NEW PRODUCT DESIGN WITH SUSTAINABILITY DRIVEN QUALITY FUNCTION DEPLOYMENT REINFORCED BY PATENT MINING

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PhD Dissertation

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FINAL APPROVAL FOR THESIS

This thesis titled NEW PRODUCT DESIGN WITH SUSTAINABILITY DRIVEN QUALITY FUNCTION DEPLOYMENT REINFORCED BY PATENT MINING has been prepared and submitted by Sezen AYBER in partial fulfillment of the requirements in "Eskişehir Technical University Directive on Graduate Education and Examination" for the Degree of PhD in Industrial Engineering Department has been examined and approved on 06/02/2023.

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ABSTRACT

NEW PRODUCT DESIGN WITH SUSTAINABILITY DRIVEN QUALITY FUNCTION DEPLOYMENT REINFORCED BY PATENT MINING

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In today's business environment, companies need a systematic new product development process that is not only a customer expectations but also sustainability requirements in a short time. QFD is a structural approach to deploy the customer expectations to the product characteristics and production parameters. Besides this, companies should adopt technological developments to their product and production process for maintaining their lives under competitive market conditions. The most reliable and safety way to be aware of the technological developments is to keep track the related patents. But the abundance of patents makes them difficult to track. Patent mining is an effective way to reach the related patents and benefit them. In this study, a new methodology is proposed for integrating sustainability requirements of product besides customer expectations named "New product design with sustainability driven QFD reinforced by patent mining". Sustainability is considered as three dimensions; economic, social and environmental issues. In the proposed methodology, the first matrix of QFD called house of quality (HoQ) is expanded by defining sustainability requirements. AHP is carried out to determine the importance degree of requirements in the HoQ matrix. An intermediate stage is injected into the process planning matrix, the third matrix of QFD, to increase the quality and inclusiveness of the inputs. In the intermediate stage, it is suggested to carry out a patent mining study for the critical processes. The case study on a proposed methodology is implemented on the horizontal stabilizer of the F-16 aircraft. Four stages of QFD are carried out that there are very few studies in the literature that do this. A patent mining study is applied to composite material technology for stabilizer parts. Lingo clustering algorithm was used to identify cluster labels. It is aimed to contribute to the increase of the locality and nationality ratio of the Turkish Air Force by making the product design of this part.

Keywords: New product development, Quality function deployment, Patent mining, Sustainability, Composite material.

ÖZET

PATENT MADENCİLİĞİ İLE GÜÇLENDİRİLMİŞ SÜRDÜRÜLEBİLİRLİK ODAKLI KALİTE FONKSİYON GÖÇERİMİ İLE YENİ ÜRÜN TASARIMI

Sezen AYBER

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Danışman: Prof. Dr. Nihal ERGİNEL

Günümüz iş ortamında şirketler, yalnızca müşteri beklentilerini değil aynı zamanda sürdürülebilirlik gereksinimlerini karşılayacak sistematik bir yeni ürün geliştirme sürecine ihtiyaç duymaktadırlar. Kalite Fonksiyon Göçerimi (KFG), müşteri beklentilerini ürün karakteristiklerine ve üretim parametrelerine dönüştürmek için kullanılan yapısal bir yaklaşımdır. Ayrıca firmalar, rekabetçi piyasa koşullarında hayatlarını sürdürebilmek için teknolojik gelişmeleri ürün ve üretim süreçlerine uyarlamak zorundadırlar. Teknolojik gelişmelerden haberdar olmanın en güvenilir yolu ilgili patentleri takip etmektir. Ancak patentlerin fazla olması takip etmeyi zorlaştırmaktadır. Patent madenciliği, ilgili patentlere ulaşmak ve onlardan fayda sağlamak için etkili bir yoldur. Bu çalışmada, ürünün sürdürülebilirlik gerekliliklerinin müşteri beklentileri ile entegre edilebilmesi için “Patent madenciliği ile güçlendirilmiş sürdürülebilirlik odaklı KFG ile yeni ürün tasarımı” isimli yeni bir metodoloji önerilmiştir. Sürdürülebilirlik, ekonomik, sosyal ve çevresel konular olmak üzere üç boyut olarak ele alınmaktadır. Önerilen metodolojide, Kalite evi (HoQ) olarak adlandırılan KFG'nin ilk matrisi, sürdürülebilirlik gerekliliklerini tanımlayarak genişletilmiştir. HoQ matrisindeki ihtiyaçların önem derecesini belirlemek için AHP kullanılmıştır. Girdilerin kalitesini ve kapsayıcılığını artırmak için KFG'nin üçüncü matrisi olan süreç planlama matrisine bi ara aşama enjekte edilmiştir. Ara aşamada, kritik olarak belirlenen süreçlere yönelik olarak patent madenciliği çalışması yapılması önerilmiştir. Önerilen yönteme ilişkin vaka çalışması, F-16 uçağının yatay stabilizatöründe yapılmıştır. KFG'nin dört aşaması da gerçekleştirilmiştir, literatürde dört aşamalı çok az çalışma bulunmaktadır. Stabilizatör parçaları için kompozit malzeme teknolojisine ilişkin patent madenciliği çalışması yapılmıştır. Küme etiketlerini tanımlamak için Lingo kümeleme algoritması kullanılmıştır. Parçanın ürün tasarımı yapılarak, Türk Hava Kuvvetleri'nin yerlilik ve milliyet oranının artmasına katkı sağlamak amaçlanmıştır.

Anahtar Sözcükler: Yeni ürün geliştirme, Kalite fonksiyon göçerimi, Patent madenciliği, Sürdürülebilirlik, Kompozit malzeme.

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I am also grateful to my dear mother and father for their love and guidance. I would like to dedicate this dissertation to my husband, Kadir and my daughter, Elif. Without Kadir's invaluable support, patience, and encouragement, it would be very difficult to complete this work.

Sezen AYBER

06/02/2023

STATEMENT OF COMPLIANCE WITH ETHICAL PRINCIPLES AND RULES

I hereby truthfully declare that this thesis is an original work prepared by me; that I have behaved in accordance with the scientific ethical principles and rules throughout the stages of preparation, data collection, analysis and presentation of my work; that I have cited the sources of all the data and information that could be obtained within the scope of this study, and included these sources in the references section; and that this study has been scanned for plagiarism with “scientific plagiarism detection program” used by Eskişehir Technical University, and that “it does not have any plagiarism” whatsoever. I also declare that, if a case contrary to my declaration is detected in my work at any time, I hereby express my consent to all the ethical and legal consequences that are involved.

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GLOSSARY OF SYMBOLS AND ABBREVIATIONS

NPD	:	New Product Development
QFD	:	Quality Function Deployment
AHP	:	Analytical Hierarchy Process
VoC	:	Voice of Customer
TRIZ	:	Theory of Inventive Problem Solving
HoQ	:	House of Quality
TOPSIS	:	Technique for Order Preference by Similarity to Ideal Solution
ELECTRE	:	Elimination and Choice Translating Reality
PROMETHEE	:	Preference Ranking Organization Method for Enrichment Evaluations
LDA	:	Latent Dirichlet Allocation
TRM	:	Technology Road Maps
LCA	:	Life Cycle Analysis
QFDE	:	Quality Function Deployment for Environment
NLP	:	Natural Language Processing
PLSA	:	Probabilistic Latent Semantic Analysis
CTM	:	Correlated Topic Model
SVD	:	Singular Value Decomposition
VSM	:	Vector Space Model
TF	:	Term Frequency
TF-IDF	:	Term Frequency with Inverse Document Frequency
WIPO	:	The World Intellectual Property Organization
USPTO	:	United States Patent and Trademark Office
TPE	:	Turkish Patent Office
EPO	:	European Patent Office
JPO	:	Japan Patent Office
CNN	:	Convolutional Neural Networks
SAO	:	Subject-Action-Object Semantic Analysis
IPC	:	International Patent Classification

1. INTRODUCTION

In the current high-tech and internationally competitive environment, the rapid delivery of products or services to customers is vital for companies to maintain existences and market shares. For these reasons, New Product Development (NPD) activities have become increasingly important in recent years (Wheelwright and Clark, 2007; Alptekin and Tolga, 2006).

Meeting different and fast changing customer demands has become an extremely important issue in the NPD process. Incomplete or unclear product descriptions lead to product errors or increased production time. A clear apprehension of customer needs in the NPD process enables us to produce successful products and reduce production time. Therefore, current industries need to use customer-oriented NPD methods effectively. The NPD process is close to the customer and occurs at the product life cycle's start point. While only 10-15% of the product life cycle passes through the NPD stage, 75-85% of the total cost of the cycle is identified in the same stage (Ehrlenspiel, 2003; Gonçalves-Coelho, Mourão and Pereira, 2005; Magrab et al., 2010). In many, 15% of these costs actually occur in the NPD phase. Besides this, the root causes of 60% of the failures of the product during the warranty period are the decisions taken during the NPD phase (Gonçalves-Coelho, Mourão and Pereira, 2005). Since the value definition of the customer is also the first stage, the decisions made at this stage have the potential to affect all business functions throughout the life of the product. Holistic studies focusing on NPD processes will directly improve the operational performance. In this respect, there is a necessary to fully understand the customer requirements, to balance them with the strategies of the producers, to offer products that satisfy the customers according to the competing products, to create a systematic customer-oriented NPD process. Quality Function Deployment (QFD) is a systematic and customer-focused method that is used for transforming customer needs into engineering characteristics (Sullivian, 1986). QFD is widely used for developing suitable products or services at each phase of the NPD and production.

While creating the customer-oriented NPD process for meeting customer needs, companies should make sustainable product designs. Sustainability aims to make social, environmental and economic improvements in a competitive environment (Carter and Rogers 2008). The 20th century witnessed the progress of technology and industrialization. However, the rapid progress came with important environmental problems by producing waste, toxic materials, consuming resources, bringing along pollution, climate change, resource deficiency, etc. (Bentley, 2002; Sepúlveda et al., 2010). As a result, these problems have created awareness and have pushed companies to develop sustainable product design. Also, various countries, such as European Union countries, USA, Japan, South Korea, have legislations that force companies to ensure sustainability (Sinha-Khetriwal, Kraeuchi and Schwaninger, 2005; Davis and Heart, 2008; Kahhat et al., 2008; Cui and Forssberg, 2003). These legislations determine permitted wastes, toxic materials, consumption levels of energy (Gurauskiene and Varzinskas, 2006). The objectives of incorporating sustainability into NPD are: protecting natural resources without contamination, obtaining economic consistency, providing safety and health for workers, consumers and society, achieving high-quality performance.

The emergence time of technological developments in recent years has considerably shortened. The present century has made incredible progress in terms of access to information and the speed of communication. Due to these competitive conditions brought by globalization, managers need to follow technological developments and keep up with these developments. Technology forecast is a systematic technique used to understand the direction, speed, characteristics and effects of technological progress. Technological changes can be made by an individual, organization, or nation. Technology should be estimated by allocating resources for specific purposes before making important decisions. The systematic inclusion of technology forecasts in the process of NPD is extremely important for the competitiveness perspective. Academic publications and patents are the first indicators of technological developments and enterprises' technology prediction studies should use them effectively. It is seen that this valuable information in the patent data contains many and complex patterns in industrial, economic and scientific terms. It is significant to extract hidden patterns from big data, such as patent databases, and to get data that every people can easily understand and use. Patent mining is a methodology to process, extract and interpret patents' data for analyzing the present and forthcoming technological trends. Patents include both structured and unstructured data. For analyzing and discovering unstructured data like patents' abstracts; text mining, which is viewed as a data mining extension, can be applied in patent mining studies.

The purpose of this thesis is to suggest an integrated and technology-based NPD methodology to fulfill customer and sustainability requirements. The suggested method is based on the four-phase model of QFD. The proposed method is named as new product design with sustainability driven QFD reinforced by patent mining. The significance of this thesis is listed as follows:

1. In classical QFD studies, only meeting customer needs is considered. In this study, customer needs and sustainability requirements are handled together to achieve sustainable production. The first matrix of QFD is extended with defining sustainability requirements. In the literature, only one aspect of sustainability is generally studied with QFD. Studies dealing with all aspects of sustainability (social, environmental and economic) with QFD are rare. Analytical Hierarchy Process (AHP) is used while determining the importance degrees of customer needs and sustainability requirements.

2. This study defines an intermediate stage for the third matrix of QFD (process planning). In classical QFD studies, in the third matrix, manufacturing operations and their target values are determined by the QFD team's experiences. This study offers an intermediate stage to enhance sources of data. We executed a patent mining research for determining manufacturing operations and their target values for the selected process. The Lingo clustering algorithm is implemented for extracting topics using the patent data on composite material technology. The cluster labels are used while identifying operations. This stage is injected to improve the quality and inclusiveness of the inputs used in the QFD. In the literature, there is no study that improves the data sources of the third matrix.

3. In the literature, mostly QFD studies terminate when the first matrix of QFD is built. In this study, all four matrices of QFD are built. QFD converts firstly customer needs into engineering characteristics, secondly converts engineering characteristics into part characteristics, thirdly converts part characteristics into manufacturing operations, then fourthly converts manufacturing operations into operations or controls.

4. Text mining is the process that extracts information from written resources by using a computer to discover previously unknown new information (Hearst, 1999). Patent mining studies can be done with approaches in the text mining. In the literature, researchers usually used patent mining for products. In addition, this study used patent mining for a production process. Composite forming production process is the selected process, and this is the first patent mining study for composite forming.

5. In this study, the horizontal stabilizer of F-16 aircraft is chosen as a case study. This stabilizer is a composite structural part of the aircraft. With using the proposed method, all product development stages of it are defined. It is approximately estimated that with the start of production of this part, an annual cost savings of one million dollars will be achieved. While calculating the annual cost savings, the cost of purchasing units from abroad and the number of materials needed annually are multiplied, and then the production cost that will occur as a result of new product development is subtracted. Also, the rate of locality and nationality of the Turkish Air Force will increase.

The rest of this thesis is arranged as: the literature review and background for the proposed methodology are presented in section 2, new product design with sustainability driven QFD reinforced by patent mining method is explained in section 3. A case study of an aircraft structural component manufacturing is represented in section 4, the results and conclusion are discussed in section 5.

2. LITERATURE REVIEW AND BACKGROUND

The literature is examined in four parts as New Product Development, Quality Function Deployment, text mining and patent mining.

2.1. New Product Development

The world is getting more and more competitive due to factors such as globalization, rapidly changing environmental conditions, market dynamics and the fast development of technology. In this matter, innovation becomes the most important issue to survive, so companies must work on sustainable innovations. The foundation of these innovations is to develop new products and work on processes because tremendous innovations and improvements can be done by products and processes.

New Product Development is a process to extend lives and markets of existed products by including devices by which a company competes like new characteristics, styles, pricing, packaging (Levitt, 1966). NPD contains dynamic and strong interactions between internal and external aspects (Harmancioglu et al., 2007). It takes place at the core of the business because NPD builds capabilities by generating knowledge, methods, abilities that runs company's future (Wheelwright and Clark, 2007). NPD is the conversion of estimates about technology, marketing opportunity and gap into a service or product (Krishnan and Ulrich, 2001).

NPD is not only producing new goods but also improving existing products, adding existing lines, repositioning current products (Palmer, 2009). NPD can be defined as the conversion process of customer needs, the push of the technology, opportunities, systematic innovations into new products, services, patents.

Takikonda and Zeithaml (2002) introduce the newness as the degree of change and Johannessen, Olsen and Lumpkin (2001) examine 6 different categories of the innovation: new products, services, production methods, markets, supply sources, organizing ways. Murthy et al. (2008) determine the newness of products by using different aspects: New to the world, new to the industry, new to the company, new to the market, new to the customer. They classify the newness as new technology, new process, new features, new uses, and new design.

NPD is vital for companies by having first-mover advantages, making competency with differentiation, creating long run achievement and sustainable performance (Ernst, 2002; McCarthy et al., 2006). NPD is a continuous process and contains two different processes: diffusion and adoption. Diffusion is a macro-process that deals with spreading out any type of innovation, like new products, services, ideas, practices to the consumer. Adoption is a micro-process that handles stages of decision making to accept or reject a new product from the customer-perspective (Schiffman and Kanuk, 1997).

The history of NPD can be summarized into six categories: the birth of NPD in the 1960s, the emphasis of NPD processes in the 1970s, the sizeable attention on NPD strategy in the 1980s, the emphasis on NPD tracking metrics in the 1990s, highlighting the knowledge management and value engineering in the 2000s, significant attentiveness to green, futuristic perspective and comprehensive methods in the 2010s (Morgan et al., 2015; Anderson, 2008; Swink and Song, 2007).

Booz, Allen and Hamilton (1982) introduced NPD in seven separate stages. These stages are described in Figure 2.1.

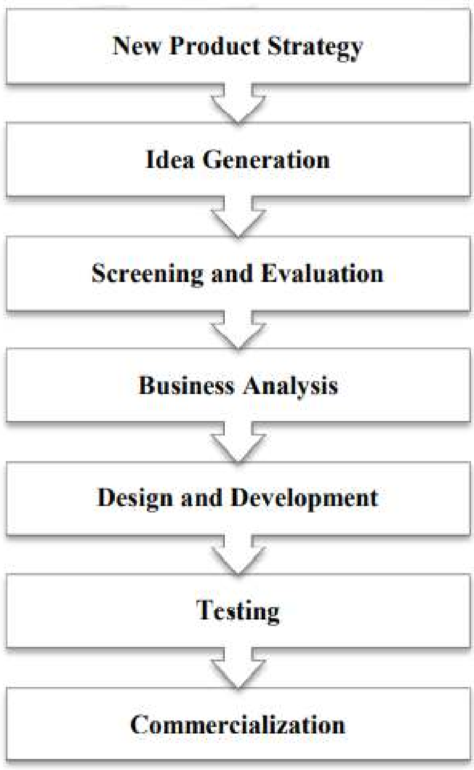


Figure 2.1. *Stages of NPD (Booz, Allen and Hamilton, 1982)*

One of the traditional path for NPD is the sequential NPD process, as seen in Figure 2.2. (Oakley, 1984; Ronkainen, 1985). The next stage cannot start before the previous stage is finished, so this process is slow.

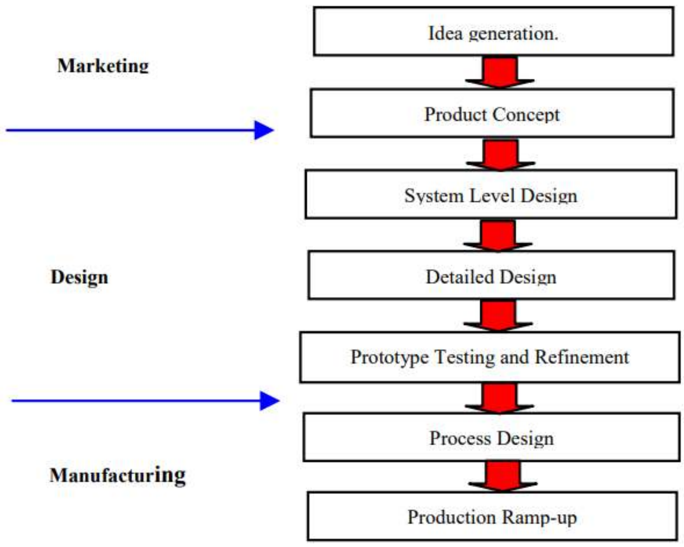


Figure 2.2. *Sequential NPD process (Oakley, 1984; Ronkainen, 1985)*

Kotler and Armstrong (2010) suggested eight major stages in NPD and Figure 2.3. shows these stages.

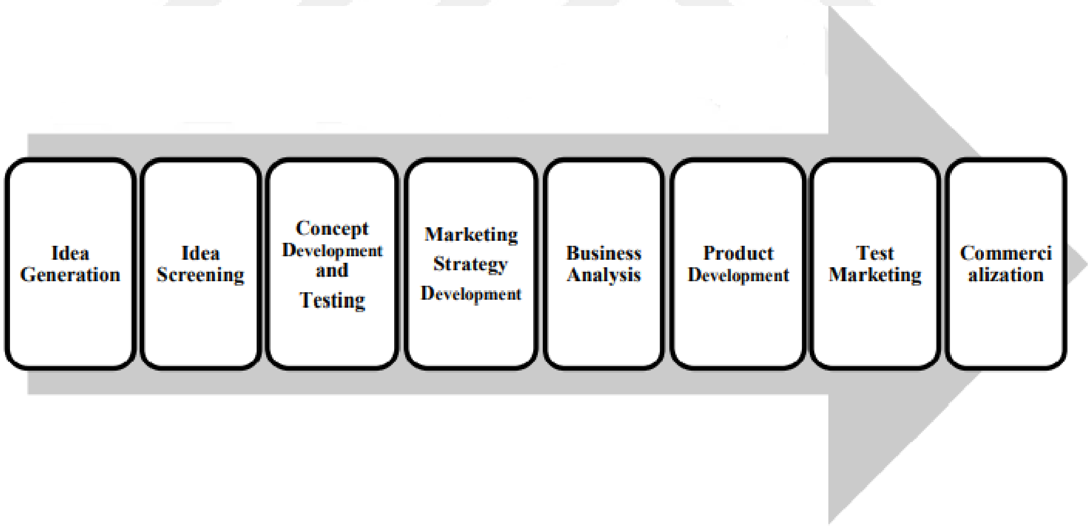


Figure 2.3. *Eight stages in NPD (Kotler and Armstrong, 2010)*

Couger (1995) presented creativity as a basic component of the entire process of innovation and Figure 2.4. describes the mentioned process.

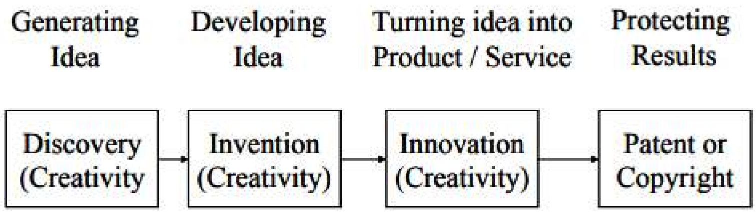


Figure 2.4. *Creativity in process of the innovation (Couger, 1995)*

Herstatt et al. (2004) suggested a process with fuzzy front end phase and the Figure 2.5. describes all phases.

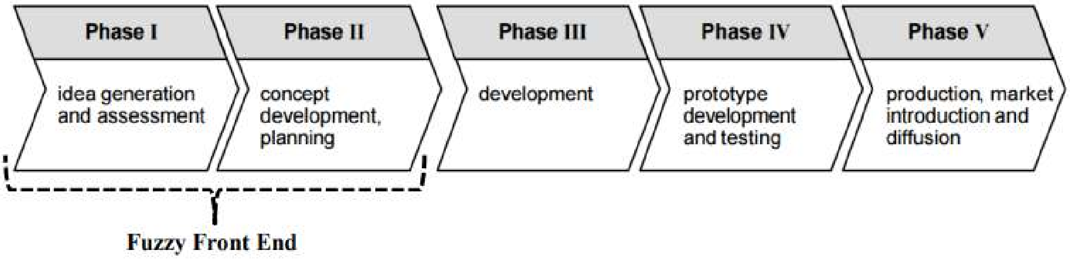


Figure 2.5. *NPD process with fuzzy front end (Herstatt et al., 2004)*

Cooper (2013) suggested a model that is named as Launch Stage-Gate System and the Figure 2.6. describes five stages and there are five gates between them.

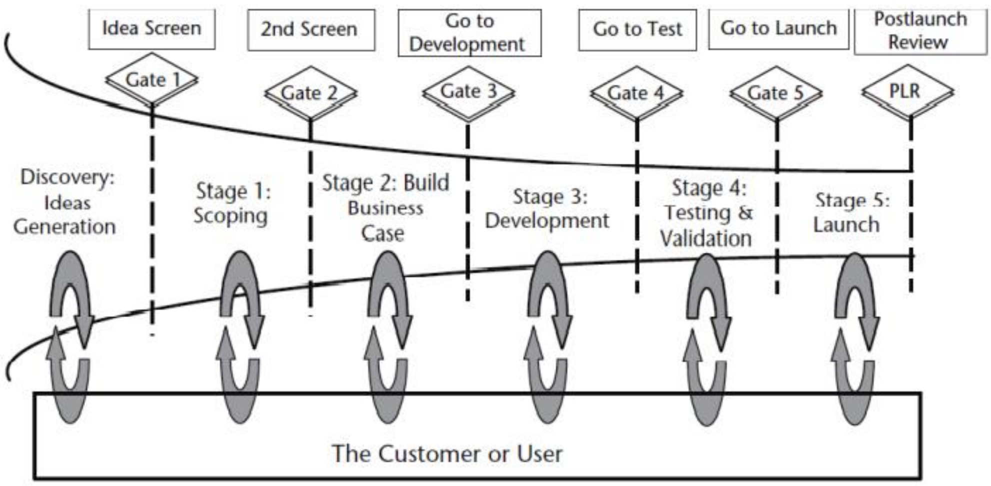


Figure 2.6. *Launch Stage-Gate System for NPD (Cooper, 2013)*

In traditional NPD models, the metaphor is relay race, and the procedure is sequential. Human capital is functional specialists, team is organizational units, work flow is phase to phase. Innovation is incremental and continuous, the approach is linear; the structure is fixed, and the array is discrete. On the other hand, in modern NPD models, the metaphor is rugby, and the procedure is overlapping. Human capital is a multidisciplinary team, the team is cross-functional, work flow is from start to finish. Innovation is highly radical and discontinuous, the approach is integrated; the structure is rule-breaking, and the array is continuous. (Davari et al., 2017).

Today, companies should focus not only on production in accordance with customer needs but also on protecting nature and providing economic and social sustainability in NPD processes. They are also looking for new methods to adapt to developing technology, increasing competition and to maximize customer satisfaction. There is a need for holistic approaches that address the market, technical, technology and social driving forces that affect the product development process together.

2.2. Quality Function Deployment

QFD is a systematic method for analyzing customer needs that are named as the Voice of the Customer (VoC) and converting customer needs into product or service technical parameters. It is also a planning process for understanding what we do and how we do by combining different departments in a company so that the big picture could be seen more easily by everyone. By using this method, technical requirements can be ranked and, according to these ranking efforts, improvement can concentrate on the most encouraging areas.

QFD is an overall concept used in the process of transforming customer needs into engineering characteristics on account of developing suitable products or services at each phase of NPD and production (Sullivan, 1986). QFD can be defined by a group of matrices that transform customer needs into engineering needs and convert them into requirements of production and assembly via deploying VoC to the company (Garwin, 1993).

The history of this method begins with Japan’s Total Quality Control movement in the 1960s. Dr. Yoji Akao conceptualized QFD firstly in 1966 and this method was used at Mitsubishi Industries’ Kobe Shipyards in 1972. Dr. Akao and Dr. Mizuno published a Japanese book about QFD namely “Deployment of the Quality Function” in 1978. Dr. Akao first presented QFD to the world in American Society for Quality Control journal in 1983 (Akao, 1990). Then, in the United States, Glenn Mazur and Richard Zultner took the leadership of QFD applications, also other pioneers of QFD were Bob King, John Hauser, Dan Clausing and Lawrence Sullivan (King, 1989; Hauser and Clausing, 1988; Sullivian, 1986), and they made successful applications and contributions to the method. Currently, it has been commonly used and carried out in several areas, such as NPD, quality management, decision sciences, all over the world (Sivasamy et al., 2016). Chan and Wu (2002) examined the literature on QFD in detail. Also, a literature research is applied within the scope of this thesis to understand past studies on QFD better. Scopus is determined as the database and 1.102 document results are attained. Searching is restricted to articles and journals, English is chosen, QFD is selected as the keyword between 2000 and 2022. 1.102 articles are examined and Figures 2.7. and 2.8. are obtained. The highest publication is with 94 articles in 2018. Subject areas that QFD is implemented are engineering with 31%, business, management, accounting with 17%, computer science with 17%, decision sciences with 8%, mathematics with 7%, social sciences with 6%, environmental science with 4%, energy with 2%, economics and finance with 2%, materials science with 2%, agricultural sciences with 1%, and others with 3%.

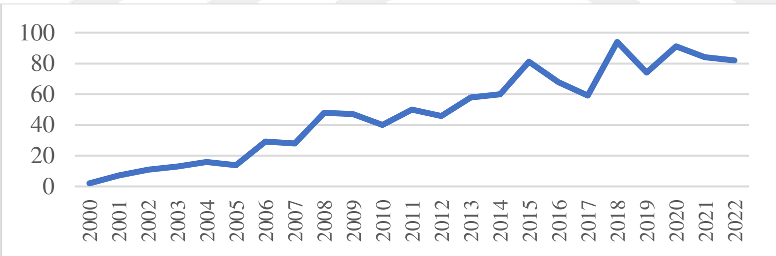


Figure 2.7. *Frequencies of publications on QFD by year*

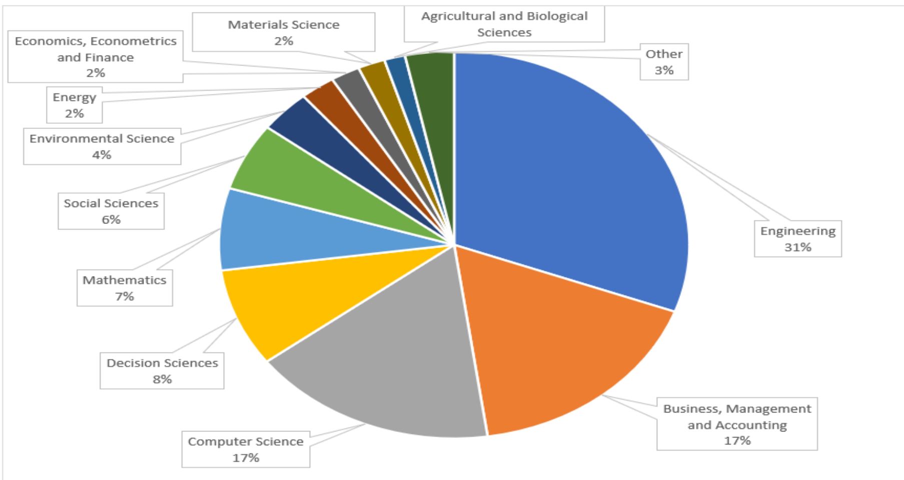


Figure 2.8. *QFD subject areas*

There are many studies in the literature on the use of the QFD method in NPD. In this part, some QFD studies related to NPD that are reached in the literature are presented. Vonderembse and Raghunathan (1997) investigated 40 different NPD projects with QFD and they showed that the NPD could accomplish decreasing cost and time, and increasing customer satisfaction via using QFD. Tan, Xie and Shen (1999) presented a case study that QFD and Kano Model were used for a NPD process and they emphasized that usage of QFD ensured the competitive advantage. Costa, Dekker and Jongen (2000) applied a case study for a firm in the food industry. Also, they discussed advantages and limitations of QFD in NPD. Pullman, Moore and Wardell (2002) presented a study that integrated profit analysis and QFD. They analyzed customer requirements and predicted NPD importances and market reactions. Sharma and Rawani (2006) suggested a product development process with using QFD method. Curcic and Milunovic (2007) carried out a QFD study for increasing the quality of product and meeting customer needs in a soap company. Miguel (2007) discussed the usability of QFD in NPD by examining different four companies' practices. Sireli, Kauffmann and Ozan (2007) applied QFD in a NASA's project that included cockpit information system and suggested a new framework for NPD. Ionica and Leba (2015) argued QFD using in NPD and they showed effective results by using QFD in the technological and medical fields. Milunovic Koprivica and Filipovic (2018) presented a study in which results were discussed by applying traditional and fuzzy QFD in the NPD process of an electric kettle. Erdil and Arani (2019) presented a framework via using QFD and conducted a case study for the ceramic tile. Wang et al. (2020) applied the fuzzy QFD and proposed a framework for a vehicle design in China. Yang et al. (2021) extended QFD by using the Theory of Inventive Problem Solving (TRIZ) and they implemented the proposed method in the wind power system design. Kulcsár, Gábor and Csiszé (2022) integrated network science into QFD and they applied a case study to the CNC machine. These mentioned studies are summed up as in the Table 2.1.

Table 2.1. *Studies related to QFD and NPD in the literature*

Source	Method	Case Study
Vonderembse and Raghunathan (1997)	A structural model to make measures of the organizational aspects of QFD	40 different companies (90% in manufacturing industry)
Tan, Xie and Shen (1999)	QFD and Kano Model	Web page design
Costa, Dekker and Jongen (2000)	QFD	Tomato ketchup
Pullman, Moore and Wardell (2002)	QFD and conjoint analysis	Climbing harness
Sharma and Rawani (2006)	Customer Driven Product Development (CDPD) based on QFD	Manufacturing industry
Curcic and Milunovic (2007)	QFD	Soap
Miguel (2007)	QFD	Electric vehicle
Sireli, Kauffmann and Ozan (2007)	A new framework via using QFD and KANO Model	NASA's cockpit information system
Ionica and Leba (2015)	QFD	Biometric identification system
Milunovic Koprivica and Filipovic (2018)	Traditional and fuzzy QFD	Electric kettle
Erdil and Arani (2019)	QFD	Ceramic tile
Wang et al. (2020)	Fuzzy QFD	A vehicle design
Yang et al. (2021)	QFD and TRIZ	Wind power system
Kulcsár, Gábor and Csiszé (2022)	Network science and QFD	CNC machine

QFD provides different advantages, such as high customer satisfaction, better communication among teams, an increase in product quality, efficiency of the process and company income, a decrease in product design time and cost. QFD focuses on positive quality and it is also proactive method. QFD aims designed-in quality (Chan and Wu, 2002).

In QFD studies, selected product and customers are defined firstly. Then, QFD uses matrices or quality charts. The four-phase model is the most commonly known model and can be seen in Figure 2.9. The first matrix is named as product planning, the second matrix is named as part deployment, the third matrix is named as process planning, and the last one is named as production/operation planning, respectively. The first matrix converts customer requirements into technical characteristics; the second one converts technical characteristics into characteristics of part; the third one converts characteristics of part into manufacturing operations; the fourth one converts manufacturing operations into operations or controls (Shillito, 1994).

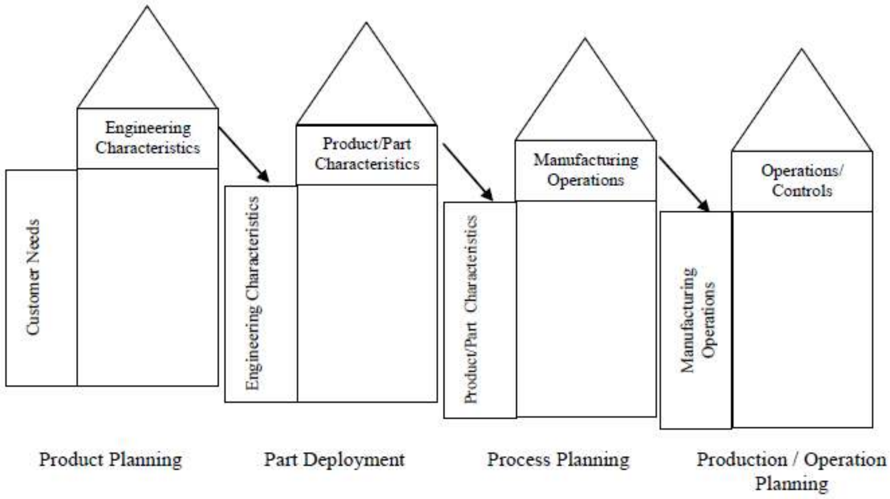


Figure 2.9. *Four-phase model of QFD (Shillito, 1994)*

The first matrix is also named as the house of quality (HoQ), and this matrix is the most used one while applying QFD in studies. Most QFD studies terminate after the HoQ is created. Han et al. (2001) stated that significant benefit could be provided from only completing the HoQ. Cox (1992) emphasized that no more than a five percent of firms go beyond the HoQ. Abdolshah and Moradi (2013) discovered that only HoQ was applied because of the concerns of time and cost in companies and academic papers.

Sawada introduced the quality chart by HoQ firstly at a conference about quality control in 1979 due to its shape (Akao, 1997). HoQ is a map that is used to plan and communicate multifunctionally (Hauser and Clausing, 1988). It contains seven parts that can be shown in Figure 2.10.

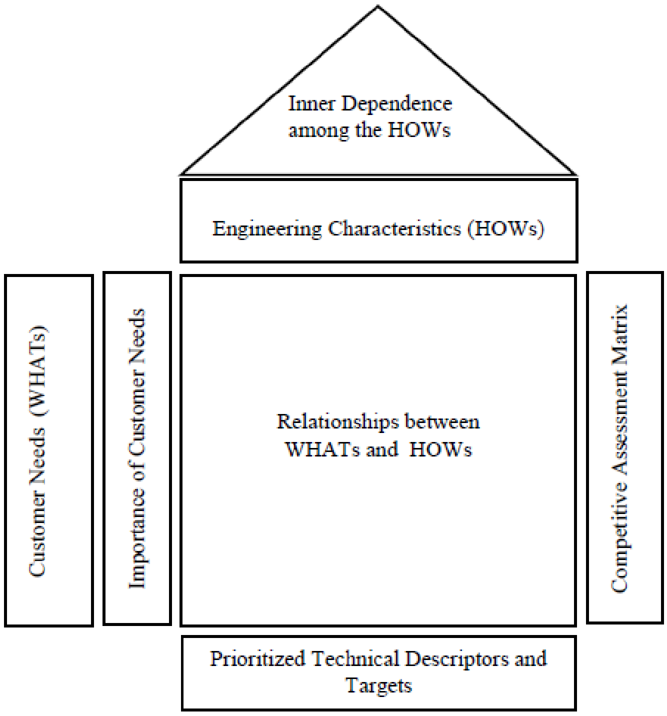


Figure 2.10. *The HoQ matrix (Hauser and Clausing, 1988)*

A reference HoQ can be found in Figure 2.11. that is proposed by ISO 16355 “Applications of Statistical and Related Methods to New Technology and Product Development Process”.

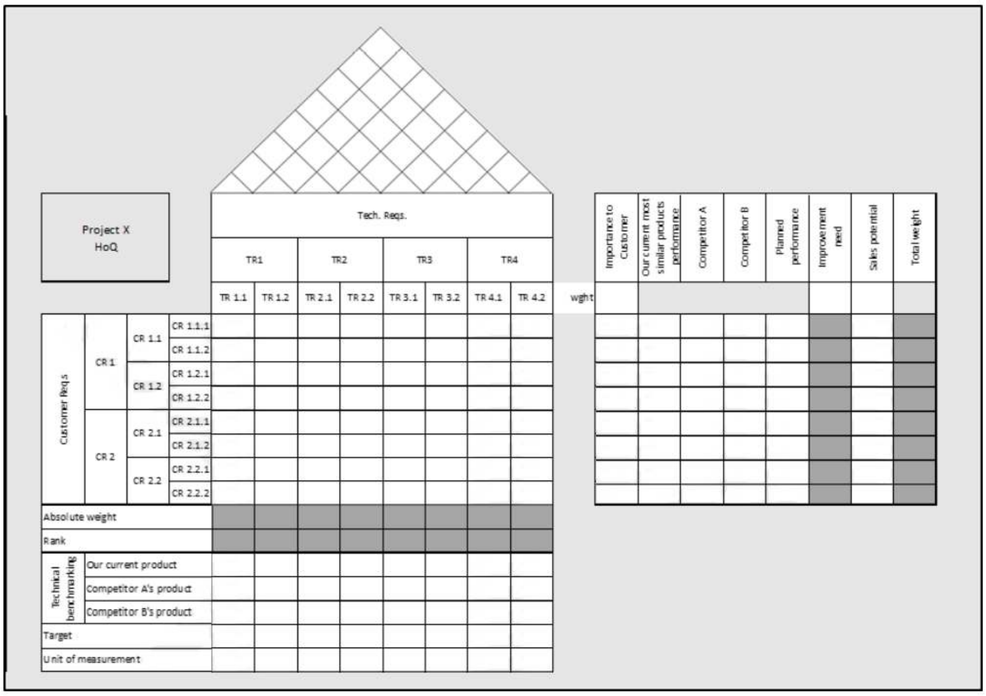


Figure 2.11. *Representative HoQ chart (ISO 16355-1, 2015)*

Definitions and variables related to HoQ are presented (Akao, 1990):

i: Customer needs' index, $1 \leq i \leq n$

j: Engineering characterictics' index, $1 \leq j \leq m$

CN_i: $Customer\ need\ i.$ The implementation of QFD based on the literature is given as follows:

Step 1. Customer needs (WHATs): The HoQ starts with the collecting process of customers' needs for the chosen product. Customers put into words what they need. The list of these needs and wants can be obtained through surveys, observations, interviews, gemba visits, studies of focus group, complaint data of customer and also customer reviews through the Internet such as blogs, social networks, E-Trade sites (Mazur, 2003; Kapucugil-İkiz and Özdağoğlu, 2015). Not all customers have to be end users.

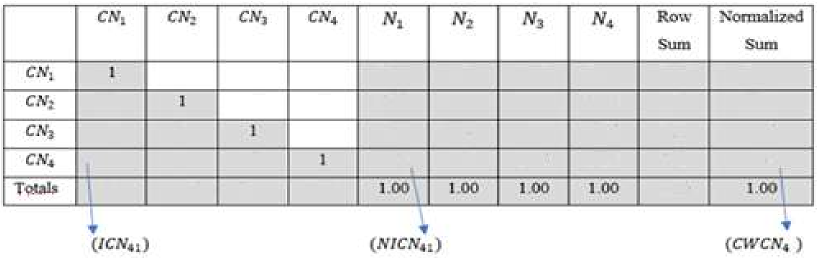
If the requirement list is long, grouping of requirements helps to handle more effectively. Hari et al. (2007) studied to handle the needs for complicated systems. Affinity diagram method, that is a method to organize similar data, can be used for managing customer needs (Köksal and Eğitman, 1998; Li et al., 2009).

For classification of customer needs, the Kano model can also be used. In this model, all requirements/attributes are not equal and they are classified into the following categories: Must-be, performance, attractive, indifference, reverse attributes (Kano et al., 1984). Kano et al. (1984) proposed a methodology that contained functional question and dysfunctional question. Kano model is useful for understanding customer needs. After the Kano model, the tree structure can be used to group customer needs and assure that all customer needs are covered.

Step 2. Engineering characteristics (HOWs): Engineering characteristics define the selected product in the company's language. Engineering characteristics must be measurable and comparable, and the QFD team defines them. While defining engineering characteristics, brainstorming technique and/or a tree analogy can be applied.

An QFD study can be implemented by an interdisciplinary team. It has members from different organization functions such as marketing, research and development (R&D), production and quality. King (1989) stated that 6–8 is the ideal number for the team.

Step 3. Importance of customer needs: Customer needs are ranked by the company for determining the most significant ones. The weighting of customer needs is usually based on experience of the QFD team or surveys. Also, quantitative techniques such as AHP, weighted sum method, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Elimination and Choice Translating Reality (ELECTRE), Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) can be used. ISO 16355 recommends weighting customer requirements using AHP, developed by Saaty in 1980 (Saaty, 2008), to have ratio scale numbers. The classical QFD uses ordinal scale numbers or some symbols (Akao, 1990). Vaidya and Kumar (2006) reviewed the literature on AHP. A representative calculation table for AHP is given in Figure 2.12.



	CN_1	CN_2	CN_3	CN_4	N_1	N_2	N_3	N_4	Row Sum	Normalized Sum
CN_1	1									
CN_2		1								
CN_3			1							
CN_4				1						
Totals					1.00	1.00	1.00	1.00		1.00

Figure 2.12. *Representative calculation table for AHP*

Grey cells are obtained automatically as follows:

i: Row number' index,

k: Column number' index

ICN_{ik}*:* The answer to the question, "How much CN_i is more important than CN_k?". Values in Table 2.2. are used to answer the question. Diagonal cells take the value 1 in Figure 2.12. and the other cells are calculated by taking the inverse of their symmetrical value with respect to the diagonal in columns CN_1 to CN_4. $NICN_{ik}$ are the normalized values.

$$NICN_{ik} = \frac{ICN_{ik}}{\sum_{k=1}^{n} ICN_{ik}} \tag{2.1}$$

Table 2.2. *AHP importance rates*

Answer	Grade
Equally important	1
Moderately more important	3
Strongly more important	5
Very strongly important	7
Extremely more important	9

Then, the row sum column is calculated by taking the sum of columns N_1 to N_4.

$$CWCN_i = \frac{\sum_{k=1}^{n} NICN_{ik}}{\sum_{i=1}^{n}\sum_{k=1}^{n} NICN_{ik}} \tag{2.2}$$

$$\sum_{i=1}^{n} CWCN_i = 1 \tag{2.3}$$

If more than one customer makes comparison, the geometric mean values of these are taken. Then, before using weights, the consistency check should be done. The Consistency Index (CI) is calculated firstly, where λ_{max} is the highest value of the AHP matrix's eigenvalues. Consistency Ratio (CR) is calculated secondly, where RI is the Random Inconsistency Index (Saaty, 2008).

$$CI = \frac{\lambda_{max} - \mathrm{n}}{n - 1} \tag{2.4}$$

$$CR = \frac{CI}{RI} \tag{2.5}$$

After the consistency check, if the calculated CR value is less than 0.10, it shows a consistent AHP calculation table for using weights.

Weighted sum method can be applied to determine importances, and Marler and Arora (2010) address the use of this method. Hwang and Yoon offered the TOPSIS technique in 1981, stands positive and negative ideal solutions for choosing. Behzadian et al. (2012) review this method and its applications. Govindan and Jepsen (2016) provide a literature review on ELECTRE, developed by Benayoun, Roy and Susman. This technique uses a pair wise comparison to rank. Brans developed PROMETHEE in 1982 and it uses pair by pair comparisons like ELECTRE and Behzadian et al. (2010) studied a detailed review. Kokaraki et al. (2019) compared these methods. Also, Singh and Kumar (2015) applied QFD via using Analytical Network Process (ANP), which is a general form of AHP.

Step 4. The assessment matrix for competitiveness: It includes an investigation of the chosen product, also products of the company's competitors. The data can be handled by enquiring the customers. A scale between 1-5 can be applied; 5 is the maximal score, while 1 is the minimal one. Also, a target value for each customer need is examined. Then, weights for each customer need are calculated and normalized.

FCN_i: Performance value of the company's for CN_i

$$1 \leq FCN_i \leq 5 \tag{2.6}$$

ACN_i: Performance value of competitor A's for CN_i

$$1 \leq ACN_i \leq 5 \tag{2.7}$$

BCN_i: Performance value of competitor B's for CN_i

$$1 \leq BCN_i \leq 5 \tag{2.8}$$

TCN_i: Target performance value for CN_i

$$1 \leq TCN_i \leq 5 \tag{2.9}$$

To determine competitive assessment matrix weights AHP method can be applied. Dolgun and Köksal (2018) used weight values as follows:

$CAWCN_i$: Weight for competitive analysis of CN_i

$$CAWCN_i = \begin{cases} 0.558\ if\ TCN_i\ is\ much\ better\ than\ FCN_i \\ 0.263\ if\ TCN_i\ is\ better\ than\ FCN_i \\ 0.122\ if\ TCN_i\ is\ almost\ equal\ to\ FCN_i \\ 0.057\ if\ FCN_i\ is\ better\ than\ TCN_i \end{cases} \tag{2.10}$$

$NCAWCN_i$: Normalized competitive analysis weight of CN_i

$$NCAWCN_i = \frac{CAWCN_i}{\sum_{i=1}^{n} CAWCN_i} \tag{2.11}$$

$SPCN_i$: Sales point for CN_i. Dolgun and Köksal (2018) defined as follows:

$$SPCN_i = \begin{cases} 0.633 \text{ if } CN_i \text{ has a major contribution to sales} \\ 0.260 \text{ if } CN_i \text{ has minor contribution to sales} \\ 0.106 \text{ if } CN_i \text{ does not contribute to sales significantly} \end{cases} \tag{2.12}$$

$NSPCN_i$: Normalized sales point coefficient for CN_i.

$$NSPCN_i = \frac{SPCN_i}{\sum_{i=1}^{n} SPCN_i} \tag{2.13}$$

w_k: Weights while calculating of the total weight of CN_i.

$$\sum_{k=1}^{3} w_k = 1 \tag{2.14}$$

$TWCN_i$: CN_i's total weight

$$TWCN_i = (w_1 x CWCN_i) + (w_2 x NCAWCN_i) + (w_3 x NSPCN_i) \tag{2.15}$$

$$\sum_{i=1}^{n} TWCN_i = 1 \tag{2.16}$$

Step 5. Relationships between WHATs and HOWs: The correlations between customer wants and engineering characteristics are usually indicated by using symbols that are transformed on a rate scale.

r_{ij}: Relationship degree between CN_i and EC_j

Relationship degrees may be determined according to two methods (ISO 16355):

Traditional QFD:

$$r_{ij} = \begin{cases} Blank\ if\ there\ is\ no\ relation \\ 1\ if\ there\ is\ weak\ relation \\ 3\ if\ there\ is\ medium\ relation \\ 9\ if\ there\ is\ strong\ relation \end{cases} \tag{2.17}$$

Modern QFD:

It uses the ratio scale because ratio scales can be used in mathematical operations. Degrees of relationships can be determined with using 5-point or 9-point scales that presented in Table 2.3. and 2.4.

Table 2.3. *5-point scale values*

Relationship	Scale
Weak	0.069
Moderate	0.135
Strong	0.267
Very Strong	0.518
Extremely Strong	1.000

Table 2.4. *9-point scale values*

Relationship	Scale
Weak	0.059
Weak to Moderate	0.079
Moderate	0.112
Moderate to Strong	0.162
Strong	0.237
Strong to Very Strong	0.344
Very Strong	0.498
Very Strong to Extremely Strong	0.712
Extremely Strong	1.000

Step 6. Inner dependency between the HOWs: The roof matrix shows how technical requirements impact each other. While a positive relationship shows that any two of them can promote each other, a negative relationship shows that two engineering characteristics correlate negatively.

c_{jl} : correlation value between engineering characteristics j and l

$$c_{jl} = \begin{cases} +1 \; if \; EC_j \; and EC_l \; correlate \; positively \\ 0 \; if \; there \; is \; no \; correlation \; between \; EC_j \; and EC_l \\ -1 \; if \; EC_j \; and EC_l \; correlate \; negatively \end{cases} \tag{2.18}$$

When negative relationships among technical requirements occur, TRIZ can be implemented (Salamatov et al., 1996). Yamashina, Ito and Kawada (2002) used QFD with TRIZ. Ilevbare, Probert and Phaal (2013) provided brief information on TRIZ in their study. The TRIZ method transforms the problem into similar standard problems by using 39 engineering problems. Then, by using the 39x39 contradiction matrix, we can solve the standard TRIZ problem. In this matrix, rows and columns are engineering parameters, cells are 40 TRIZ innovative principles. The standard TRIZ solution transforms into the special solution by interpreting innovative principles (Chen, Wu and Chen 2022).

Step 7. Prioritized engineering characteristics and targets of them: This section shows the effects of defined variables. It can also contain target degrees (Shillito, 1994).

$AWEC_j$: Absolute weight of EC_j

$$AWEC_J = \sum_{i=1}^{n} (r_{ij}\, x NTWCN_i) \tag{2.19}$$

$NWEC_j$: Normalized weights of EC_j

$$NWEC_J = \frac{AWEC_J}{\sum_{j=1}^{m} AWEC_J} \tag{2.20}$$

$$\sum_{j=1}^{m} NWEC_J = 1 \tag{2.21}$$

REC_j: Rank of EC_j

REC_j is discovered by ordering ECs according to the NWEC values.

FEC_j: The company's performance value for EC_j

AEC_j: Performance value of competitor A's for EC_j

BEC_j: Performance value of competitor B's for EC_j

TEC_j: Target value for EC_j

A major output of a first matrix of QFD is the prioritized engineering characteristics. The next matrix can be built using these engineering characteristics. Also, the HoQ gives advantages in identifying redundancies or missed engineering characteristics.

In classical QFD, after the HoQ is created, other matrices are formed sequentially in a similar way. Inputs of each matrix are the outputs of the previous matrix. In recent years, classical QFD has changed. Modern QFD, based on Blitz QFD, that applies HoQ but a more tailored process through to the company has emerged. The QFD Institute applied QFD to QFD, new techniques were adapted. Modern QFD focuses on businessaligned processes that reveal where to most effectively utilize resources that create value for customers and the business. It focuses on speed and efficiency and the mathematics of it can be integrated into six sigma phases. The ratio scale was developed using the AHP method, rather than using an ordinal scale. Figure 2.13. shows the stages of Modern QFD (Jayaswal, Patton and Zultner, 2007). These stages are: determination of project goals, identifying customer segments, constructing customer process model, listening to the voice of the customer, identifying customer needs, classifying of customer needs, determining the importance levels of the customer needs and converting prioritized customer needs to technical requirements.

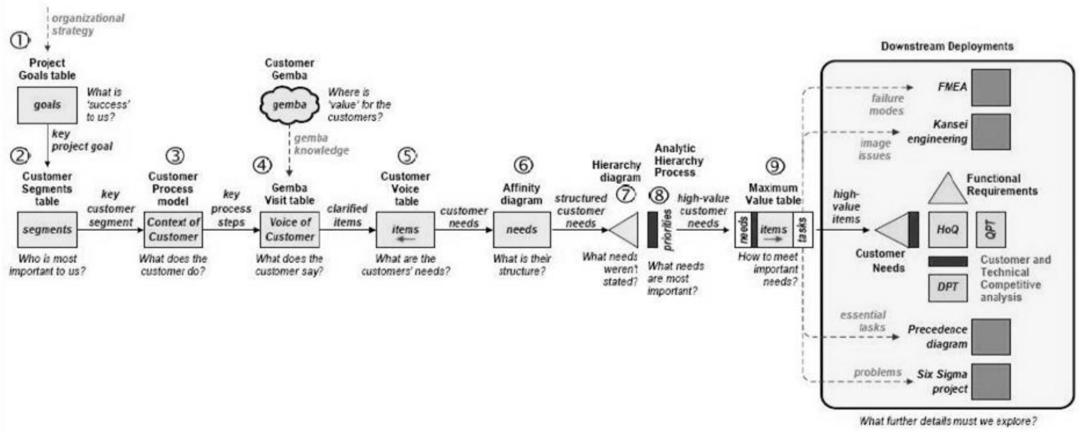


Figure 2.13. *Modern QFD approach (Jayaswal, Patton and Zultner, 2007)*

QFD researchers come to an agreement that there are no strict rules, structures, or symbols while implementing studies. Otherwise, an ISO standard, ISO 16355, contains the QFD method. This standard is published for guiding researchers while using QFD.

In the literature, QFD is integrated with other methods, such as quantitative analysis and statistical methods. Wang, Xie and Goh (1998) examined AHP and prioritization matrix method, and they proposed AHP if the accuracy was an important requirement. Lin et al. (2008), Erkarslan and Yilmaz (2011) applied AHP to ranking customer needs and engineering characteristics. Raharjo, Xie and Brombacher (2011) used AHP and time series analysis and proposed a QFD model to examine the VoC. Prasad and Chakraborty (2013) presented a QFD study for selecting materials and developed a software for this problem. For managing energy security, Shin, Shin and Lee (2013) suggested a model with using QFD and system dynamics methods. Liu (2012) used QFD with a Kano model in NPD. Singh et al. (2014) suggested QFD for research and development management.

Sularto and Yunitasari (2015) presented a QFD case study for the service quality of a restaurant. Wang, Lee and Trappey (2017) proposed a service design via using QFD, TRIZ and service blueprint methods and they applied a case study to self-service restaurants. He et al. (2017) suggested an enhanced Kano model, and they integrated this model with QFD. Akkawuttiwanich and Yenradee (2018) developed a QFD method to handle the supply chain key performance indicators. Jafarzadeh, Akbari and Abedin (2018) suggested a method that integrated data envelopment analysis with fuzzy QFD. Babbar and Amin (2018) presented a new fuzzy QFD model that included two stages and they also used a stochastic model. Aktar Demirtaş and Köksal (2018) proposed a new HoQ approach based on Servqual with using ratio scales.

Nowadays, there is a significant attention to green and sustainable product design and development. A literature review on QFD studies is presented considering the environmental and sustainability requirements. Linton, Klassen and Jayaraman (2007) defined the sustainability as ‘‘utilizing sources to satisfy present's necessities without conceding the capability of future generations to satisfy their necessities’’. Sustainable production aims to make improvements in social, environmental and economic issues so that businesses can protect their assets in a competitive business environment (Carter and Rogers, 2008). Zhang, Wang and Zhang (1999) developed green QFD-II in which integrated QFD with the life cycle analysis (LCA) and cost issues. Masui et al. (2003) presented QFD-for environment (QFDE) for NPD that was based on four phases. Reyes and Wright (2001) suggested a QFD method of combining strategies of eco-profile and eco-performance. Halog, Schultman and Rentz (2001) proposed a method for selecting the most sustainable alternative for the improvement of the system. Madu, Kuei and Madu (2002) proposed an approach for QFD studies. AHP and Taguchi design methods were used in their study. Bovea and Wang (2003) presented a method for determining improvements environmentally by handling the LCA and fuzzy QFD. Sakao (2007) improved QFDE with TRIZ. Kuo, Wub and Shieh (2009) suggested a new QFD method that was named as Eco-QFD. Utne (2009) carried out a QFD study for achieving sustainability of the Norway’s fishing fleet production. Vinodh and Chintha (2011) implemented a fuzzy QFD study to enable sustainable production. Roach (2014) suggested a method for designing sustainable products via using QFD. Fargnoli et al. (2018) offered an approach that combined QFD, LCA and Screening Life Cycle Modelling methods for examining customer needs and market demands. Al-Aomar

(2019) proposed a method to achieve sustainability at the system level and carried out a case study on the sustainable building. Finger and Lima-Junior (2022) suggested a model that used QFD and hesitant fuzzy sets for making supplier development programs. When the literature is examined, one of features of sustainability generally studied with QFD. Studies dealing with all aspects of sustainability (social, environmental and economic) with QFD are rare. Table 2.5. summarizes these studies.

Table 2.5. *Studies related to QFD with environmental, sustainable conscious in the literature*

Source	Method	Aspects of Sustainability
Zhang, Wang and Zhang (1999)	Green QFD-II	Environment, cost
Masui et al. (2003)	QFDE	Environment
Reyes and Wright (2001)	A QFD method with eco-profile	Environment
Halog et al. (2001)	A modified QFD, House of Ecology	Environment
Madu, Kuei and Madu (2002)	QFD, AHP and Taguchi design method	Environment, cost
Bovea and Wang (2003)	Fuzzy QFD, LCA	Environment
Sakao (2007)	QFDE, TRIZ, LCA	Environment
Kuo, Wub and Shieh (2009)	Eco-QFD, fuzzy theory	Environment
Utne (2009)	Eco-QFD, LCA, Systems engineering	Environment, cost, social
Vinodh and Chintha (2011)	Fuzzy QFD	Environment, cost, social
Roach (2014)	QFD	Environment, cost, social
Fargnoli et al. (2018)	QFD, LCA, Screening Life Cycle Modelling	Environment, cost
Al-Aomar (2019)	QFD	Environment, cost, social
Finger and Lima-Junior (2022)	QFD, Hesitant Fuzzy Sets	Environment, cost, social

In this thesis, customer needs and sustainability requirements are handled together to achieve sustainable production. The first matrix of QFD is extended with defining sustainability requirements.

2.3. Text Mining

In this thesis, we have integrated patent mining with QFD. For analyzing and discovering unstructured data like patents' abstracts; text mining can be applied in patent mining studies. Therefore, text mining is explained in this section.

With the data produced by individuals and organizations reaching enormous sizes, it has become inevitable to develop methods and technologies that will enable the effective use of big data. Data produced by humans estimated to be 2.5 quintillion (2.5 x 10^{18}) bytes per day (Price, 2015). In other words, 1 billion gigabytes of data are produced every day. Most of this generated data is coded as text provided through blogs, tweets, web pages, articles and books (Correia, Teodoro and Lobo, 2018). The fact that the data produced on a daily is so large and continues to increase rapidly has made it necessary to understand of big data. With the improvement of technologies to understand big data, new concepts such as data mining and text mining have entered our lives.

Data mining can be defined as the process to identify patterns in data sets and it is at the junction of machine learning, database systems, and statistics. Especially in the 1990s, data mining techniques were began to use very fastly because of technological developments' effects. Researchers can extract hidden relationships by using data mining. Some trends of data mining were given as follows: Web Mining, Text Mining, Multimedia Mining, Security and Privacy, Metadata Mining, Mining Distributed, Heterogeneous Databases (Han, Kamber and Pei, 2012).

Text mining is the process that extracts information from written resources by using a computer to discover previously unknown new information (Hearst, 1999). The difference between data mining and text mining is that data mining deals with structured data, on the other hand, text mining deals with unstructured or semi-structured data. Html documents and emails can be given as examples of unstructured data (Gupta and Lehal, 2009).

Practice areas of text mining are information retrieval, document clustering, document classification, concept extraction, information extraction, web mining and natural language processing (Miner et al., 2012). Information retrieval is the bringing of relevant information in accordance with the user's search query so that users can access the useful information they need (Zhai and Massung, 2016). It includes storage of documents, access by search engines. Document clustering includes categorizing documents and terms by applying data clustering techniques. Text data using unsupervised machine learning algorithms are divided into groups with similar characteristics. (Miner et al., 2012). Document classification includes categorizing documents and terms applying data classification techniques. Text data using supervised machine learning algorithms are assigned a known set of labels (Miner et al., 2012). Concept extraction is a technique that consists of two main processes: identifying all possible concepts in the text and identifying the most important ones (summarizing)

(Villalon & Calvo, 2009). Information extraction is the extraction of relationships and information from text data that is unstructured. It is the process of obtaining structured data from unstructured or semi-structured text data (Miner et al., 2012). Web mining is the field where supervised or unsupervised machine learning methods are used to discover documents on the web automatically, extract information from these sources, and reveal general patterns (Saini and Mohan Pandey, 2015). Web mining is implemented by professionals on the internet to assess their customer's comments and reviews. Natural language processing (NLP) is a robust tool that provides convenient inputs, like part-of-speech tags and phrase boundaries (Miner et al., 2012). Semantic analysis, text preprocessing such as stemming, tokenization, part-of-speech tagging, lemmatization are included in this field. Apart from these, sentiment analysis, text summarization methods, such as topic modeling and entity identification, are also included in this field (Arnarsson et al., 2021).

Text mining begins with collecting of documents, then they are pre-processed by controlling format, characters through a text mining framework. After the text is ready for the examination, a model is built to apply selected algorithms for discovering a pattern or extracting information (Gupta and Lehal, 2009). Then, post-processing steps like visualization and validation knowledge are done. Figure 2.14. shows the process of text mining.

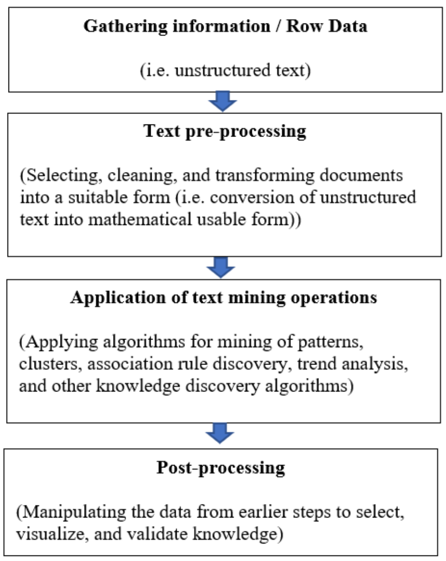


Figure 2.14. *The process of text mining (Zhang, Chen and Liu, 2015)*

Text pre-processing is a stage of the text mining process that converts gathered information into the standard format. There are some text pre-processing steps explained as follows:

Normalization of text: Upper cases convert into lower cases. Punctuations and numbers are removed. Stopwords that are common words like “a”, “the”, “an” etc. are eliminated. These words do not include valuable information (For example, “a TEXT MINING!1” converts into “text mining”).

Tokenization: This step divides texts into small pieces that are called tokens. Tokens can be a number, a symbol, a word form. Components of sentences are determined. Tokens are separated by space. For example, for the sentence “I like text mining”, after the tokenization, it appears as “I”, “like”, “text”, “mining”.

Stemming: It converts words into their stems that are root forms. Porter stemming or Lancaster stemming algorithms can be used (For example, “looked” converts into “look”, “problems” converts into “problem”, “studies” converts into “studi”, “studying” converts into “study”).

Lemmatization: This step takes account of the morphological information. The algorithm uses dictionaries. It identifies the lemma of a token (For example, “studies” converts into “study”, “studying” converts into “study”. Because both of lemmas of “studies” and “studying” are identified as “study”).

Part of Speech Tagging (POS): This step assigns a part-of-speech tag, which is determined according to the words’ structure. A part-of-speech is a category in the lexicon. It can be noun, verb, determiner, adjective, adverb, preposition, pronoun, conjunction or interjection, etc. (For example, “text” (single noun, NN), “texts” (plural noun, NNS), “it” (personal pronoun, PRN), “look” (verb base form, VB)).

Chunking: After tokenization and parts-of-speech, chunking groups tokens into chunks. Chunks are unique information units. They correspond to a syntactical unit as a noun phrase (NP) or a verb phrase (VP) (For example, chunking converts “I saw the black cat” into "I-NP", “the black cat-NP") (Btoush and Hammad, 2015).

Named entity recognition: It is the process of discovering units in text and classifying them into categories. These categories are predefined, such as people’s names, organizations' names, areas’ names.

The methods used in text mining largely benefit from machine learning methods. For this reason, before discussing the methods under the umbrella of text mining, it is useful to explain the main machine learning methods. These methods are generally separated into two basic categories: supervised and unsupervised. While classification and regression analyze are covered by supervised machine learning methods, clustering and association analysis are covered by unsupervised machine learning methods (Paturi and Cheruku, 2021). Decision trees, k-nearest neighbor (KNN) algorithm, naive bayes algorithm, support vector machine (SVM) are main classification methods. Linear regression and logistics regression are main regression methods; Apriori algorithm, FP-Growth are the main association methods. The k-means algorithm, DBSCAN clustering algorithm, self-organizing map algorithm are main clustering methods (Kotu and Deshpande, 2019). In supervised learning methods, the model is first trained according to the labeled training data, then the labels of the test data are estimated according to the developed model. In unsupervised learning methods, the structure that best reveals the relationships between the data in line with a specific objective function is discovered without the need for any prior knowledge (Verma, Singh and Dixit, 2022).

In the following paragraphs, the principles and application areas of the main text mining methods will be given.

1. Word Association Mining: Two types of relations between words have been defined generally. The first of these is paradigmatic relation, and the second one is syntagmatic relation. If the two words can be used interchangeably, it can be said that there is a paradigmatic relationship. Otherwise, if two words tend to appear in the same syntax in a sentence, there is a syntagmatic relationship. In the case of a paradigmatic relationship, two different words belong to the same semantic/syntactic class. Therefore, when one of the word is replaced with the other, the meaning of the sentence does not change. Word association analysis also makes it possible to group similar terms by considering the relationships between words mentioned above (Zhai and Massung, 2016). In this analysis, paradigmatic and syntagmatic relations between words should be searched together. Paradigmatic relationships incline to have a syntagmatic relationship for the same word (Correia, Teodoro and Lobo, 2018).

In word association analysis, the bag-of-words model can be used to display text data. The basic assumption of this model is that the order of the words in the document is not important (Miner et al., 2012). The usage of the bag-of-word model is seen as a comprehensive solution for many analyzes in text mining. An example sentence in the bag-of-word model is given below:

Example sentence: Patent mining is important.
Bag of words: {"Patent", "mining", "is", "important"}

In cases where the order of the words is important for the researcher, the n-gram model is used. In n-gram models, the spatial information of the words in the document is also stored. N-gram models can be called as unigram, bigram, trigram according to the number of words to be grouped together. The bigram (2-gram) representation of the same sentence above is given below:
Bigram model of the example sentence: {"patent mining", "mining is", "is important"}

As a result of the word association analysis, the relationships between the words in the document are discovered. A visualized example of this analysis's output is given in Figure 2.15.

Figure 2.15. *A visualized example of the word association analysis*

2. Text classification: Clustering techniques are used where unsupervised learning methods are used and there is no label variable in the dataset. However, in many cases, text objects need to be grouped according to predetermined categories. In cases where the categories are predetermined, the groups and categories obtained as a result of the cluster analysis may differ from each other. For solving this problem, text classification methods using supervised learning methods should be used (Zhai and Massung, 2016).

After the preprocessing processes, classifiers such as decision trees, naive bayes, k-nearest neighbor, support vector machines, artificial neural networks are used. In text classification methods, the dataset is separated into two parts as training dataset and test dataset, and then a classification model is developed according to the training dataset containing the label variable. The developed classification model is tested using the test dataset and the performance indicators of the model are obtained. The basic process diagram of the classification models is shown in Figure 2.16.

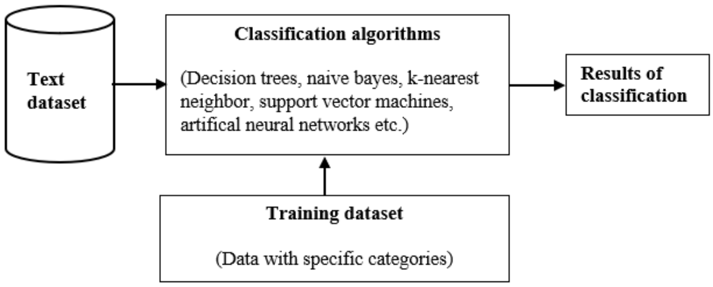


Figure 2.16. *The process of text classification models*

3. Topic modeling: Today, one of the most prominent areas within the scope of text mining is topic modelling. A topic is a concept that we can all perceive intuitively, but which is very difficult to define formally. It is possible to talk about the subject of a speech, a sentence, a paragraph or a text dataset according to different levels of detail. The application areas also differ according to the level of subjects' detail (Zhai and Massung. 2016). Topic modeling is simply finding out what a document is about. There are many applications that require the discovery and analysis of topics in text data.

The main methods used in topic modeling are: Latent Semantic Analysis (LSA), Probabilistic Latent Semantic Analysis (PLSA), Latent Dirichlet Allocation (LDA), Correlated Topic Model (CTM).

Deerwester et al. (1989) developed LSA, that is a method to infer the relationships and meanings of the expected contextual uses of words in technical documents (Tonta and Darvish, 2010). LSA is not an artificial intelligence technique or NLP, as it does not use any human-created dictionary, knowledge base, semantic web, grammar, syntactic parser or morphology. Instead, the LSA method uses Singular Value Decomposition (SVD), which is a general form of factor analysis, and reduces the large word-document matrix to a smaller matrix (Kitajima et al., 2005).

LSA uses a reduced-dimensional coordinate system to connect similar ideas and basically uses the Vector Space Model (VSM). VSM demonstrates documents using a bag-of-words and syntactic features are ignored (Sezgen, Mason and Mayer, 2019). In the literature, LSA is called as Latent Semantic Indexing (Can and Alatas, 2017).

PLSA, developed by Hoffman (2001), is a technique used for the analysis of bimodal and cooccurring data. This method is based on a mixture of decomposition derived from the latent class model. For this reason, results based on a more robust statistical basis are obtained (Hoffman, 2001). PLSA determines the components and ratios in the mixture model the probability function by using the maximum likelihood method (Güven, Diri and Çakaloğlu, 2020).

The LDA method is a generative probabilistic method based on Bayes' theorem, which is used for modelling discrete data such as text collections (Blei, Ng and Jordan, 2003). In the LDA method, documents are modeled as a finite mix over a set of latent topics and an infinite mix over a range of latent topic possibilities. In this way, topic probabilities provide a clear representation of documents in the context of text modelling (Arora and Ravindran. 2008). In other words, a topic defined by LDA is the probability distribution of the words assigned to the subject; documents are modeled to express the probability distribution of the subjects assigned to the documents (Güven, Diri and Çakaloğlu, 2020). LDA is a popular topic modeling method in machine learning and NLP, assuming that each document can be represented as a probabilistic distribution of latent topics and that the topic distribution in all documents share a common Dirichlet premise (Lucini et al., 2020).

CTM, developed by Blei and Lafferty (2005), is a technique that is particularly advantageous in cases where there is a hunch that the topics are correlated with each other (Lebryk, 2021). In order to reveal the correlations, the multivariate normal distribution is used instead of the Dirichlet distribution.

4. Sentiment Analysis: It is a technique for detecting positive and negative opinions about certain assets, such as institutions, people, products, services, events in the textual data stack. It offers opportunities in a large variety of application areas as risk management, competition analysis and marketing analysis (Nasukawa and Yi, 2003). It is generally divided into three types: document-level sentiment analysis, sentence-level sentiment analysis, and fine-grained sentiment analysis. Most sentiment analysis methods use prepared lexicon, that is, a list of all words belonging to a particular language, topic or dictionary to identify sentiments in the text. For this reason, it is stated in the literature, sentiment analysis is a semi-supervised learning technique (Sun, Luo and Chen, 2017). Also, machine learning approaches can also be used in sentiment analysis instead of lexicons (Can and Atlas, 2017). The classification of sentiment at the document level as positive, negative or neutral and the classification of subjectivity and objectivity at the sentence level are the most popular studies in the literature (Liu, 2010). After the text preprocessing steps, the sentiment class is determined by calculating the polarity values

for the relevant analysis unit (document, sentence, entity, etc.) of the text data. Calculation of the polarity value may vary according to the analysis tool used.

5. Text clustering: It is one of the methods used in exploratory text analytics. It enables the discovery of some natural structures within the corpus by clustering objects together and collecting similar objects together. The objects can be documents, sentences, and words (Zhai and Massung, 2016). Text clustering analysis is an unsupervised method in which objects are grouped without predefined categories (Zhang, Chen and Liu, 2015). With the unstructured text data being brought to a structured format after text preprocessing processes, objects are separated into clusters with similar properties using clustering algorithms. An example of clustering analysis is demonstrated in Figure 2.17.

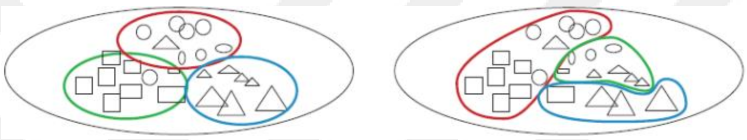


Figure 2.17. *An example demonstration of text clustering (Clustering by shape similarity, size similarity)*

Text clustering is used in many areas to find similar documents, organize big text data set, detect duplications in data set, optimize searching and set up a system for recommendation. It consists of three steps: preprocessing, selecting representation and applying algorithms for clustering. Preprocessing step includes same methods as given in text mining like stemming, tokenization, etc. Also, it includes feature extraction and selection. Representation of the document step includes various methods like binary, term frequency (TF) and term frequency with inverse document frequency (TF-IDF). TF-IDF is the most widely used one and calculated as follows (Shah and Mahajan, 2012).

$$TFIDF(t,d,D) = TF(t,D)xIDF(t,D) \quad (2.22)$$

Where TF(t,d) represents how many times the term occurs in a given document, d. IDF(t,D) measures how much the term t is important in all the documents in the dataset (D):

$$IDF(t,D) = log_2(\frac{N}{DF}) \quad (2.23)$$

N: Total number of documents, DF: The number of documents which include the term t.

In most algorithms, the text dataset is represented as vectors. Clustering algorithms rely on similarity measurements between the vectors. The most widely applied similarity measures are euclidean distance, cosine similarity, jacard coefficient, pearson correlation coefficient and relative entropy (Huang, 2008). Euclidean distance is an ordinary distance measure between two points, it is measured with a ruler. K-means algorithm uses euclidean distance as the default value. Cosine similarity is measured by calculating the cosine of the angle between vectors. The Jaccard coefficient compares the sum weight of shared terms to the sum weight of terms that are present in either of the two documents but are not the shared terms. Pearson correlation coefficient measures the linear correlation between two variables. Relative entropy is a measure for evaluating the differences between the two probability distributions.

There are different types of clustering algorithms like hierarchical algorithms, k-means algorithm, partitioning algorithms, document clustering, term clustering, semantic clustering. They have various benefits and drawbacks. The methods to be used vary according to the aim of the study and the structure of the data.

Text clustering is separated into two categories: disjoint and overlapping. While every document must be allotted to one cluster in disjoint clustering, in overlapping clustering, each document can be assigned to multiple clusters. Overlapping clustering consists of three subsections as follows (Chen, Tseng and Liang, 2010):

Partitioning clustering assigns text data into a definite number of clusters. The most popular algorithm is the K-means in partitioning clustering methods. The K-means algorithm assigns a number of documents to a number of clusters, randomly. Means of clusters are calculated, and each document is reallocated to the nearest one at every iteration. The algorithm terminates if there is any difference between iterations. Partitioning methods are convenient for large text data because their time complexity is linear. But K-means algorithm is sensitive to the chosen initial separation (Cui and Potok, 2005).

Hierarchical clustering creates a cluster's tree that is called as a dendrogram. It is divided into two subcategories, as follows. Agglomerative methods define each document as a cluster. Two most related clusters are merged until the predefined expiration criteria is satisfied. Intra Cluster Similarity Technique, Unweighted Pair Group Method with Arithmetic Mean and Centroid Similarity Technique are agglomerative methods. Divisive methods define a cluster that includes all documents. One cluster is chosen and divided into smaller ones until the criteria of termination is satisfied. The bisecting-K-means is in this subcategory. Hierarchical methods create better clustering results, but their time complexity is quadratic (Shah and Mahajan, 2012).

Frequent item set based methods use frequent items that are determined by association rules. These methods have two advantages: They decrease the term features' dimensionality for large text data and they have cluster labels (Chen, Tseng and Liang, 2010). There are various algorithms in the literature, such as term based clustering, frequent item set based hierarchical clustering and fuzzy frequent item set based clustering (Beil, Ester and Xu, 2002; Fung, Mang and Ester, 2003; Chen, Tseng and Liang, 2009).

Also, there are search results clustering algorithms that cluster text data correctly and produce meaningful and clear cluster labels. Suffix Tree Clustering (STC) (Zamir and Etzioni, 1998) and Lingo algorithms are the most widely used in search results clustering algorithms. Lingo algorithm, a type of clustering algorithm, integrates common phrase discovery and latent semantic indexing techniques for separating results into groups, and it has been proposed for generating more refined topics compared with other clustering algorithms (Ena et al., 2016) and can determine topic labels automatically (Osinski and Weiss, 2005). Osinski, Stefanowski and Weiss (2004) proposed Lingo algorithm that is based on SVD for clustering data. It focuses on quality of labeling; cluster labels are first revealed, then it assigns documents to them. Lingo includes four steps, and these are explained as follows: Preprocessing (text filtering for non-letter characters, identification of language, stemming and stop word elimination), Frequent phrase extraction (Choosing phrases as candidate cluster labels if they are a complete phrase, stay in sentence boundaries and appear more than term frequency threshold), Cluster label induction (Term-document matrix generating, exploration of abstract concepts, label pruning), Cluster content discovery (Assigning documents to related labels with using VSM) (Osinski, Stefanowski and Weiss, 2004). Osinski and Weiss (2005) demonstrated in their study by using Open Directory Project data that the Lingo algorithm gives better results than the STC algorithm in labeling of clusters and separating documents' topics.

Text mining approaches are studied using with QFD in the literature. Text mining is generally used to identify customer needs. Zhao et al. (2005) suggested a framework that mined classes and attributes. Coussement and Van den Poel (2008) proposed a decision support system that customer e-mails were used. Zhang, Cheng and Chu (2010) suggested a text mining approach for QFD that was based on the Apriori algorithm. Park and Lee (2011) developed a framework that transformed online opinions into customer needs in QFD. Liu et al. (2013) evaluated the utility of online customer reviews from a product designer's perspective, and they offered four features categories that indicate interests of designers in deciding review utility. Kapucugil-İkiz and Özdağoğlu (2015) proposed text mining as a support process for analysing and clarifying the voice of the customer. They used text clustering for VoC clarification and presented a case study with using diaper bag's customer reviews. Wang, Feng and Dai (2018) suggested a framework using online reviews to examine customer choices for two products via a text mining method. Shen et al. (2022) developed a solution for product improvement by examining online customer reviews. They used text mining, neutral network and fuzzy inference techniques. They used text mining for the VoC determination. Huang et al. (2022) proposed a new QFD model by integrating the interval grey number and text mining algorithms like LDA and Apriori algorithms. They used online reviews to understand customer requirements and market competitiveness. Asadabadi et al. (2022) developed an approach by combining natural language processing and QFD. They obtained VoC via using online product reviews. In these studies, text mining approaches are mostly used for VoC determination. In addition to them, there are few studies that enhance QFD with patent documents in the literature. Park, Yoon and Kim (2013) applied a patent analysis to define areas of the new technologies and they extracted function information. Ju and Sohn (2015) developed a QFD framework that has three stages for the technology selection. They applied this framework to robotics technology. Jin, Jeong and Yoon (2015) examined technology road maps (TRM) with QFD to get competitiveness for NPD. Trappey et al. (2018) offered a new QFD methodology that the manufacturer's patent portfolio was added in the methodology. They applied a case study with using the new approach. Three smart phones were chosen. Information about the manufacturer's patent portfolio was used in HoQ. Ha and Geum (2022) suggested a method to determine new services via using QFD, text clustering and morphological analysis techniques. These mentioned studies in which text mining approaches are used are summed up as in the Table 2.6.

Table 2.6. *Studies related to QFD and text mining in the literature*

Source	The Purpose of Using Text Mining
Zhao et al. (2005)	VoC and technical requirements determination
Coussement and Van del Poel (2008)	VoC determination
Zhang, Cheng, Chu (2010)	Association rules extraction
Park and Lee (2011)	VoC determination
Liu et al. (2013)	VoC determination
Park, Yoon and Kim (2013)	Function information extraction
Ju and Sohn (2015)	QFD framework that has 3 stages for the technology selection
Kapucugil-İkiz and Özdağoğlu (2015)	VoC determination
Jin, Jeong and Yoon (2015)	Product, market, technology keywords extraction for drawing TRM
Wang, Feng and Dai (2018)	VoC determination
Trappey et al. (2018)	VoC and the manufacturer's patent portfolio determination in HoQ
Shen et al. (2022)	VoC determination
Huang et al. (2022)	VoC, market competitiveness determination
Asadabadi et al. (2022)	VoC determination
Ha and Geum (2022)	Service actions and contents extraction

In this thesis, patent mining was done with using text mining approaches. The purpose of using text mining is to determine manufacturing operations and their target values for the selected production process.

2.4. Patent Mining

Nowadays, the key factor for a successful company is research and development. Companies want systems to follow improvements in technology on products, processes and innovations that competitors have carried out. Technology mining guides companies for conducting a market survey, analyzing or monitoring the business value. Therefore, companies can determine the future's technological trends. It is significant for the investment decision-making process. Today, emerging and leading technologies contain information, material, bio, and nano technologies (Day et al., 2000). Determining these technologies' trends earlier than competitors is important for companies to obtain a first-mover gains for sustainability and competitiveness. A technological trend is a field that is constantly evolving in a particular pattern at a particular time (Ena et al., 2016). Many sources, like patent documents, social media, academic papers, can be used to extract data and determine trends in technology mining. Technology mining is used for determining the intelligences of market, competitiveness and technical, forecasting and assessing the technology and drawing the technology road maps (Porter and Cunningham, 2004).

Patent documents are documents in which inventors who want to obtain patent rights describe their inventions in all technical aspects. People who develop an invention in every field of technique and technology apply for patents while their inventions are at the idea stage in order to prevent their inventions from being imitated by others. Thus, the emerging technical innovations first appear in the world of science and technology with patent documents. This has ensured that patent databases are the largest, reliable and most up-to-date source among the information sources where technical information is stored (Schwander, 2000; Noh, Jo and Lee, 2015). In addition, it is a situation mentioned in the literature that most of the information in patent documents is not included in other information sources; patent documents offer unique information to researchers (Asche, 2017). The World Intellectual Property Organization (WIPO) indicates that global patents include more than 90% of all R&D results in the world. Also, WIPO estimates that there may be a 40% reduction in R&D time and cost with the analysis of patents (Idris, 2008).

Every country has patent offices, like USPTO, TPE, EPO, JPO to manage patents. These offices open their databases freely. Also, there are some private databases, such as Google Patents and Free Patents Online. In addition to this, several tools like Patbase Analytics, Thomson Reuters, Patent Integration etc. are there to analyze patents, but they are so expensive. Patent documents include both structured and unstructured data. Patent number and dates are examples for structured data, whereas descriptions, abstracts and claims are examples for unstructured data. The information that can be obtained from patent databases by analyzing the technical explanation texts in patent documents, which is a significant source of technical information, will make a great contribution to the technique and technology. However, it is obvious that such a large amount of technical data cannot be processed manually (Shalaby and Zadrozny, 2019). At this point, there is a great need for data science methods, especially text mining methods (Madani and Weber, 2016). Recently, the concept of patent mining has emerged as data analysts focus on these opportunities offered by patent documents (Madani and Weber, 2016). The term Patinformatics has also been used for this branch of data science, which expresses the discovery of information from patent sources (Abbas, Zhang and Khan, 2014). Patent mining is a new technology mining area. A classical patent mining system has several steps: Determining the scope and searching, preprocessing, abstracting, clustering, visualizations and interpretations.

Patent mining has been used for many purposes in the literature. These are listed as follows:

1. Patentability detection: The invention, which is the content of the patent appeal, must be new compared to the known state-of-the art, also have characteristics of an inventive step to receive the patent right. The known state-of-the art consists of all written, verbal and visual information accessible to the public until the patent's appeal date. Since the most of the technical information is in the patent databases, the most important issue determining the patentability status is the other published patent documents. It is decided whether the invention is new and whether it meets the inventive step criteria by examining and comparing the patent documents that have similar features with the invention that are the subject of the application in detail. As with the registration authority, this comparison can be made by the applicants in order to evaluate their invention before the application. Because all published patent documents can be accessed by anyone through patent search engines. The main activity in the determination of patentability is the comparison of documents with each other in terms of the technical content. Text mining methods used for document similarity detection are also used to determine patentability. Hido et al. (2012) suggested a new statistical model using logistics regression and TF-IDF methods for patentability detection. Wang and Chen (2019) used LSA for extracting relations and suggested a new statistical technique for detecting outliers. Lei, Qi and Zheng (2019) applied feature VSM model based on convolutional neural networks (CNN). Wang et al. (2019) used subject–action–object (SAO) semantic analysis and proposed a new index, DWSAO, for determining the similarity between patent documents.

2. Patent infringement detection: Owners of patented inventions can object to other patent documents that they think violate the scope of protection they have obtained. This objection can be made to the registration authority during the registration process, and to the relevant judicial authorities if the registration process has been completed. In the detection of patent infringement, the technical similarity of the documents to each other is considered. Park, Yoon and Kim (2012) used SAO and patent map analyzes for detecting patent infringement. Zou, Zhen and Wu (2019) applied VSM and Word2Vec methods to decide whether there was an infringement from the obtained similarity ratios.

3. Patent classification: Each published patent document has patent class codes assigned to express the invention subject it contains. These codes are assigned by the patent experts during the registration process of the application. Patent class information is used with keywords to reach the right documents in patent searches and help researchers. Although there are patent classification systems used by some countries for their national applications, International Patent Classification (IPC) is the most commonly and internationally used classification system. In order to determine the IPC class of patent applications, the content of the document is analyzed and the relevant code is determined. Most applications have more than one IPC code, as they are related to more than one technical field. Since this process is mostly done manually, it can take time and there is a possibility of error. Incorrect IPC assignment may prevent access to the relevant document in subsequent patent searches. Chen and Chang (2012) proposed a method that included three steps and they applied VSM, K-means and KNN methods for the categorization. Li et al. (2018) introduced a new algorithm, DeepPatent, based on Word2Vec and CNN methods. Chen et al. (2022) presented a methodology that used a deep learning model and association rules for classification.

4. Patent summarization: Patent documents are long and have a unique structure and language. Making full use of these documents takes time and requires a certain expertise. This situation prevents many researchers from benefiting from patent documents. With patent mining, patent documents that seem to be complex can be summarized, thus enabling researchers to benefit from technical information quickly and easily. Trappey, Trappey and Wu (2009) used a method using with ontology based clustering technique and TF-IDF method to summarize patent documents automatically. Kim and Yoon (2022) proposed a new approach, multi-patent summarization, and they used generative adversarial network. They applied their method to the drone field.

5. Patent analysis for technology management: Patent documents have a purely technical character and are the resources containing the most up-to-date technical information. Patent analysis can be used for analysis of technological trends, technology forecasting, R&D planning and strategic planning studies. Yang, Huang and Su (2018) proposed an enhanced SAO method to define technology trends, and they applied their method to graphene technology. Li et al. (2019) suggested a framework to determine technology trends by using patent mining and sentiment analysis. They used the LINGO algorithm to cluster patent documents and Twitter data to understand users' sentiments.

They compared patent data and Twitter data, also presented two evolution maps for the technology of solar cell, in order to predict the technological possibilities that may arise in the future. Kim et al. (2019) created TF-IDF matrices by examining the patent documents published in the field of wireless power transfer and they extracted hidden technological topics with LDA algorithm. Then, the time series and technology innovation cycles obtained from the distribution of patent applications published in the relevant technical field by years were applied to the results, and important and unimportant technology areas for the future were estimated. Moehrle and Caferoglu (2019) proposed a method for identifying and monitoring emerging technologies. They used technological speciation analysis and semantic patent analysis, also applied their method to the camera technology. Wang et al. (2019) suggested a method to determine technological convergence's emergent topics. They used IPC codes to define the technological convergence environment for 3D printing. They calculated emergence scores to emergence terms and clustered them with using Principal Components Analysis.

6. Patent valuation: Although the legal protection of every invention that can obtain a patent registration is the same, the economic value of each patent is not the same. For example, there will be a greater demand for inventions that meet a more important need. The determination of inventions' economic value of the subject to the patent is called patent valuation. Falk and Train (2017) proposed a patent valuation approach based on statistical analysis and estimation. Mukundan et al. (2019) developed a multi-criteria patent quality model that was supported by AHP and TOPSIS to measure the patent portfolio. Table 2.7. summarizes these studies.

Table 2.7. *Studies related to patent mining in the literature*

Source	Method	Purpose of patent mining
Hido et al. (2012)	Logistics regression and TF-IDF	Patentability detection
Wang and Chen (2019)	LSA	Patentability detection
Lei, Qu and Zheng (2019)	Feature VSM, CNN	Patentability detection
Wang et al. (2019)	SAO	Patentability detection
Park, Yoon and Kim (2012)	SAO, patent map analysis	Patent infringement detection
Zou, Zhen and Wu (2019)	VSM, Word2Vec	Patent infringement detection
Chen and Chang (2012)	VSM, K-means and KNN	Patent classification
Li et al. (2018)	Word2Vec, CNN	Patent classification
Chen et al. (2022)	Deep learning	Patent classification
Trappey, Trappey and Wu (2009)	Ontology based cluster tech., TF-IDF	Patent summarization
Kim and Yoon (2022)	Generative adversarial network	Patent summarization
Yang, Huang and Su (2018)	SAO	Technology management
Li et al. (2019)	LINGO, sentiment analysis	Technology management
Kim et al. (2019)	TF-IDF, LDA, time series analysis	Technology management
Moehrle and Caferoglu (2019)	Technological speciation analysis, semantic patent analysis, bi-gram	Technology management
Wang et al. (2019)	Principal components analysis	Technology management
Falk and Train (2017)	Poisson model	Patent valuation
Mukundan et al. (2019)	AHP-TOPSIS	Patent valuation

In the literature, researchers have used patent mining for many purposes. We used patent mining for the technology management in this thesis. Studies usually used patent mining for products in the technology management. In addition, this study used patent mining for a production process. Composite material forming is the selected process, and this is the first patent mining study for composite forming.

3. NEW PRODUCT DESIGN WITH SUSTAINABILITY DRIVEN QUALITY FUNCTION DEPLOYMENT REINFORCED BY PATENT MINING

Today, product life cycles are shortening, technology is developing rapidly, and the tendency towards environmentally friendly production and sustainability concepts is increasing. This situation has made it necessary for companies to develop new products and improve their existing products to be competitive. Companies are seeking new methods to adapt technology, competition and to maximize customer satisfaction. There is a need for holistic approaches that address the market, technical, technology and social driving forces that affect the product development process together. This study proposes an integrated and technology-based NPD methodology that is named as “New product design with sustainability driven QFD reinforced by patent mining” to meet customer and sustainability requirements. It has two important contributions. First, sustainability requirements are integrated into the HoQ. Second, in the third house phase, patent mining was used to identify manufacturing operations. New product design with sustainability driven QFD reinforced by patent mining method is shown in Figure 3.1. The extended QFD framework is given in Figure 3.2.

In many classical QFD studies, in the first house of QFD, only meeting customer needs is considered. In this study, for the first contribution, customer needs and sustainability requirements are handled together to achieve sustainable production. The HoQ is expanded by defining sustainability requirements, as seen in Figure 3.2. at the Stage 1: Product Planning. All aspects of sustainability (social, environmental and economic) as requirements are handled. Customer requirements and sustainability requirements are deployed to the other three houses. Thus, these requirements are considered at every stage.

One of the most important factors affecting the efficiency of a product is how it is produced. Therefore, it is critical that the process planning is done correctly. In classical QFD studies, in the process planning matrix (the third house of QFD), manufacturing operations and their target values are determined by the QFD team’s experiences. For the second contribution of the proposed methodology, an intermediate stage is injected into the process planning matrix to increase the quality and inclusiveness of the inputs. This intermediate stage is shown in Figure 3.1. with red lines. Patents are the first indicators of technological developments. Patent databases store large, reliable technical information. So, it is very valuable to use patent information in process planning studies.

In the intermediate stage, it has been suggested to carry out a patent mining study for the critical processes. Patent documents include both structured and unstructured data. In this thesis, patents' abstracts, which are unstructured data, are used; so text mining is applied to discover data in the patent mining study. Clustering techniques are used because there is no label variable in the data set obtained from patent documents. The Lingo clustering algorithm is implemented for extracting topics using the patent data. The Lingo algorithm is chosen because it focuses on the quality of labeling. This algorithm generates better results in labeling of clusters while comparing with other algorithms and determines labels automatically. Via using cluster labels, users can understand what a cluster is about. Cluster labels are used to determine manufacturing operations and better reflect the latest advances.

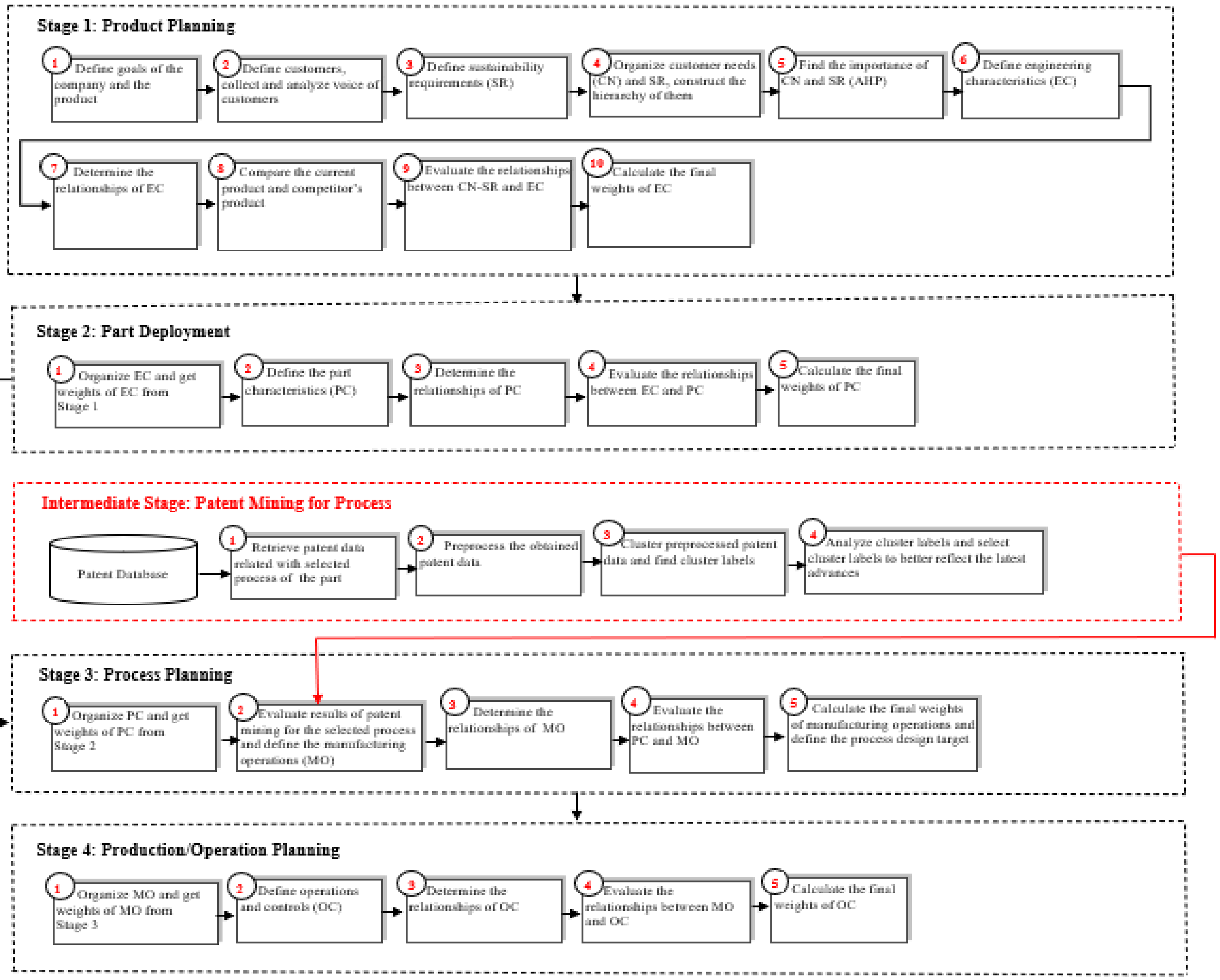


Figure 3.1. *New product design with sustainability driven QFD reinforced by patent mining method*

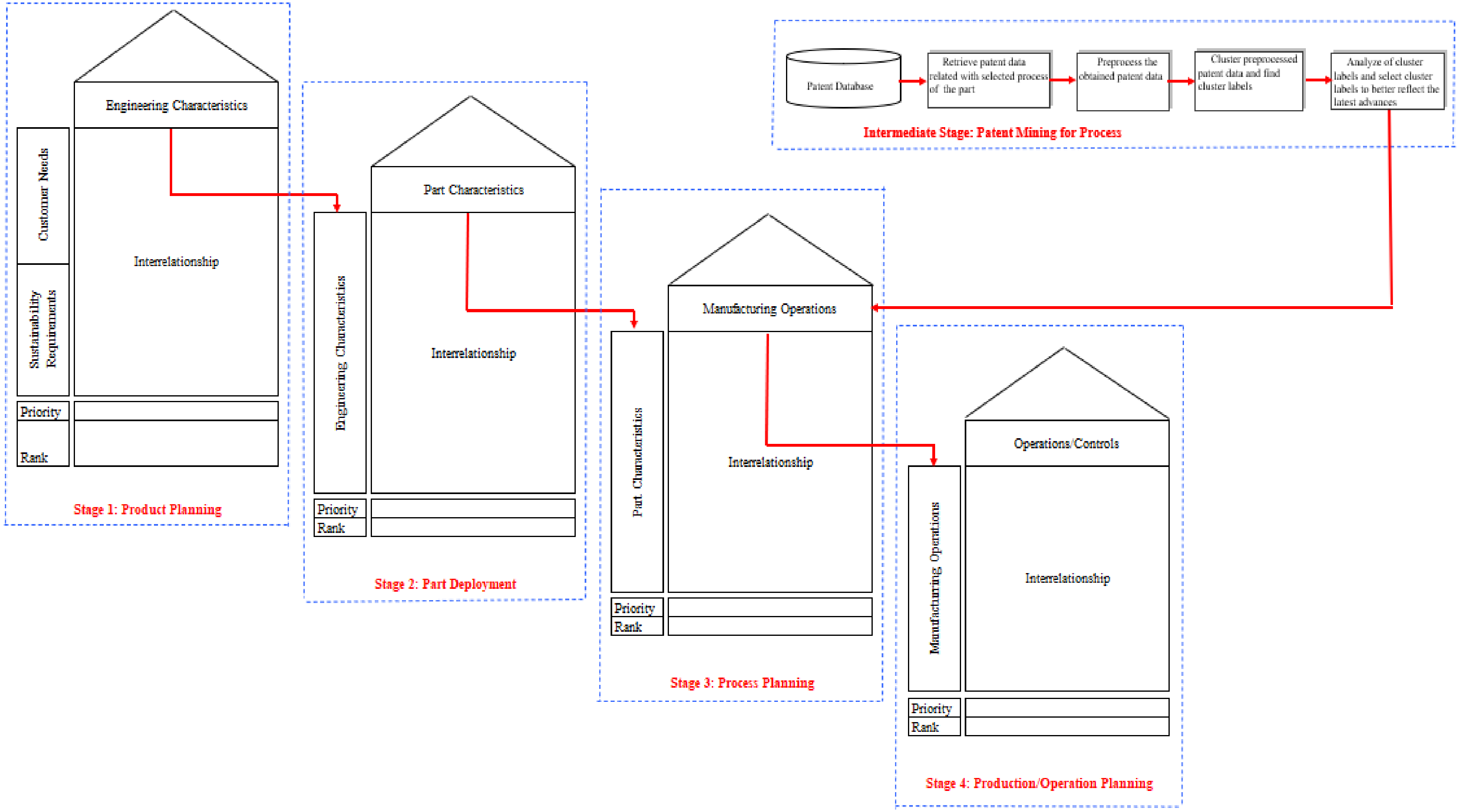


Figure 3.2. *The extended QFD framework*

New product design with sustainability driven QFD reinforced by patent mining method consists of serial stages. The stages of the proposed method are as follows:

Stage 1: Product Planning: In Stage 1, customer needs and sustainability requirements are translated into measurable engineering characteristics. The steps of the Stage 1 are as follows:

Step 1.1: Define goals of the company and the product: First of all, it is necessary to determine the primary objectives of the company and on which objectives the available resources will be concentrated. The support of the management team should be obtained. For the product development process, the product is chosen and the QFD team is created. It should be ensured that each team member in the QFD team acquires sufficient knowledge about QFD. The implementation and time planning of the QFD process should be done.

Step 1.2: Define customers, collect and analyze the voice of customers: Customers are defined clearly by determining the customer group. Then, the product planning matrix starts with the collecting process of customers' needs for the chosen product. What the customer needs should be listened to using their own words. While determining customer needs and expectations, surveys, one-to-one interviews with customers, gemba visits, focus group studies, complaints and comments reports of customers, and also customer reviews through the Internet can be used.

Step 1.3: Define sustainability requirements: All aspects of sustainability (social, environmental and economic) requirements are defined. Customer needs and sustainability requirements are located in the rows of the planning matrix.

Step 1.4: Organize customer needs and sustainability requirements, construct the hierarchy of them: If the requirement list is long, grouping of requirements helps to handle more effectively. Affinity diagram should be used.

Step 1.5: Find the importance of customer needs and sustainability requirements: In order to transform the needs expressed by customers in customer language into engineering characteristics, it should be continued by asking customers why they actually want this feature. In this step, the balance between the cost of fulfilling the need and the benefits offered to the customer gains importance. AHP is used while determining the importance degrees of customer needs and sustainability requirements. AHP is explained in detail in Section 2. With using Table 2.2. and equations from 2.1. to 2.5., we can calculate importances.

Step 1.6: Define engineering characteristics: Engineering characteristics define the selected product in the company's language. It is the answer to how to meet customer needs and sustainability requirements. These characteristics must be measurable. They are located in the columns of the planning matrix.

Step 1.7: Determine the relationships of engineering characteristics: This step forms the roof of the product planning matrix and shows how engineering characteristics impact each other. "+" shows a positive correlation, "-" shows a negative correlation and blank represents no correlation.

Step 1.8: Compare the current product and competitors' products: It includes an investigation of the chosen product and products of the company's competitors. The assessments for competitiveness can be done with using equations 2.6. to 2.16.

Step 1.9: Evaluate the relationships between customer needs, sustainability requirements and engineering characteristics: It covers the area at the center of the product planning matrix, where the engineering characteristics are digitized how much benefit can be brought to customer and sustainability expectations. This matrix indicates the relationship and relationship strength between the Whats (customer needs, sustainability requirements) and the Hows (engineering characteristics). Degrees of relationships are determined by using the 5-point scale in Table 2.3.

Step 1.10: Calculate the final weights of engineering characteristics: This section, which is located at the base of the planning matrix, contains the calculated importance scores of the engineering characteristics. The priority of engineering characteristics that can bring customer needs and sustainability requirements to the highest degree is determined. The final weights of engineering characteristics are obtained through multiplying importances levels of customer needs and sustainability requirements by relationship values of customer needs, sustainability requirements and engineering characteristics. Then, relative importance degrees are calculated for each engineering characteristic. We divide the final weights of each engineering characteristic into the cumulative degree of weights and rank engineering characteristics.

Stage 2: Part Deployment: In Stage 2, engineering characteristics are translated into part characteristics. Stage 2 is the prioritization of part characteristics that are deployed to the Stage 3. The steps of the Stage 2 are as follows:

Step 2.1: Organize engineering characteristics and get weights of engineering characteristics from Stage 1: By creating a matrix, the engineering characteristics in the columns of the product planning matrix are written in the rows. Also, weights of engineering characteristics from Stage 1 are written for each engineering characteristic.

Step 2.2: Define the part characteristics: The parts that make up the product are located in the columns of the matrix. Part characteristics should be defined in detail.

Step 2.3: Determine the relationships of part characteristics: This step forms the roof of the part deployment matrix and shows how part characteristics impact each other. "+" shows a positive correlation, "-" shows a negative correlation and blank represents no correlation.

Step 2.4: Evaluate the relationships between engineering characteristics and part characteristics: The level of relationship between each part characteristic and the engineering characteristic is determined by using 5-point scale in Table 2.3.

Step 2.5: Calculate the final weights of part characteristics: After the correlation scores between engineering characteristics and part characteristics are determined, these scores are multiplied by the importance degrees of the engineering characteristics and the column total is obtained for each part characteristic. The column totals are normalized to determine the relative absolute importance of the part characteristics.

Intermediate Stage: Patent Mining for the Process:

Step I.1: Retrieve patent data related to the selected process of the part: After creating part deployment matrix, we should determine manufacturing operations and their target values for creating process planning matrix. QFD team decides for which process the patent mining will be done. Patent data for the selected critical process are retrieved. To do this firstly, patent data source is chosen. Patent offices in various countries, such as USPTO, EPO and JPO, can be used to collect patent data. These offices open their databases freely and they are reliable sources. EPO provides an API that is a website for collecting patent data related to selected search query words. Therefore, the EPO database was chosen. Secondly, search keywords (For example, composite material) are determined. While determining the search keyword, experts in the QFD team can be asked for opinions to define more specific subjects. Then we decide patents' section like abstract and claim. Finally, the search is done through the API and the patents are downloaded according to the restrictions, such as search keyword, patent filing date, and the patent section. Patent documents can be downloaded in XML format.

Step I.2: Preprocess the obtained patent data: In this study, patents' abstracts, which are unstructured data, are used; so text mining is applied to discover data in the patent mining study. After collecting of patents in Step I.1, patents' abstracts are pre-processed by controlling format, characters through a text mining framework. In this step, we transform documents into a suitable form and convert gathered information into the standard format. Firstly, downloaded XML format is transformed into text format. XML tags (e.g. <head>, <results>) are removed. Then, following text pre-processing operations are executed. Upper cases are converted into lower cases. Punctuations and non-letter characters (e.g. $, %, #) are removed. Stopwords that are common words like "a", "the", "an" etc. are eliminated. These words do not include valuable information. Tokenization that divides texts into small pieces that are called tokens is used. Components of sentences are determined. Tokens are separated by space. Then, stemming is used. It converts words into their stems that are root forms.

Step I.3: Cluster preprocessed patent data and find cluster labels: After the text is ready for the examination, we cluster documents with using the Lingo clustering algorithm. Lingo algorithm is executed in three sub-steps: Frequent phrase extraction, Cluster label induction and Cluster content discovery. We choose phrases as candidate cluster labels if they are a complete phrase, stay in sentence boundaries and appear more than the term frequency threshold. VSM and SVD are applied for inducing cluster labels. We use cosine similarity of the cluster labels and input documents. If this similarity score exceeds the pre-defined threshold, documents are assigned to the corresponding cluster. Carrot2 workbench, which includes the Lingo algorithm, can be used to cluster and then obtain cluster labels. Cluster labels tell us what a cluster is about. Cluster labels are used to determine manufacturing operations.

Step I.4: Analyze of cluster labels and select cluster labels to better reflect the latest advances: After cluster labels are determined in Step I.3, the QFD team decides on cluster labels to be used in the process planning matrix as manufacturing operation. The QFD team selects cluster labels that best reflect the production process and latest advances by making group studies. The extended QFD framework proposed by this thesis is shown in Figure 3.2. The cluster labels are used while identifying operations. This stage is injected to improve the quality and inclusiveness of the inputs used in the QFD.

Stage 3: Process Planning: After the part deployment phase is complete, there is a need to know how to produce the design. This stage converts part characteristics into manufacturing operations. While defining the process design target, results of patent mining for selected process are evaluated.

Step 3.1: Organize part characteristics and get weights of part characteristics from Stage 2: By creating a matrix, the part characteristics in the columns of the part deployment matrix are written in the rows. Also, weights of part characteristics from Stage 2 are written for each part characteristic.

Step 3.2: Evaluate results of patent mining for the selected process and define the manufacturing operations: QFD team decides which cluster labels will be used that obtained patent mining in the Intermediate Stage. These selected cluster labels are used as defining manufacturing operations. Also, if there are non-patent mined manufacturing operations, they are also defined by the QFD team. Then, all manufacturing operations are placed in the columns of the process planning matrix.

Step 3.3: Determine the relationships of manufacturing operations: This step forms the roof of the process planning matrix and shows how manufacturing operations impact each other. "+" shows a positive correlation, "-" shows a negative correlation and blank represents no correlation.

Step 3.4: Evaluate the relationships between part characteristics and manufacturing operations: The level of relationship between each part characteristic and the manufacturing operation is determined by using 5-point scale in Table 2.3.

Step 3.5: Calculate the final weights of manufacturing operations and define the process design target: After the correlation scores between part characteristics and manufacturing operations are determined, these scores are multiplied by the importance degrees of the part characteristics and the column total is obtained for each manufacturing operation. The column totals are normalized to determine the relative absolute importance of the manufacturing operations. Targets about manufacturing operations are defined by the QFD team using team's experiences and patent mining results. The patents on the cluster labels selected for the manufacturing operation are examined in detail. From the detailed analysis of the patents, the QFD team gains a better understanding of the selected manufacturing operation and determines the required target values to keep the process under control. Target values and their unit of measurement are written in the bottom row of the matrix.

Stage 4: Production/Operation Planning: This stage converts manufacturing operations into operations & controls.

Step 4.1: Organize manufacturing operations and get weights of manufacturing operations from Stage 3: By creating a matrix, manufacturing operations in the columns of the process planning matrix are written in the rows. Also, weights of manufacturing operations from Stage 3 are written for each manufacturing operation.

Step 4.2: Define operations & controls: Operations and controls that use in the production are located in the columns of the matrix.

Step 4.3: Determine the relationships of operations & controls: This step forms the roof of the production/operation planning matrix and shows how operations and controls impact each other. “+” shows a positive correlation, “-“ shows a negative correlation and blank represents no correlation.

Step 4.4: Evaluate the relationships between manufacturing operations and operations & controls: The level of relationship between each manufacturing operation and each operation is determined by using 5-point scale in Table 2.3.

Step 4.5: Calculate the final weights of operations & controls: After the correlation scores between manufacturing operations and operations & controls are determined, these scores are multiplied by the importance degrees of the manufacturing operations and the column total is obtained for each operation & control. The column totals are normalized to determine the relative absolute importance of the operations & controls.

4. A CASE STUDY ON THE HORIZONTAL STABILIZER

The case study of new product design with sustainability driven QFD reinforced by patent mining method was carried out in a military factory. This center carries out aircraft programmed depot maintenances, aircraft engine overhauls, heavy maintenance activities, avionics depot level maintenance, accessory overhauls within the inventory of the Turkish Air Force and spare parts manufacturing. Goals of this factory are to support weapons systems under its responsibility in a safe, effective and economical way; to provide rapid and uninterrupted support, and to reduce foreign dependency.

During the service life of aircraft, it is necessary to check the structural parts periodically, repair the damaged parts, and produce new parts to replace the ones that cannot be repaired. By designing and manufacturing new products, it is aimed to provide uninterrupted support to the Turkish Air Force, to reduce foreign dependency, to provide cost advantage, and to reduce the grounding time of the aircraft, which causes weakness in combat readiness in military aircraft, to a minimum.

In this thesis, the horizontal stabilizer of F-16 aircraft is chosen as a case study. This stabilizer is a composite structural part of the aircraft. Using new product design with sustainability driven QFD reinforced by patent mining method, all stages are applied by a taking view of the expert team. We executed a patent mining research for determining manufacturing operations and their target values for composite material forming. First of all, information about the factory and the selected product will be given, and then the application stages of new product design with sustainability driven QFD reinforced by patent mining method in the case study will be explained in this section.

4.1. Information About the Factory

The aircraft maintenance facilities were established and aircraft maintenance services began in 1926. Jet aircraft maintenance began in 1950 and the first jet engine was overhauled in 1967. After 1979, F-4E aircraft programmed depot level maintenance began in this factory. Modernization programs such as F-4E 2020, F-5 2000 initiated early in 1997 and continued with national indigenous design and application of RF-4 aircraft in 2004, engine test cell design and development in 2006. In 2013 modernization program for F-16 and in 2016 avionics modernizations for T-38 were executed. After the foundation in 1926, this center has performed more than 5.000 aircraft depot level maintenance. In addition, more than 9.000 aircraft engines have been overhauled.

Facilities to carry out mission are located in an area of 46 million square feet, 2.1 million square feet of which is an in-door area. It has a manpower of about 2.100 personnel. It has the capacity of 80 aircraft, 150 engines, 40.000 repairable units and 100.000 productions per year. This factory possesses the engineering capability and resources to perform the necessary duties under Technical Management Responsibility for the following weapon systems: F-16, F-4, NF-5, T-38 and KT-1T aircraft within the inventory of the Turkish Air Force. Similarly, it has capabilities to perform the Technical Management Responsibility duties for the various types of engines (F110, J79, J85, PT-6, TYNE-MK-22, T56, CT-7, MAKILA1, T53 etc.). This center carries out aircraft Programmed Depot Maintenance (PDM), aircraft engine overhauls. During the PDM process, each aircraft spends a certain period to be structurally inspected, repaired, renewed, and functionally checked before returning to their operational unit. Also, heavy maintenance activities (scheduled checks and PDMs, modifications, major repairs, special inspections/non-destructive inspections, wiring harness manufacturing, upgrades, fleet modernization), avionics depot level maintenance (flight control systems, fire control systems, CNI systems, aircraft engine electronics), accessory overhauls (hydraulic& servo systems, electrical power systems, oil & fuel systems, brake & landing gear systems, gears and bearings, pneumatic systems) are performed in this factory. To support aircraft and engine repair shops and operational bases, spare parts such as aircraft structural parts, engine parts, tubes, hose assemblies and tooling are manufactured. It utilizes state-of-the-art technology such as machining, sheet metal, tube and hoses, heat treatment, computer aided design and manufacturing, coordinate measurement machine, painting (polyurethane, synthetic), rubber based internal aircraft fuel tank and leak test, forging, sand casting, plating, electro discharge machining, electromechanical milling, wedding. This center utilizes all None-Destructive Inspection (NDI) techniques, and it has chemistry, environmental and metallurgy, precision measurement equipment calibration labs for the highest quality products. This factory has quality certificates: AQAP 2110, AQAP 160, TS EN ISO 9001-2000, 14001, 45001, NADCAP (X-Ray Process), AS 9110 and AS 9100. Goals of it are to support weapons systems under its responsibility in a safe, effective and economical way; to provide rapid and uninterrupted support and to reduce foreign dependency. The Turkish Air Force and other Turkish Armed Forces are the main customers. It is also allowed to provide industrial services to domestic and international customers under the provisions of a special law, called non-appropriated fund.

4.2. Information About the Selected Product

The development of engineering materials has accelerated with aviation materials. The materials used in aircraft, which became a common means of transportation after the Wright brothers' first flight, have always led to the evolution of the aircraft. Wood to metal, metal to composites has become an important parameter seeking increasingly lighter, high-temperature stability and corrosion resistance properties.

The use of composite materials is increasing day by day due to conditions such as high strength, thermal resistance, electrical conductivity and lightness in aviation. Sandwich-type honeycomb structures and glass fiber reinforced composites came into use in the 1940s (Herman, Zahlen and Zuardy, 2005; Haresceugh, 2007). Carbon fiber reinforced composites started to be used in the 1960s (Soutis, 2005). Firstly, these composite materials were used in non-structural and secondary parts in the military aircraft (Haresceugh, 2007; Kassapoglou, 2013; Hiken, 2017). Then, composite materials started to be utilized in the military aircraft' structural parts until the 1980s (Hiken, 2017). Today, it is also used extensively in the structural parts of commercial aircraft (Haresceugh, 2007). For instance, almost 50% of the Boeing 787 aircraft's structures are composite materials (Roach and DiMambro, 2006).

Composite-based aircraft components have some advantages when compared to parts produced from conventional materials, such as aluminum. Composite materials permit for the manufacturing of better aerodynamically effective parts (Haresceugh, 2007; Hadcock, 1998) They exhibit high specific strength, specific stiffness, and fatigue characteristics, also good temperature resistance, corrosion resistance, and radar absorption and suppression (Roach and DiMambro, 2006; Hadcock, 1998). They are also lighter compared to aluminum, so using these materials can decrease consumption of the fuel, direct operating costs while increasing efficiency of aircrafts (Kassapoglou, 2013; Gopal, 2016). Composite materials have great tensile strength, compression resistance. This situation makes them convenient for using in aircraft parts. Other advantages contain their advanced corrosion and fatigue resistances. These advantages take a role when we want to reduce costs of the aircraft in the long run, to improve the efficiency. Also, there is a transformation to develop more definitely towards green product design. As discussed formerly, composite materials have a lighter weight while similar strength measurements like heavier ones. When we transport the lighter composite, there is a lower environmental load while comparing to the heavier options. Composites will be used longer because of these corrosion-resistant features when we compare metallic materials. These factors make them the best option from an environmental aspect.

Composites have the advantage that companies can form them into approximately any shape but modelling of their compounds is difficult. A significant disadvantage of the use of these materials is having high cost. This situation is also referred to as the labor intensive, complex production process. Thus, before the making investment decisions, the process of composite material forming must be analyzed and monitored seriously. This knowledge is vital for countries, research and development, strategic planning, and companies' practices.

The use of composite materials in aircraft construction is increasing. It is very important to consider and examine how these materials are produced. With the production of structural parts for aircraft in the Turkish Air Force inventory, the rate of locality and nationality will increase.

In this study, horizontal stabilizer of F-16 aircraft is chosen as a case study. Because it has a high annual usage amount, and it is important in terms of flight safety and cost advantage. The principal load-carrying sections or components of an airplane are fuselage, wings, landing gear, control surfaces, stabilizers. Control surfaces include ailerons, flaps, trim tabs, spoilers, rudder and any other movable surface used for changing the aircraft's attitude while on flights. For the F-16, control surfaces consist of rudder, flaperon (combination aileron and flaps) and horizontal stabilizers. Figure 4.1. demonstrates a light airplane with various components identified.

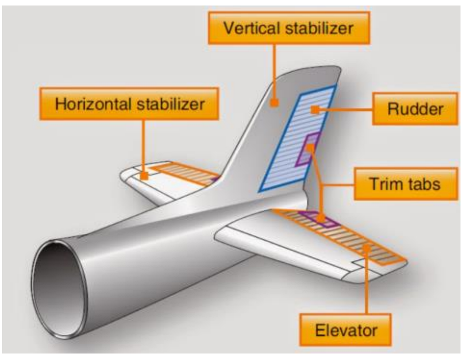


Figure 4.1. *Light airplane*

Figure 4.2. shows airframe materials of the F-16 aircraft. Materials for the F-16 fighter were chosen for the convenience of design, manufacturing and assembly at minimum cost, while keeping design integrity and reliability. Materials problems encountered with other aircraft like F-4 aircraft, in the past, were taken into account while selecting materials. The selected materials provided lower maintenance costs, better performance and longer product life, while preventing stress corrosion and brittle fracture. Materials used in the airframe and landing gear structures consist of approximately the following composition breakdown, by weight: Aluminum 83%, Steel 5%, Titanium 2%, Composite 2%, Other materials 8%.

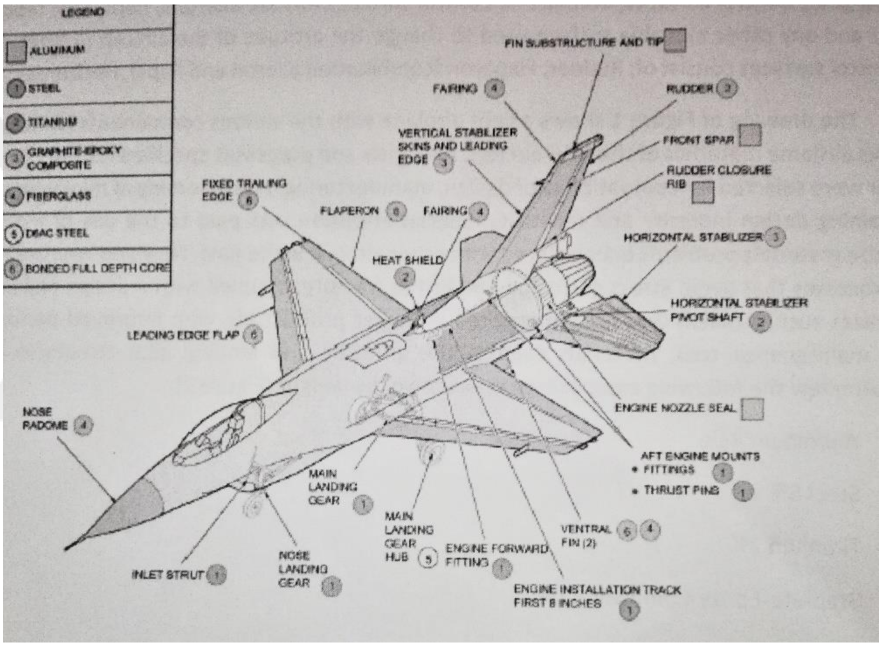


Figure 4.2. *Airframe materials*

Horizontal stabilizer is a stabilizer mounted horizontally on an airplane affording horizontal stability and to which elevators are attached. Figure 4.3. shows a horizontal stabilizer. It is built up structure consisting of graphite-epoxy skin, rip spar, bushing, fitting, closure, retainer and finish. Horizontal movement of pitch is provided by two servo actuators. The stabilizers are interchangeable, left and right, and provide pitch and roll control through differential deflection.

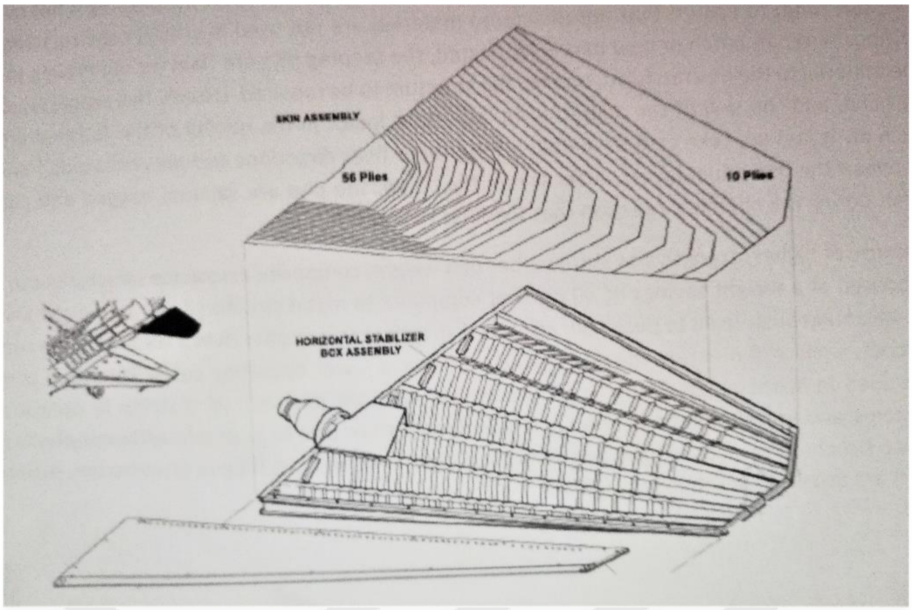


Figure 4.3. *Horizontal stabilizer*

A composite is a combination of two or more different materials at the macroscopic level. Composite materials that are used in aircraft comprise a resin matrix and fibers. The fibers provide strength and stiffness. Many varieties of fibers and resins can be used with different combinations. Fibers can be made from glass, boron, graphite or kevlar. Thermosetting resins are the most popular resin and the most common thermosets are epoxies and polyesters. Also, there are polyamides and bismaleimides as thermosetting resins. Aerospace composite elements, such as glass-epoxy and carbon-epoxy, can be manufactured as laminar and sandwich structures. Horizontal stabilizer of F-16 is graphite-epoxy and can be manufactured as laminar.

4.3. Stage 1: Product Planning

In Stage 1, customer needs and sustainability requirements are translated into measurable engineering characteristics. The steps of the Stage 1 are as follows:

Step 1.1: Define goals of the company and the product: In Table 4.1., the planning details of the case study are examined.

Table 4.1. *Planning details of the case study*

What to do?	What has been done?
Setting goals	Before starting the proposed methodology, product development, process improvement and quality enhancement priority targets have been determined. Acquiring the manufacturable capability of the horizontal stabilizer, which is the structural part of the F-16 aircraft, has been determined as the main target.
Providing QFD team and management team support	The support of the management team has been obtained. The subject was summarized for the unit employees who will take part in the QFD team, and it was ensured that they gained sufficient knowledge about QFD.
Deciding on the product	The horizontal stabilizer of F-16 aircraft has been chosen.
Time planning	Planning of the case study has been made. It is planned between 2021 - 2022.
Creating the QFD team	The QFD team consists of five people, including two aeronautical engineers, a mechanical engineer, a chemical engineer, and an industrial engineer. They have a minimum of ten years of experience.
Determining the customer	The Turkish Air Force and other Turkish Armed Forces are the main customers. It is also allowed to provide industrial services to domestic and international customers under the provisions of a special law, called a non-appropriated fund. In this case study, the customer is the internal customer.

Step 1.2: Define customers, collect and analyze the voice of customers: In this case study, the customer is the internal customer. The internal customer group was selected from the department that will assemble the horizontal stabilizer to be produced on the aircraft. This group consists of five people, including two aeronautical engineers, three mechanical engineers. While determining customer needs and expectations, one-to-one interviews, Gemba visits, focus group studies, complaints and comments reports of the main customers were used. Customer needs are listed in Table 4.2.

Table 4.2. *Customer needs (Ayber and Erginel, 2022)*

Number	Customer Needs
CN1	Ease of installation and integrity
CN2	It must be performed flight control mission
CN3	No corrosion
CN4	Resistant to environmental conditions while performing the flight mission
CN5	Strength to flight loads
CN6	Easy to repair
CN7	No surface damage and edge delamination
CN8	Electrical property suitability
CN9	Resistant to shock loads and blast
CN10	Interchangeability
CN11	Accuracy in horizontal stabilizer width&height&thickness

Step 1.3: Define sustainability requirements: All aspects of sustainability requirements have been defined, and they have collected via focus group studies. These are given in Table 4.3. Customer needs and sustainability requirements are located in the rows of the planning matrix. SR1 and SR2 are considered as environmental aspects of sustainability. SR3 is related to an economic aspect of sustainability, whereas SR4 is related to a social aspect of sustainability.

Table 4.3. *Sustainability requirements (Ayber and Erginel, 2022)*

Number	Sustainability Requirements
SR1	Long life cycle
SR2	It can be provided fuel savings
SR3	Low manufacturing cost
SR4	Suitable for flight safety

Step 1.4: Organize customer needs and sustainability requirements, construct the hierarchy of them: Figure 4.4. represents the affinity diagram of customer needs and sustainability requirements. Sustainability, operation, maintenance and design are the main groups.

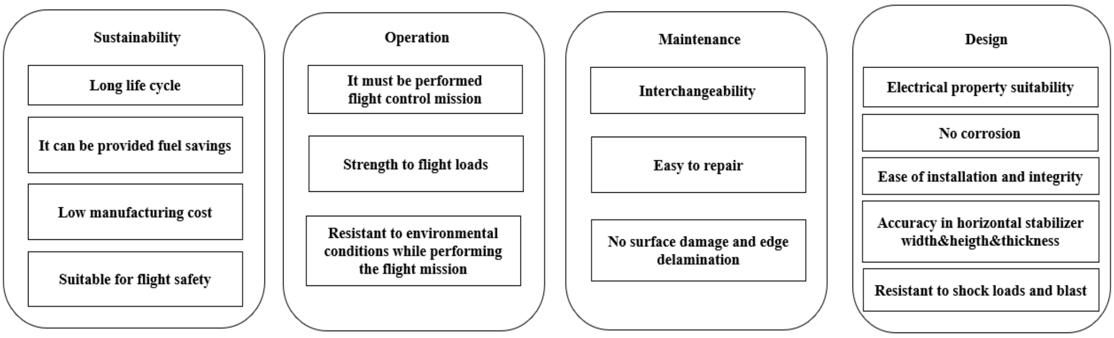


Figure 4.4. *Affinity diagram*

Step 1.5: Find the importance of customer needs and sustainability requirements: AHP has been used while determining the importance degrees of customer needs and sustainability requirements as explained in Section 2.2 The internal customer group compared the importances of the CN in the row with the CN in the column and they assigned a grade by using rates in Table 2.2. With using equations from 2.1. to 2.5., we have calculated importances. Figure 4.5 demonstrates AHP rates for each customer needs and sustainability requirements.

Criteria	CN1	CN2	CN3	CN4	CN5	CN6	CN7	CN8	CN9	CN10	CN11	SR1	SR2	SR3	SR4	AHP Rates
CN1	1.00	0.20	0.33	1.00	0.20	0.33	0.33	0.33	0.33	0.33	1.00	0.33	1.00	0.20	0.33	0.020
CN2	5.00	1.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	0.325
CN3	3.00	0.11	1.00	1.00	0.33	1.00	1.00	1.00	3.00	0.33	1.00	1.00	3.00	3.00	0.33	0.036
CN4	1.00	0.11	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	3.00	1.00	3.00	3.00	0.33	0.042
CN5	5.00	0.11	3.00	1.00	1.00	3.00	3.00	3.00	1.00	3.00	5.00	3.00	5.00	5.00	1.00	0.085
CN6	3.00	0.11	1.00	1.00	0.33	1.00	1.00	1.00	0.33	1.00	3.00	3.00	5.00	0.20	0.33	0.041
CN7	3.00	0.11	1.00	1.00	0.33	1.00	1.00	1.00	0.33	0.33	5.00	3.00	5.00	0.33	0.33	0.041
CN8	3.00	0.11	1.00	1.00	0.33	1.00	1.00	1.00	0.20	0.20	3.00	3.00	1.00	0.20	0.33	0.033
CN9	3.00	0.11	3.00	1.00	1.00	3.00	3.00	5.00	1.00	1.00	7.00	3.00	5.00	3.00	0.33	0.076
CN10	3.00	0.11	3.00	1.00	0.33	1.00	3.00	5.00	1.00	1.00	7.00	3.00	3.00	3.00	0.14	0.065
CN11	1.00	0.11	1.00	0.33	0.20	0.33	0.20	0.33	0.14	0.14	1.00	1.00	1.00	0.20	0.11	0.016
SR1	3.00	0.11	1.00	1.00	0.33	0.33	0.33	0.33	0.33	0.33	1.00	1.00	3.00	3.00	0.20	0.031
SR2	1.00	0.11	0.33	0.33	0.20	0.20	0.20	1.00	0.20	0.33	1.00	0.33	1.00	0.33	0.11	0.015
SR3	5.00	0.11	0.33	0.33	0.20	5.00	3.00	5.00	0.33	0.33	5.00	0.33	3.00	1.00	0.20	0.054
SR4	3.00	0.11	3.00	3.00	1.00	3.00	3.00	3.00	3.00	7.00	9.00	5.00	9.00	5.00	1.00	0.118
Sums	43.00	2.64	29.00	23.00	15.80	30.20	30.07	37.00	18.54	25.34	61.00	37.00	57.00	36.47	14.10	1.000

Figure 4.5. *AHP pairwise matrix for customer needs and sustainability requirements weights*

Step 1.6: Define engineering characteristics: Engineering characteristics have defined in the company's language by the QFD team. They are located in the columns of the planning matrix. Engineering characteristics are given in Table 4.4.

Table 4.4. *Engineering characteristics (Ayber and Erginel, 2022)*

Number	Engineering Characteristics
EC1	Mechanical strength
EC2	Fatigue strength
EC3	Corrosion resistance
EC4	Weight
EC5	Dimensional stability
EC6	Thermal insulation
EC7	Electrical conductivity
EC8	Thermal expansivity
EC9	Stiffness
EC10	Moisture resistance
EC11	Aeroelasticity
EC12	Surface geometry
EC13	Wear tolerance
EC14	Abrasion resistance
EC15	Drag resistance
EC16	Projection area

Step 1.7: Determine the relationships of engineering characteristics: This step forms the roof of the product planning matrix and shows how engineering characteristics impact each other. "+" shows a positive correlation, "-" shows a negative correlation and blank represents no correlation. Figure 4.6. demonstrates the roof of the product planning matrix.

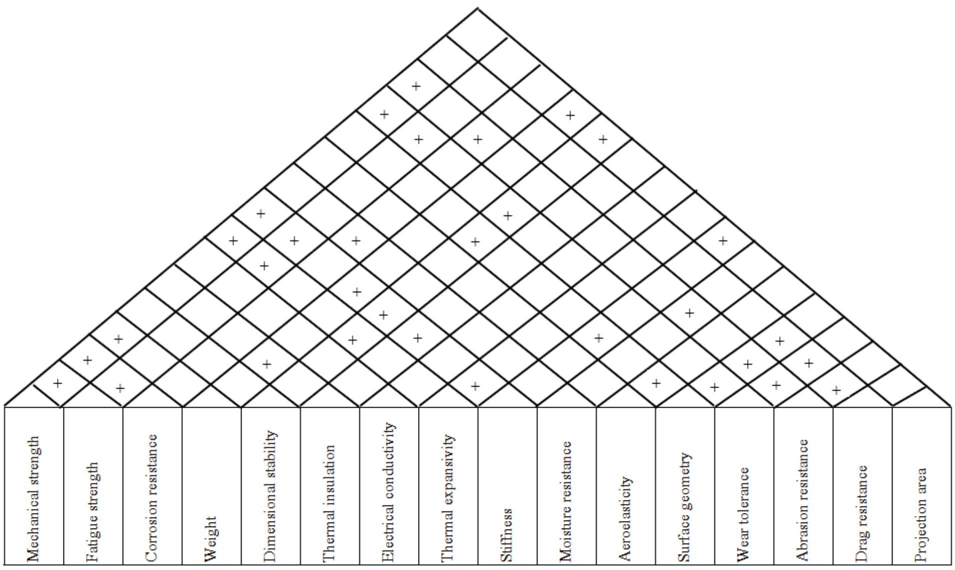


Figure 4.6. *The roof of the product planning matrix*

Step 1.8: Compare the current product and competitor's product: The assessments for competitiveness could not be made because there is no competitor against the military factory in the case study.

Step 1.9: Evaluate the relationships between customer needs, sustainability requirements and engineering characteristics: This matrix indicates the relationship and relationship strength between the Whats (customer needs, sustainability requirements) and the Hows (engineering characteristics). Degrees of relationships are determined by using the 5-point scale in Table 2.3. 0.069 indicates weak relationship, 0.135 indicates moderate relationship, 0.267 indicates strong relationship, 0.518 indicates very strong relationship and 1 indicates extremely strong relationship. QFD team assigned relationship degrees that are demonstrated in Figure 4.7.

WHATS \ HOWS				Importance Evaluations	EC1	EC2	EC3	EC4	EC5	EC6	EC7	EC8	EC9	EC10	EC11	EC12	EC13	EC14	EC15	EC16
Customer needs	Design	CN1	Ease of installation and integrity	0.020					0.267				0.267		0.069	0.267	0.267			0.069
	Operation	CN2	It must be performed flight control mission	0.325	0.267	0.267		0.267				0.267			1	0.518	0.267		1	0.267
	Design	CN3	No corrosion	0.036	0.267		1							0.518				0.267		
	Operation	CN4	Resistant to environmental conditions while performing the flight mission	0.042	0.518	0.518	1			0.518		0.518		1				0.267		
	Operation	CN5	Strength to flight loads	0.085	0.267	0.267		0.267				0.267			1	0.518	0.267		1	0.267
	Maintenance	CN6	Easy to repair	0.041	0.267	0.267	0.267				0.267			0.267			0.267	0.518		
	Maintenance	CN7	No surface damage and edge delamination	0.041	0.267	0.267	0.267				0.267			0.267			0.267	0.518		
	Design	CN8	Electrical property suitability	0.033							1									
	Design	CN9	Resistant to shock loads and blast	0.076	0.518	0.518	0.518				0.267	0.267		0.267		0.267	0.267	0.267	0.267	
	Maintenance	CN10	Interchangeability	0.065					0.267		0.267				0.267	0.267				0.267
	Design	CN11	Accuracy in horizontal stabilizer width&height&thickness	0.016					1			0.518	0.518							0.267
Sustainability requirements	Sustainability	SR1	Long life cycle	0.031	1	1	1					0.267		0.267			0.267	0.267		
	Sustainability	SR2	It can be provided fuel savings	0.015				1	0.267							1			1	
	Sustainability	SR3	Low manufacturing cost	0.054	0.267		0.267		0.267	0.267	0.267			0.267	0.518	0.518	0.518	0.267	0.267	0.267
	Sustainability	SR4	Suitable for flight safety	0.118	0.518	0.518	0.518				0.267	0.267		0.267			0.267	0.267		

Figure 4.7. *Relationships between customer needs, sustainability requirements and engineering characteristics*

Step 1.10: Calculate the final weights of engineering characteristics: This section, which is located at the base of the planning matrix, contains the calculated importance scores of the engineering characteristics. The priority of engineering characteristics that can bring customer needs and sustainability requirements to the highest degree is determined. The final weights of engineering characteristics are obtained through multiplying importances levels of customer needs and sustainability requirements by relationship values of customer needs, sustainability requirements and engineering characteristics. Then, relative importance degrees are calculated by summing for each engineering characteristic. We divide the final weights of each engineering characteristic into the cumulative degree of weights and rank engineering characteristics.

The calculation is examined in the example below based on the engineering characteristic of fatigue strength (EC2). Figure 4.7. shows that the relationship between EC2 and CN2 is 0.267. The importance degree for CN2 is 0.325. When these values were multiplied by each other, the value of 0.087 was obtained. There are seven more relationship values for the fatigue strength engineering characteristic. A total of 8 multiplications were made and then the obtained values were added. The sum of these values was calculated as 0.285 and written in the absolute importance line under the column related to the fatigue strength engineering characteristic. By repeating the process for each of the engineering characteristic, the line of absolute importance was completed and shown in Figure 4.8.

CN2 It must be performed flight control mission;	0.325 x 0.267 = 0.087
CN4 Resistant to environmental conditions;	0.042 x 0.518 = 0.022
CN5 Strength to flight loads;	0.085 x 0.267 = 0.023
CN6 Easy to repair;	0.041 x 0.267 = 0.011
CN7 No surface damage and edge delamination;	0.041 x 0.267 = 0.011
CN9 Resistant to shock loads and blast;	0.076 x 0.518 = 0.039
SR1 Long life cycle;	0.031 x 1.000 = 0.031
SR4 Suitable for flight safety;	0.118 x 0.518 = 0.061
Sum	**0.285**

Then, relative absolute importances were calculated as follows:

Relative absolute importance (%) = (Absolute importance/∑ Absolute importance) x 100

For example, relative absolute importance for fatigue strength engineering characteristic is calculated as follows:

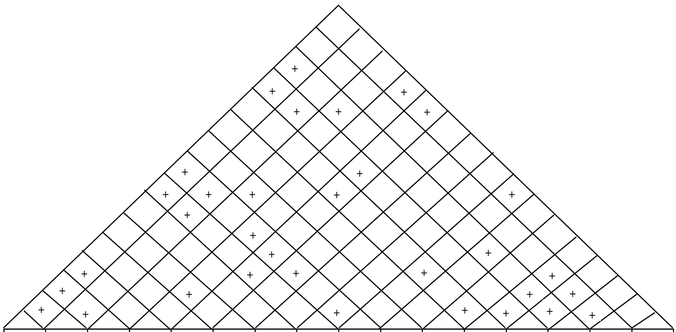
[0.285/(0.309+0.285+0.246+0.125+0.057+0.036+0.139+0.200+0.014+0.157+0.458+0.299+0.225+0.138+0.461+0.147)] x100 = 8.646

WHATS \ HOWS	Importance Evaluations	Mechanical strength	Fatigue strength	Corrosion resistance	Weight	Dimensional stability	Thermal insulation	Electrical conductivity	Thermal expansivity	Stiffness	Moisture resistance	Aeroelasticity	Surface geometry	Wear tolerance	Abrasion resistance	Drag resistance	Projection area
		EC1	EC2	EC3	EC4	EC5	EC6	EC7	EC8	EC9	EC10	EC11	EC12	EC13	EC14	EC15	EC16
Absolute importance		0.309	0.285	0.246	0.125	0.057	0.036	0.139	0.200	0.014	0.157	0.458	0.299	0.225	0.138	0.461	0.147
Relative absolute importance (%)		9.375	8.646	7.457	3.789	1.744	1.098	4.219	6.065	0.415	4.762	13.888	9.078	6.832	4.182	13.979	4.470

Figure 4.8. *Importance degrees for engineering characteristics*

Further efforts are needed to improve the engineering characteristic, which has of the highest importance. The most important engineering characteristic in meeting customer needs and sustainability requirements are “Drag resistance”, “Aeroelasticity” and “Mechanical strength”. Figure 4.9. demonstrates product planning matrix.

Drag is a force that acts on the aircraft moving through the air parallel and is in the opposite direction of motion. Drag affects the aircraft negatively. It causes problems such as increased fuel consumption, reduced maximum range of the vehicle, irregular airflow. Care must be taken in every area, from design to manufacturing, to reduce drag. For example, we can avoid sharp transitions in design and keep surface roughness to a minimum in terms of manufacturing. Aeroelasticity examines the effects of interacting aerodynamic, elastic and inertial forces on aerospace structures. Aeroelastic effects often negatively contribute to the performance and safe flying of an aircraft. For this reason, it is vital that aeroelastic analyzes are started from the early stages of the design and that the designs are changed in advance, if necessary, to avoid critical situations. Mechanical strength is very important in aircraft parts in terms of flight safety. The mechanical properties of the manufactured part can be affected by factors such as the type of material used, environmental conditions (temperature, humidity, etc.) and production parameters. So, mechanical behavior of the horizontal stabilizer must be investigated.



WHATS / HOWS				Importance Evaluations	EC1 Mechanical strength	EC2 Fatigue strength	EC3 Corrosion resistance	EC4 Weight	EC5 Dimensional stability	EC6 Thermal insulation	EC7 Electrical conductivity	EC8 Thermal expansivity	EC9 Stiffness	EC10 Moisture resistance	EC11 Aeroelasticity	EC12 Surface geometry	EC13 Wear tolerance	EC14 Abrasion resistance	EC15 Drag resistance	EC16 Projection area
Customer needs	Design	CN1	Ease of installation and integrity	0.020					0.267				0.267		0.069	0.267	0.267			0.069
Customer needs	Operation	CN2	It must be performed flight control mission	0.325	0.267	0.267		0.267				0.267			1	0.518	0.267		1	0.267
Customer needs	Design	CN3	No corrosion	0.036	0.267		1							0.518				0.267		
Customer needs	Operation	CN4	Resistant to environmental conditions while performing the flight mission	0.042	0.518	0.518	1			0.518		0.518		1				0.267		
Customer needs	Operation	CN5	Strength to flight loads	0.085	0.267	0.267		0.267				0.267			1	0.518	0.267		1	0.267
Customer needs	Maintenance	CN6	Easy to repair	0.041	0.267	0.267	0.267				0.267			0.267			0.267	0.518		
Customer needs	Maintenance	CN7	No surface damage and edge delamination	0.041	0.267	0.267	0.267				0.267			0.267			0.267	0.518		
Customer needs	Design	CN8	Electrical property suitability	0.033							1									
Customer needs	Design	CN9	Resistant to shock loads and blast	0.076	0.518	0.518	0.518				0.267	0.267		0.267		0.267	0.267	0,267	0.267	
Customer needs	Maintenance	CN10	Interchangeability	0.065					0.267		0.267				0.267	0.267				0.267
Customer needs	Design	CN11	Accuracy in horizontal stabilizer width&height&thickness	0.016					1			0.518	0.518							0.267
Sustainability requirements	Sustainability	SR1	Long life cycle	0.031	1	1	1					0.267		0.267			0.267	0.267		
Sustainability requirements	Sustainability	SR2	It can be provided fuel savings	0.015				1	0.267							1			1	
Sustainability requirements	Sustainability	SR3	Low manufacturing cost	0.054	0.267		0.267		0.267	0.267	0.267			0.267	0.518	0.518	0.518	0.267	0.267	0.267
Sustainability requirements	Sustainability	SR4	Suitable for flight safety	0.118	0.518	0.518	0.518				0.267	0.267		0.267			0.267	0.267		
				Absolute importance	0.309	0.285	0.246	0.125	0.057	0.036	0.139	0.200	0.014	0.157	0.458	0.299	0.225	0.138	0.461	0.147
				Relative absolute importance (%)	9.375	8.646	7.457	3.789	1.744	1.098	4.219	6.065	0.415	4.762	13.888	9.078	6.832	4.182	13.979	4.470

Figure 4.9. *HoQ for Stage 1*

4.4. Stage 2: Part Deployment

In Stage 2, engineering characteristics are translated into part characteristics. Stage 2 is the prioritization of part characteristics that are deployed to the Stage 3. The aim is to identify the critical parts and try to develop these parts, and to distribute the resources effectively. The steps of the Stage 2 are as follows:

Step 2.1: Organize engineering characteristics and get weights of engineering characteristics from Stage 1: By creating a matrix, the engineering characteristics in the columns of the product planning matrix are written in the rows. Also, weights of engineering characteristics from Stage 1 are written for each engineering characteristic.

Step 2.2: Define the part characteristics: The parts that make up the product are located in the columns of the matrix. QFD team defined part characteristics in seven main categories as: skin, rip spar, bushing, fitting, closure, retainer and finish. 27 part characteristics defined are presented in the Table 4.5.

Table 4.5. *Part characteristics*

Number	Part	Part Characteristics
PC1	Skin	Accuracy in skin assembly width&height
PC2	Skin	Hole diameter
PC3	Skin	Hole location
PC4	Skin	Contour
PC5	Skin	Abrasion resistance
PC6	Skin	Number of layers
PC7	Skin	Skin's weight
PC8	Skin	Surface smoothness
PC9	Skin	Matrix
PC10	Skin	Reinforcing fibers
PC11	Rip Spar	Accuracy in rip spar width&height
PC12	Rip Spar	Material type
PC13	Rip Spar	Repair or replace situation
PC14	Bushing	Accuracy in bushing width&height
PC15	Bushing	Material type
PC16	Bushing	Repair or replace situation
PC17	Fitting	Accuracy in fitting width&height
PC18	Fitting	Material type
PC19	Fitting	Repair or replace situation
PC20	Closure	Accuracy in closure width&height
PC21	Closure	Material type
PC22	Closure	Repair or replace situation
PC23	Retainer	Accuracy in retainer width&height
PC24	Retainer	Material type
PC25	Retainer	Repair or replace situation
PC26	Finish	Thickness
PC27	Finish	Coating

Step 2.3: Determine the relationships of part characteristics: This step forms the roof of the part deployment matrix and shows how part characteristics impact each other.

“+” shows a positive correlation, “-“ shows a negative correlation, and blank represents no correlation. Figure 4.10. demonstrates the roof of the part deployment matrix.

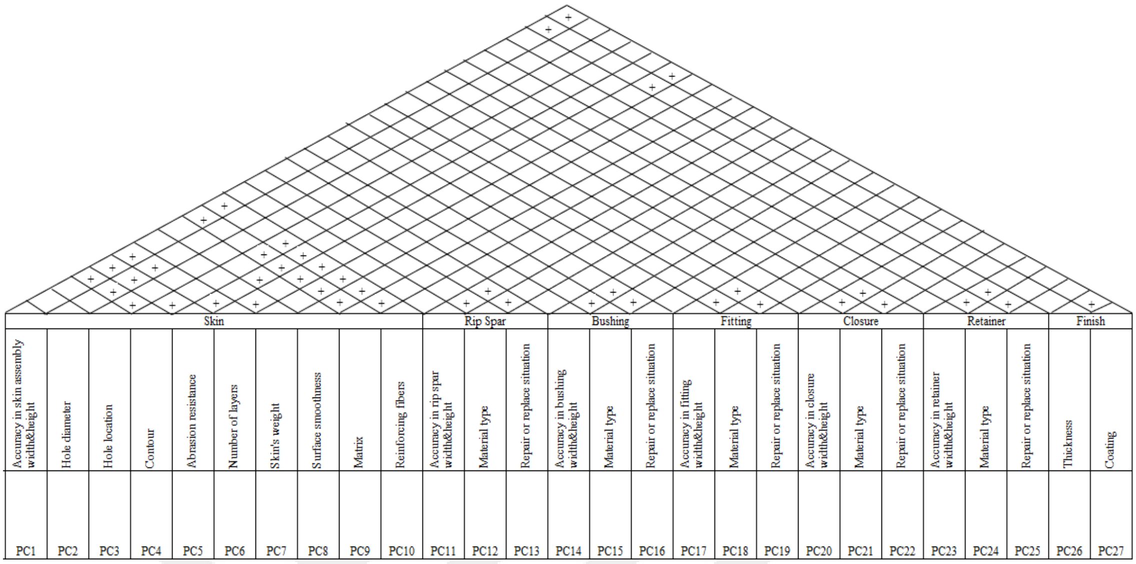


Figure 4.10. *The roof of the part deployment matrix*

Step 2.4: Evaluate the relationships between engineering characteristics and part characteristics: The level of relationship between each part characteristic and the engineering characteristic was determined by using 5-point scale in Table 2.3. Assigned relationship degrees by QFD team are demonstrated in Figure 4.11.

WHATS / HOWS			Importance Evaluations	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC15	PC16	PC17	PC18	PC19	PC20	PC21	PC22	PC23	PC24	PC25	PC26	PC27
Engineering Characteristics	EC1	Mechanical strength	9.375						1			1	0.267		1			1			1			1			1			
	EC2	Fatigue strength	8.646						0.518			1	1		1			1			1			1			1			
	EC3	Corrosion resistance	7.457												1			1			1			1			1			1
	EC4	Weight	3.789		0.069	0.069			1	1		1	1		1			1			1			1			1			1
	EC5	Dimensional stability	1.744	1			0.069				0.267	0.267	0.267	1			1			1			1			1				
	EC6	Thermal insulation	1.098									1	1																1	1
	EC7	Electrical conductivity	4.219										1		1			1			1			1			1			1
	EC8	Thermal expansivity	6.065						1			1	1		1			1			1			1			1			
	EC9	Stiffness	0.415	0.069					1	0.267		1	1	0.069	1		0.069	1		0.069	1		0.069	1		0.069	1			
	EC10	Moisture resistance	4.762		0.267	0.267		0.267			0.267	0.518	0.518																0.518	1
	EC11	Aeroelasticity	13.888		0.267	0.267	1				1																			1
	EC12	Surface geometry	9.078	0.069	0.069	0.069	1							0.069			0.069			0.069			0.069			0.069				
	EC13	Wear tolerance	6.832					1			1					0.518			0.518			0.518			0.518			0.518		0.518
	EC14	Abrasion resistance	4.182					1			1	0.518	0.518		1	0.518		1	0.518		1	0.518		1	0.518		1	0.518	0.518	0.518
	EC15	Drag resistance	13.979				1			1	1																			0.267
	EC16	Projection area	4.470	0.069							1																			

Figure 4.11. *Relationships between engineering characteristics and part characteristics*

Step 2.5: Calculate the final weights of part characteristics: After the correlation scores between engineering characteristics and part characteristics are determined, these scores are multiplied by the importance degrees of the engineering characteristics and the column total is obtained for each part characteristic. The column totals are normalized to determine the relative absolute importance of the part characteristics.

The calculation is examined in the example below based on the part characteristic of skin abrasion resistance (PC5). Figure 4.11. shows that the relationship between PC5 and EC10 is 0.267. The importance degree for EC10 is 4.762. When these values were multiplied by each other, the value of 1.271 was obtained. There are two more relationship values for the skin's abrasion resistance part characteristic. A total of 3 multiplications were made and then the obtained values were added. The sum of these values was calculated as 12.285 and written in the absolute importance line under the column related to the skin's abrasion resistance part characteristic. By repeating the process for each of the part characteristic, the line of absolute importance was completed and shown in Figure 4.12.

EC10 Moisture resistance;	4.762 x 0.267 = 1.271
EC13 Resistant to environmental conditions;	6.832 x 1.000 = 6.832
EC14 Strength to flight loads;	4.182 x 1.000 = 4.182
Sum	**12.285**

Then, relative absolute importances were calculated as follows:

Relative absolute importance (%) = (Absolute importance/∑ Absolute importance) x 100

For example, relative absolute importance for the skin's abrasion resistance part characteristic is calculated as follows:

[12.285/(2.707+5.868+5.868+37.066+12.285+24.123+17.879+45.089+34.486+31.833+2.399+44.148+5.705+2.399+44.148+5.705+2.399+44.148+5.705+2.399+44.148+5.705+2.399+44.148+5.705+5.731+44.651)] x100 = 2.323

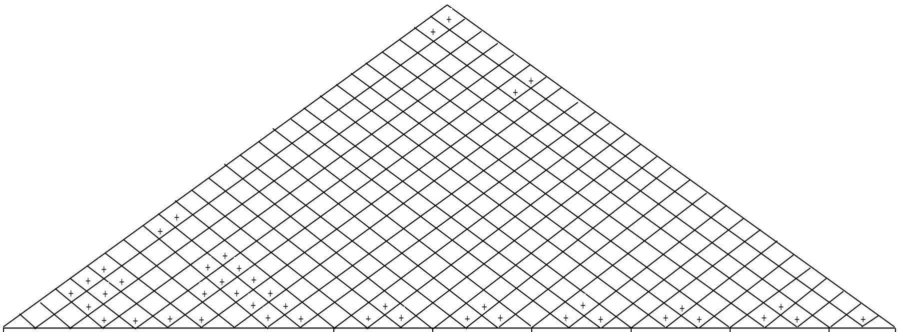
	Skin										Rip Spar		
	Accuracy in skin assembly width&height	Hole diameter	Hole location	Contour	Abrasion resistance	Number of layers	Skin's weight	Surface smoothness	Matrix	Reinforcing fibers	Accuracy in rip spar width&height	Material type	Repair or replace situation
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13
Absolute importance	2.707	5.868	5.868	37.066	12.285	24.123	17.879	45.089	34.486	31.833	2.399	44.148	5.705
Relative absolute importance (%)	0.512	1.110	1.110	7.009	2.323	4.561	3.381	8.526	6.521	6.019	0.454	8.348	1.079

	Bushing			Fitting			Closure			Retainer			Finish	
	Accuracy in bushing width&height	Material type	Repair or replace situation	Accuracy in fitting width&height	Material type	Repair or replace situation	Accuracy in closure width&height	Material type	Repair or replace situation	Accuracy in retainer width&height	Material type	Repair or replace situation	Thickness	Coating
	PC14	PC15	PC16	PC17	PC18	PC19	PC20	PC21	PC22	PC23	PC24	PC25	PC26	PC27
Absolute importance	2.399	44.148	5.705	2.399	44.148	5.705	2.399	44.148	5.705	2.399	44.148	5.705	5.731	44.651
Relative absolute importance (%)	0.454	8.348	1.079	0.454	8.348	1.079	0.454	8.348	1.079	0.454	8.348	1.079	1.084	8.443

Figure 4.12. *Importance degrees for part characteristics*

More efforts are needed to improve the part characteristic, which has of the highest importance. Figure 4.13. demonstrates part deployment matrix. At the second matrix, surface smoothness with 8.526, coating with 8.443 and material type of parts with 8.348 are determined to be the most important part characteristics.

The most important part was found as the skin. Skin is a composite based material. Therefore, it is critical that correct planning of the skin's manufacturing process and determining of target values for manufacturing operations.



			Skin										Rip Spar			Bushing			Fitting			Closure			Retainer			Finish	
			Accuracy in skin assembly width&height	Hole diameter	Hole location	Contour	Abrasion resistance	Number of layers	Skin's weight	Surface smoothness	Matrix	Reinforcing fibers	Accuracy in rip spar width&height	Material type	Repair or replace situation	Accuracy in bushing width&height	Material type	Repair or replace situation	Accuracy in fitting width&height	Material type	Repair or replace situation	Accuracy in closure width&height	Material type	Repair or replace situation	Accuracy in retainer width&height	Material type	Repair or replace situation	Thickness	Coating
WHATS \ HOWS		Importance Evaluations	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC15	PC16	PC17	PC18	PC19	PC20	PC21	PC22	PC23	PC24	PC25	PC26	PC27
Engineering Characteristics EC1	Mechanical strength	9.375						1			1	0.267		1			1			1			1			1			
EC2	Fatigue strength	8.646						0.518			1	1		1			1			1			1			1			
EC3	Corrosion resistance	7.457												1			1			1			1			1			1
EC4	Weight	3.789		0.069	0.069			1	1		1	1		1			1			1			1			1			1
EC5	Dimensional stability	1.744	1			0.069				0.267	0.267	0.267	1			1			1			1			1				
EC6	Thermal insulation	1.098									1	1																1	1
EC7	Electrical conductivity	4.219										1		1			1			1			1			1			1
EC8	Thermal expansivity	6.065						1			1	1		1			1			1			1			1			
EC9	Stiffness	0.415	0.069					1	0.267		1	1	0.069	1		0.069	1		0.069	1		0.069	1		0.069	1			
EC10	Moisture resistance	4.762		0.267	0.267		0.267			0.267	0.518	0.518																0.518	1
EC11	Aeroelasticity	13.888		0.267	0.267	1				1																			1
EC12	Surface geometry	9.078	0.069	0.069	0.069	1							0.069			0.069			0.069			0.069			0.069				
EC13	Wear tolerance	6.832					1			1					0.518			0.518			0.518			0.518			0.518		0.518
EC14	Abrasion resistance	4.182					1			1	0.518	0.518		1	0.518		1	0.518		1	0.518		1	0.518		1	0.518	0.518	0.518
EC15	Drag resistance	13.979				1			1	1																			0.267
EC16	Projection area	4.470	0.069							1																			
Absolute importance			2.707	5.868	5.868	37.066	12.285	24.123	17.879	45.089	34.486	31.833	2.399	44.148	5.705	2.399	44.148	5.705	2.399	44.148	5.705	2.399	44.148	5.705	2.399	44.148	5.705	5.731	44.651
Relative absolute importance (%)			0.512	1.110	1.110	7.009	2.323	4.561	3.381	8.526	6.521	6.019	0.454	8.348	1.079	0.454	8.348	1.079	0.454	8.348	1.079	0.454	8.348	1.079	0.454	8.348	1.079	1.084	8.443

Figure 4.13. *QFD matrix for Stage 2*

4.5. Intermediate Stage: Patent Mining for the Process

In the intermediate stage, we executed a patent mining research for determining manufacturing operations and their target values for composite material forming. The Lingo clustering algorithm is implemented for extracting topics using the patent data on composite material technology. The cluster labels are used while identifying operations. This stage is injected to improve the quality and inclusiveness of the inputs used in the QFD. The steps of the intermediate stage are as follows:

Step I.1: Retrieve patent data related to the selected process of the part: EPO database was used as the patent data source for data collection. The term “composite material forming" was chosen as the query to search the patent data in abstract fields from EPO API and retrieved 30.000 patents from the database. Abstract fields that are in text format give a summary about patent documents. In Figure 4.14., a sample XML page can be seen. An example patent link is shown in Figure 4.14. Patent documents were downloaded in XML format.


```xml
<?xml version="1.0"?><sparql xmlns="http://www.w3.org/2005/sparql-results#">
 <head>
  <variable name="publication"/>
  <variable name="title"/>
  <variable name="abstract"/>
 </head>
 <results>
  <result>
   <binding name="publication">
    <uri>http://data.epo.org/linked-data/data/publication/EP/3446963/A1/-</uri>
   </binding>
   <binding name="title">
    <literal xml:lang="en">CO-CURED SPAR AND STRINGER CENTER WING
BOX</literal>
   </binding>
   <binding name="abstract">
    <literal xml:lang="en">A center wing box assembly for an aircraft which includes: a
composite lower wing skin, a composite upper wing skin and a composite spar which
extends between the composite lower wing skin and the composite upper wing skin. The
center wingbox assembly further includes a composite stringer which extends along a web
of the composite spar in a wing span direction. The composite spar has a co-cure
securement with the composite lower wing skin and with the composite upper wing skin
and the composite stringer has a co-cure securement with the web of the composite spar.
</literal>
   </binding>
  </result>
```


Figure 4.14. *A sample XML page*

Step I.2: Preprocess the obtained patent data: After collecting of patents in Step I.1, patents' abstracts are pre-processed by controlling format, characters through a text mining framework. In this step, we transformed documents into a suitable form and converted gathered information into the standard format. Firstly, downloaded XML format was transformed into text format. XML tags (e.g. <head>, <results>) were removed. Then, following text pre-processing operations were executed. Upper cases converted into lower cases. Punctuations and non-letter characters (e.g. $, %, #) were removed. Stopwords that are common words like "a", "the", "an" etc. were eliminated. Tokenization that divides texts into small pieces that are called tokens was used.

Components of sentences were determined. Tokens were separated by space. Then, stemming was used for converting words into their stems that are root forms.

Step I.3: Cluster preprocessed patent data and find cluster labels: After the text is ready for the examination, we clustered documents with using the Lingo clustering algorithm. Carrot2 workbench, which includes the Lingo algorithm, was used to cluster and then obtained cluster labels. Carrot2 is a framework for retrieving web information and mining web and it is an open source. It is used as the basic tool for the study, by implementing and evaluating various algorithms for clustering in the frame. Carrot2 reduces the effort that is required to create a valid clustering system in academic and commercial studies. Weiss created Carrot in 2003, the initial version of Carrot2. Carrot was first applied for analyzing the original Suffix Tree Clustering (STC) algorithm. It was also carried out for implementing a hierarchical variation of STC algorithm (Maslowska and Slowiriski, 2003). Continuous developments on Carrot forced to Carrot2, which included implementations of classic agglomerative techniques, K-means, fuzzy clustering (Ngo and Nguyen, 2004), biology-inspired clustering (Schockaert, 2004) and Lingo (Osinski, Stefanowski and Weiss, 2004) together with STC (Zamir, 1999). Carrot2 presents a workbench, also an application in web. Algorithm parameters' effects can be analyzed via the workbench. Data from the Open Directory Project show that Lingo is better than STC in cluster labeling and separating mixed documents to their topics (Osinski and Weiss, 2005). Therefore, the Lingo clustering algorithm was chosen. We set Lingo algorithm parameters as follows: Minimum cluster size is two, cluster merging threshold is 0.7 and ratio of size score sorting is 1.0. There are 96 clusters, as shown in Table 4.6.

Table 4.6. *Cluster labels*

No	Cluster Labels	No	Cluster Labels	No	Cluster Labels
1	Material comprising	33	Method for forming a composite layer	65	Comprising a first electrically
2	Composite material forming	34	Forming a third layer of composite material	66	Composite includes a first coating
3	Material includes	35	Temperature while finishing	67	Curing time
4	Material having	36	Matrix material	68	Pressure provides
5	Composite material is used	37	Resin material	69	Second layer material
6	Material layer	38	Composite signal	70	Firstly heated
7	Composite particles	39	Material particles	71	Plurality of composite signals
8	Layer formed	40	Particles and method	72	Surface layers formed
9	Layer comprising	41	Cutting layers right	73	Formed composite image
10	Method for forming composite materials	42	Generating a first composite	74	Imaging apparatus
11	Surface materials	43	Fabrication of composite materials	75	Signal and transmits
12	Material of the invention	44	Comprising particles	76	Particle layer formed
13	Obtain a first composite	45	Layered structure	77	Overlies the first surface
14	Having a first surface	46	Oriented at a first angle	78	Signal generator
15	Layer includes	47	Parallel to the first surface	79	Painting time
16	Providing a layer	48	Composite image	80	Respective first and second
17	Portion of the first composite	49	Particles contain	81	Temperatures such that
18	Surface layer	50	Metal layer	82	Composite signal
19	Composite materials is presented	51	Composite particles includes	83	Binder of the first composite material
20	Layer having	52	Surfaces of the first and second	84	Vacuum bag
21	Composite material structure	53	Vacuum of composite	85	Heating said first part
22	Fiber material	54	Finishing accuracy	86	Process of using said composite material
23	Material and process	55	Fabric layer	87	Volume of composite
24	Composite material produced	56	Second layer	88	Humid environment
25	Includes first and second composite	57	Invention provides a composite particle	89	Particles formed
26	Composite material manufacturing	58	Coating layer type	90	Providing at least one first face
27	Materials thickness	59	Particle dispersion	91	Surface portion of the composite structure
28	Method for bonding a composite material	60	Producing composite particles	92	Silicon oxide particles of the first composite
29	Metal material	61	Joined to the first composite	93	Acquired image at a first contrast level
30	Material containing	62	Portion of the first composite layer	94	Causing the first resolution composite image
31	Cutting layers speed	63	Plurality of first composite layers	95	Respect to the first surface
32	Having first and second	64	Providing the first composite part	96	Other topics

Step I.4: Analyze of cluster labels and select cluster labels to better reflect the latest advances: After cluster labels were determined in Step 3, the QFD team decided on cluster labels to be used in the process planning matrix as manufacturing operation. The QFD team selected cluster labels and merged some of them that best reflected the production process and the latest advances by making group studies. These manufacturing operations are given in the Table 4.7.

Table 4.7. *Determined manufacturing operations from patent mining*

Number	Main Group	Manufacturing Operations
MO3	Orientating laminate	Configuration
MO4	Cutting layers	Speed
MO5	Cutting layers	Precision
MO8	Bonding	Thickness
MO9	Packing before cure	Vacuum bag molding
MO10	Curing	Time
MO11	Curing	Temperature
MO12	Curing	Pressure
MO13	Curing	Vacuum
MO23	Finishing	Precision
MO24	Finishing	Temperature
MO25	Finishing	Humidity
MO26	Finishing	Time
MO27	Finishing	Coating type

4.6. Stage 3: Process Planning

After the part deployment phase is complete, there is a need to know how to produce the design. This stage converts part characteristics into manufacturing operations. While defining the process design target, results of patent mining for selected process that are obtained from the Intermediate Stage are evaluated.

Step 3.1: Organize part characteristics and get weights of part characteristics from Stage 2: By creating the third matrix of QFD, the part characteristics in the columns of the part deployment matrix are written in the rows. Also, weights of part characteristics in the second matrix of QFD are translated to the importance levels of part characteristics in the third matrix of QFD.

Step 3.2: Evaluate results of patent mining for the selected process and define the manufacturing operations: QFD team decided which cluster labels were used that obtained patent mining in the Intermediate Stage. These selected cluster labels, that were highlighted in gray in the process planning matrix, were used as defining manufacturing operations. In addition, the QFD team defined manufacturing operations that did not come from the patent mining operation for completing the third matrix of QFD. Then, all manufacturing operations are placed in the columns of the process planning matrix. Manufacturing operations are listed in Table 4.8.

Table 4.8. *All manufacturing operations*

Number	Main Group	Manufacturing Operations
MO1	Obtaining raw materials	Speed
MO2	Keeping at room temperature without humidity	Time
MO3	Orientating laminate	Configuration
MO4	Cutting layers	Speed
MO5	Cutting layers	Precision
MO6	Cleaning surface	Time
MO7	Cleaning surface	Temperature
MO8	Bonding	Thickness
MO9	Packing before cure	Vacuum bag molding
MO10	Curing	Time
MO11	Curing	Temperature
MO12	Curing	Pressure
MO13	Curing	Vacuum
MO14	Drilling	Speed
MO15	Drilling	Precision
MO16	Controlling	Non-destructive tests
MO17	Controlling	Lap shear test
MO18	Controlling	Peel test
MO19	Controlling	Leakage test
MO20	Bending	Precision
MO21	Milling	Speed
MO22	Milling	Precision
MO23	Finishing	Precision
MO24	Finishing	Temperature
MO25	Finishing	Humidity
MO26	Finishing	Time
MO27	Finishing	Coating type

Step 3.3: Determine the relationships of manufacturing operations: This step forms the roof of the process planning matrix and shows how manufacturing operations impact each other. "+" shows a positive correlation, "-" shows a negative correlation and blank represents no correlation. Figure 4.15. demonstrates the roof of the process planning matrix.

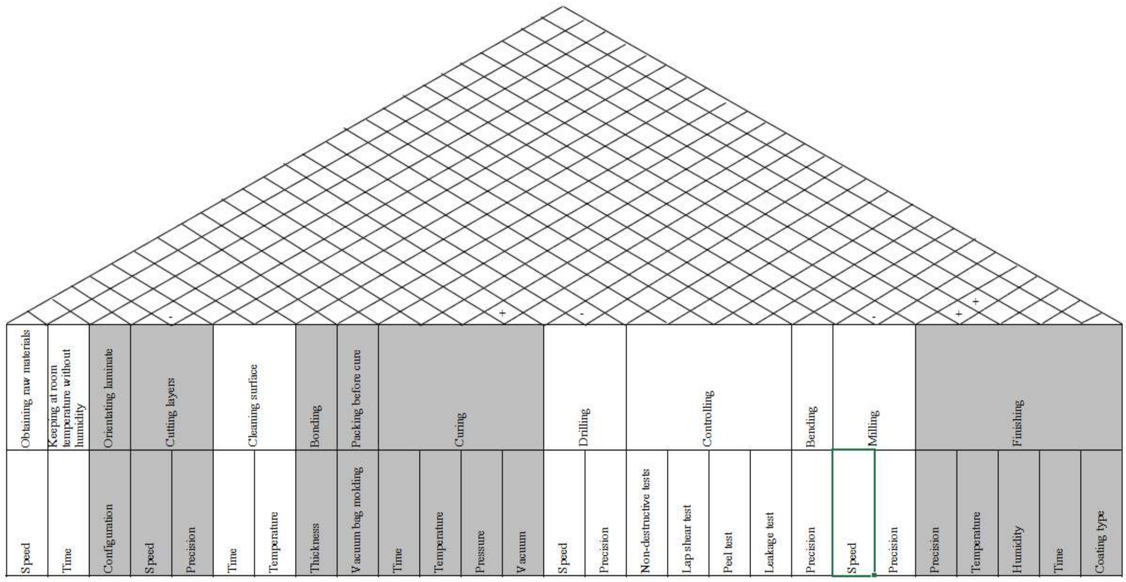


Figure 4.15. *The roof of the process planning matrix*

Step 3.4: Evaluate the relationships between part characteristics and manufacturing operations: The level of relationship between each part characteristic and the manufacturing operation is determined by using 5-point scale in Table 2.3. Assigned relationship degrees by QFD team are demonstrated in Figure 4.16.

WHATS \ HOWS				Importance Evaluations	MO1	MO2	MO3	MO4	MO5	MO6	MO7	MO8	MO9	MO10	MO11	MO12	MO13	MO14	MO15	MO16	MO17	MO18	MO19	MO20	MO21	MO22	MO23	MO24	MO25	MO26	MO27
Part Characteristics	PC1	Skin	Accuracy in skin assembly width&height	0.512			0.267	0.135	1			1				0.135	1										1		0.135		1
	PC2		Hole diameter	1.110		1				0.135	0.267							1	1												0.135
	PC3		Hole location	1.110			0.267					0.267				0.267	0.267	1	1												
	PC4		Contour	7.009			1		1			1	1		0.518	1	1														
	PC5		Abrasion resistance	2.323			0.267					1															1	1	1		1
	PC6		Number of layers	4.561								1	0.518			0.518	0.518														
	PC7		Skin's weight	3.381			0.267		0.267			1	1	1	1	1	1										1	1	1	1	1
	PC8		Surface smoothness	8.526		0.135			1	1	1	1	1	0.267	0.267	0.267	0.267		0.267	0.267				1		1	1	1	1	1	1
	PC9		Matrix	6.521	1	0.267						1	1	1	1	1	1			1	1	1	1								
	PC10		Reinforcing fibers	6.019	1	0.267	1					1								1	1	1	1								
	PC11	Rip Spar	Accuracy in rip spar width&height	0.454																					1	1					
	PC12		Material type	8.348																1				1	1	1					
	PC13		Repair or replace situation	1.079	1															1							1				0.518
	PC14	Bushing	Accuracy in bushing width&height	0.454																					1	1					
	PC15		Material type	8.348																1				1	1	1					
	PC16		Repair or replace situation	1.079	1															1							1				0.518
	PC17	Fitting	Accuracy in fitting width&height	0.454																					1	1					
	PC18		Material type	8.348																1				1	1	1					
	PC19		Repair or replace situation	1.079	1															1							1				0.518
	PC20	Closure	Accuracy in closure width&height	0.454																					1	1					
	PC21		Material type	8.348																1				1	1	1					
	PC22		Repair or replace situation	1.079	1															1							1				0.518
	PC23	Retainer	Accuracy in retainer width&height	0.454																					1	1					
	PC24		Material type	8.348																1				1	1	1					
	PC25		Repair or replace situation	1.079	1															1							1				0.518
	PC26	Finish	Thickness	1.084																							1	1	1	1	1
	PC27		Coating	8.443																							1	1	1	1	1

Figure 4.16. *Relationships between part characteristics and manufacturing operations*

Step 3.5: Calculate the final weights of manufacturing operations and define the process design target: After the correlation scores between part characteristics and manufacturing operations are determined, these scores are multiplied by the importance degrees of the part characteristics and the column total is obtained for each manufacturing operation. The column totals are normalized to determine the relative absolute importance of the manufacturing operations.

The calculation is examined in the example below based on the manufacturing operation of curing temperature (MO11). Figure 4.16. shows that the relationship between MO11 and EC4 is 0.518. The importance degree for EC4 is 7.009. When these values were multiplied by each other, the value of 3.631 was obtained. There are three more relationship values for the curing temperature. A total of four multiplications were made and then the obtained values were added. The sum of these values was calculated as 15.809 and written in the absolute importance line under the column related to the curing temperature. By repeating the process for each of the manufacturing operation, the line of absolute importance was completed and shown in Figure 4.17.

PC4 Contour;	7.009 x 0.518 = 3.631
PC7 Skin's weight;	3.381 x 1.000 = 3.381
PC8 Surface smoothness;	8.526 x 0.267 = 2.276
PC9 Matrix;	6.521 x 1.000 = 6.521
Sum	**15.809**

Then, relative absolute importances were calculated as follows:

Relative absolute importance (%) = (Absolute importance/∑ Absolute importance) x 100

For example, relative absolute importance for curing temperature is calculated as follows:

(15.809 / 591.236) x100 = 2.674

	Obtaining raw materials	Keeping at room temperature without humidity	Orientating laminate	Cutting layers		Cleaning surface		Bonding	Packing before cure
	Speed	Time	Configuration	Speed	Precision	Time	Temperature	Thickness	Vacuum bag molding
	MO1	MO2	MO3	MO4	MO5	MO6	MO7	MO8	MO9
Absolute importance	17.934	5.609	14.984	0.069	16.949	8.676	8.822	39.149	27.800
Relative absolute importance (%)	3.033	0.949	2.534	0.012	2.867	1.467	1.492	6.622	4.702
Target	60	30	0°-90°, ±45°	9.000	±0.03	10	67-77	0.016-0.065	24±4
Unit of Measurement	Day	min		rpm	inch	min	F°	inch	inHg

	Curing				Drilling		Controlling		
	Time	Temperature	Pressure	Vacuum	Speed	Precision	Non-destructive tests	Lap shear test	Peel test
	MO10	MO11	MO12	MO13	MO14	MO15	MO16	MO17	MO18
Absolute importance	12.178	15.809	21.915	22.358	2.219	4.495	61.950	12.540	12.540
Relative absolute importance (%)	2.060	2.674	3.707	3.782	0.375	0.760	10.478	2.121	2.121
Target	60	350±5	20.3-101.5	25	9.000	±0.09	Real Time X-Ray, Ultrasonic	50	11
Unit of Measurement	min	F°	PSI	inHg	rpm	inch		PSI	PSI

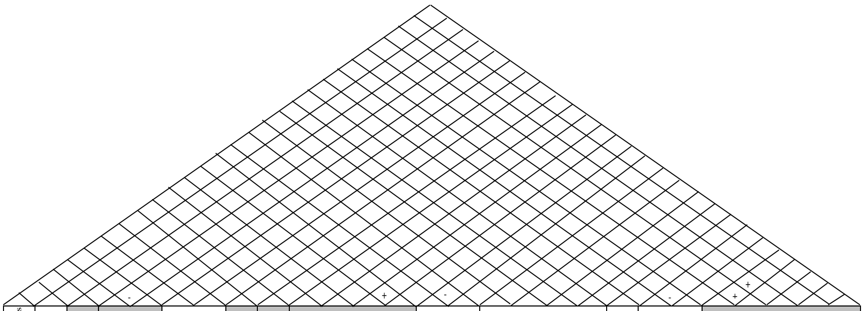
	Controlling	Bending	Milling		Finishing				
	Leakage test	Precision	Speed	Precision	Precision	Temperature	Humidity	Time	Coating type
	MO19	MO20	MO21	MO22	MO23	MO24	MO25	MO26	MO27
Absolute importance	12.540	50.265	44.008	52.534	29.662	23.757	23.826	21.433	27.212
Relative absolute importance (%)	2.121	8.502	7.443	8.885	5.017	4.018	4.030	3.625	4.603
Target	70-75	±0.01	10.000	±0.01	±0.01	15-32	30-80	72	Colour
Unit of Measurement	C°	inch	rpm	inch	inch	C°	%	h	

Figure 4.17. *Importance degrees for manufacturing operations*

Targets about manufacturing operations are defined by the QFD team using team’s experiences and patent mining results. The patents on the cluster labels selected for the manufacturing operation are examined and read in detail. From the detailed analysis of the patents, the QFD team gained a better understanding of composite material operations and determined the required target values to keep the process under control. Target values and their unit of measurement are written in the bottom rows in Figure 4.18.

At the third matrix, non-destructive test, precision for milling and bending, bonding thickness are identified as the most important operations. More efforts are needed to improve the manufacturing operation, which has the highest importance. Figure 4.19. demonstrates process planning matrix. Non-destructive test with 10.478 is determined to be the most important manufacturing operation. Due to the fact that the production method of composite materials is different from the classical production methods and due to aviation safety requirements, it must be checked periodically and continuously. During the production phase of the composite aircraft part, the test materials that simulate the composite structure in the original part produced together with the part are checked destructively, while the original parts are checked non-destructively. Composite materials need periodic non-destructive inspection throughout their service life. Non-destructive control methods can be real time X-Ray and ultrasonic control.

During the controls, the duration of the aircraft on the ground causes a lack of combat readiness in military aircraft and cost losses in civilian aircraft. Therefore, it is important to choose a fast and effective non-destructive control method. Periodic checks of composite structures, especially on flight control surfaces, which are the first priority areas for aircraft, are very important. Separation, non-adhesion, deterioration of the internal structure, humidity, breakage, holes and dents are typically detected. In order to control these damages, besides the various non-destructive testing methods, the parts need to be disassembled on the aircraft or disassembled from the aircraft and checked at special stations. The disassembly, assembly, adjustment of the parts on the aircraft and the full qualification of the aircraft cause these checks to be prolonged and increase the cost. In addition, special equipment costs and calibrations to be used also require extra cost and time. Real time X-Ray and ultrasonic control were chosen as non-destructive control methods for the horizontal stabilizer.



				Obtaining raw materials	Keeping at room temperature without humidity	Orientating laminate	Cutting layers		Cleaning surface		Bonding	Packing before cure	Curing				Drilling		Controlling				Bending	Milling		Finishing				
				Speed	Time	Configuration	Speed	Precision	Time	Temperature	Thickness	Vacuum bag molding	Time	Temperature	Pressure	Vacuum	Speed	Precision	Non-destructive tests	Lap shear test	Peel test	Leakage test	Precision	Speed	Precision	Precision	Temperature	Humidity	Time	Coating type
WHATS		HOWS	Importance Evaluations	MO1	MO2	MO3	MO4	MO5	MO6	MO7	MO8	MO9	MO10	MO11	MO12	MO13	MO14	MO15	MO16	MO17	MO18	MO19	MO20	MO21	MO22	MO23	MO24	MO25	MO26	MO27
Part Characteristics – Skin	PC1	Accuracy in skin assembly width&height	0.512			0.267	0.135	1			1				0.135	1										1		0.135		1
Skin	PC2	Hole diameter	1.110		1				0.135	0.267							1	1												0.135
Skin	PC3	Hole location	1.110			0.267					0.267				0.267	0.267	1	1												
Skin	PC4	Contour	7.009			1		1			1	1		0.518	1	1														
Skin	PC5	Abrasion resistance	2.323			0.267					1															1	1	1		1
Skin	PC6	Number of layers	4.561								1	0.518			0.518	0.518														
Skin	PC7	Skin's weight	3.381			0.267		0.267			1	1	1	1	1	1										1	1	1	1	1
Skin	PC8	Surface smoothness	8.526		0.135			1	1	1	1	1	0.267	0.267	0.267	0.267		0.267	0.267				1		1	1	1	1	1	1
Skin	PC9	Matrix	6.521	1	0.267						1	1	1	1	1	1			1	1	1	1								
Skin	PC10	Reinforcing fibers	6.019	1	0.267	1					1								1	1	1	1								
Rip Spar	PC11	Accuracy in rip spar width&height	0.454																					1	1					
Rip Spar	PC12	Material type	8.348																1				1	1	1					
Rip Spar	PC13	Repair or replace situation	1.079	1															1							1				0.518
Bushing	PC14	Accuracy in bushing width&height	0.454																					1	1					
Bushing	PC15	Material type	8.348																1				1	1	1					
Bushing	PC16	Repair or replace situation	1.079	1															1							1				0.518
Fitting	PC17	Accuracy in fitting width&height	0.454																					1	1					
Fitting	PC18	Material type	8.348																1				1	1	1					
Fitting	PC19	Repair or replace situation	1.079	1															1							1				0.518
Closure	PC20	Accuracy in closure width&height	0.454																					1	1					
Closure	PC21	Material type	8.348																1				1	1	1					
Closure	PC22	Repair or replace situation	1.079	1															1							1				0.518
Retainer	PC23	Accuracy in retainer width&height	0.454																					1	1					
Retainer	PC24	Material type	8.348																1				1	1	1					
Retainer	PC25	Repair or replace situation	1.079	1															1							1				0.518
Finish	PC26	Thickness	1.084																							1	1	1	1	1
Finish	PC27	Coating	8.443																							1	1	1	1	1
Absolute importance				17.934	5.609	14.984	0.069	16.949	8.676	8.822	39.149	27.800	12.178	15.809	21.915	22.358	2.219	4.495	61.950	12.540	12.540	12.540	50.265	44.008	52.534	29.662	23.757	23.826	21.433	27.212
Relative absolute importance (%)				3.033	0.949	2.534	0.012	2.867	1.467	1.492	6.622	4.702	2.060	2.674	3.707	3.782	0.375	0.760	10.478	2.121	2.121	2.121	8.502	7.443	8.885	5.017	4.018	4.030	3.625	4.603
Target				60	30	0°-90°, ±45°	9.000	±0.03	10	67-77	0.016-0.065	24±4	60	350±5	20.3-101.5	25	9.000	±0.09	Real Time X-Ray, Ultrasonic	50	11	70-75	±0.01	10.000	±0.01	±0.01	15-32	30-80	72	Colour
Unit of Measurement				Day	min		rpm	inch	min	F°	inch	inHg	min	F°	PSI	inHg	rpm	inch		PSI	PSI	C°	inch	rpm	inch	inch	C°	%	h	

Figure 4.18. *QFD matrix for Stage 3*

4.7. Stage 4: Production/Operation Planning

Step 4.1: Organize manufacturing operations and get weights of manufacturing operations from Stage 3: By creating a matrix, manufacturing operations in the columns of the process planning matrix are written in the rows. Also, weights of manufacturing operations from Stage 3 are written for each manufacturing operation.

Step 4.2: Define operations & controls: Operations and controls that use in the production are located in the columns of the matrix. QFD team decided operations and controls that are listed in Table 4.9.

Table 4.9. *Operations & controls*

Number	Operations & controls
OC1	Automate, semi-automate
OC2	Jig
OC3	Mistake-proofing
OC4	Operator training
OC5	Ergonomics/concentration
OC6	QMS documentation
OC7	Collect measures
OC8	Review and approval (record)
OC9	Health & safety
OC10	Special control/requirement

Step 4.3: Determine the relationships of operations & controls: This step forms the roof of the production/operation planning matrix and shows how operations and controls impact each other. "+" shows a positive correlation, "-" shows a negative correlation and blank represents no correlation. Figure 4.19. demonstrates the roof of the production/operation planning matrix. QFD team decided these correlations.

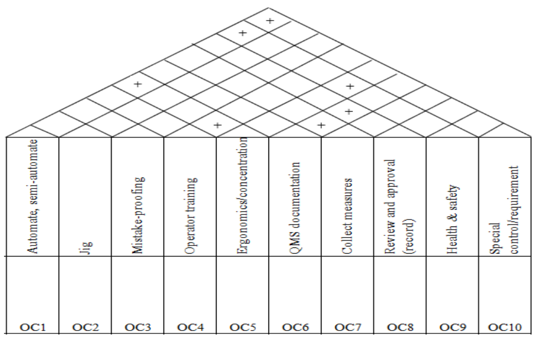


Figure 4.19. *The roof of the production/operation planning matrix*

Step 4.4: Evaluate the relationships between manufacturing operations and operations & controls: The level of relationship between each manufacturing operation and each operation is determined by using 5-point scale in Table 2.3. Relationship degrees, which were assigned by the QFD team, are demonstrated in Figure 4.20.

WHATS \ HOWS				Importance Evaluations	OC1	OC2	OC3	OC4	OC5	OC6	OC7	OC8	OC9	OC10
Part Characteristics	MO1	Obtaining raw materials	Speed	3.033										1
	MO2	Keeping at room temperature without humidity	Time	0.949	0.518	1	0.518	1	1	1	1			
	MO3	Orientating laminate	Configuration	2.534			1	1		1	0	0.518		
	MO4	Cutting layers	Speed	0.012		1		1	0.518				1	1
	MO5		Precision	2.867		1		1	1					1
	MO6	Cleaning surface	Time	1.467	1	1		1	0.267		1	1		1
	MO7		Temperature	1.492	1	1		1	0.518		1	1		1
	MO8	Bonding	Thickness	6.622				1	0.518	1	1	1		1
	MO9	Packing before cure	Vacuum bag molding	4.702	0.518			1		1	1	1		1
	MO10	Curing	Time	2.060	1	1		1	0.518	1	1			1
	MO11		Temperature	2.674	1	1		1	0.518	1	1		1	1
	MO12		Pressure	3.707	1	1		1	0.518	1	1		1	1
	MO13		Vacuum	3.782	1	1		1	0.518	1	1		1	1
	MO14	Drilling	Speed	0.375				1	0.518					1
	MO15		Precision	0.760				1	0.518			1	0.518	1
	MO16	Controlling	Non-destructive tests	10.478				1	0.518	1	1	1		1
	MO17		Lap shear test	2.121				1	0.518	1	1	1		1
	MO18		Peel test	2.121				1	0.518	1	1	1		1
	MO19		Leakage test	2.121				1	0.518	1	1	1		1
	MO20	Bending	Precision	8.502	0.518	1		1	0.518			1	0.518	1
	MO21	Milling	Speed	7.443	0.518	1		1	0.518			1	0.518	1
	MO22		Precision	8.885	0.518	1		1	0.518			1	0.518	1
	MO23	Finishing	Precision	5.017		1		1	0.518	1	1			1
	MO24		Temperature	4.018	1	1		1	0.518	1	1	1		1
	MO25		Humidity	4.030	1	1		1	0.518	1	1	1		1
	MO26		Time	3.625	1	1		1	0.518	1	1	1		1
	MO27		Coating type	4.603				1	0.518	1	1	1	1	1

Figure 4.20. *Relationships between manufacturing operations and operations & controls*

Step 4.5: Calculate the final weights of operations & controls: After the correlation scores between manufacturing operations and operations & controls are determined, these scores are multiplied by the importance degrees of the manufacturing operations and the column total is obtained for each operation & control. The column totals are normalized to determine the relative absolute importance of the operations & controls.

The calculation is examined in the example below based on the mistake-proofing (OC3). Figure 4.20. shows that the relationship between MO2 and OC3 is 0.518. The importance degree for MO2 is 0.949. When these values were multiplied by each other, the value of 0.492 was obtained. There is one more relationship value for the mistake-proofing. A total of four multiplications were made and then the obtained values were added. The sum of these values was calculated as 3.026 and written in the absolute importance line under the column related to the mistake-proofing. By repeating the process for each of the operations & controls, the line of absolute importance was completed and shown in Figure 4.21.

MO2 Time of keeping at room temperature without humidity;	0.949 x 0.518 = 0.492
MO3 Configuration of orientating laminate;	2.534 x 1.000 = 2.534
Sum	**3.026**

Then, relative absolute importances were calculated as follows:

Relative absolute importance (%) = (Absolute importance/∑ Absolute importance) x 100

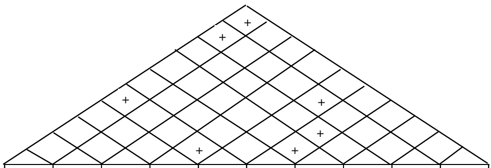
For example, relative absolute importance for curing temperature is calculated as follows:

(3.026 / 578.861) x100 = 0.523

WHATS / HOWS	Importance Evaluations	Automate, semi-automate	Jig	Mistake-proofing	Operator training	Ergonomics/concentration	QMS documentation	Collect measures	Review and approval (record)	Health & safety	Special control/requirement
		OC1	OC2	OC3	OC4	OC5	OC6	OC7	OC8	OC9	OC10
Absolute importance		42.644	59.062	3.026	96.967	47.559	65.163	65.588	74.304	28.033	96.517
Relative absolute importance (%)		7.367	10.203	0.523	16.751	8.216	11.257	11.330	12.836	4.843	16.674

Figure 4.21. *Importance degrees for operations & controls*

The production planning matrix is in the form of a checklist used in the planning of operations and controls rather than a matrix. Thus, production planning is connected to the voice of the customer. Figure 4.22. demonstrates production planning matrix that is the fourth matrix of QFD. Operator training, special control/requirement collecting measures and Quality Management System (QMS) documentation are determined to be the most important operations and controls.



WHATS \ HOWS				Importance Evaluations	OC1 Automate, semi-automate	OC2 Jig	OC3 Mistake-proofing	OC4 Operator training	OC5 Ergonomics/concentration	OC6 QMS documentation	OC7 Collect measures	OC8 Review and approval (record)	OC9 Health & safety	OC10 Special control/requirement
Part Characteristics	MO1	Obtaining raw materials	Speed	3.033										1
	MO2	Keeping at room temperature without humidity	Time	0.949	0.518	1	0.518	1	1	1	1			
	MO3	Orientating laminate	Configuration	2.534			1	1		1	0	0.518		
	MO4	Cutting layers	Speed	0.012		1		1	0.518				1	1
	MO5		Precision	2.867		1		1	1					1
	MO6	Cleaning surface	Time	1.467	1	1		1	0.267		1	1		1
	MO7		Temperature	1.492	1	1		1	0.518		1	1		1
	MO8	Bonding	Thickness	6.622				1	0.518	1	1	1		1
	MO9	Packing before cure	Vacuum bag molding	4.702	0.518			1		1	1	1		1
	MO10	Curing	Time	2.060	1	1		1	0.518	1	1			1
	MO11		Temperature	2.674	1	1		1	0.518	1	1		1	1
	MO12		Pressure	3.707	1	1		1	0.518	1	1		1	1
	MO13		Vacuum	3.782	1	1		1	0.518	1	1		1	1
	MO14	Drilling	Speed	0.375				1	0.518					1
	MO15		Precision	0.760				1	0.518			1	0.518	1
	MO16	Controlling	Non-destructive tests	10.478				1	0.518	1	1	1		1
	MO17		Lap shear test	2.121				1	0.518	1	1	1		1
	MO18		Peel test	2.121				1	0.518	1	1	1		1
	MO19		Leakage test	2.121				1	0.518	1	1	1		1
	MO20	Bending	Precision	8.502	0.518	1		1	0.518			1	0.518	1
	MO21	Milling	Speed	7.443	0.518	1		1	0.518			1	0.518	1
	MO22		Precision	8.885	0.518	1		1	0.518			1	0.518	1
	MO23	Finishing	Precision	5.017		1		1	0.518	1	1			1
	MO24		Temperature	4.018	1	1		1	0.518	1	1	1		1
	MO25		Humidity	4.030	1	1		1	0.518	1	1	1		1
	MO26		Time	3.625	1	1		1	0.518	1	1	1		1
	MO27		Coating type	4.603				1	0.518	1	1	1	1	1
Absolute importance					42.644	59.062	3.026	96.967	47.559	65.163	65.588	74.304	28.033	96.517
Relative absolute importance (%)					7.367	10.203	0.523	16.751	8.216	11.257	11.330	12.836	4.843	16.674

Figure 4.22. *QFD matrix for Stage 4*

By applying the proposed method, all product development stages of the horizontal stabilizer were defined. Engineering characteristics, part characteristics, manufacturing operations and controls were ranked and improvement areas were suggested for each stage. Customer needs and sustainability requirements were directly reflected in the design. The right design was done at the first time, while minimizing redesign and engineering changes. A higher quality and reliable product was produced with lower product development time. Thanks to the prioritization of needs, the company's resources were primarily spent in critical areas that would satisfy the customer. Also, the proposed methodology improved effective communication between departments of the company.

Manufacturing operations and their target values by using patent mining and expert judgments were determined. Patent mining was used for a production process. Composite forming production process was the selected process, and this is the first patent mining study for composite forming. The wide and rich technical information contained in patent documents was clustered, so the quality and inclusiveness of the inputs used in the QFD were improved. With patent mining, experts benefited from technical information quickly and easily.

By designing and manufacturing the horizontal stabilizer, it is approximately estimated that an annual cost savings of one million dollars will be achieved. Also, the rate of locality and nationality of the Turkish Air Force will increase.

5. CONLUSION

The rapidly increasing competition causes an increase in the customer expectations. Today, product life cycles are shortening, technology is developing rapidly, and the tendencies towards environmentally friendly production and sustainability concepts are increasing. Therefore, companies should develop new products and improve their existing products to compete. Innovation and NPD activities that are at the heart of every business have become increasingly important in recent years. Companies are looking for new methods to adapt to developing technology and to maximize customer satisfaction. There is a need for holistic approaches that address the market, technical, technology and social driving forces that affect the product development process together.

Companies need a new methodology that integrates sustainability requirements besides the customer expectations during new product development in order to meet the social, economical and environmental issues. Because the market has a deep sensitivity to environmental protection of the earth. Also, nowadays customers consider the social and economic dimensions of the product. Besides this, companies should adapt technological developments to their product and production process to maintain their lives under competitive market conditions. For this reason, an integrated and technology-based new product development methodology to meet customer and sustainability requirements is presented in the study. The proposed new product design with sustainability driven QFD reinforced by patent mining method is based on the four-stage model of the QFD method. It considers the sustainability requirements in the HoQ matrix and the production process parameters are determined based on the analysis of related patents by using patent mining.

This study makes significant contributions to the literature. QFD translates customer needs into related parameters of product and process. In classical QFD studies, only meeting customer needs is considered. In the study, customer needs and sustainability requirements are handled together to achieve sustainable production. The product planning matrix is expanded by defining sustainability requirements. AHP is used while determining the importance degrees of customer needs and sustainability requirements.

In classical QFD studies, in the process planning matrix, manufacturing operations and their target values are determined by only the QFD team's experiences. An intermediate stage is injected into the process planning matrix to increase the quality and inclusiveness of the inputs. Patents are the first indicators of technological developments. Patent databases store large, reliable and up-to-date technical information in patent documents. So, it is very valuable to use patent information in process planning studies. The use of valuable information obtained from patent mining in determining process parameters increases productivity and efficiency in production. It also shortens product development time by avoiding many trial-and-error processes. In the intermediate stage, it has been suggested to carry out a patent mining study for the critical processes. In the literature, researchers usually used patent mining for products, not production processes until now.

The horizontal stabilizer of F-16 aircraft is chosen as a case study. Since the problem addressed in this thesis is a real-life problem, it includes contributions to the field of application, as well as theoretical contributions. This stabilizer is a composite structural part of the aircraft. With using the proposed method, all product development stages of it are defined. In the intermediate stage, composite material forming is the selected process, and this is the first patent mining study for composite forming. The production of composite parts is a developing new field, so the information to be obtained from patent documents is very valuable. Patent documents include both structured and unstructured data. In this thesis, patents' abstracts, which are unstructured data, are used; so text mining is applied to discover data in the patent mining study. Clustering techniques are used because there is no label variable in the data set obtained from patent documents. EPO database is used as the patent data source for data collection. The term "composite material forming" is chosen as the query to search the patent data in abstract fields from EPO API and retrieved 30.000 patents from the database. The Lingo clustering algorithm is implemented for extracting topics using the patent data. The Lingo algorithm is chosen because it focuses on the quality of labeling. This algorithm generates better results in labeling of clusters while comparing with other algorithms and determines labels automatically. Via using cluster labels, users can understand what a cluster is about. Cluster labels are used to determine manufacturing operations and better reflect the latest advances. Also, target values about manufacturing operations are defined by the QFD team using team's experiences and patent mining results. By using patent mining, experts benefited from technical information quickly and easily.

Engineering characteristics, part characteristics, manufacturing operations and controls are ranked one by one and improvement areas are suggested for each stage. By designing and manufacturing the horizontal stabilizer, it is approximately estimated that an annual cost savings of one million dollars will be achieved. Also, the rate of locality and nationality of the Turkish Air Force will increase.

In the literature, mostly QFD studies terminate when the first matrix of QFD is built. In this thesis, all four matrices of QFD are built. Also, when the literature is examined, there is no previous study on the horizontal stabilizer of an aircraft. In this context, the study is the first study in the sector and it is thought that it will make contributions to the field of application.

This study has some limitations. The assessments for competitiveness could not be made because there is no competitor against the military factory in the case study. Only EPO is chosen as the patent data source. Other patent offices in various countries, such as USPTO, EPO and JPO, can be used to collect patent data. In addition, the guidance of the expert QFD team and management support are needed during the implementation phase of the proposed new product design with sustainability driven QFD reinforced by patent mining method.

In the future studies, critical processes other than composite processes can be studied for patent mining. Other critical aircraft parts can be chosen. Patent mining can be done dynamically over the web. So that, the developments in the technology can be followed continuously. A decision support system can be designed for the proposed method. Fuzzy logic supported models can be beneficial at the stages where decision makers have difficulty in making numerical evaluations. Also, learning algorithms can be employed in QFD.

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