the feature in this work is defined as the geometrical volume that can be added/built by at least one additive manufacturing process and be subtracted/removed/machined by at least one subtractive manufacturing process as well.

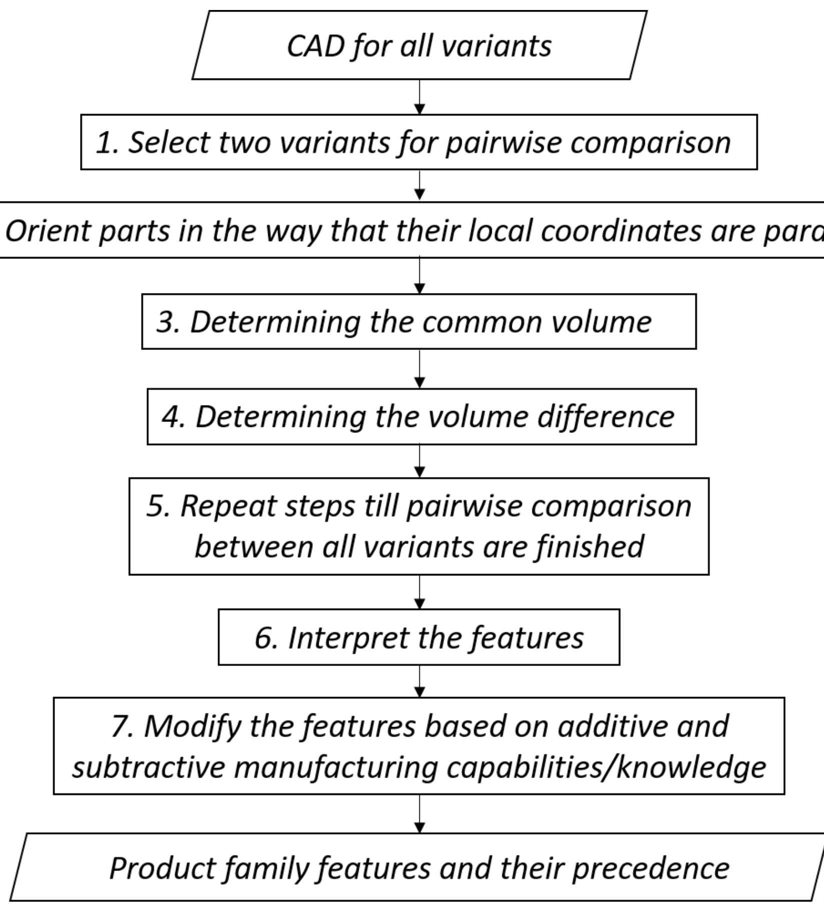


Figure 4-3 Product Family Features Extraction Procedure

The proposed feature extraction procedure consists of seven (7) steps as shown in Figure 4-3. The information including the dimensions, material, quality, and shape of all the product variants of the considered family as well as their CAD drawings are available for the feature extraction process and represent the input of the procedure. First, two product variants are selected for pairwise comparison. Then, the two selected product variants are oriented in the way that their local coordinates are parallel and the common volume between them is maximized. The intersect Boolean operation in the CAD software is used to determine the common volume between the two product variants, as shown in Figure 4-4 and equation 4.1.

{Common volume} = {1st selected variant} INTERSECT {2nd selected variant} (4.1)

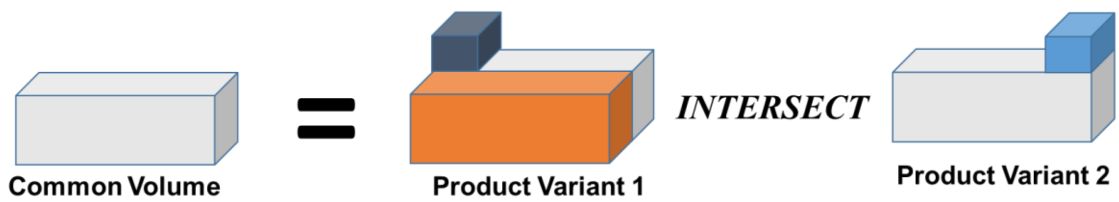


Figure 4-4 The intersect Boolean operation between two product variants

Afterwards, the difference in volume between the common volume and each product variant is determined using the subtract Boolean operation in the CAD software, as shown in Figure 4-5 and equations 4.2 and 4.3.

{1st Difference in volumes} = {1st selected variant} SUBTRACT {Common volume} (4.2)

{2nd Difference in volumes}= {2nd selected variant} SUBTRACT {Common volume} (4.3)

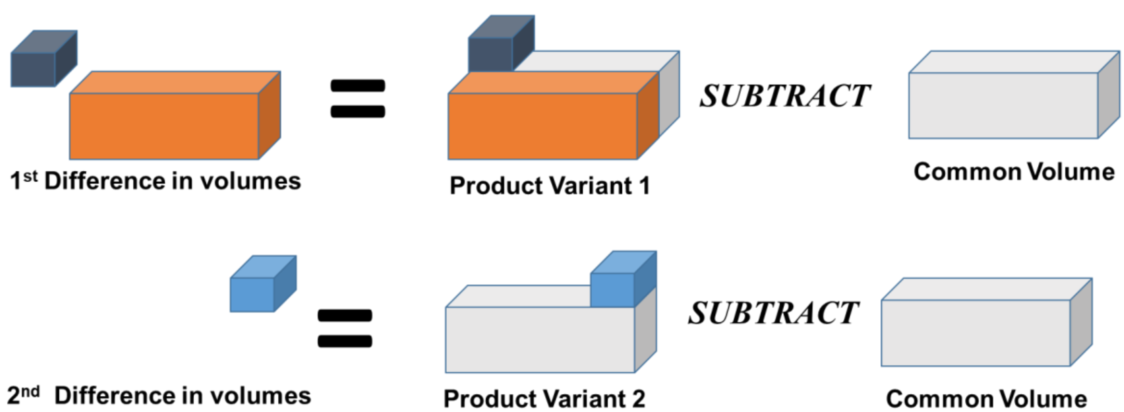


Figure 4-5 The subtract Boolean operations between both selected product variants and the common volume

These steps of the pairwise comparison are repeated until all the product variants within the product family are compared to each other, and three volumes are determined, namely the common volume, the volume difference between the common volume and the 1st selected product variant, and the volume difference between the common volume and the 2nd selected product variant. The output of the pairwise comparisons is studied in order to determine the features. This feature interpretation step is based on that each feature is represented by a unique volume and the volume of one feature cannot be included in other features. After the feature interpretation step, which is done manually, the final step is that the features are modified based on the knowledge of the existing additive and subtractive manufacturing processes. In other words, feature modification is performed to ensure that the generated feature can be manufactured by at least one additive manufacturing process and at least one subtractive manufacturing process. The required knowledge of both additive and subtractive manufacturing to perform the final step is covered in the following subsections. In many cases, the features from the interpretation step are decomposed into basic shapes such as cylinders and cuboids in the feature modification step. In addition, the final step helps in deciding which type of additive and subtractive manufacturing processes should be used and capable of manufacturing the feature. This decision is made based on the knowledge about the additive and subtractive manufacturing processes.

4.5.1. Knowledge of additive manufacturing processes and their capabilities

Additive manufacturing is a solid free-form fabrication technology that allows physical models and functional components to be made from virtual three-dimensional (3D) computer models by building the component layer-by-layer until the part is complete (Hashmi 2014, Adeyeri et al. 2019). The additive manufacturing technologies can be classified based on the building material as plastic-based, metal-based and paper-based (Singh and Singh 2017). In this work, the metal-based additive manufacturing is considered. The most popular metal-based additive manufacturing processes are the powder bed fusion (PBF) processes (e.g. EBM and SLM) and the directed energy deposition (DED) processes (e.g. DMD). In the following paragraphs, a discussion that covers the process descriptions and the main advantages and disadvantages of each process. The main characteristics that are considered in the discussion are the building direction, number of different materials used in a single build, surface roughness, part volume constraint and ability to build overhanging features.

Directed energy deposition (DED) refers to a category of additive manufacturing techniques in which a material in the form of wire or powder is deposited on to a base or component from a nozzle mounted on a multi-axis arm. Then, a focused energy source (plasma arc, laser beam, and electron beam) is utilized to melt the feed material into a pool of molten metal on the previous layer within an inert atmosphere; and the parts are then built layer by layer. Figure 4-6 shows the DED process.

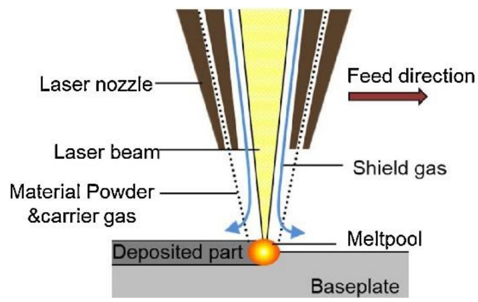


Figure 4-6 Schematic of direct energy deposition (DED) process (Koike et al. 2018)

The DED is capable of producing larger build volume and has higher build rate than other additive manufacturing technologies. Moreover, it has flexible build directions due to the fact that the nozzle can be installed to a 3-axis or 5-axis CNC machine configuration. Furthermore, multiple materials can be used in a single build. The building direction is the normal vector of planar surfaces or a local normal vector of 3D surfaces. This gives an advantage to the DMD in building on exiting parts. The surface roughness of the products built by DMD depends on the beam size, and it ranges between 20 and 50 μm, which is acceptable in many industries (Dutta and Froes 2015). The main limitations of the DMD are in building internal structures and overhanging structures (Herzog et al. 2016, Smith et al. 2016).

Commercial machines for the DED techniques are available in the market. For instance, DMG Mori produces the LASERTEC 65 3D which is a machine that is geared solely towards laser deposition welding which is one of the DED techniques. In addition, DMG Mori has performed successfully on the market since 2013 with the combination of laser deposition welding and metal-cutting machining on the machines of the LASERTEC 3D hybrid series (DMG Mori 2020a). Figure 4-7 shows the LASERTEC 3D series.

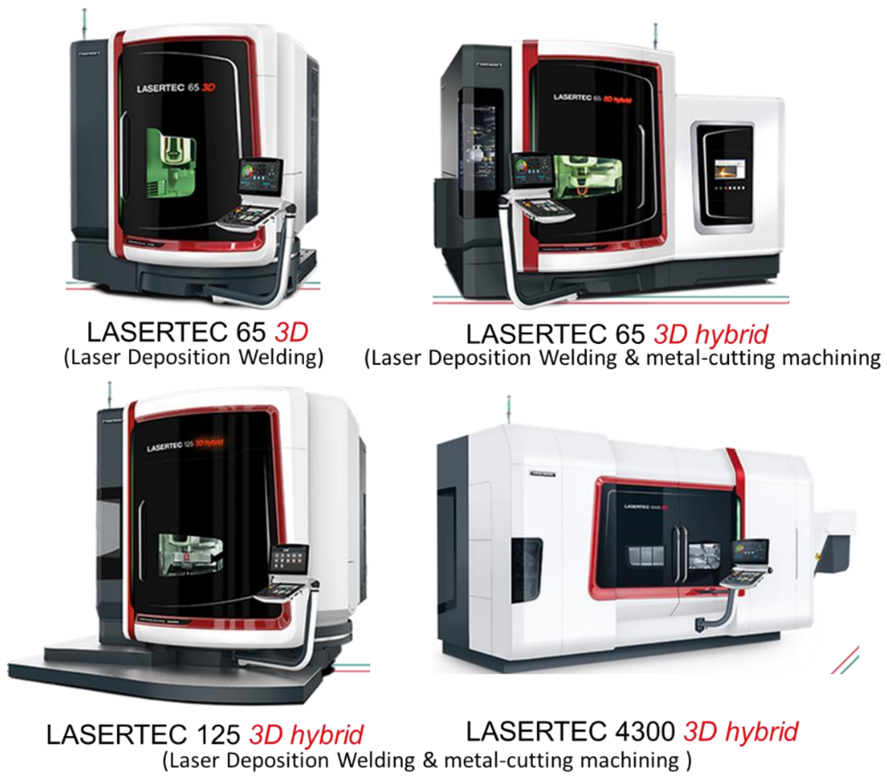


Figure 4-7 DMG Mori LASERTEC 3D series (DMG Mori 2020a)

The kinematics of the DED machine, which represents the axes of motion of the machine, plays a crucial role in both the accessibility during the process and the resulting accuracy (Cortina et al. 2018). Figure 4-8 shows the most common kinematic schemes of 5-axis DED machines. The schemes are classified from left to right based on their ability to manufacture heavier parts.

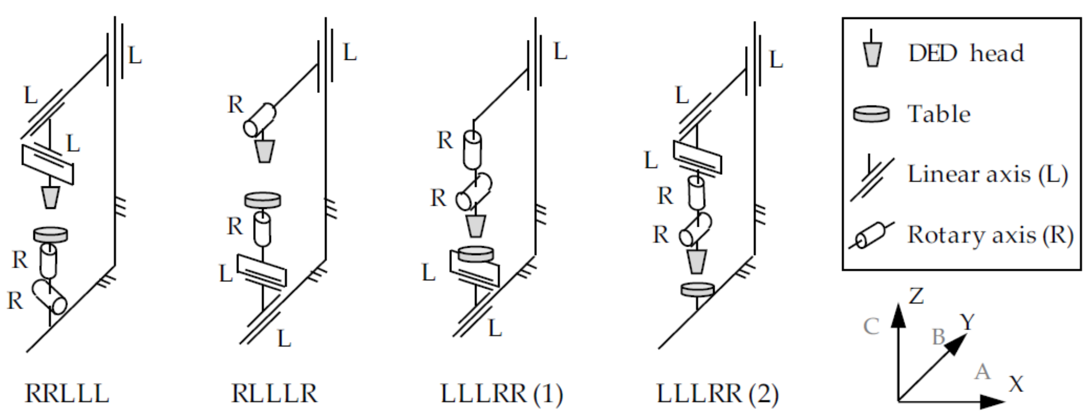


Figure 4-8 Most common kinematic schemes of DED machines (Cortina et al. 2018).

On the other hand, powder bed fusion is a subset of additive manufacturing whereby a build platform containing powder material is used. A heat source (laser or electron beam) is applied to particles contained within a powder bed to selectively melt or sinter these particles together at specific points and once a layer of the object is completed, the platform gradually indexes down and new powder is spread over the build area till the part is completed. Figure 4-9 shows a schematic diagram of the bed fusion process.

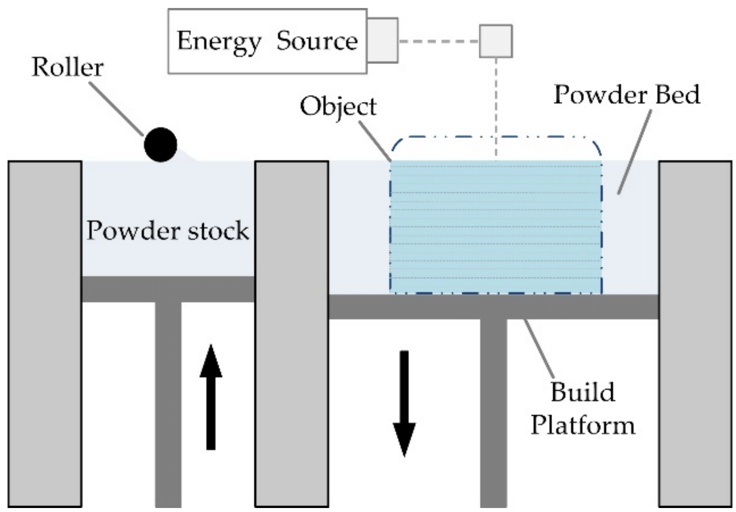


Figure 4-9 Schematic of Powder Bed Fusion process (Bai et al. 2019)

The PBF has an outstanding ability in building parts with complex geometries and overhanging features. The surface roughness ranges from 9 – 26 µm for SLM-built parts (Yap et al. 2015) and 25–35µm EBM-built parts (Suard et al. 2015, Vayre et al. 2012, Froes and Dutta 2014). It has only one building direction, which is the normal vector of a planar surface, on which materials will be deposited. Thus, the part building must start from a flat surface, which may result in some cases to machine the existing part to obtain such a surface. Only one material can be used in a single build, and the volume of the built part is limited to the machine build envelope.

Commercial machines that utilize the PBF techniques are available in the market. For instance, DMG Mori produces LASERTEC 12 SLM and LASERTEC 30 DUAL SLM. The LASERTEC SLM series are additive manufacturing machines that uses selective laser melting (SLM) which is one of the PBF techniques (DMG Mori 2020b). In addition, Sodick , a Japanese company, produces the OPM series, comprised by OPM250L and OPM350L which perform both SLM and high-speed milling (Sodick 2020). Figure 4-10 shows the OPM series.

Figure 4-10 Sodick OPM series (Sodick 2020)

It is worth to mention that DED is extremely well suited to add new material to the existing parts and component repair since a flat starting surface is not necessarily the case (Zenou and Grainger 2018). Thus, DED is suitable for more cases than PBF.

4.5.2. Knowledge of subtractive manufacturing processes and their capabilities

Subtractive manufacturing processes are the processes that involve removing particles of material in the form of the chips from a solid block of starting raw material or from an unfinished part by the cutting edges of a tool to create or modify shapes (Toenshoff 2014). It has been used for decades for the production of parts made from a wide variety of different materials. Turning and milling are the most common subtractive manufacturing processes that are used. Turning processes are used for machining/cutting rotational/cylindrical parts, while milling processes are used for the non-rotational and prismatic parts.

The main characteristics to be considered concerning the usage of subtractive manufacturing in removing a feature from the platform are depending on the machine capability such as machine axes and working envelope dimensions.

The machine axes refer to the degree of freedom or a collection of all allowable motions of a manufacturing instrument. The available machine axes can be 3 axes transitional in the Cartesian directions X, Y and Z and 3 rotational about the Cartesian directions A, B and C. Examples for 5-axis and 3-axis machines are shown in Figure 4-11. The working envelope dimensions represent the maximum allowable workpiece volume to be machined by the machine tool, as shown in Figure 4-11.

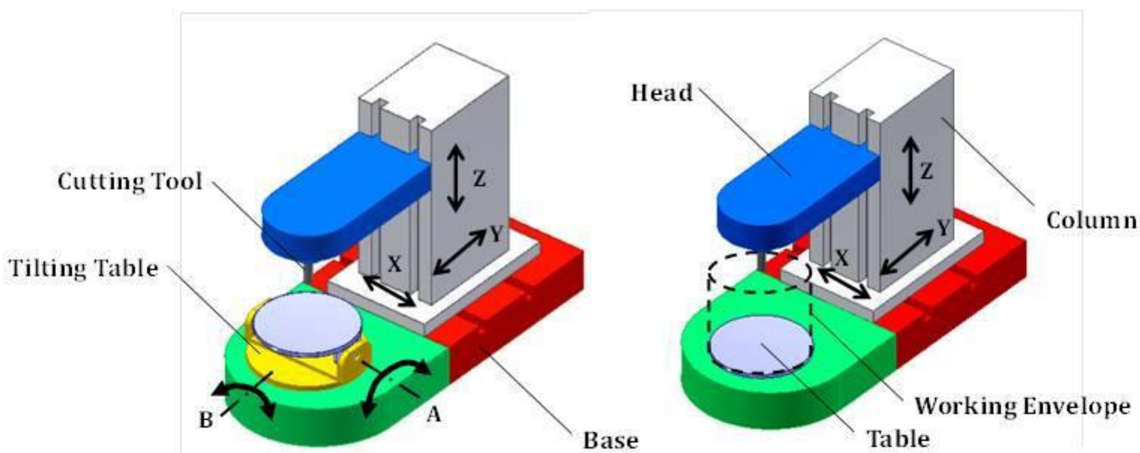


Figure 4-11 Machining capabilities for 5-axis CNC machine (left) and 3-axis CNC machine (right) (Abbas 2016)

Finally, the knowledge of the additive and subtractive manufacturing is used in determining the required process based on the feature geometry, surface finish and feature position within the workpiece. It is essential to mention that the main issue considered in selecting the process type is the ability of the tool (nozzles in DED processes, or powder distributors in PBF processes, or cutting tools in machining) to avoid with parts during the manufacturing processes.

4.6 Mathematical Model for Generating Single Platform and Macro Process Plans

A MILP model is developed based on the proposed methodology to generate the product platform and determine the types of processes required (either additive or subtractive) to transform the product platform into the different product variants. The model parameters include:

K the set of product variants in the product family, $k \in K$.

J the features set $j \in J$.

D_k the demand of the kth product variant (units).

Cp_j the cost of mass production of the j_{th} feature using a platform.

Ca_j the cost of adding the j_{th} feature/material to form a product variant ($Ca_j > Cp_j$)

Cr_j the cost of removing the j_{th} feature/material ($Cr_j > Cp_j$) from the platform to form a product variant

V the product matrix with

$$v_{jk} = \begin{cases} 1 \text{ if product k requires feature j} \\ 0 \text{ otherwise} \end{cases}$$

f_{jlk} elements in the features precedence

$$f_{jlk} = \begin{cases} 1 \text{ if feature j precedes feature l} \\ 0 \text{ otherwise} \end{cases}$$

The binary decision variables are:

x_j to indicate that feature j is included in the platform;

$$x_j = \begin{cases} 1 \text{ if the platform contains feature j} \\ 0 \text{ otherwise} \end{cases}$$

a_{jk} to denote that feature j is added to the platform to customize it to form product k;

$$a_{jk} = \begin{cases} 1 \text{ if feature j is added to the platform to form product k} \\ 0 \text{ otherwise} \end{cases}$$

r_{jk} to show that feature k is removed from the platform to customize to form product k.

$$r_{jk} = \begin{cases} 1 \text{ if featurej is removed from the platform to form product k} \\ 0 \text{ otherwise} \end{cases}$$

The optimal platform design and required hybrid manufacturing processes determination problem can be formulated as:

Minimize

$$\sum_{j \in J} \sum_{k \in K} Cp_j \, x_j \, D_k + \sum_{j \in J}^{J} \sum_{k \in K}^{K} Ca_j \, a_{jk} \, D_k + \sum_{j \in J}^{J} \sum_{k \in K}^{K} Cr_j \, r_{jk} \, D_k \tag{4.4}$$

Subject to

$$a_{jk} + x_j \leq 1 \quad \forall j, \forall k \tag{4.5}$$

$$a_{jk} + x_j \geq v_{jk} \quad \forall j, \forall k \tag{4.6}$$

$$v_{jk} \geq a_{jk} \quad \forall j, \forall k \tag{4.7}$$

$$x_j \geq r_{jk} \quad \forall j, \forall k \tag{4.8}$$

$$r_{jk} + x_j + v_{jk} \leq 2 \quad \forall j, \forall k \tag{4.9}$$

$$1 + x_j \geq f_{jlk} + x_l \quad \forall j, \forall k \tag{4.10}$$

$$a_{jk} + r_{jk} \leq 1 \quad \forall j, \forall k \tag{4.11}$$

$$x_j, a_{jk}, r_{jk} \in \{0,1\} \quad \forall j, \forall k \tag{4.12}$$

The objective function (4.4) minimizes the total cost of manufacturing the different product variants according to the demands. It has three main terms representing the cost of: mass-producing the platform features and platform customization either by adding features with additive manufacturing (e.g. DMD, FFF) or by removing features with subtractive manufacturing (e.g. CNC technology).

Constraints (4.5), (4.6) and (4.7) restrict feature j to be added to the platform to make product k only if it is not already part of the platform. Thus, feature j is required for product variant k. Constraints (4.8) and (4.9) state that a feature j may be removed from the platform if it is not required in product variant k, and it is already present in the platform. Constraint (4.10) checks the manufacturing (technological) feasibility so that if feature l is included in the platform and it precedes feature j in product variant k, then feature j must be included in the platform. Constraint (4.11) prevents the same feature from being added and removed from the platform to produce the same product variant. Constraint (4.12) ensures that those decision variables are binary.

4.7 Family of Guiding Bushes Case study

A case study for the guiding bushes family is presented for illustration. They are used in different applications such as automotive, power transmission, locomotive, manufacturing machinery and conveyors to align parts together. The considered guiding bushes family consists of five variants, and its relevant information has been retrieved from Rabourdin Industry (http://www.rabourdin.fr/) with minor changes in some variants for better illustration of the model application. Figure 4-12 shows the five variants of the guiding bushes family. Figure 4-13 presents the decomposed features and the features composition of each variant. Table 4-1represents the overall dimensions of the considered variants.

Figure 4-12 Guiding Bushes Product Family

Table 4-1 Overall dimensions of the guiding bush variants

Product Variant	Max. Outer Diameter (mm)	Min. Outer Diameter (mm)	Overall length (mm)	Inner Diameter (mm)
V1	55	40	60	25
V2	40	35	80	25
V3	40	35	110	25
V4	40	35	105	25
V5	40	35	105	25

Table 4-2 provides the features in each variant and their precedence relations. The corresponding costs for mass producing, adding (additive manufacturing) or removing (subtractive manufacturing) of each feature is provided in Table 4-4. The corresponding costs for using each manufacturing method/process (mass production, additive and subtractive) are assumed based on the cost study of (Manogharan et al. 2016) and the 3D hubs network online platform (https://www.3dhubs.com/). The 3D Hubs network is a global network that has over 240 partners offering CNC Machining, 3D printing, Injection Molding and Sheet Metal Fabrication in over 60 different materials. The 3D hubs network has an online platform that provides automated Design for Manufacturing (DfM), which helps in determining the manufacturability of each feature, instant pricing and allowing for efficient quote management.

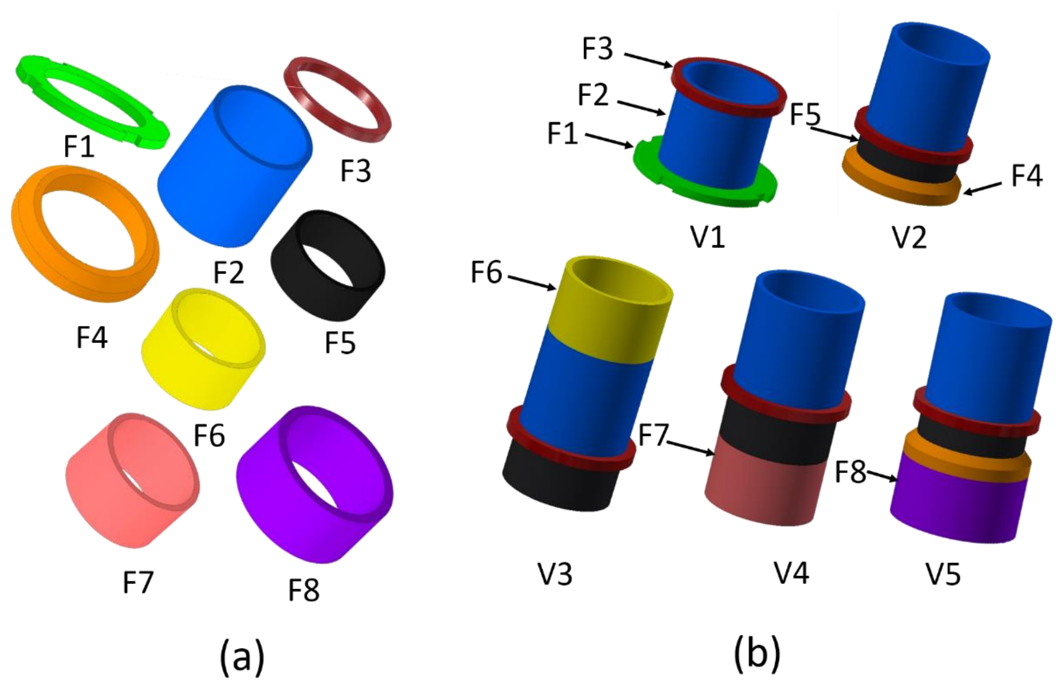


Figure 4-13 (a) Decomposed Features (b) the features composition of the guiding bush variants.

Table 4-2 Features Precedence, costs and features/ variants relationships

Feature	Precedence	Cp	Ca	Cr	V1	V2	V3	V4	V5
F1	F2	1	7	2	X				
F2		2	12	4	X	X	X	X	X
F3	F2	0.5	5	2	X	X	X	X	X
F4	F5	1	7	3		X			X
F5	F2	1.5	8	2		X	X	X	X
F6	F2	2	10	3			X		
F7	F5	2	10	3				X	X
F8	F5, F7	1.5	12	2					X

4.8 Results and discussion

The five variants are decomposed into features, and the precedence relationships between features are determined. The mathematical model generated the product platform and determined the features to be added and/or removed and minimized the total manufacturing cost for the specified product variants' demands while observing the stated constraints. It is written in AMPL – A Mathematical Programming Language (http://ampl.com/). The optimal result (minimum cost) is obtained in about 1 second, on a PC of Intel Core i7 3.40 GHz processor and 16 GB RAM, using Gurobi Optimizer 8.1 solver (http://www.gurobi.com/). Various cases of demand scenarios are examined to illustrate the effect of the demand on the product platform and its features. The demand scenarios, optimum platform and the minimum cost for each scenario are presented in Table 4-3.

For scenario 1, when the demand for each product variant is the same, the PPFs are F2, F3, F5 and F7. For scenarios 2,3,4,5 and 6, when the demand for a specific product variant is significantly higher than other product variants, the product platform contains more features of that product variant. The model is capable of determining the type of the required processes (additive or subtractive or both) to form each product variant. Figure 4-14 illustrates graphically how the five variants are produced based on demand in scenario 1 where 250 units of each variant is required.

Table 4-3 Demand scenarios and the results

Scenario	Demand					Product Platform (PPF)	Cost ($)
	V1	V2	V3	V4	V5		
1	250	250	250	250	250	F2,F3,F5,F7	21000
2	750	250	250	250	250	F1,F2,F3,F5	26250
3	250	750	250	250	250	F2,F3,F4,F5	23750
4	250	250	750	250	250	F2,F3,F5,F6	27250
5	250	250	250	750	250	F2,F3,F5,F7	24000
6	250	250	250	250	750	F2,F3,F4,F5,F7, F8	26125
7	100	500	500	100	50	F2,F3,F4,F5,F6	16100

The model is capable of determining the type of the required processes, either additive, subtractive or both, to form each product variant. The sequence of the processes are determined based on the output of the mathematical model and the features precedence. The feature precedence is determined from the procedure explained in section 4.5. Considering the results of scenario 1, the following processes are needed for each variant:

- V1 will be produced from the platform. F7 and F5 features are required to be removed from the platform using CNC technology. Afterwards, F1 is added through additive manufacturing. Additive layers will be directly deposited on the outer surface of F2 feature until the F1 feature is obtained.
- V2 will be produced from the platform by cutting F7 feature through subtractive manufacturing (CNC technology). F4 feature is added by DMD technology to the outer surface of F5 feature.
- V3 will be produced from the platform by using CNC technology to cut F7 feature then using DMD technology to add F6 feature on the head of feature F2.
- V4 will not need any further processing as the platform is similar to this variant.
- V5 will be produced by using DMD technology to add F4 feature to the outer surface of F5 feature, then add F8 feature to the outer surface of F7 feature.

It is worth mentioning that, in some cases, some of these processes may be combined together in one process on one machine during the micro process planning.

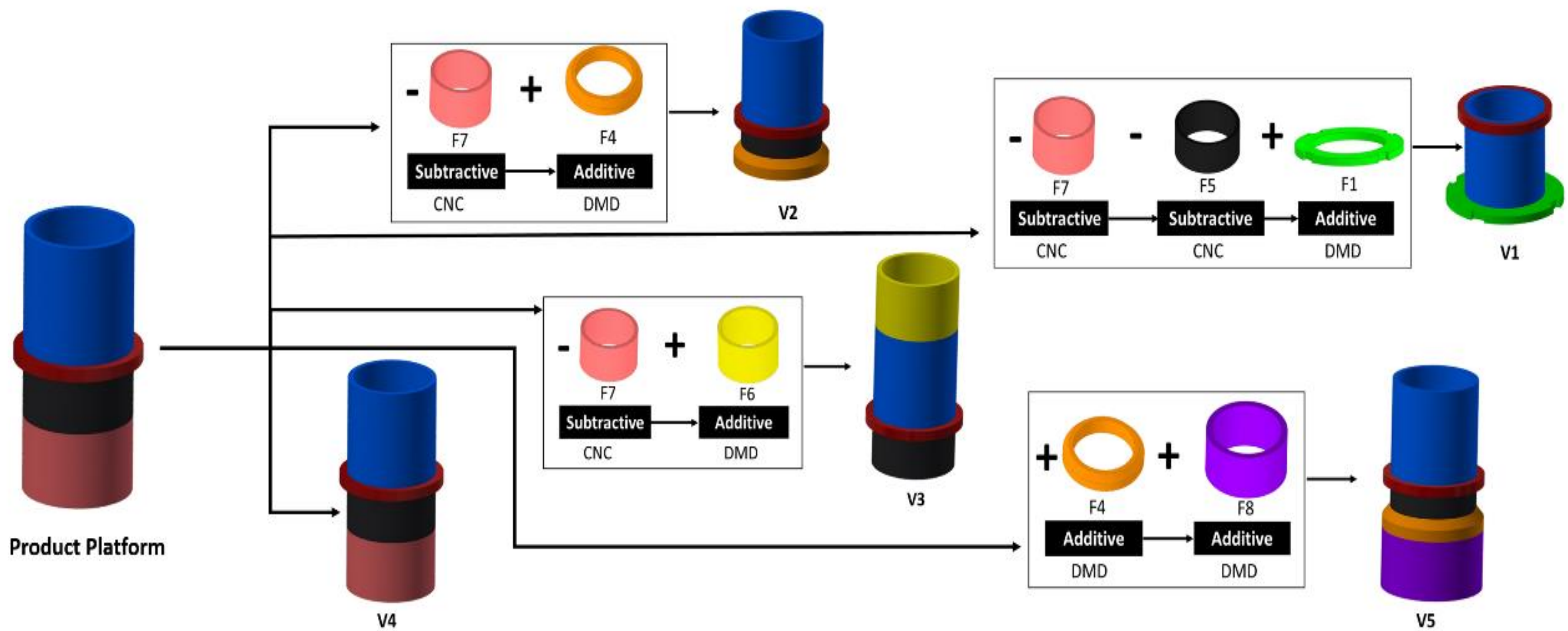


Figure 4-14 Manufacturing the five variants from scenario 1 Product Platform

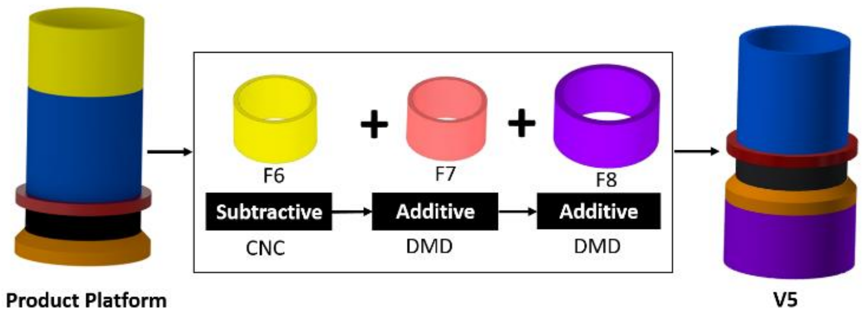


Figure 4-15 Manufacturing of Variant 5 from Scenario 7 Product Platform

The total demand for all variants in both scenario 1 and 7 is the same (1250 units); however, the product variant mix is different which leads to a difference in the features that form the product platform and the required processes to produce each variant from a different platform in both scenarios. Figure 4-15 shows the product platform and required processes for manufacturing variant 5, as an example, from scenario 7 platform. Both figures 4 and 5 illustrate the difference in the platform and the required process based on the change in the product variant mix.

4.9 Summary and Conclusions

This chapter introduces a novel concept in the field of product variety management by designing product family platforms for customization into different product variants utilizing additive and subtractive processes. Such a concept supports product design changes, and variants demand fluctuations. Hybrid manufacturing macro process planning for product family was presented. A feature extraction procedure was developed to extract the additive and subtractive features that form the different product variants within a considered family. The procedure is based on the additive and subtractive manufacturing process capabilities. A mixed-integer linear programming model was formulated for designing the optimal product platform and determining the type and sequence of additive and/or subtractive processes to transform the product platform into different product family variants and minimizing the total manufacturing cost. The proposed methodology can be enhanced by adding automated pre-processing modules to extract the product variants' features and establish the precedence relationships, which would be helpful particularly for large product families and more complex shapes of features. Inventory costs for storing the platforms until customization into product variants may also be investigated as future work.

CHAPTER 5. MULTI-PLATFORM GENERATION AND PRODUCT FAMILY PROCESS PLAN FOR HYBRID MANUFACTURING USING MEDIAN-JOINING PHYLOGENETIC NETWORK

5.1 Overview

After obtaining a single platform and process plan for the product family in chapter 4, this chapter aims to generate multi-platforms and their associated process plans. The advantage of using multi-platforms over a single platform is the ability to optimally match variants to a particular platform. The Median Joining Phylogenetic Network Algorithm, typically used in biology, is utilized to generate the multi-platforms and their process plans.

5.2 Introduction

Benefiting from the combination of additive and subtractive manufacturing, a product variety management methodology based on the delayed product differentiation strategy is proposed. One or more platforms are mass-produced and stored until customers' orders are placed. These platforms represent the most common features between different product variants. Based on the customers' orders, additive and/or subtractive manufacturing may be used for further processing the platforms into different product variants. Thus, some features may be added to the platform by additive manufacturing and other features may be removed from the platform by subtractive manufacturing. This work focuses on the metal-based additive manufacturing; however, the same methodology can be applied to plastic-based additive manufacturing.

The proposed methodology is achieved through three main steps phases. Figure 5-1 shows the proposed variety management methodology and its three steps. In the first step, the product family features and their precedence relationships are extracted from the available information and CAD models of the product variants. This step is detailed in section 4.5 and is performed taking into account the available additive and subtractive manufacturing capabilities. The second step is concerned by the multiple product platforms design based on the extracted features and their precedence. The last step focuses on assigning product variants to product platforms and determining the additive and/or the subtractive manufacturing processes to realize each product variant starting with its assigned product platform(s). Each step answers one of the following major questions:

- How the product family features and their precedence relationships are extracted?
- How many platforms should be formed? What are the features that the platform is made from?
- What are the macro process plans to further manufacture the platform into different product variants?

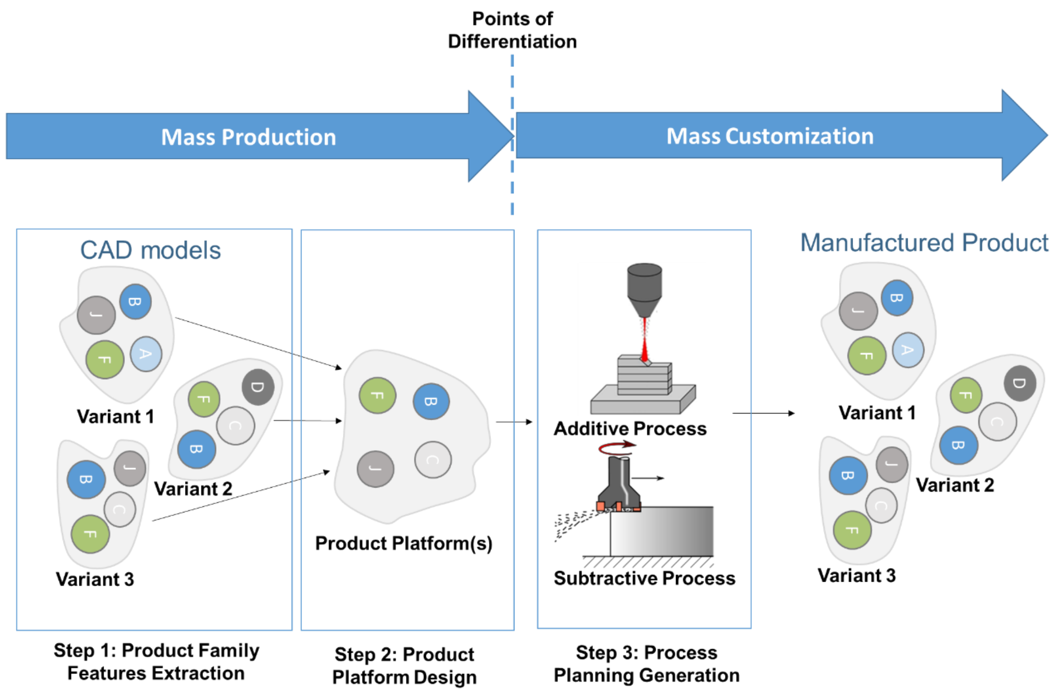


Figure 5-1 Delayed Product Differentiation utilizing Additive and Subtractive Manufacturing

An IDEF-0, shown in Figure 5-2, is used to represent the inputs, outputs, constraints and mechanisms for each step of the proposed methodology. The input of the IDEF0 is the CAD model of features of each variant. These features are extracted from the variants based on the manufacturing capabilities. Thus, the manufacturing capabilities represent the controls. The mechanisms are the feature extraction procedure and the median-joining phylogenetic network algorithm. The output is the number of the platforms, the features that form each platform and the required processes for platform customization into different product variants within the considered product family. Afterwards, the sequence of the processes is determined manually taking into consideration the features precedence and the model output. For instance, if feature A is built on feature B, then feature B must be built first. The following section discusses the second and third steps of the methodology in detail.

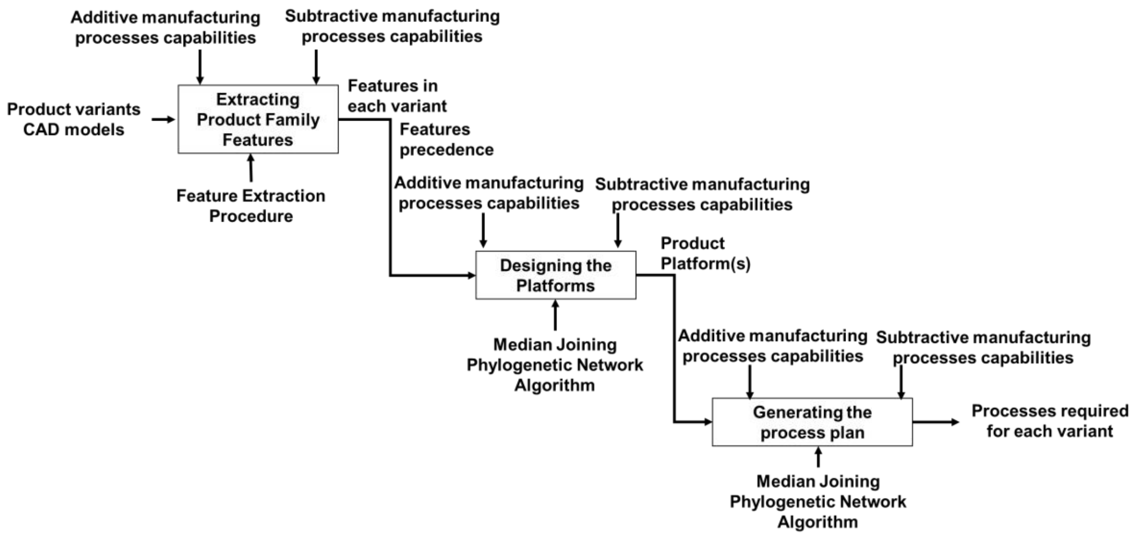


Figure 5-2 IDEF0 of the proposed product variety management methodology

5.3 Multi-Platform Design and Macro Process Planning of Hybrid Manufacturing Using Median Joining Phylogenetic Network

Networks have gained much attention in the phylogenetic and biological studies. The phylogenetic networks can be categorized based on the objective into explicit and abstract networks. The explicit network narrates the evolutionary history, i.e. ancestor-descendant relationships, while the explicit network visualizes the incompatible data sets. Moreover, these networks can be classified depending on the shape into rooted and unrooted networks. The rooted network is a Direct Acyclic Graph (DAG) that can be either abstract or explicit based on their construction algorithm and interpretation. The unrooted network is an undirected graph that represents an abstract network.

Median-joining phylogenetic networks (MJPNs) are among the most widely used unrooted network due to their simple computation and visual attractiveness. They are distance-based un-rooted branching networks that infer phylogenetic relationships.

The network consists of two types of nodes. The first type represents the different DNA sequences that the relationship between them is required to be determined. The other type represents the median vector, which represents the common characteristics between different sequences connected to this node. Each sequence is connected to at least one median vector by a link. From a biological analogy point of view, the median vector can be considered as an ancestral sequence, i.e. intermediates. The differentiating characteristics between the sequences and the median vectors appear on each link. Figure 5-3 shows an example of the MJPN network.

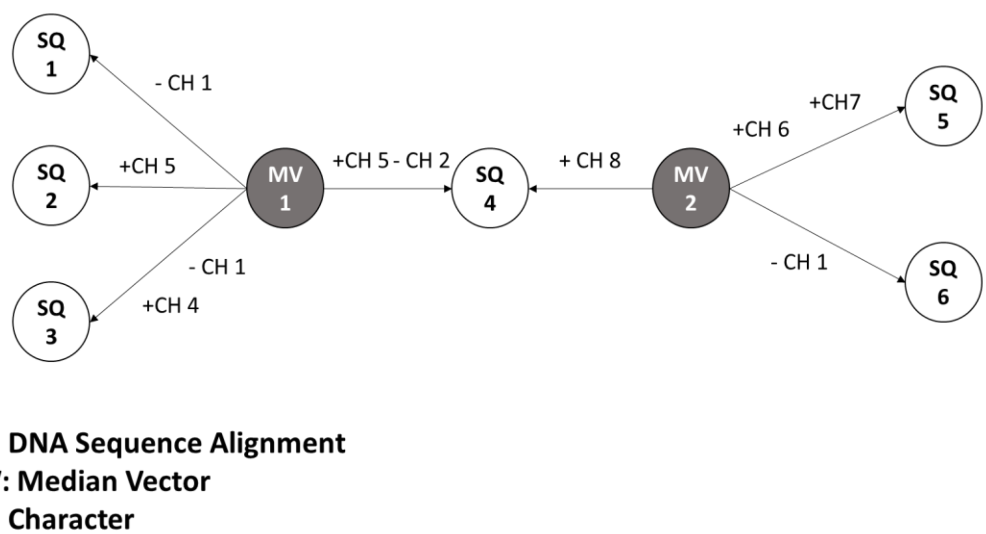


Figure 5-3 Example of Median-Joining Phylogenetic Network

This sub-section illustrates how the MJPN network can be interpreted to determine the features that form platforms based on the commonality of the product variants and the required processes to customize the platform into different variants. The DNA sequence alignment represents a product variant within the considered family. Thus, the different product variants are represented in the form of string made of cells (characters). Each cell (character) represents a specific feature of the product family. Hence, the number of cells is equal to the total number of the product family features. The cell can take either value of 1 in case of the feature corresponding to this cell exists or value of zero in case the feature does not exist. The median vectors represent the product platforms with the common features among product variants. The differentiating characteristics on the links can represent the differentiating features between the product variant and the product platform. Thus, the features to be added to the product platform and the feature to be removed from the product platform to produce different product variants are determined. Accordingly, the type of the required processes, either additive or subtractive, that are needed to customize the platform to different product variants can be easily figured out. If the feature is not in the product platform and in the product variant, then an additive manufacturing process is needed, and if it is included in the product platform and not a part of the product variant, then a subtractive manufacturing process is needed. Figure 5-4 shows a MJPN network that is interpreted as discussed before.

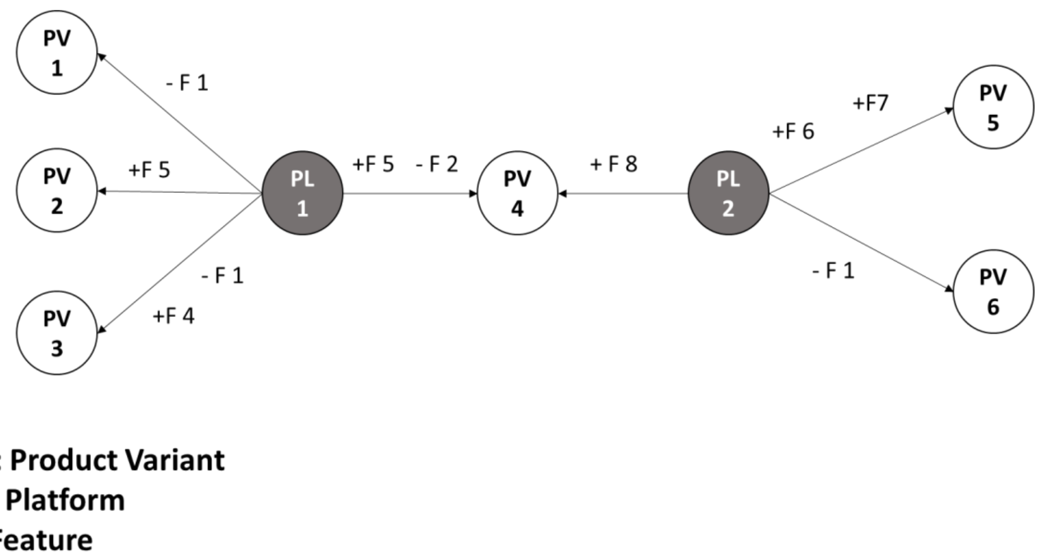


Figure 5-4 Example of Median-Joining Network for a Product Family

The MJPN network is generated by a median-joining (MJ) algorithm. The MJ was introduced for the first time in 1999. It is developed based on the integration of the Minimum Spanning Network (MSN) and Quasi-Median Network algorithms to create the network.

The input of the algorithm is the multiple product variants strings. The number of differences between product variants' strings is measured by the 'Hamming distance' technique. The Hamming distance is a method used to quantify the extent to which two strings of the same dimension differ (Bookstein et al. 2002). Based on the Hamming distance, links between sequence pairs are created. The median vector that represents a product platform is generated between every three strings with at least two links. The median vector represents the commonality between every three sequences. Then, these median vectors are added to the pool of strings. This process is repeated until no further median vectors (product platforms) can be generated. The output is the MJPN network with links in minimal length connections. The algorithm is detailed in (Bandelt et al. 1999).

The Network program is a software used by the biologists to construct phylogenetic networks, infer ancestral types, and potential types and evolutionary branchings. Two different methods are implemented in this program to generate the network, including the MJ algorithm proposed by Bandelt et al. (1999).

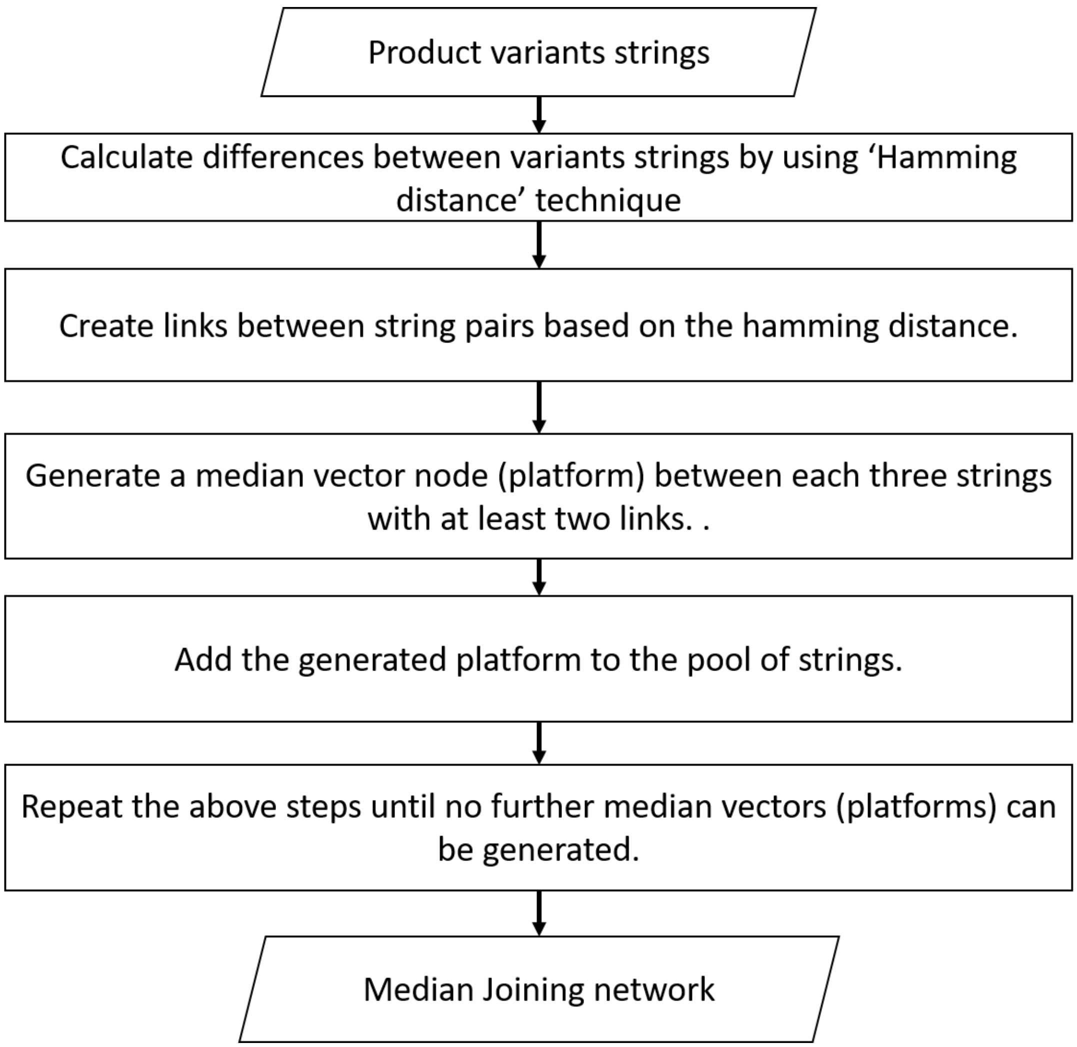


Figure 5-5 Median Joining Algorithm proposed by Bandelt et al. (Bandelt et al. 1999)

5.4 Family of Guiding Bushes Case Study

A family of guiding bushes, presented in Chapter 4, is used as a case study. The guiding bushes are used in different applications such as automotive, power transmission, locomotive, manufacturing machinery and conveyors to align parts together. The network software is used to generate the MJPN for the guiding bushes family. Each product variant is represented as a string of 8 cells. Each cell represents one of the features. The five product variant strings are shown in Table 5-1. These strings are the input for the Network program.

Table 5-1 Strings of the Guiding Bushes Variants

	Features							
Variants	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

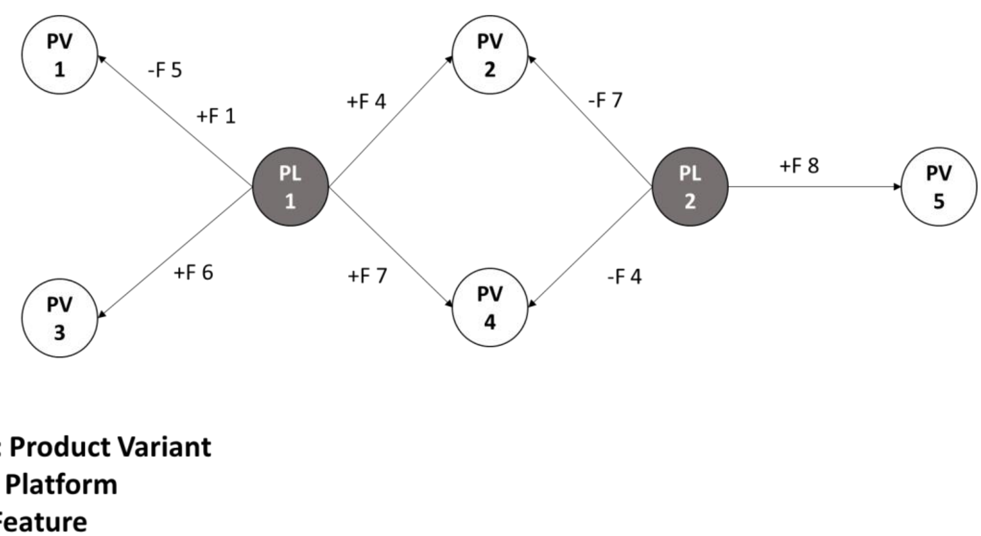


Figure 5-6 Median Joining Phylogenetic Network for the Guiding bushes family

The output is a network that generates two product platforms (median vectors) and maps the relationship between the five product variants and the two generated product platforms, as shown in Figure 5-6. The first platform is formed from features F2, F3 and F5 while the other platform is formed from features F2, F3, F4, F5 and F7. Platform 1 can be customized into variants V1, V2, V3 and V4, while platform 2 can be customized into variants V2, V4 and V5.

For product platform 1, feature F1 would be added using additive manufacturing and feature F5 would be machined (cut) by subtractive manufacturing to produce product variant V1. Only feature F3 would be added to product platform 1 to obtain variant V3. For product platform 2, product variant V5 is obtained by adding feature F8 to the platform. Product variant V2 can be produced either by adding feature F4 to product platform 1 or by machining (removing) feature F7 from product platform 2. Similarly, product variant V4 can be produced using either product platform 1 by adding feature F7 or product platform 2 by machining (removing) feature F4.

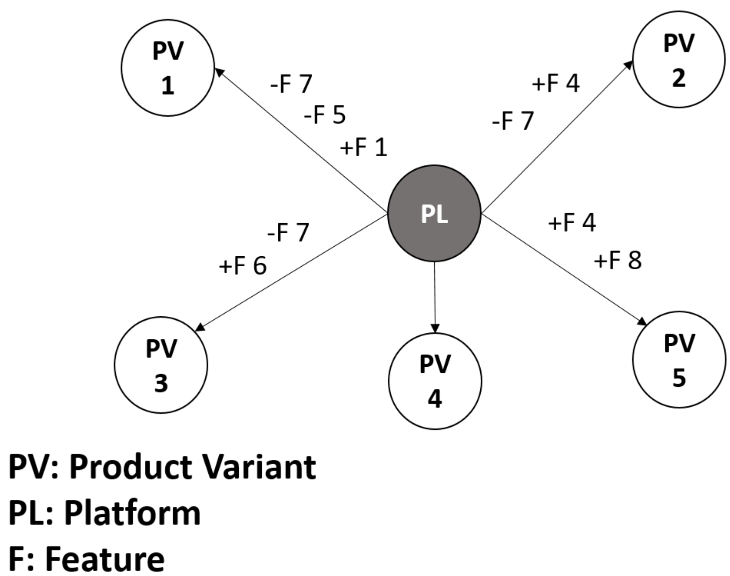


Figure 5-7 Network obtained using the mathematical model in chapter 4

It is informative to compare the results obtained using the mathematical model in Chapter 4 and the proposed MJPN method for the same case study. The mathematical model formed only one common product platform for the five product variants with an equal demand of 100 parts for each product variant as shown in Figure 5-7, while the MJPN method formed two product platforms. To assess the quality of both methods, a metric is contrived to compare the effectiveness of the methods to respond to customer demands. Responsiveness is the ability of the system to quickly and efficiently respond to the fluctuation in demand (Gindy et al. 1999). Thus, responsiveness can be measured by determining the average number of manufacturing processes needed to customize the platform since the platform is stored until customer orders are placed. The responsiveness metric can be expressed as the summation of all the processes needed in customizing the product platform(s) divided by the number of the product variants in the considered family as in equation 5.1:

$$Responsiveness\ metric = \frac{\sum_{i=1}^{n} Q_i X_i}{\sum_{i=1}^{n} Q_i} \tag{5.1}$$

Where,

n	Total number of product variants
i	index of product variants
Q_i	Quantity needed of product variant i
X_i	minimum number of features to be added to and/or removed from the product platforms to produce the product variant i

The above equation is the general form for the responsiveness metric. The MJPN method is used in cases when the manufacturer is uncertain about the demand or when equal variants' demand is required. Therefore, the quantity needed of the product variant (Q) can be removed from the equation for this case, and equation is modified to

$$Responsiveness\ metric = \frac{\sum_{i=1}^{n} X_i}{n} \tag{5.2}$$

The responsiveness metric is a relative measure. The smaller the value of the metric means better responsiveness to the customer demand. By applying equation 5.2 on both results:

For the MJPN result:

$$Responsiveness\ metric = \frac{2\ +1+1+1+1}{5} = \frac{6}{5} = 1.2$$

For the mathematical model result:

$$Responsiveness\ metric = \frac{3\ +2+2+0+2}{5} = \frac{9}{5} = 1.8$$

The responsiveness metric value for the MJPN result is less than the value for the mathematical model result. Thus, the MJPN model result is superior over the result of the mathematical model in terms of responsiveness.

Another point that shows the superiority of the results of the MJPN is the product mix flexibility. Since variants V2 and V4 can be produced from both platforms, this increases the flexibility in producing these variants as selecting which platform to use can depend on the current production status and inventory level on the shop floor. For example, if there is an increase in the demand for variant V2, both platforms can be utilized in varying proportions in order to produce the demand.

5.5 Family of Flanges Case Study

Another case study for a family of flanges is considered. Flanges are used in connecting pipes, valves, pumps and other equipment to form a piping system, and they facilitate the cleaning, inspection or modification of the system. Flanges are commonly used in the petro and chemical industry. A real case company, Maass Flange Corporation (www.maassflange.com/), that specializes in producing flanges with different types and sizes, is considered. The company's mission is to supply its worldwide customers with the highest quality product along with fast delivery, all at a competitive price. Thus, the company follows the make-to-stock (MTS) strategy in which it stores a combination of products to suit the needs of their customers. The result of the implementation MTS strategy has led to a high level of inventory, which forms a large portion of the company costs. Since customers order medium volume batches of the flanges, applying the delayed product differentiation strategy will result in increasing operational efficiency and reducing production and storage costs.

The flange types considered in the case study are: Slip On Flange, Lap Joint Flange and Blind Flange. Many users prefer the slip-On flange because of the reduced accuracy required in cutting the pipe to length, and the ease of the assembly alignment. They have raised face on one side and hub on the other side. Lap Joint Flanges are used in systems that require frequent inspection and cleaning. Moreover, they have all the same common dimensions as any other flange, but it does not have a raised face. Blind Flanges are used to blank off the ends of piping, valves and pressure vessel openings. They have raised face on one side and no hub, and manufactured without a bore. Figure 5-8 shows the three considered types of flanges. The slip-on flange and the blind have the same raised face while the slip-on and lap joint flanges both have hubs.

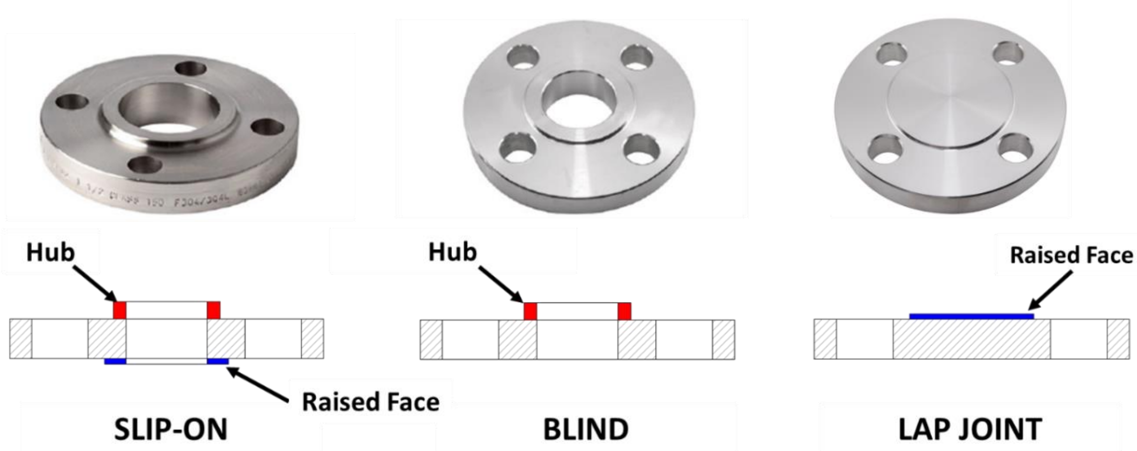
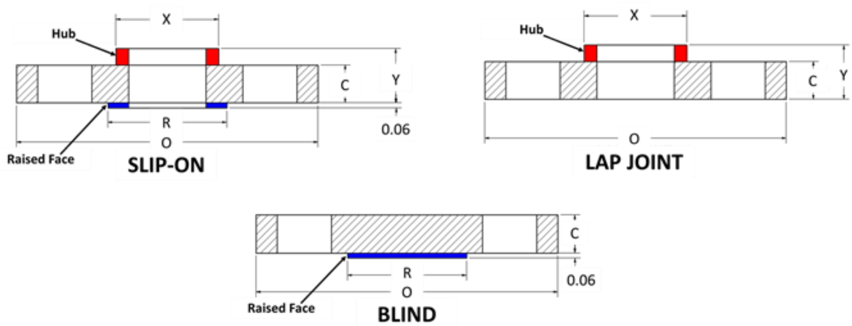


Figure 5-8 Three types of flanges: Slip-On, Blind and Lap Joint



Pressure Class	Nominal Size(NPS)*	Out-side Dia.* O	Thk.* C	Raised Face Dia.* R	Hub Dia.* X	Length Through Hub* Y	Bolt Circle*	Dia. Holes*	No. Holes
150	1/2	3.50	0.44	1.38	1.19	0.63	2.38	0.63	4
	3/4	3.88	0.50	1.69	1.50	0.63	2.75	0.63	4
	1	4.25	0.56	2.00	1.94	0.69	3.13	0.63	4
	11/4	4.63	0.63	2.50	2.31	0.81	3.50	0.63	4
300	1/2	3.75	0.56	1.38	1.50	0.88	2.63	0.63	4
	3/4	4.63	0.63	1.69	1.88	1.00	3.25	0.75	4
	1	4.88	0.69	2.00	2.13	1.06	3.50	0.75	4
	11/4	5.25	0.75	2.50	2.50	1.06	3.88	0.75	4

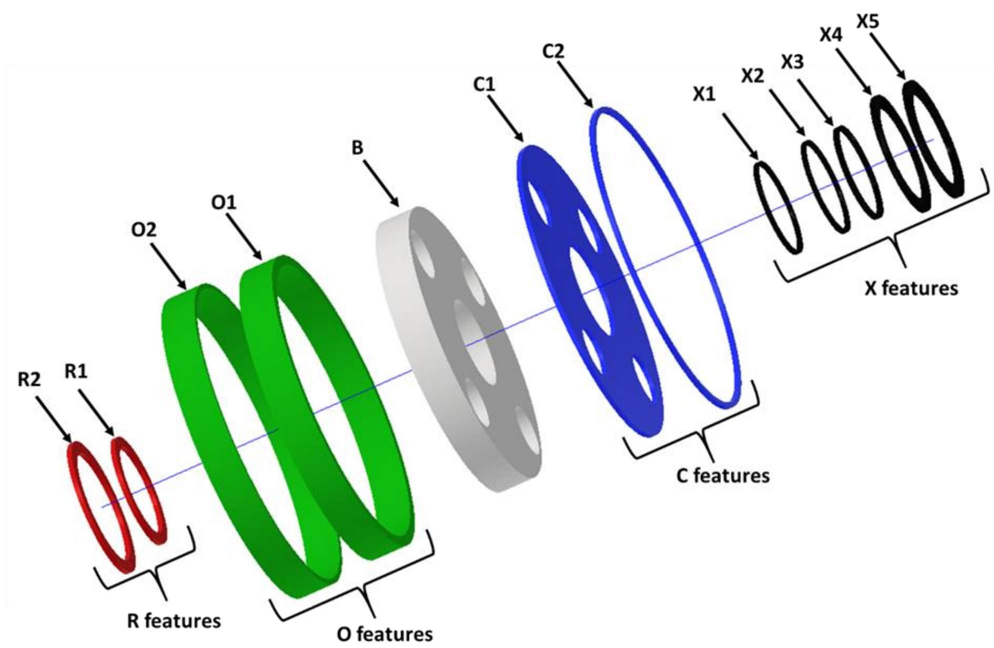
*** Dimensions are in inch.**

Figure 5-9 main dimensions for all the product variants of the flanges family

Each flange type has a number of standard dimensions that vary with the nominal pipe size (NPS) and pressure classes. The flanges with higher pressure class are constructed with more metal (larger volume/dimensions) and can withstand more pressure. The pressure classes considered in the case study are 150 and 300, and the NPSs 0.5, 0.75, 1 and 1.25 inches.

Considering three types, two pressure classes and four NPSs leads to 24 variants. The main dimensions for all the product variants are represented in Figure 5-9.

By applying the feature extraction procedure, 43 features are extracted. These features represent variation in the flanges that includes the changes in the thickness of the flange (C1-C7 features), outer diameter (O1-O6 features), with or without raised face (R1-R4 features) and/or hub (X1-X25 features) and the basic feature (B feature) which is a cylinder with diameter 3.5'' and thickness 0.44'' and appears in all variant. Based on the feature modification step, all the drilling process for the inner diameter (bores) and the holes pattern are processed at the last manufacturing stage (i.e. after the product platform customization). Figure 5-10 shows an example of one of the flanges (Slip-on Flange for 150 class and NPS 0.75) decomposed into its features.



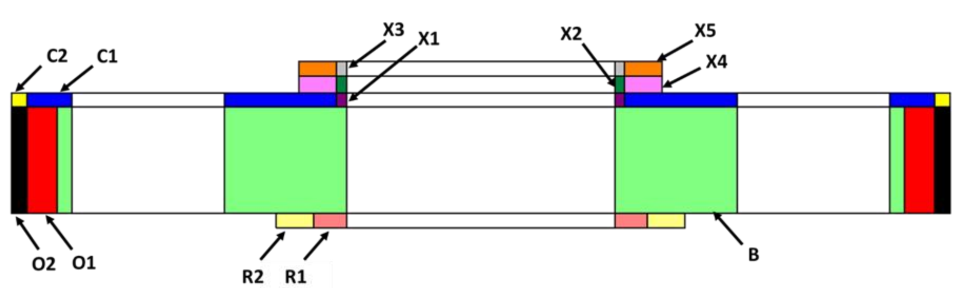


Figure 5-10 Slip on Flange for 150 class and NPS 0.75 decomposed into features

Table 5-2 Strings for the Flanges Product Family

Type	Pressure Class	NPS	B	R1	R2	R3	R4	O1	O2	O3	O4	O5	O6	C1	C2	C3	C4	C5	C6	C7	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21	X22	X23	X24	X25
Slip On	150	1/2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		3/4	1	1	1	0	0	1	1	0	0	0	0	1	1	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		1	1	1	1	1	0	1	1	1	0	0	0	1	1	1	1	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
		11/4	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	0	1	1	0	0	0	0	1	1	1
	300	1/2	1	1	0	0	0	1	0	0	0	0	0	1	0	1	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		3/4	1	1	1	0	0	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0
		1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1
		11/4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Lap Joint	150	1/2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		3/4	1	0	0	0	0	1	1	0	0	0	0	1	1	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		1	1	0	0	0	0	1	1	1	0	0	0	1	1	1	1	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
		11/4	1	0	0	0	0	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	0	1	1	0	0	0	0	1	1	1
	300	1/2	1	0	0	0	0	1	0	0	0	0	0	1	0	1	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		3/4	1	0	0	0	0	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0
		1	1	0	0	0	0	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1
		11/4	1	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Blind	150	1/2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		3/4	1	1	1	0	0	1	1	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		1	1	1	1	1	0	1	1	1	0	0	0	1	1	1	1	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		11/4	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	300	1/2	1	1	0	0	0	1	0	0	0	0	0	1	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		3/4	1	1	1	0	0	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1
		11/4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	0	0	0	1	0	0	0	0	0	1	0	1

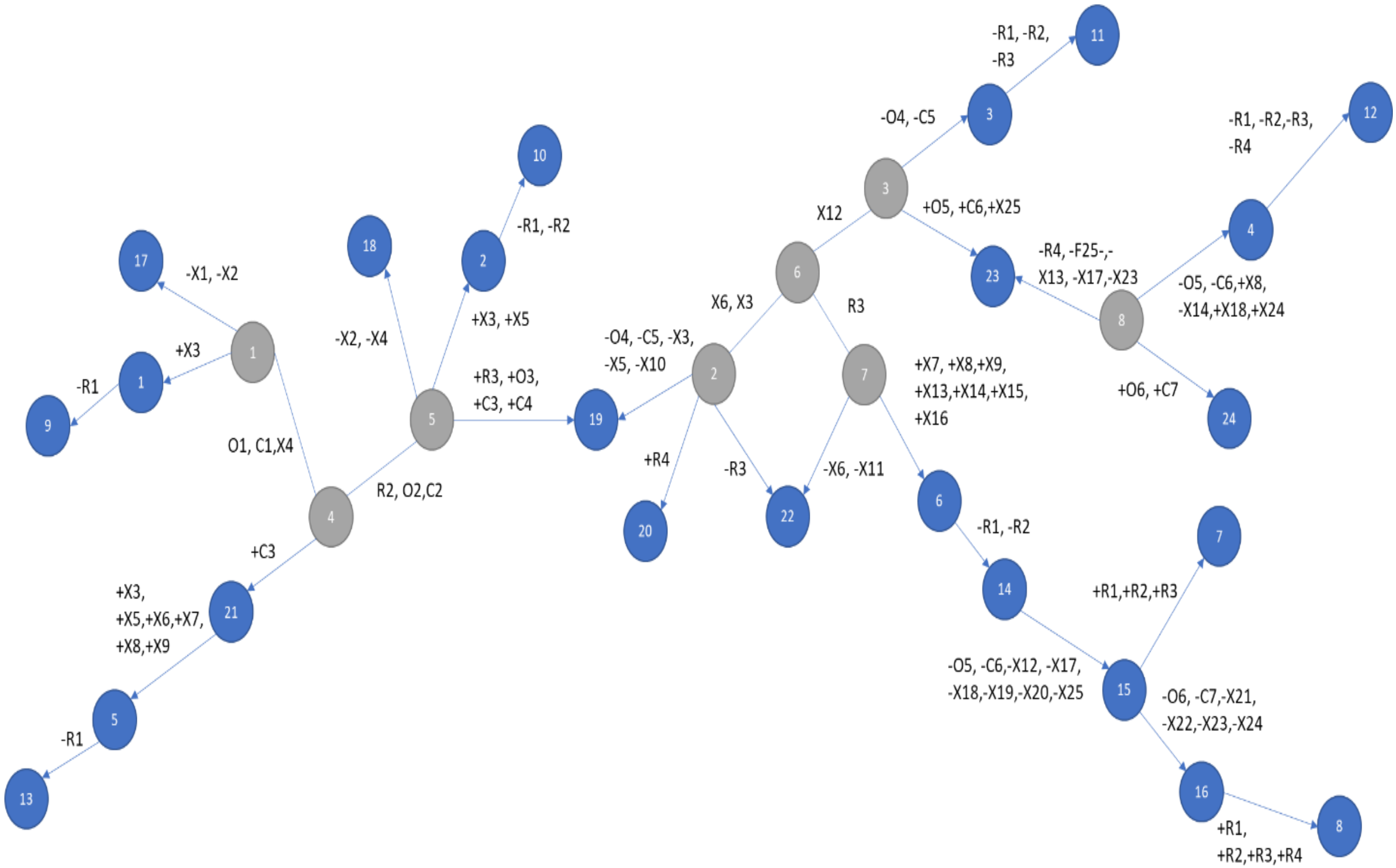


Figure 5-11 MJPN network for Flanges Product Family

The variants are written in strings of zeros and ones based on the features' existence in each variant and shown in Table 5-2. Then, these strings are inputted into the network program. The output is the MJPN network formed of eight (8) product platforms, and the relation between the variants and platforms, as shown in Figure 5-11. These eight product platforms can be customized into the 24 variants for the considered family by utilizing additive and subtractive manufacturing processes.

Compared to the current production strategy (MTS), in which the company stocks the 24 variants of flanges, following the strategy proposed in this chapter, 8 flange platforms are manufactured and stored till the customers place their orders. This will lead to a reduction of 66% of the stored item and, consequently, significant savings in storage and handling costs.

5.6 Summary and Conclusions

Product proliferation, as a result of the changes in customer needs, technology, regional and environmental regulations, is one of the main challenges that the manufacturers are facing in recent decades. A new delayed product differentiation strategy benefiting from the integration of two manufacturing technologies (additive manufacturing and subtractive manufacturing) is proposed. The concept of multi-platform and their process plans to produce a family of product by combining additive, and subtractive manufacturing is addressed for the first time. In many cases, using more than a single platform to produce the part/product family is cheaper. A method of generating a Median-joining Phylogenetic network, used in biology and phylogenetic contexts, is used to design the multiple product platforms and generate the process plans required to customize these platforms into different product variants based on the customer demands. This method was capable of determining the features that form the platform, assignment of the product variants to each platform and the required manufacturing processes either to add features to the platform through additive manufacturing or remove features from the platform through subtractive manufacturing to produce different variants.

Two case studies are considered. The first case study highlights the superiority of the network generated from the proposed MJPN model over the network generated from a model from literature in terms of flexibility and responsiveness. The second case study shows the ability of the MJPN model to handle a large number of product variants and their associated features. Moreover, it illustrates the benefit of the proposed delayed product differentiation strategy in decreasing the holding and inventory costs. The proposed method is well suited to the cases when the manufacturer is uncertain about demand or the manufacturing costs for the product variants or when an equal demand for the product variants is required as it generates product platforms formed from the majority consensus of features. It is worth mentioning that the manufacturing costs and demand are not considered while determining the platforms in this chapter.

CHAPTER 6. MULTI-PLATFORM GENERATION AND PRODUCT FAMILY PROCESS PLAN FOR HYBRID MANUFACTURING CONSIDERING DEMAND AND COSTS

6.1 Overview

The drawback of the method explained in the previous chapter is that it only considers the commonality between the product variants. Other aspects should be considered, such as manufacturing costs and the demand that will definitely affect the decision on which features should be included in the platform, number of the platforms and the macro process planning of the product family. Therefore, the problem with the consideration of theses aspects is addressed in this chapter.

6.2 Introduction

The purpose of this chapter is to develop a model in order to manufacture a product family using multiple product platforms cost-effectively. Thus, this model aims at determining the optimal number of the product platforms and their configurations (i.e. the features that form each platform), the assignment of each product variant to a particular product platform, while minimizing the overall family manufacturing costs.

Since the quantity of the platform is large, the manufacturer could invest in the product platform setup cost, such as preparing dedicated fixtures and jigs, automated production methods, etc. This setup cost inhibits/ holds back the manufacturer from having a separate product platform for each product variant.

The model is capable of designing product platforms that are responsive to the changing market demand. In other words, the product platform features changes based on the customer demands.

6.3 Problem Description

Consider a given set of product variants of a product family with different features. It is required to find the optimal set of features that form product platforms and determine the manufacturing processes needed to customize the platforms into the different variants. The platforms configurations are determined based on the commonality of the features among the different product variants, each variant demand, feature precedence constraints, the manufacturing costs associated with different manufacturing processes (mass production, additive and subtractive) and the platform setup costs.

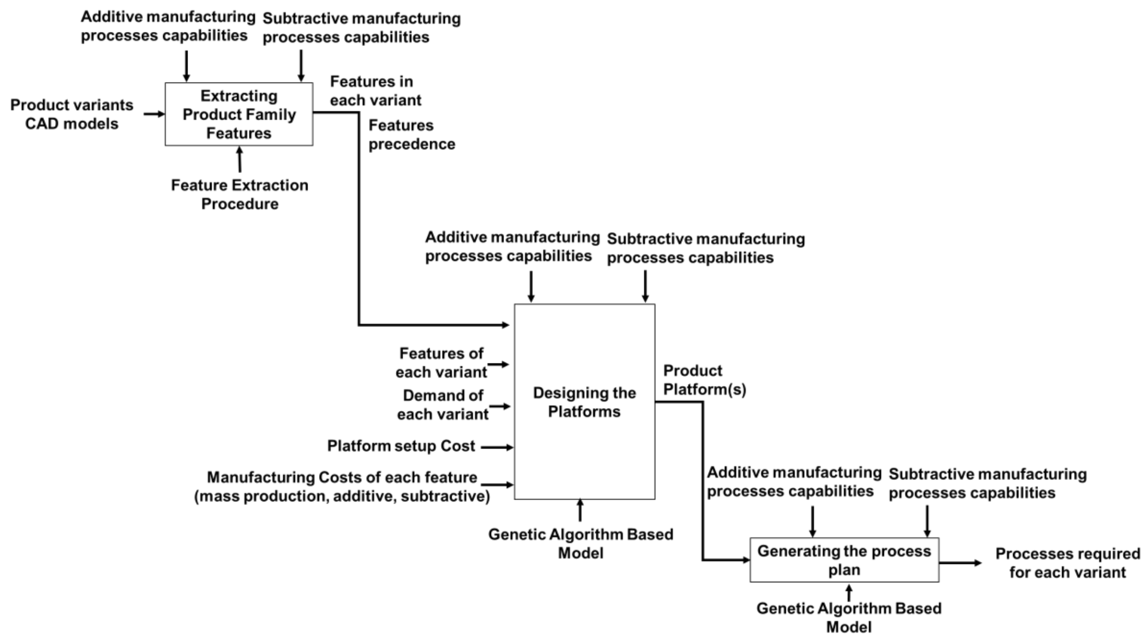


Figure 6-1 IDEF0 for Multi-Platform Generation and Product Family Process Plan for Hybrid Manufacturing using Genetic Algorithm

Figure 6-1 illustrates the proposed methodology in the form of an IDEF0 diagram showing the main activities along with inputs, outputs, controls and mechanisms. The main outputs are the number of the platforms, set of features that form the platforms and the required processes for customizing the platform into different variants while minimizing the total manufacturing cost for the product family. The distinctive characteristic of this model is the inclusion of variants' demand, feature precedence constraints, the manufacturing costs associated with different manufacturing processes (mass production, additive and subtractive) and the platform setup costs. The feature extraction was detailed in chapter 4.

6.4 Genetic Algorithm-based Model for Generating Multi-Platform and Macro Process Plans

A genetic algorithm-based model is used to handle the addressed problem. The following subsections illustrate how the genetic algorithm-based model is used to find the optimal/ near-optimal solution of the problem.

6.4.1. Encoding/ Decoding Scheme

A solution for the problem is encoded in a finite length string called a chromosome. Each chromosome is formed of fragments (i.e., substrings) represent candidate platform(s). The number of the substrings is equal to the maximum possible number of platforms that can be used to produce each variant of the considered product family. The maximum possible number of platforms is equal to the number of product variants as each product variant is assigned to a separate platform in this case. Each substring comprises a set of elements called genes. Each gene represents a feature in the considered product family. A binary value (0-1) is assigned to each gene. The gene has a value of one (1) if the feature represented by this gene is included in the platform represented by this substring. A value of zero (0) is assigned to the gene if the platform does not contain the feature represented by this gene. There may be some empty substrings (substrings with all its genes equal to zero). The actual number of platforms (non-empty substrings) is automatically determined by the GA. Figure 6-2 illustrates the encoding scheme.

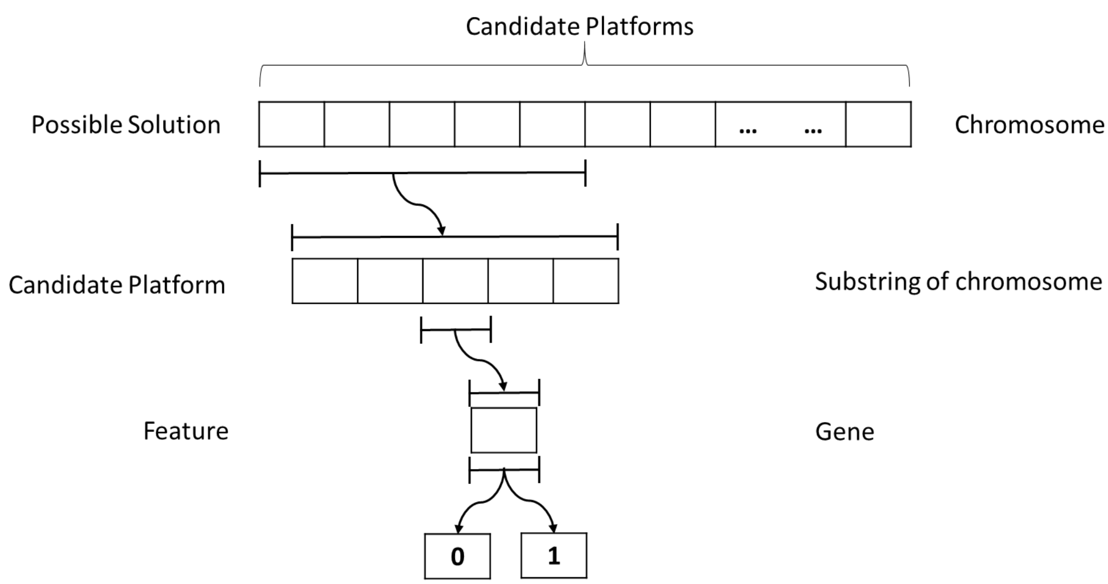


Figure 6-2 The encoding scheme illustration

For more illustration, an example of a product family consists of three (3) variants and includes five (5) features is shown in Figure 6-3. The maximum possible number of platforms equals to 3 (maximum number of variants). Thus, the chromosome would be formed of 15 genes (3 possible platforms multiply 5 features).

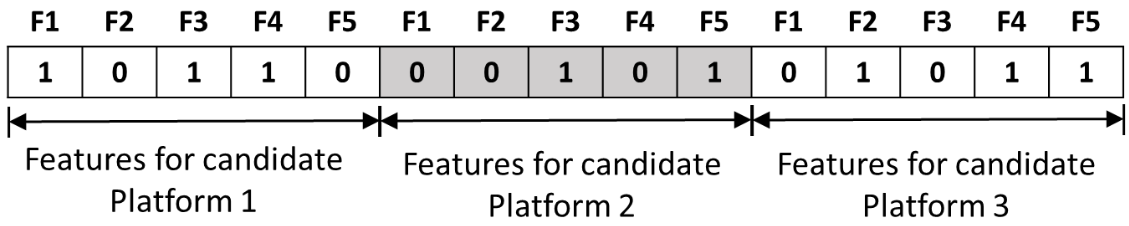


Figure 6-3 Candidate Platforms chromosome

6.4.2. Initial Population

The initial population is an initial set of solutions in which the GA starts with. It is randomly generated candidate platforms (feasible solutions) that lies within the search space. Each solution is encoded in the form of a chromosome, as described in the previous section. The initial population is formed of u chromosomes, where u is the population size. The population size is decided based on the number of variants and the total number of different features within the considered family. A random binary value is assigned for each feature (gene) of the candidate platforms chromosome. To ensure that every candidate platforms chromosome is feasible, a feasibility check is needed. The infeasibility of the chromosome may occur as a result of the violation of the precedence constraints. In other words, some features are created which depend on other features. Thus, the dependant features cannot exist in the platform unless the features, that the dependant features are depend/created on, are in the platform. This means that if the dependent feature (B) gene takes value 1 then the gene representing the feature (D) that the feature (B) depends on must be equal 1. The feasibility correction is working as the following, based on the feature precedence, if a dependant feature takes a value of 1 then a 1 is added to the feature that the dependant feature depends on. For example, the generated chromosome is shown in Figure 6-4a for a family of 3 variants and 5 features. Feature 3 is dependent on feature 5 and for candidate platform 1 and 3, feature 3 takes a value of 1 while feature 5 takes a value of 0. Then, a 1 must be added to the feature 5 genes in both candidate platforms 1 and 3. Figure 6-4a shows an infeasible chromosome and Figure 6-4b shows the chromosome after adding 1 to include feature 5 in both platforms.

F1	F2	F3	F4	F5	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
1	0	1	1	0	1	0	0	0	1	0	1	1	1	0

(a)

F1	F2	F3	F4	F5	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
1	0	1	1	1	1	0	0	0	1	0	1	1	1	1

(b)

Figure 6-4 Feasibility Correction mechanism

6.4.3. Fitness Function

The fitness function is a function that is used to evaluate the fitness of each candidate platforms chromosome as a solution with respect to the problem in consideration. The calculation of the fitness value is repeatedly performed for each chromosome within the population for the entire generations until the GA search stops, and an optimal or near-optimal solution is reached. The fitness function is to minimize the total cost of manufacturing the considered family. Figure 6-5 shows the flowchart of the fitness function.

The first cost that should be included in the fitness function is the manufacturing cost for each product variant from each candidate platform (extracted from the chromosome). The variant manufacturing cost consists of three terms. The first term is the cost of mass manufacturing the features of the platform. The cost of customizing the platform into the product variant by adding features to the platform by additive manufacturing is represented by the second term, while the third term is for the cost of customizing the platform into the product variant by removing some features from the platform by subtractive manufacturing.

The variant manufacturing cost is the minimum summation of these three terms among the candidate platforms. Equation (6.1) represents the variant manufacturing cost:

$$VC_k = \min_{\forall i}\left(\sum_{j \in J} Cp_j\, x_{ij}\, D_k + \sum_{j \in J} Ca_j\, a_{ijk}\, D_k + \sum_{j \in J} Cr_j\, r_{ijk}\, D_k\right) \tag{6.1}$$

where,

VC_k the manufacturing cost of variant k

K the set of product variants in the product family, k ∈ K.

J the features set, j ∈ J.

I represents the platforms, i ∈ I.

D_k the demand of the kth product variant (units).

Cp_j the cost of mass production of the j_{th} feature using a platform.

Ca_j the cost of adding the j_{th} feature/material to form a product variant (Ca_j>Cp_j)

Cr_j the cost of removing the j_{th} feature/material ($Cr_j > Cp_j$) from the platform to form a product variant

x_{ij} to indicate that feature j is included in the platform i;

$$x_{ij} = \begin{cases} 1 \text{ if the platform i contains feature j} \\ 0 \text{ otherwise} \end{cases}$$

a_{ijk} to denote that feature j is added to the platform i to customize it to form product k;

$$a_{ijk} = \begin{cases} 1 \text{ if feature j is added to the platform i to form product k} \\ 0 \text{ otherwise} \end{cases}$$

r_{ijk} to show that feature k is removed from the platform i to customize to form product k.

$$r_{jk} = \begin{cases} 1 \text{ if featurej is removed from the platform i to form product k} \\ 0 \text{ otherwise} \end{cases}$$

Another cost that should be considered in the fitness function is the total setup cost of manufacturing multiple platforms. It includes the costs associated with preparing the required machine tool, cutting tools, fixtures, automated production methods/ programming and labour training,…etc for constructing each platform. This cost controls the formation of new platforms. Equation (6.2) represents the total setup cost:

$$SC = \sum_{i=1}^{I} Cs\, Z_i \tag{6.2}$$

where,

SC the total setup cost of manufacturing multiple platforms

Cs the setup cost of one platform.

Z_i to indicate that feature j is included in the platform i;

$$Z_i = \begin{cases} 1 \text{ if the platform i is used to produce at least one variant} \\ 0 \text{ otherwise} \end{cases}$$

Based on equations (6.1) and (6.2), the fitness function can be formulated as in equation (6.3):

$$fitness\ function = \sum_{k=1}^{K} VC_k + SC \tag{6.3}$$

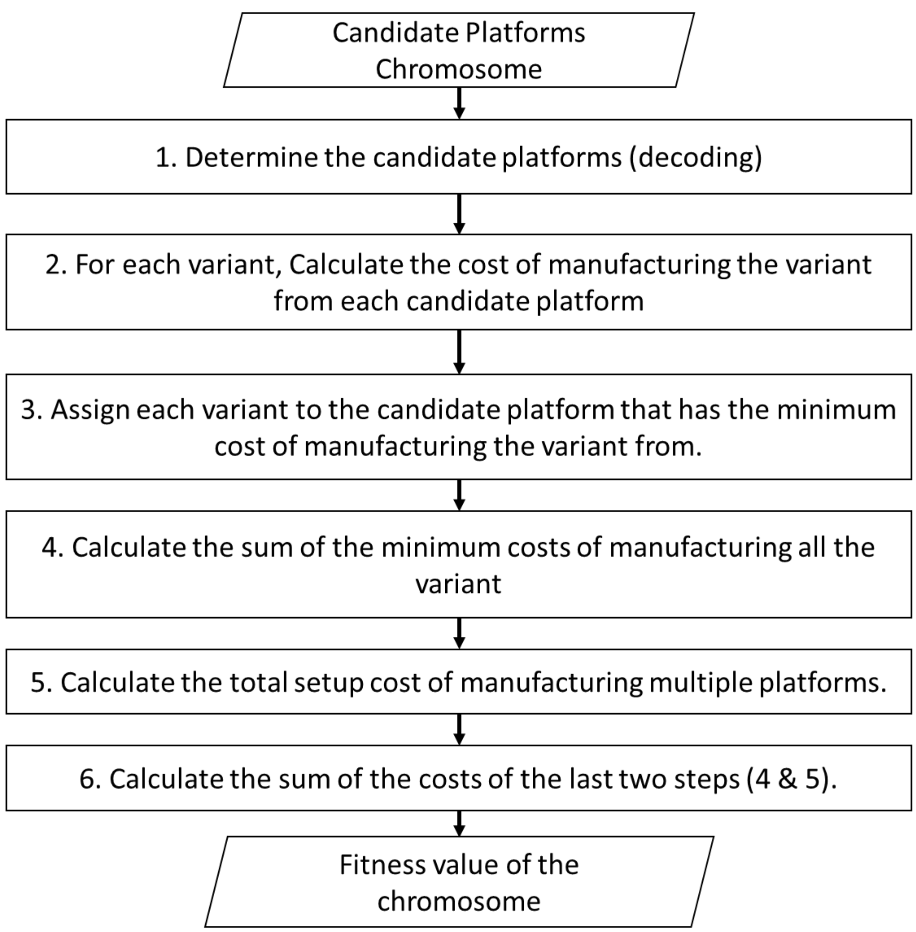


Figure 6-5 Fitness Function Flowchart

6.4.4. Selection

The selection is the process in which the candidate platforms chromosomes are selected from the current population to be the parents used for mating (crossover and mutation) to generate the next generation population (offspring). The selected parents are added to a mating pool according to their total manufacturing cost of the family (fitness value). In this model, the Roulette wheel selection is applied where all chromosomes in the current population are placed on a roulette wheel. The area of the section of the wheel corresponding to each chromosome is proportional to its fitness value. Thus, the chromosome with a lower total manufacturing cost of the family (higher fitness) has a higher probability of being selected more times. Then, a random number is generated to select one of the candidate platforms chromosomes.

6.4.5. Elitism

The elitism is the process in which the best candidate platforms chromosome or a few best chromosomes of the current population, the chromosome(s) with the lowest total manufacturing cost of the family (highest fitness value) in the current population, are added to the next population. The elitism process prevents the loss of the best-found chromosome(s) during the creation of the next population's chromosomes by crossover and mutation processes. Thus, the elitism may have a significant effect on the performance of the GA.

6.4.6. Genetic algorithm operators

Two genetic operators, namely crossover and mutation, are used in order to generate the next generation population. The crossover and mutations operators have an influence on the performance of a genetic algorithm. The choice of crossover and mutation types is based on the encoding and the problem nature. In the following subsections, the proposed crossover and mutation for the addressed problem are discussed.

6.4.6.1 Crossover

The crossover is analogous to the reproduction process in which two selected parents (product platforms chromosomes) produce two offspring. The offspring inherit their parents' features (genes). Two crossover operators are applied.

The first crossover operator is a problem specific crossover operator, developed by the authors, is applied. As mentioned before, each chromosome is divided into substrings that represent the potential platforms. These platforms can take numbers from 1 to the total number of variants. The developed crossover procedure is that a random set of numbers with values between 1 and the total number of variants is generated. The generated numbers represent the platforms (substrings) from one of the parents that are inherited into the offspring, and the rest of the offspring's platforms (substrings) are taken from the other parent. For example, consider parents 1 and 2 for a family of four variants, and the total number of features is six, as shown in Figure 6-6. The randomly generated numbers are 2 and 3. This means that the offspring will inherit substrings representing platform 2 and platform 3 from one of the parents and the rest of the substrings that represents platform 1 and platform 4 from the other parent.

Another crossover operator, namely, the position based crossover proposed by Syswerda (1991), is applied. The proposed crossover operator works as follows. First, a random set of feature positions in one of the parent candidate platforms chromosomes is selected. The values of the selected features in that parent are imposed into the corresponding feature positions of the other parent. For example, consider parents 1 and 2 for a family of three product variants with a total number of five features as in Figure 6-7, and suppose that the third, fifth and eighth positions are selected. The offspring will have the values of 1, 0, and 1 at the third, fifth and eighth positions respectively taken from parent 1 and the rest of the offspring genes take their values from parent 2. This example of applying the proposed crossover is illustrated in Figure 6-7.

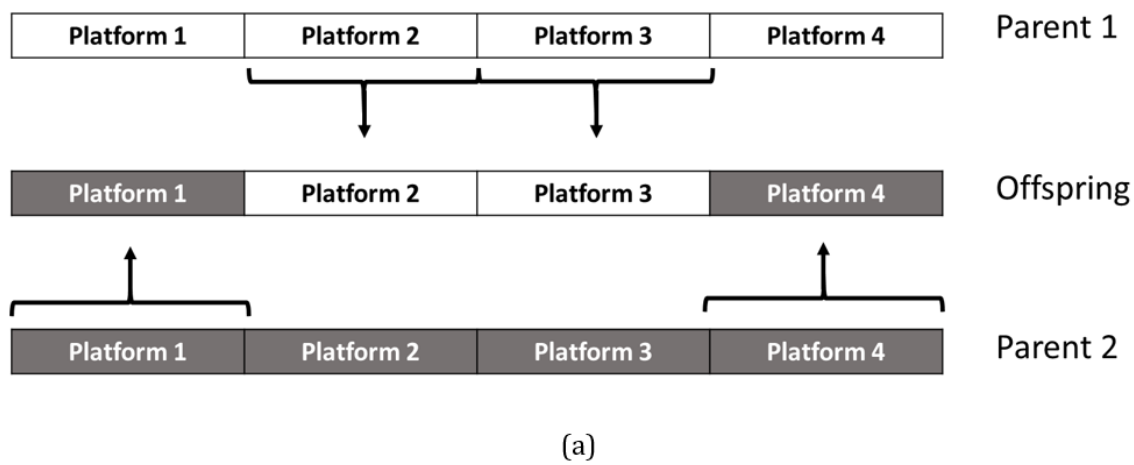


Figure 6-6 The first proposed crossover

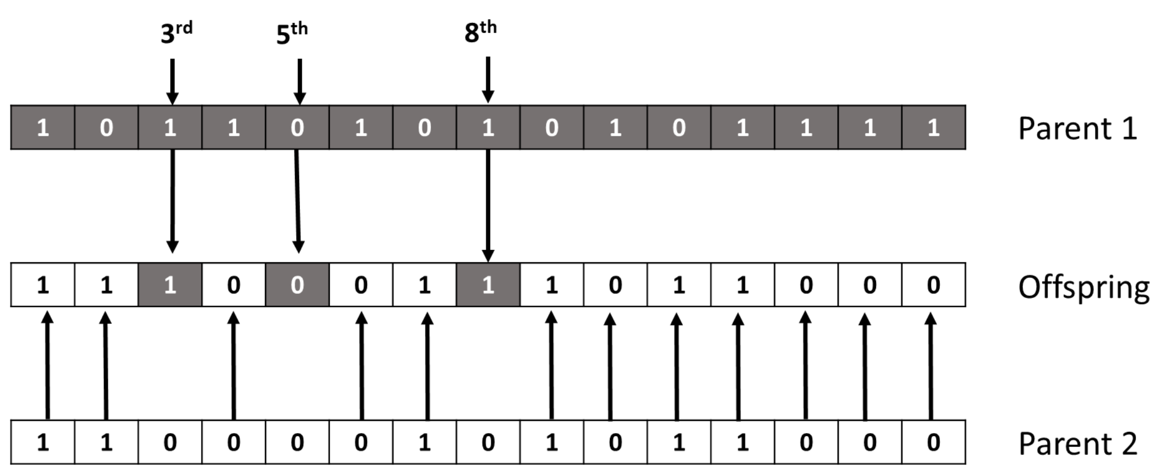


Figure 6-7 The second proposed crossover

6.4.6.2 Mutation

The mutation is the process in which a small random modification is applied to one selected parent in order to produce offspring. The mutation plays a crucial role in the exploration of the search space by introducing diversity in the genetic population. It is crucial for the convergence of the genetic algorithm. Since the chromosome is encoded in binary form, the bit flip mutation operator is applied. The bit flip mutation procedure is that a random set of positions in the parent candidate platforms chromosomes is selected. The value of the features (genes) corresponding to these positions in the parent is flipped (0 to 1 and 1 to 0) to form an offspring. For example, consider a parent for a family of three variants with a total number of five features. The generated numbers are for the second, seventh and twelfth positions. This will lead to an offspring similar to the parent in all features (gene) except for the second, ninth and eleventh features (genes) will be changed from 1, 0 and 1 to 0, 1 and 0, respectively. This example is shown in Figure 6-8.

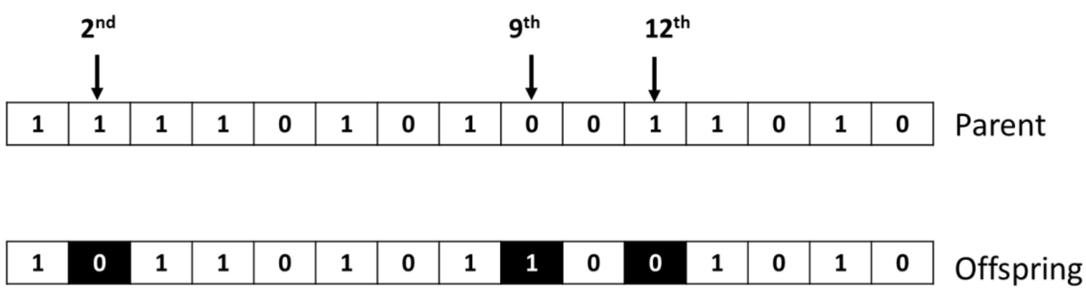


Figure 6-8 The proposed mutation

It is worth to mention that the same feasibility check and correction mechanism discussed in initial population section is applied for the crossover and mutation offspring

6.4.7. Stopping Criteria

The genetic search operations are repeated until pre-defined stopping conditions are reached. The stopping conditions considered in the proposed algorithm are reaching a pre-selected number of generations, or the best solution remains unchanged for a certain number of successive generations. Similar to the population size, the decision regarding the stopping criteria are based on the number of the variants and the total number of features within the considered family.

6.5 Family of Guiding Bushes Case Study

The same case study of the guiding bushes family from chapter 4 will be considered in this chapter. The input parameters are taken from Table 4-2. The setup cost of one platform (Cs) for the guiding bushes' case study is estimated to be $1500 based on the industrial experts' opinion. No special fixture is needed since the fixation of the product variants can be done using a universal chuck. The factors that are considered during the setup cost estimation platform includes but not limited to the costs associated with preparing the required machine tool, cutting tools, fixtures, automated production methods/ programming and labour training,…etc.

The developed model is implemented using MATLAB®. The following GA parameters are used: 0.8 for the crossover ratio, 0.15 for the mutation ratio and the population size is 1000. The stopping criteria are either reaching 100 generations or no change in the best solution for 300 generations. The guiding bushes case study is solved optimally, and the results for the various scenarios of demand were obtained in 10 seconds using a PC of Intel Core i7 3.40 GHz processor and 16 GB Ram. The prices for the variants from the manufacturer (www.rabourdin.fr/en/home/) are $41.83, $51.08, $51.72, $51.72 and $58.25 for V1, V2, V3, V4 and V5 respectively. Hence, the average price of these variants is $50.92.

Table 6-1 compares the results from having a single platform obtained by the mathematical model in chapter 4 and the results from having multiple platforms using the proposed genetic algorithm-based model. Furthermore, it should be noted that the mathematical model does not consider the platform setup cost. Thus, the results from the mathematical model have been modified by adding the setup cost of one platform in order to enable the comparison of the results of both models. In this comparative study, different demand scenarios are considered.

Table 6-1 Comparison between Multiple Platform Model and Single Platform Model

Scenario	Product Variant Demand [V1, V2, V3, V4, V5]	Multiple Platform			Single Platform		
		Product Platforms	Total Manufacturing Cost ($)	Average Cost per guiding bush ($)	Product Platform	Total Manufacturing Cost ($)	Average Cost per guiding bush ($)
1	[100, 100, 100, 100, 100]	• Variants V2, V4 and V5 are served by one platform of features [F2, F3, F4, F5, F7, F8] • Variants V1 and V3 are served by one platform of features [F1, F2, F3, F5, F6]	8650	17.3	• All variants are served by one platform of features [F2, F3, F5, F7]	9900	19.8
2	[700, 100, 100, 100, 100]	• Variants V2, V4 and V5 are served by one platform of features [F2, F3, F4, F5] • All other variants (V1, V3) are produced in separate platforms.	11100	10.1	• All variants are served by one platform of features [F1, F2, F3, F5]	14800	13.45
3	[100, 700, 100, 100, 100]	• Variants V4 and V5 are served by one platform of features [F2, F3, F4, F5, F7, F8] • Variants V1, V2 and V3 are served by one platform of features [F2, F3, F4, F5]	12200	11.1	• All variants are served by one platform of features [F2, F3, F4, F5]	13000	11.82
4	[100, 100, 700, 100, 100]	• Variants V2, V4 and V5 are served by one platform of features [F2, F3, F4, F5, F7, F8] • Variants V1 and V3 are served by one platform of features [F2, F3, F5, F6]	12550	11.40	• All variants are served by one platform of features [F2, F3, F5, F6]	14800	13.45

Scenario	Product Variant Demand [V1, V2, V3, V4, V5]	Multiple Platform			Single Platform		
		Product Platforms	Total Manufacturing Cost ($)	Average Cost per guiding bush ($)	Product Platform	Total Manufacturing Cost ($)	Average Cost per guiding bush ($)
5	[100, 100, 100, 700, 100]	• Variants V2 and V5 are served by one platform of features [F2, F3, F4, F5, F7, F8] • Variants V1 and V3 are served by one platform of features [F1, F2, F3, F5, F6] • Variant (V4) is produced in a separate platform	13000	11.82	• All variants are served by one platform of features [F2, F3, F5, F7]	13500	12.27
6	[100, 100, 100, 100, 700]	• Variants V2, V4 and V5 are served by one platform of features [F2, F3, F4, F5, F7, F8] • Variants V1 and V3 are served by one platform of features [F1, F2, F3, F5, F6]	13750	12.5	• All variants are served by one platform of features [F2, F3, F4, F5, F7,F8]	15350	13.95
7	[100, 500, 500, 100, 50]	• Variants V1, V2, V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	13350	10.68	• All variants are served by one platform of features [F2, F3, F4, F5, F6]	17600	14.08
8	[50, 100, 50, 50, 50]	• All variants are served by one platform of features [F2, F3, F4, F5]	6000	20	• All variants are served by one platform of features [F2, F3, F4, F5]	6000	20

Scenario	Product Variant Demand [V1, V2, V3, V4, V5]	Multiple Platform			Single Platform		
		Product Platforms	Total Manufacturing Cost ($)	Average Cost per guiding bush ($)	Product Platform	Total Manufacturing Cost ($)	Average Cost per guiding bush ($)
9	[10, 10, 10, 10, 10]	• No platform (All variants are built completely by additive manufacturing)	1800	36	• All variants are served by one platform of features [F2, F3, F5, F7]	2340	46.8
10	[500, 500, 500, 500, 500]	• Each variant is produced by a separate platform	22000	8.8	• All variants are served by one platform of features [F2, F3, F5, F7]	43500	17.4

The results of the study show that the total cost of the single platform model is larger than that of multiple platform model. For the first demand scenario, all the product variants have equal demand of 100 units. For scenario 1, two platforms are formed, and only subtractive manufacturing is used for customization. The first platform is formed of features F1, F2, F3, F5, and F6 that serves the production of variants 1 and 3 by only removing both, features F5 and F6 to obtain variant 1, and by only removing feature F1 to obtain variant 3. The second platform is formed of features F2, F3, F4, F5, F7, and F8 that produces variant 5 without any further processing Variant 2 is obtained by machining features F7 and F8, and variant 4 by machining feature F7.

Moreover, the scenarios from 2 to 6 each, has one variant with a very high demand with respect to other variants. In the aforementioned scenarios, the platform obtained from the mathematical model is formed from the features of the product variant with the very high demand with respect to the other product family variants. Furthermore, the multiple platform model for scenarios 2-6 produces one platform similar to the very high demand product variant and one or two platforms that serve other variants.

In scenario 7, two platforms are formed to produce the variants. Variants (V2, V4 and V5) are produced using the first platform [F2, F3, F4, F5, F7, F8]. Variant V2 is produced by machining feature F7 and F8; while machining features F4 and F8 from the platform leads to producing variant V4. Variant V5 has the same features of the first platform. The second platform [F1, F2, F3, F5, F6] is customized into variant V1 by machining features F5 and F6, and into variant V3 by machining F1. Thus, in this scenario, the product variants are customized using only subtractive manufacturing,

The demand for variants in scenario 7 is 100, 500, 500, 100, 50 units for variants V1, V2, V3, V4 and V5, respectively. In this demand scenario, product variant 3 is produced separately, and product variants V1, V2, V4 and V5 are produced using platform [F2, F3, F4, F5], which is identical to variant V2. Variant V1 is produced by machining features F4 and F5, and adding feature F1. Variant V4 is produced by machining feature F4 and adding feature F7; while adding features F7 and F8 to the platform leads to producing variant V5. The large demand for Product variants V2 and V3 forces the model to recommend producing each one of them separately.

The multiple platform model results in lower total manufacturing cost for all the scenarios compared to the single platform model. Since the multiple platform model has the ability to produce one or more platforms; hence, if having a single platform is the optimum solution, then the multiple platform model will produce the single platform as in scenario 8. This concludes that both models will produce a single platform. Thus, the multiple platform model will allow more freedom in deciding the number of platforms by neither specifying it a priori nor limiting it to one platform. In addition, having single platform requires more customization processes than having multiple platforms. Since in case of multiple platforms are required, this means that each platform shares more features with the variants assigned than the single platform. Thus, the total manufacturing cost of the product variants is lower in the case of using multiple platforms.

The demand for all variants in scenario 9 is very low. This is an example of typical cases where manufacturing all the variants by additive manufacturing without utilizing platforms is recommended. As mentioned earlier, the single platform model produces one platform whatever the demand is, as the setup cost of one platform was not considered in the objective function. This is why for this scenario the single platform model produces variants with relatively high manufacturing cost. In scenario 10, the demand for all variants is high; each product variant is produced in a separate platform.

6.5.1. Cost Sensitivity Analysis

A one-at-a-time sensitivity analysis in which variations in base values of the input costs; namely, the setup of one platform, feature additive, subtractive, and mass-producing costs, is performed to measure their effect on the total manufacturing cost. Graphs are constructed to express the impact on the total manufacturing cost caused by these variations in these input costs. All these studies are performed on the guiding bushes product family. However, it is important to mention that this section will include hypothetical assumptions for the studied costs for the sole propose of analyzing and studying the trends of changing these costs. In other words, the decrease and the increase of these costs with respect to the actual estimated costs (in the above section) are not calculated but they are assumed only for showing the effect of these changes on the results.

6.5.1.1 Effect of changing setup cost of one platform (Cs)

The data presented in Table 6-2 is plotted in the graph shown in Figure 6-9 to illustrate further the effect of the setup cost of one platform (Cs) on the total manufacturing cost and the number of platforms. The effect of the setup cost of one platform is tested by changing its value as a percentage of the cost previously considered in the case study. All other costs remain the same as mentioned before in the case study and demand scenario 1, which is 100 units is required for each variant, is used.

Table 6-2 Effect of changing the setup cost of one platform

Percentage of Setup cost of one platform (Cs)	Product Platform [Considered Demand: (100, 100, 100, 100, 100) for (V1, V2, V3, V4, V5)]	Total Manufacturing Cost ($)	No. of Platforms
50%	• All variants (V1, V2, V3, V4, V5) are produced in separate platforms.	6650	5
55%	• Variants V4 and V5 are served by one platform of features [F2, F3, F4, F5, F7, F8] • All other variants (V1, V2, and V3) are produced in separate platforms.	6950	4
60%	• Variants V2, V4 and V5 are served by one platform of features [F2, F3, F4, F5, F7, F8] • Variant (V1 and V3) are produced in separate platforms	7200	3
100%	• Variants V2, V4 and V5 are served by one platform of features [F2, F3, F4, F5, F7, F8] • Variants V1 and V3 are served by one platform of features [F1, F2, F3, F5, F6]	8650	2
175%	• All variants are served by one platform of features [F2, F3, F5, F7]	11025	1

The data presented in Table 6-2 shows that when the setup cost of one platform (Cs) increases, it is more economical to reduce the number of platforms. Similarly, in the case where the setup cost of one platform (Cs) is reduced, having more platforms results in a lower manufacturing cost. Furthermore, in the case where the setup cost of one platform (Cs) is very high (around six times the setup cost for this considered demand scenario), building the product variants completely by additive manufacturing without platforms leads to lower manufacturing cost.

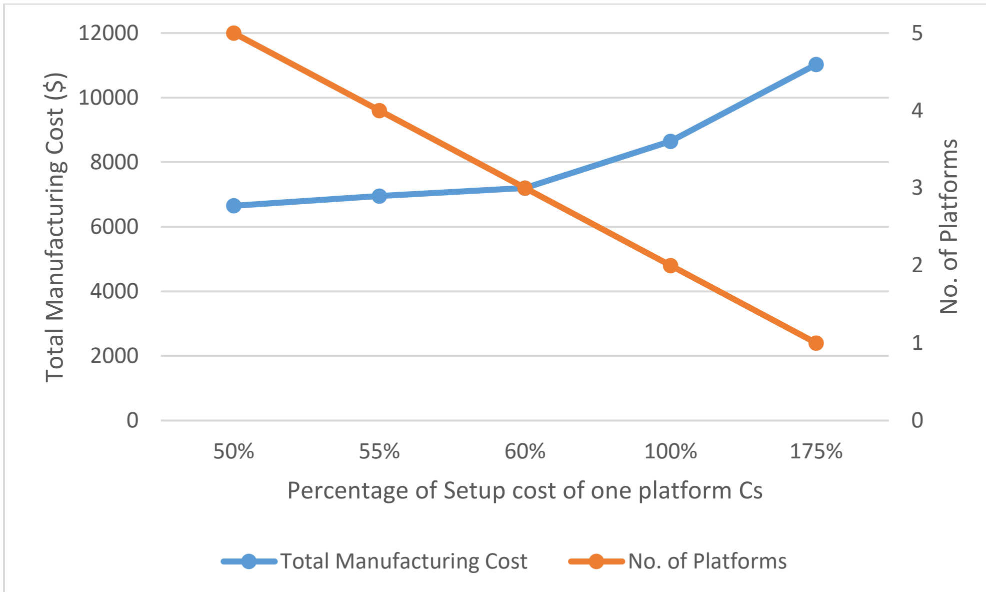


Figure 6-9 Effect of changing setup cost of one platform (Cs)

6.5.1.2 Effect of changing feature additive cost (C_a)

The effect of changing the feature additive cost on the total cost is also studied. In this study, different percentages of feature additive cost mentioned in the case study are considered. The considered demand scenario in this study is scenario 7 in which 100, 500, 500, 100 and 50 units are needed for product variants V1, V2, V3, V4 and V5, respectively. Thus, the results of the study, shown in Figure 6-10 and Table 6-3, prevailed that the increase of the feature additive cost increases the total manufacturing cost and the number of platforms to a point where the platforms are customized by subtractive manufacturing only. At this point, any increase in the additive cost will neither affect the total manufacturing nor the number of platforms (as in considering 130% of the feature additive cost in this case study scenario). As for the decrease in feature additive costs, it leads to that some variants are built by additive manufacturing without platforms until it reaches a point where all variants are built by additive manufacturing without platforms.

Table 6-3 Effect of changing feature additive cost (Ca)

Percentage of feature additive cost (Ca)	Product Platform [Considered Demand: (100, 500, 500, 100, 50) for (V1, V2, V3, V4, V5)]	Total Manufacturing Cost ($)
50%	• Variants V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant V3 is produced in a separate platform • Variant V1 is entirely built by additive manufacturing	11800
60%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	12230
70%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	12510
80%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	12790
90%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	13070
100%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	13350
110%	• Variants V1 and V2 are served by one platform of features [F2, F3, F4, F5] • Variants V4 and V5 are served by one platform of features [F2, F3, F5, F7, F8] • Variant (V3) is produced in a separate platform	13480
120%	• Variants V1 and V2 are served by one platform of features [F2, F3, F4, F5] • Variants V4 and V5 are served by one platform of features [F2, F3, F5, F7, F8] • Variant (V3) is produced in a separate platform	13585
130%	• Variants V4 and V5 are served by one platform of features [F2, F3, F4, F5, F7, F8] • All other variants (V1, V2, V3) are produced in separate platforms.	13625
140%	• Variants V4 and V5 are served by one platform of features [F2, F3, F4, F5, F7, F8] • All other variants (V1, V2, V3) are produced in separate platforms.	13625
150%	• Variants V4 and V5 are served by one platform of features [F2, F3, F4, F5, F7, F8] • All other variants (V1, V2, V3) are produced in separate platforms.	13625

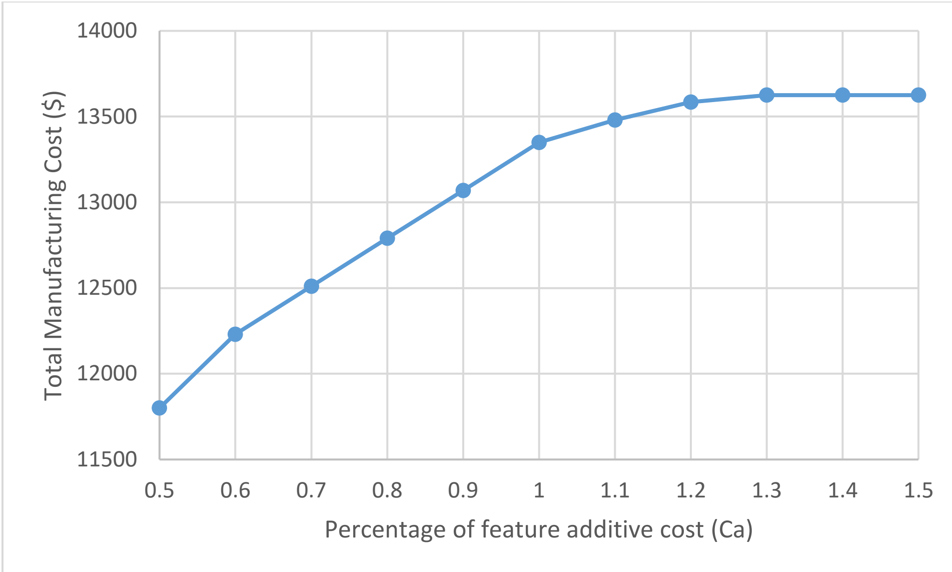


Figure 6-10 Effect of changing feature additive cost

6.5.1.3 Effect of changing feature subtractive cost (C_r)

Similarly, the effect of feature subtractive cost is tested by changing its value as a percentage of the cost previously considered in the case study. All other costs remain unchanged and the considered demand for the product variants V1, V2, V3, V4 and V5 is 100, 500, 500, 100 and 50 units. The increase in the feature subtractive cost directly increases the total manufacturing cost indicating a direct proportional relationship between them. This is because, in many cases, the model uses subtractive manufacturing for customizing the product platform for its lower cost.

Table 6-4 Effect of changing feature subtractive cost (Cr)

Percentage of feature subtractive cost (Cr)	Product Platform [Considered Demand: (100, 500, 500, 100, 50) for (V1, V2, V3, V4, V5)]	Total Manufacturing Cost ($)
50%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	12950
60%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	13030
70%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	13110
80%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	13190
90%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	13270
100%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	13350
110%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	13430
120%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	13510
130%	• Variants V1 and V2 are served by one platform of features [F2, F3, F4, F5] • Variants V4 and V5 are served by one platform of features [F2, F3, F5, F7, F8] • Variant (V3) is produced in a separate platform	13585
140%	• Variants V4 and V5 are served by one platform of features [F2, F3, F5, F7, F8] • All other variant (V1, V2, V3) are produced in separate platforms.	13605
150%	• Variants V4 and V5 are served by one platform of features [F2, F3, F5, F7, F8] • All other variant (V1, V2, V3) are produced in separate platforms.	13625

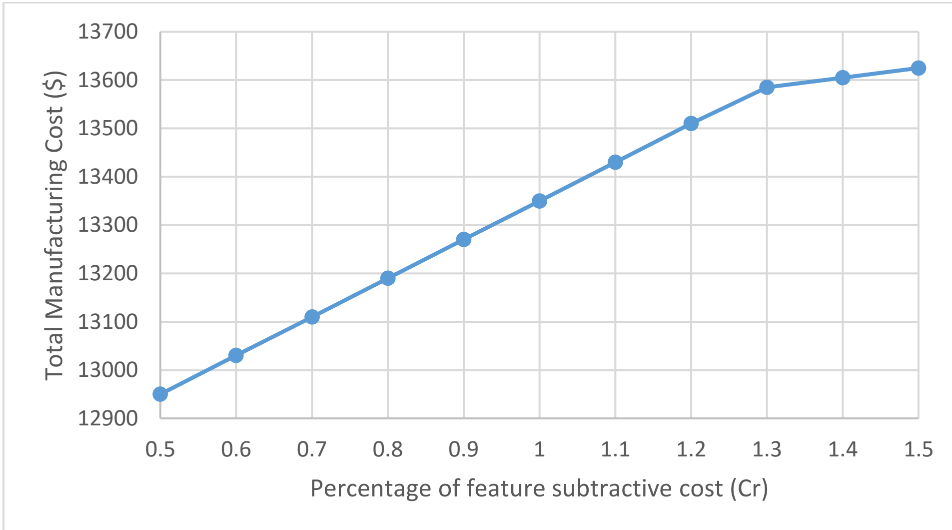


Figure 6-11 Effect of changing feature subtractive costs (Cr)

6.5.1.4 Effect of changing feature mass production cost (C_p)

The effect of feature mass production cost the features on the total manufacturing cost is studied in the same way the feature additive and subtractive costs effects have been studied. The demand scenario 7, in which 100, 500, 500, 100 and 50 units are needed for product variants V1, V2, V3, V4 and V5 respectively, is considered. In this study, only the feature mass production cost is considered to be changing while the other costs remain the same. The results show that both the total manufacturing cost and the feature mass production cost are directly proportional.

Table 6-5 Effect of changing feature mass production cost (Cp)

Percentage of feature mass production cost (Cp)	Product Platform [Considered Demand: (100, 500, 500, 100, 50) for (V1, V2, V3, V4, V5)]	Total Manufacturing Cost ($)
50%	• Variants V1 and V2 are served by one platform of features [F2, F3, F4, F5] • Variants V4 and V5 are served by one platform of features [F2, F3, F5, F7, F8] • Variant (V3) is produced in a separate platform	9812.5
60%	• Variants V1 and V2 are served by one platform of features [F2, F3, F4, F5] • Variants V4 and V5 are served by one platform of features [F2, F3, F5, F7, F8] • Variant (V3) is produced in a separate platform	10525
70%	• Variants V1 and V2 are served by one platform of features [F2, F3, F4, F5] • Variants V4 and V5 are served by one platform of features [F2, F3, F5, F7, F8] • Variant (V3) is produced in a separate platform	11237.5
80%	• Variants V1 and V2 are served by one platform of features [F2, F3, F4, F5] • Variants V4 and V5 are served by one platform of features [F2, F3, F5, F7, F8] • Variant (V3) is produced in a separate platform	11950
90%	• Variants V1 and V2 are served by one platform of features [F2, F3, F4, F5] • Variants V4 and V5 are served by one platform of features [F2, F3, F5, F7, F8] • Variant (V3) is produced in a separate platform	12662.5
100%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	13350
110%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	14025
120%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	14700
130%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	15375
140%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	16050
150%	• Variants V1, V2 ,V4 and V5 are served by one platform of features [F2, F3, F4, F5] • Variant (V3) is produced in a separate platform	16725

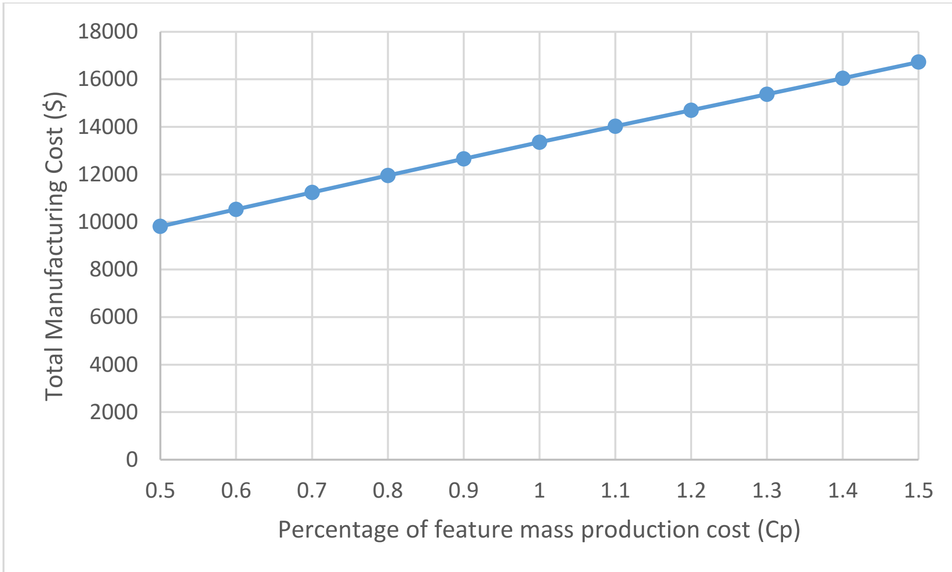


Figure 6-12 Effect of changing feature mass production cost (Cp)

6.6 Family of Gear Shafts Case study

A case study of a family of gear shafts, adopted from www.gearmotions.com, is used to demonstrate the developed model. Gear shafts provide the rotation that allows one gear to engage with and turn another and contain gear teeth integrated into the shaft. Gear shafts are commonly found in engines and have many applications in the automotive and aerospace industries. The considered family consists of 8 product variants composed of 21 different features. The features that form the product family are determined using the feature extraction procedure discussed in chapter 4. Figure 6-13 shows the product variants, while Figure 6-14 shows the 21 features. Table 6-6 represents the overall dimensions of the considered variants.

Table 6-7 shows the features from which each product variant is formed. Table 6-8 shows the precedence relationship between the features of the gear shaft family. The DMD is utilized since many of the addition of the features will be built on a non-planner surface. CNC turning and milling machines are required for cutting the cylindrical geometries and opening the gear teeth. Based on the prices from McMASTER-CARR company (www.mcmaster.com) for similar products, the prices for variants V1, V2, V3, V4, V5, V6, V7 and V8 are $161, $189, $228, $176, $203, $262, $163, and $192 respectively. Thus, the average price of these variants is $196.75.

The costs for mass producing, additive manufacturing and subtractive manufacturing of features are shown in Table 6-9 and determined based on quotations from the 3D Hubs network (https://www.3dhubs.com/) and the cost study of (Manogharan et al. 2016).

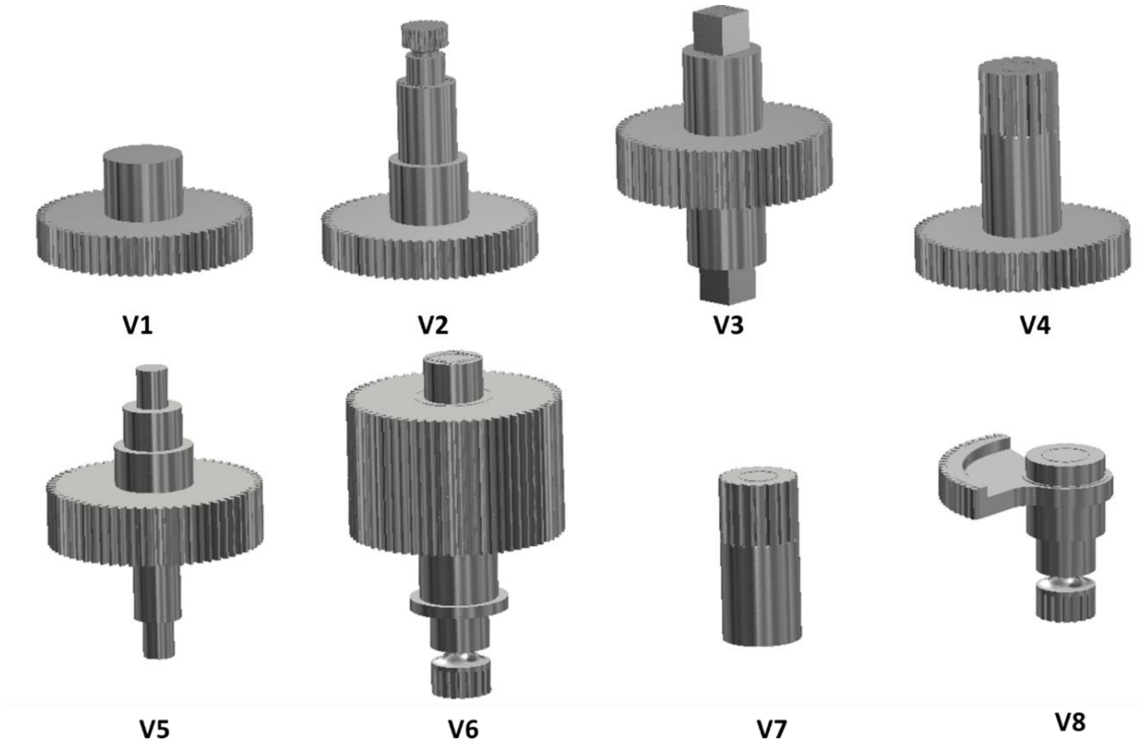


Figure 6-13 The eight variants of the gear shaft product family

Table 6-6 Overall dimensions of the gear shaft variants

Product Variant	Max. Diameter (mm)	Min. Diameter (mm)	Overall length (mm)
V1	100	40	50
V2	100	20	130
V3	100	20	150
V4	100	40	110
V5	100	16	150
V6	100	30	180
V7	40	40	90
V8	90	30	90

Table 6-7 Product variant / feature relationships for the gear shaft family

Product Variant	Feature																				
	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21
V1	1			1																	
V2	1			1		1	1	1	1	1	1										
V3	1	1		1	1	1	1		1				1	1	1	1			1		
V4	1			1	1	1	1	1	1	1			1								1
V5	1	1		1		1			1				1	1					1		
V6	1	1	1	1	1	1	1	1	1				1	1	1	1	1	1	1	1	
V7				1	1	1	1	1	1	1											1
V8												1	1	1	1	1	1		1	1	

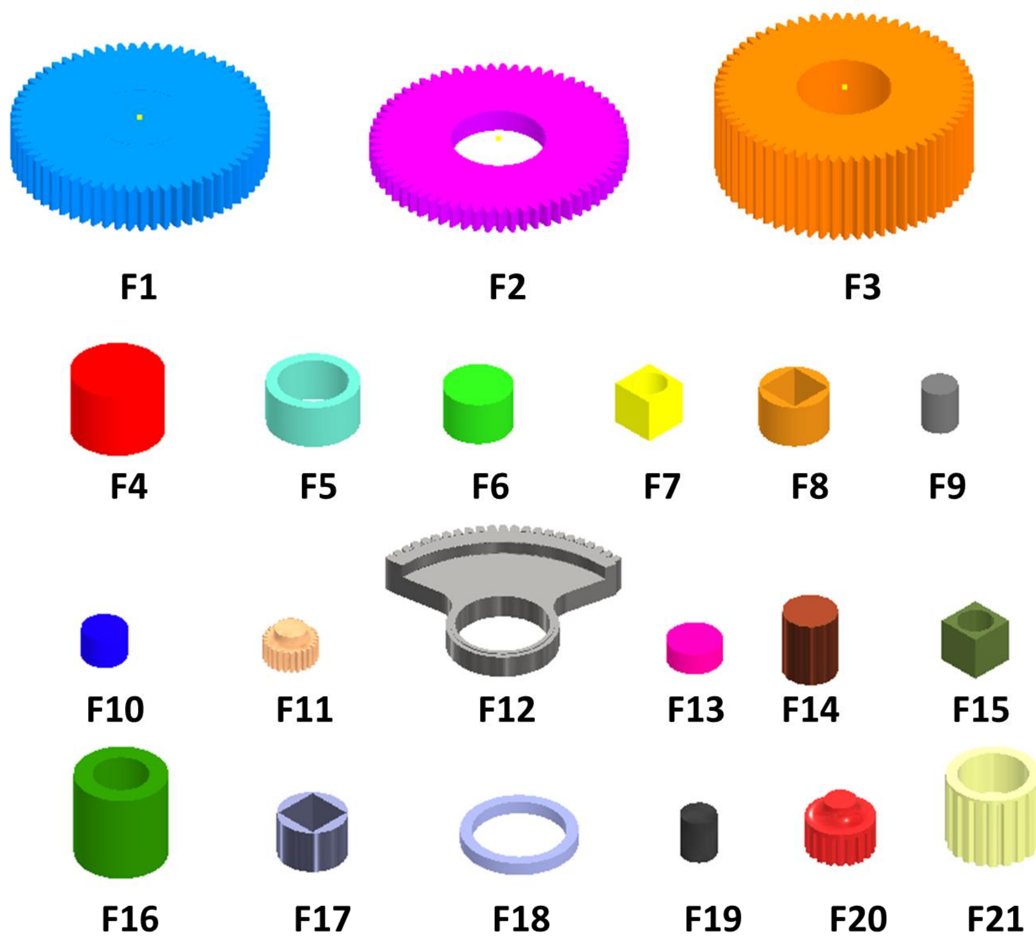


Figure 6-14 Features of the Gear Shafts product family

The setup cost of a platform for the gear shafts case study is $5000. This value for the setup cost is determined based on discussions with industry experts. This setup cost is estimated taken into consideration the costs associated with preparing the required machine tool, cutting tools, fixtures, automated production methods/ programming and labour training,…etc .

Table 6-8 Features precedence for the gear shaft family

		Feature																			
		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21
Feature	F1																					
	F2				X																	
	F3				X	X	X															
	F4																					
	F5				X		X															
	F6																					
	F7									X												
	F8							X														
	F9																					
	F10																					
	F11										X											
	F12																X					
	F13																					
	F14																					
	F15																			X		
	F16													X	X							
	F17																X					
	F18																	X				
	F19																					
	F20															X		X				
	F21									X	X											

Various cases of demand scenarios are examined to illustrate the effect of the demand on the product platform. The demand scenarios, optimum platforms and the minimum manufacturing cost for each scenario are presented in Table 6-10. The following GA parameters are used: 0.75 for the crossover ratio, 0.1 for the mutation ratio and the population size is 1000. The stopping criteria are either reaching 500 generations or no change in the best solution for 100 generations. Each solution was obtained in 255 seconds using a PC of Intel Core i7 3.40 GHz processor and 16 GB Ram.

Table 6-9 Mass production, additive manufacturing, subtractive manufacturing costs for features of the gear shaft family

Feature	Ca ($)	Cp ($)	Cr ($)
F1	53.9	11.19	12.2
F2	39.8	9.9	10.8
F3	80.1	11.94	12.4
F4	25	4.65	5.8
F5	21.4	5.35	6.7
F6	19.9	3.87	4.9
F7	17.6	5.01	6.5
F8	19.4	5.62	6.9
F9	16.4	3.2	4.7
F10	16.6	3.26	4.8
F11	18	6.25	7.4
F12	33.9	10.31	11.6
F13	16.9	2.83	3.9
F14	19.8	3.15	4.3
F15	17.6	5.01	6.5
F16	26.6	6.15	7.7
F17	19.4	5.62	6.9
F18	18.9	5.76	6.8
F19	16.4	3.2	4.7
F20	20.6	5.93	6
F21	25.5	7.12	8

Table 6-10 Demand Scenarios for Gear Shaft Family, the optimal platforms and the results

Scenario	Product Variants Demand [V1, V2, V3, V4, V5, V6, V7, V8]	Optimal multiple platforms	Total Manufacturing Cost ($)	Average Cost per gear shaft ($)
1	[100, 100, 100, 100, 100, 100, 100, 100]	• Variants V3 and V5 are served by one platform of features [F1, F2, F4, F5, F6, F7, F9, F13, F14, F15, F16, F19] • Variants V2, V4 and V7 are served by one platform of features [F1, F4, F5, F6, F7, F8, F9, F10, F13, F21] • All other variants (V1, V6, and V8) are in separate platforms.	76984	96.23
2	[100, 25, 50, 150, 200, 25, 250, 50]	• Variants V2 and V4 are served by one platform of features [F1, F4, F5, F6, F7, F8, F9, F10, F13, F21] • Variants V3, V5 and V6 are served by one platform of features [F1, F2, F4, F6, F9, F13, F14, F19] • All other variants (V1, V7, and V8) are in separate platforms.	69993.8	82.35
3	[25, 50, 200, 50, 25, 100, 50, 250]	• Variants V2, V4 and V7 are served by one platform of features [F1, F4, F5, F6, F7, F8, F9, F10, F13, F21] • Variants V3 and V5 are served by one platform of features [F1, F2, F4, F5, F6, F7, F9, F13, F14, F15, F16, F19] • Variants (V6 and V8) are in a separate platforms • Variants V1 is built completely by additive manufacturing	67785.3	90.38
4	[500, 150, 100, 200, 100, 250, 100, 500]	• Variants V3 and V5 are served by one platform of features [F1, F2, F4, F5, F6, F7, F9, F13, F14, F15, F16, F19] • Variants V4 and V7 are served by one platform of features [F1, F4, F5, F6, F7, F8, F9, F10, F13, F21] • All other variants (V1, V2, V6, and V8) are in separate platforms.	122755	64.61

The following conclusions can be drawn from the results of both case studies and the cost sensitivity analysis:

- The average manufacturing costs per guiding bushes and the gear shafts are less than their average prices of the considered guiding bushes and gear shafts respectively. Thus, using platforms is economically justified. The difference between the average manufacturing costs and the average price can be explained as the price includes other elements such as profit margin, administrative overheads and manufacturing overheads in addition to the manufacturing cost.
- In the case where the demand of a particular product variant is very high with respect to other variants, one of the platforms is formed from the features of that variant and is dedicated to it; even if other variants do not share these features. For example, if the demand of V2 is very high with respect to others in the family, one of the platforms, in this case, is the product V2 itself.
- The decrease in the additive manufacturing cost, the increase in setup cost and the decrease in the demand are among the factors that promote the use of additive manufacturing to build the product variants without platforms.
- The model may select using only one manufacturing technology in customization of the product platform or even not using platform at all. Such decisions are affected by various factors such as the demand for each variant, the manufacturing costs and the features decomposition of the variants.
- The results are naturally case-specific and dependent on the values of different parameters such as the demand, the features of each variant and different costs. This is why the use of the developed model would be helpful in deciding on which is the best mass customization approach to use.

6.7 Summary and Conclusions

A novel genetic algorithm-based model was developed. Additional aspects were considered, such as all associated manufacturing costs, precedence constraints and the product demand. This model was successfully able to determine the optimal number of platforms, the set of features that forms each platform, assignment of the product variants to each platform and the manufacturing processes either additive or subtractive that is needed to customize the platforms into different product variants. The model benefits from the increase of commonalities between the variants as the result of utilizing additive and subtractive manufacturing for customizing the platforms. However, it is worth mentioning that the number of the platform, the platform configuration and accordingly, the process plans are changed by considering more aspects in the genetic model that was not considered in the phylogenetic median-joining network. Two case studies for a guiding bushes family and a gear shaft family were used for demonstration.

The benefits of combining additive and subtractive manufacturing are strongly emphasized by the genetic algorithm-based model results. The model can choose whether to either include platforms that will be customized by either subtractive only, additive only, with both subtractive and additive, or without platforms by building the variants with additive manufacturing only depending on the interaction and trade-off between the various criteria and variables.

CHAPTER 7. DISCUSSION AND CONCLUSION

7.1 Overview

This chapter presents the synopsis of the novelty and contribution achieved, as well as highlights the industrial significance of the research. The future work and the conclusions are presented in this chapter as well.

7.2 Discussion

In the assembly domain, the research work focuses on finding alternative assembly sequences for product variants. This work is a retrieval method that depends on utilizing the available legacy data. The research in the hybrid manufacturing covers designing the product platforms and generating process plans for hybrid manufacturing. The developed methods and models in hybrid manufacturing domain are generative process planning methods in which decisions related to the type of process either subtractive or additive processes and the sequence of the processes are generated. Finally, the research work for both domains falls under the macro process planning type.

Although the additive manufacturing, sensor technology and data availability, that the current work is based on, are not very new and were available during the 3^{rd} industrial revolution, utilizing these technologies was limited due to their unsuitability for industrial use. With the introduction of the 4^{th} industrial revolution, there is a breakthrough in computing power and the reduction in cost for acquiring and use these technologies makes them capable of industrial use. The developed models and methods can be utilized in any manufacturing systems that allow alternative assembly sequences in case of assembly domain and have the capabilities for additive and subtractive manufacturing in case of hybrid manufacturing. Thus, they are more suitable for the 4^{th} Industrial revolution. Moreover, the developed methods and models can also be used in the coming 5^{th} industrial revolution by making the process plans more interactive. This can be made by allowing more real-time human inputs for reviewing and feedbacks on the process plans decisions.

7.3 Engineering Thesis Questions

In this sub-section, it would be useful to conclude with the answer of the typical engineering thesis questions based on the conducted research as follow:

7.3.1. What Is the Engineering Problem to Be Solved?

Nowadays, the manufacturers face several challenges to responsively and cost-effectively handle the product proliferation. Meanwhile, various technological advances are introduced in manufacturing associated with the rise of new manufacturing paradigms such as Smart Manufacturing (Industry 4.0). These technological advances could provide great support to the manufacturers to cope with the increasing product variety management challenges; however, there is a lack of utilizing these technologies to support the rapid changes of the products. Accordingly, two manufacturing domains, namely assembly and hybrid manufacturing, have been addressed through process planning models in a smart manufacturing environment that allow changes in the routing of the material handling equipment or hybrid manufacturing.

7.3.2. In What Sense Are Previous Solutions to this Problem Insufficient?

Assembly Domain: Generating assembly sequence from scratch without benefit from the legacy data is a time-consuming and exhaustive activity. On the other hand, the existing retrieval based assembly sequence methods are not able to retrieve multiple different assembly sequences for the same combination of parts. In addition, some of them are limited to retrieving the most similar existing product variant with respect to the commonality of product parts. Thus, they are not able to retrieve assembly sequence containing groups of parts that did not exist together in any of the considered individual variants. Hence, the used material handling system has limited flexibility as it follows a single pre-determined path.

Hybrid Manufacturing Domain: Only a few methods developed in the literature regarding the process planning for both additive and subtractive processes. All of these works focus on the manufacturing or remanufacturing of a single part. None of them considers the manufacturing of a product family, considering both additive and subtractive processes.

7.3.3. What Are the Developed Solutions in this Research?

Assembly domain: a new approach has been developed for assembly sequence retrieval inspired by the concept of soft-wired galled networks found in phylogenetics and evolutionary studies. It is able to retrieve alternative assembly sequences for products containing groups of parts that did not exist together in any of the considered individual variants. Thus, material handling such as smart AGVs with built-in intelligence can act on requests received digitally or via distributed sensors for changing assembly sequence, and change the processing routes according to pre-planned flow sequence alternatives generated by the new approach.

Hybrid Manufacturing Domain: Three models and approaches are proposed to handle the addressed problem. A novel Mixed Integer Programming model has been developed that generates a process plan for hybrid manufacturing of a product family. Moreover, the model is capable of determining a single product family platform taking into consideration combining both additive and subtractive processes. The other two approaches consider the generation of multi-platform and their process plans to produce the product family variants. The advantage of using multi-platforms over a single platform is the ability to optimally match variants to a particular platform. The Median-Joining Phylogenetic Network Algorithm, which is used in biology to infer the relations between DNA sequence alignment, is utilized to solve the problem. This method depends on only the commonality between the variants. A novel genetic algorithm model has been developed, taking into consideration all associated manufacturing costs, precedence constraints and the product demand.

7.4 Novelty and Contribution

The following sub-sections summarize the novelty and contribution achieved in this research at each addressed domain. As mentioned before, this research addressed two manufacturing domains namely assembly and hybrid manufacturing.

7.4.1. Assembly Domain

This domain was covered in Chapter 3. The contributions are as follows:

- A new approach for the knowledge-based assembly was developed in chapter 2 inspired by the concept of soft-wired galled networks found in biology and phylogenetics.
- A master assembly network that contains alternative assembly sequences for a specific product family is derived from a set of existing assembly sequence trees for variants of the considered family.
- An assembly sequence network for a new product variant that falls within, or significantly overlap with, the boundary of the considered product family can be extracted from the generated master assembly network.
- Alternative assembly sequences for already existing variants can be extracted from the master assembly network.
- A novel GA based model, with a custom-designed crossover and mutation operators, has been developed for generating the master assembly sequence network.

7.4.2. Hybrid Manufacturing Domain

- A novel concept was introduced for the first time in the field of product variety management by designing product family platforms for customization into different product variants utilizing additive and subtractive processes.
- The considered problem of generating product platform(s) for hybrid manufacturing has never been addressed in the literature.
- Hybrid manufacturing macro process planning for product family (variety) was presented for the first time.
- A novel mixed-integer linear programming model was formulated for designing the optimal product platform and determining the type and sequence of additive and/or subtractive processes to transform the product platform into different product family variants and minimizing the total manufacturing cost.
- A novel genetic algorithm based model was developed for determining the optimal number of platforms, the set of features that forms each platform, assignment of the

product variants to each platform and the manufacturing processes either additive or subtractive that is needed to customize the platforms into different product variants.

- A new approach for generating multi-platform and product family process plan utilizing hybrid manufacturing inspired by the concept of median joining phylogenetic networks found in biology and phylogenetics is developed.

7.5 Significance

For the assembly domain, the proposed research presents a logical enabler for adaptive assembly systems by allowing smart AGVs to change their routes to handle any real-time workshop disruptions in Industry 4.0 type of assembly systems. The proposed retrieval process sequence planning method avoids re-generating new assembly sequences every time a new product variant is considered. Hence, it contributes to reducing the overall process planning time and cost. Moreover, the extracted assembly network has multiple alternative assembly sequences that increase the flexibility and adaptability of the system to deal with real-time workshop disruptions. These disruptions may include, but are not limited to, new process-machine assignments, machines breakdown, and machine overload causing bottlenecks and delays. Manufacturers of assembled products (such as valves, household appliances, power tools,…etc.) can apply the developed process planning models

For the hybrid manufacturing domain, the proposed research presents a logical enabler for the manufacturers to combine two technological processes, namely additive and subtractive manufacturing processes, to better manage the product variety. The delayed product differentiation strategy is enhanced by increasing the commonality of features by using additive and subtractive platform concept. Thus, manufacturers become more responsive and adaptable to fluctuating markets and customer demands. The developed models can handle with complex shapes (e.g. gear shafts family) with rotational and prismatic features. Hence, they can be utilized in automotive, aerospace, hydraulic components, instrumentation and medical industries.

Generally, the proposed models have significant benefits as they act as logical enablers for manufacturers to utilize technological advances of the new manufacturing system paradigms such as smart manufacturing (Industry 4.0) to manage the product variety effectively through process planning of product families. The application of this research work would enhance productivity and decrease the manufacturing cost and, hence, provide manufacturers with a competitive edge in responding to the product proliferation.

7.6 Limitations

The models introduced have some limitations. For the assembly sequence model, the GA model does not guarantee the optimality of the solution; however, it is capable of handling large size problems. Like any retrieval method, the quality of the proposed solutions is always subject to the quality of existing data. Hence, planning for future products based on extracted knowledge from these data does not necessarily guarantee the best outcome. The developed method is limited to the products that fall within the scope of available data; human intervention is required for new products that involve new parts that are not existing database. However, continuous updating of available data should improve the quality and widen the scope of extracted knowledge. For the hybrid manufacturing domain, human intervention is required for determining the features and their precedence for the different product variants. The mathematical model is capable of finding the optimum single platform for different product variants. The median-joining phylogenetic algorithm does not consider the demand and the manufacturing costs. The demand for the product family for all models is for a single period. Some features cannot be manufactured by additive manufacturing or subtractive manufacturing. For instance, additive manufacturing cannot fill the small holes with material in case that is needed for customization. Another example, internal features cannot be manufactured by subtractive processes.

7.7 Future work

In this section, several extensions can be considered as a part of future work. These extensions can be summarized in the following points:

7.7.1. Assembly Domain

- Applying the concept of the soft-wired galled network to other manufacturing processes such as machining operations.
- Developing a method for automatically allocating the new parts in the network. In the proposed method, if a new part is introduced in the new variant, a planner assigns the new part location within the network manually.

- Developing a mathematical optimization model to guarantee the optimality of the solution (Master assembly network).
- Assigning higher weights to the existing assembly sequences of those product variants with higher demand.
- Applying a merit-based ranking of generated alternative process sequences to select the best candidate to use when disruptions occur on the shop floor.
- Considering the production volumes in the developed model for knowledge-based assembly sequencing.
- Quantifying cost saving realized by using the developed knowledge-based model compared to traditional (e.g. generative) methods.
- Adding module for allowing real time human feedback on the changing in routing decisions as part of making the method ready for the 5th industrial revolution.

7.7.2. Hybrid Manufacturing Domain

- Adding automatic pre-processing modules to extract the product variants features and establish the precedence relationships that would be helpful particularly for large product families and more complex shapes of features.
- Considering probabilistic demand scenarios for the different product variants be included in the proposed model.
- Investigating the inventory costs for storing the platforms until customization into product variants.
- Quantifying cost saving realized by manufacturing using the proposed hybrid manufacturing platform concept compared to the traditional manufacturing methods.
- Adding module for making the decisions related to the process plans more interactive and user- centered as a need for the 5th industrial revolution.
- Working on integrating hybrid manufacturing and assembly process plans by studying the product architecture to identify which parts should be assembled and which parts should be hybrid manufactured to produce the product family.

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