A decision support framework for concurrent multi-DFX implementation to optimize the machine design process

by

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ABSTRACT

Industry 4.0 has sparked rapid changes in the manufacturing and construction sectors, leading to a major shift in how prefab construction machines are designed and manufactured in a concurrent engineering environment. Design for X (DFX) is one of the most effective methods for implementing in concurrent engineering as a methodical and proactive approach to machine design that maximizes total benefits over the entire product lifecycle. However, this task is challenging and time-consuming considering the vast number of feasible permutations involved. The unresolved challenge is how the information contained within Multi-DFX (MDFX) can be organized such that the implications of decisions are proactively evaluated and implemented. For this purpose, designers require robust decision-making tools for supporting MDFX techniques in machine design. Because if applied, they can generate a propagation effect that spans multiple life phases. Also, the necessity is growing for a design decision support system to guide designers and alert them to what possible consequences they could encounter in the downstream life-cycle phases if MDFX is applied. Therefore, to overcome these challenging tasks, designers have recently started to utilize innovative searching and optimizing methods that can aid them in the MDFX trade-off analysis and in finding the optimal utilization plan for design development. To cope with this, a functional collaborative DFX scheme mitigated with Stuart Pugh: Total Design Activity Model is developed in this research where various DFX techniques are grouped and allocated to different phases of the machine development lifecycle. Furthermore, the research progressed to analyze the conflict arising from the application of MDFX in a machine design problem and automatically resolve the conflict of design experts' opinion by

simulating the MDFX interactions and design decision criteria multi-layers in the developed aggregated matrix model. However, for any machine design development project, there are specific product design specifications that a designer must attend to during the design and aim to satisfy the client needs in the final machine. Therefore, to balance the allocation and control the integration of MDFX techniques in each design criterion, this research proposed a hybrid multi-objective optimization model based on the fuzzy set theory. This model was integrated with an intelligently automated searching model that focuses on finding the optimal MDFX utilization solutions. These solutions minimize the machine design development cost and time while maximizes its quality. Also, this model can analyze these results from a financial perspective by aggregating the performance metrics and by accounting for machine design specific constraints. The proposed research materials are applied in various machine design real-world case studies to validate their feasibility, applicability, and effectiveness in a dynamic machine development environment and in visualizing the optimal trade-offs among MDFX metrics while coupling their engineering-financial terms for a better decision-making process within the domain of machine design for prefabricated construction.

PREFACE

This thesis is the original work by Anas Itani. Two journal papers and two conference papers related to this thesis have been submitted or published and are sequentially listed below with number list that represents their respective chapters. This thesis is organized in paper format by following the paper-based thesis guideline.

2. **Itani, A**., Ahmad, R., and Al-Hussein, M. "A collaborative scheme for DFX techniques in concurrent engineering mitigated with total design activity model." *2019 Modular and Offsite Construction Summit.* **(under review)**
3. **Itani, A**., Ahmad, R., and Al-Hussein, M. "A decision tool to simulate the concurrent interdependencies between Multi-DFX techniques in machine design conflict resolution." *2019 International Symposium on Automation and Robotics in Construction and Mining (ISARC).* **(under review)**
4. **Itani, A**., Ahmad, R., and Al-Hussein, M. "Hybrid FEAM-TOPSIS Decision Support System to Support Multi-DFX Applications in Machine Design Concurrent Engineering: An Empirical Study." *Journal of Engineering Design.* **(under review)**
5. **Itani, A**., Ahmad, R., and Al-Hussein, M. "Decision Support Approach for Multi-DFX Trade-off Optimization in Machine Design: Hybridization of Genetic Algorithm and Pareto Optimality." *International Journal of Production Economics.* **(under review)**

The data collection and interviews conducted for this research was approved by University of Alberta Research Ethics Boards 2 (REB2) with application number Pro00084419 dated on November 7, 2018, under the title "Investigating the interactions and links between

DFX techniques and analyzing their concurrent interdependence's effect in concurrent engineering."

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LIST OF ABBREVIATIONS

CE	Concurrent Engineering
DFX	Design for X
MDFX	Multiple Design for X
CAX	Computer-Aided Technologies
CAD	Computer-Aided Design
CAPP	Computer Aided Production Planning
CAM	Computer Aided Manufacturing
CAPM	Computer Aided Production Management
MCDM	Multiple Criteria Decision-Making
PDS	Product Design Specifications
AHP	Analytic Hierarchy Process
TFNs	Triangular Fuzzy Numbers
FEAM	Fuzzy Extent Analysis Model
TOPSIS	Technique for Order Performance by Similarity to Ideal Solution
NPV	Net Present Value
IRR	Internal Rate of Return
DDSS	Design Decision Support System
GAs	Genetic Algorithms
PF	Pareto Front

Chapter 1 : Introduction

1.1 Background and Motivation

In 2018, Canada records a hike in the residential construction sector where 215,725 housing starts were recorded (Statistics Canada). It is expected that the residential construction for housing stays close to 200,000 units in 2019 (Housing Market Outlook, Fall 2018). On the other hand, commercial construction is expected in 2018 to grow by 6%; this is due to the economy shifting to a more automated, autonomous, customized production economy by applying Industry 4.0 principles (Oldcastle Business Intelligence). Industry 4.0 is the combination of digital processes such as the Internet of Things (IoT), automation, robotics, and additive manufacturing (AM) has a significant impact on machine design (ASME). Not only do designers required to redesign methodologies, processes, and manufacturing to accommodate these new technological advancements, Industry 4.0 targets how they design machines for increasingly smart autonomous manufacturing factories. It encourages forward-thinking designers to embrace these digital tools and technologies. This allows them to design and manufacture higher-quality prefab production construction machines more efficiently and react instantaneously to shifting client demands, gaining client loyalty and increasing market share. To support the continuous demand in the Canadian market for both residential and commercial construction sectors, panelized construction is becoming a cost-effective building option. Compared to the conventional "stick frame" construction, panelized construction enables the builders to relocate the framing of housing components under-a-roof to an off-site factory production thus securing a controlled and high-efficient construction environment. By utilizing the automation technologies in the prefab factory-built construction to produce a higher quality housing with a reduction in the site disruptions, weather fluctuations, higher safety, and rapid construction. Li (2016) concluded that the construction sector could achieve 30-50% time savings by adapting the off-site modern production technologies. However, to gain the full advantages of off-site construction, the automated construction machines and supporting processes must improve.

To implement Industry 4.0 principles and improve the competition in the Canadian prefab off-site construction sector, effective and proactive design methodologies and tools must be utilized by designers while shaping the best-optimized machine design in a dynamic concurrent engineering domain. Thus, improving machine quality, lower cost, shorten the development cycle time and fulfill customers' requirements. Understanding the effective design tools such as DFX and how it can be implemented in a machine design problem in a harmonized way is becoming crucial for designers to know. Furthermore, in concurrent engineering machine design, it is crucial to comprehensively evaluate the application of MDFX during conceptual and detailed design. But due to a lack of information in the design's early stages, the designer is faced with multiple obstacles that can challenge him /her in the evaluation process, such as, for example, when the design information is fuzzy, or the designer's goal is known only imprecisely. The designer should consider the MDFX concurrent effects on the machine design over the whole product lifecycle. If the previous design decision is faulty, the preceding machine design stages will be significantly affected. Hence, implementing an incorrect decision in the design process can lead to cost over-expenditure associated with machine remanufacture, redesign, and recall. These unpredictable expenses could result in not only machine profit loss but can also threaten the successfulness of the commercialization strategy of the machine. Most of today's DFX techniques (e.g., design manuals, manufacturing guidelines, analysis software, and design checklists) examine the product and process machine design in a unilateral approach e.g., centered around machine manufacturing or assembly. In order to have a better understanding on the main application, advantages, and disadvantages of current methods/tools and proposed researched method, a summarized matrix including the most up-to-date techniques in machine design were compared as shown in Figure 1.1. Thus, this research aims to develop an MDFX multi-stage decision-making framework that can be implemented in the prefab production machine design development by non-expert designers who aim to seek for an optimized and flawless design plan. The following sections provide detailed information related to each of the proposed research motivations.

Method/Tool	Product Lifecycle Phase: Specification	Concept	Embodiment	Detailed	Manufacture	Purpose	Advantages	Disadvantages	Optimized Tradeoff: Cost	Time	Quality	Input	Output	References
House of Quality	✓	×	×	×	×	Structured approach to identify client requirements and translating them into design plans to produce products that meets the characteristics.	1-An effective communications and quality planning tool. 2-Enables the product development team to focus on the customer requirements. 3-Framework for benchmarking of all competitors. 4-Comprehensive and concise visual format of several related blocks.	1-Emphasis on quality at expense of optimal design. 2-Limitations in global implementation. 3-Overreliance on market surveys. 4-In ability to implement the dynamic customer needs.	×	×	✓	What-How Crisp Data (1 to 9)	Product Planning Matrix	Chan, L. K., & Wu, M. L. (2002). Quality function deployment: A literature review. European journal of operational research, 143(3), 463-497.
Target Costing Comparison	×	✓	✓	✓	✓	It is an approach for the development of new products in the industry, aimed at reducing their life-cycle costs while ensuring quality, reliability and other client requirements, by examining all possible ideas for cost reduction.	1-Product cost optimization. 2-Systematic design. 3-Reduced development cycle and redesign 4-Increase market profitability.	1-Relies on estimating the final selling price. 2-Compormize the product quality on the expense of the cost. 3-Marekting strategy effect the price of the product.	✓	✓	×	Market-driven target costing survey	Cost reduction strategies	Melo, R. S. S. D., Kaushik, A., Koskela, L., Granja, A. D., Keraminiyage, K., & Tzortzopoulos, P. (2014, June). Target costing in construction: a comparative study. IGLC.
Failure Modes and Effects Analysis (FEMA)	×	×	×	✓	✓	It is a system reliability study reviewing as many components, assemblies, and subsystems as possible to identify failure modes, and their causes and effects.	1-Documented method for selecting a design with a high probability. 2-Assessing potential failure mechanisms, failure modes and their impact on system operation. 3-Evaluating the effect of proposed changes to the design and/or operational procedures.	1-Relies on the team members' subjective analysis, knowledge, and expertise. 2-Inability to prioritizing failure modes according to their risk. 3- Time consuming and tedious to trace failure through FMEA charts.	✓	×	✓	Potential failure scenarios	Risk assessment matrix	Stamatis, D. H. (2003). Failure mode and effect analysis: FMEA from theory to execution. ASQ Quality Press.
Process Planning Matrix (Control Plan)	×	×	×	✓	✓	It is a document that describes the actions (measurements, inspections, quality checks or monitoring of process parameters) required at each phase of a process to assure the process outputs will conform to pre-determined requirements.	1-Reduce or eliminate waste in a process. 2-Improves product quality by identifying the sources of variation in a process and establishing controls to monitor them. 3-Eliminates costly reworks and prevent defective product from reaching the customer.	1-Relies on the team members' subjective analysis, knowledge, and expertise.. 2-Time consuming and tedious to prepare the planning documents.	✓	×	×	Process flow diagram	Control plan matrix	Thomas E.. Vollmann, William L.. Berry, & Whybark, D. C. (1988). Manufacturing planning and control systems. Irwin.
Concept Selection Matrix	×	✓	✓	×	×	It is a qualitative technique used to rank the multi-dimensional options of an option set. It is frequently used in engineering for making design decisions.	1-It rely on subjective opinions about one alternative versus another. 2-Sensitivity analysis can be performed. 3-The team lists the strengths and weaknesses of each concepts in a SWOT matrix.	1-Can become very complex if used beyond the simplified version. 2-It is difficult to distinguish between direct and indirect impacts. 3-It heavily rely on knowledge and data.	✓	×	×	Team preferences and remarks	Selection matrix	King, A. M., & Sivaloganathan, S. (1999). Development of a methodology for concept selection in flexible design strategies. Journal of Engineering Design, 10(4), 329-349.
Value Engineering (VE)	✓	✓	✓	×	×	It is a systematic method to improve the value of products and services by using an examination of function and it can be manipulated by either improving the function or reducing the cost.	1-Reduces the cost by eliminating the unnecessary functions in the product. 2-Emphasizes on seeking the alternatives for achieving the function and on applying the best alternative among the various courses of actions available.	1-Heavy reliance on experts systems. 2-Requires lot of effort and time to complete the whole process and to point out the problems in the various parts of the manufacturing units. 3-The financial value analysis are always calculated for a single period.	✓	×	✓	Value of a product and its alternatives	Function/cost matrix	Miles, L. D. (2015). Techniques of value analysis and engineering. Miles Value Foundation.
Axiomatic Design Method (AD)	✓	✓	×	×	×	It is a systems design methodology using matrix methods to systematically analyze the transformation of customer needs into functional requirements, design parameters, and process variables.	1-A structured foundation for concept design. 2-Domains can be well defined in terms of process. 3-Coupled, uncoupled and decoupled options.	1-Lack of information sharing. 2-Customer attributes are vague. 3-Distances between domains are large and lengthy. 4-Information content is difficult to apply.	✓	×	×	Customer needs	Quantitative decision matrix	Suh, N. P. (1998). Axiomatic design theory for systems. Research in engineering design, 10(4), 189-209.
The Taguchi Method	×	✓	✓	×	×	It is a statistical methods that improve the quality of manufactured products and engineering productivity. By consciously considering the noise factors (environmental variation during the product's usage, manufacturing variation, and component deterioration) and the cost of failure while improving the fundamental function of the product or process.	1-Improve the robustness of basic design technologies. 2-Analyze the functional behaviour in depth. 3-Optimization of control factors.	1-No process can be applied in the conceptual design. 2-Limited to one concept. 3-Black box approach.	×	×	✓	Mathematical modeling of the problem	Experimental engineerin matrix	Unal, R., & Dean, E. B. (1990). Taguchi approach to design optimization for quality and cost: an overview.
Group Technology (GT)	×	×	×	✓	✓	It is a manufacturing technique in which parts having similarities in geometry, manufacturing process and/or functions are manufactured in one location using a small number of machines or processes.	1-Enable cellular manufacturing. 2-Accelerate product development and reduce its cost. 3-Simplify process planning and reduce tooling/machining costs. 4-Simplify purchasing and increase supply chain efficiency.	1-Less manufacturing flexibility or modularity. 2-Increase the machine failure, maintenance, and down-time due to parts grouping as cells.	✓	✓	×	Parts and assemblies plans	Grouping matrix	Kusiak, A. (1987). The generalized group technology concept. International journal of production research, 25(4), 561-569.
Just in Time (JIT) Production	×	×	×	✓	✓	It is a methodology aimed primarily at reducing times within production system as well as response times from suppliers and to customers. Also, it is a management strategy that aligns raw material orders from suppliers directly with production schedules. Manufacturing companies use this inventory strategy to increase efficiency and decrease waste by receiving goods only as they need them for the production process, which reduces inventory costs and forecast demand accurately.	1-Prevents over-production by streaming the saved resources. 2-Minimize the waiting times and transport costs. 3-Decrease product defects.	1-Requires a major overhaul of business systems 2-Difficult and expensive to introduce. 3-Exposing the supply chain to more risks such as no stock, late delivery, weather conditions, etc.	×	✓	×	Supply chain details	Optimized production and delivery schedule	Schonberger, R. J. (1982). Some observations on the advantages and implementation issues of just-in-time production systems. Journal of Operations Management, 3(1), 1-11.
Proposed MDFX Framework	✓	✓	✓	✓	✓	It is a multi-objective optimization hybrid model to support the cost-time-quality trade-off analysis of MDFX by minimizeing machine design development cost and time while maximizing its quality. Also, it enables designers to better interpret the whole evaluation process and provides a more precise, systematic, and effective design decisions with no conflict. The framework reliably estimate and verify the benefits of applying MDFX in a harmonized way in machine design by enabling the designers to foresee and explore lifecycle consequences before MDFX techniques can be applied.	1-Analyzes the design decisions from economic perspective. 2-Generates the best utilization solutions for MDFX for each design criteria. 3-Eliminates the design decision imprecision and uncertainty. 4-Mitigate quantitative and qualitative design critical together. 5-Generates a ranked list of MDFX stating when, where, and which technique to be implemented and in which order to optimize the entire product lifecycle. 6-Eliminates the incorrect decisions that can lead to cost over-expenditure associated with machine lifecycle.	1-Depends on the design expert's assessment and evaluation. 2-In some cases the structure of the problem's hierarchy and the design attributes are closely inter-related. 3-Performs random search which can take longer computational processing time. 4-Subjectivity in weighting the DFX guidelines in the aggregated conflict matrix	✓	✓	✓	Design criteria and list of available DFXs	Optimimized MDFX ranked list	

Figure 1.1 Comparison Matrix Between Current and Proposed Methods

1.1.1 A collaborative scheme for DFX techniques mitigated with total design activity model

Concurrent engineering which seeks to close the gap between design and manufacturing sectors provides an ideal environment for machine development. It is a systematic approach to integrate machines holistic concurrent design activities and their related processes. Competition arising in the marketplace for newly developed machines is driving modifications in the way machine designers develop production machines (Ahmad et al., 2015). Thus, to boost the efficiency in concurrent machine development, appropriate evaluation, and decision analysis tools required to be developed and utilized. Currently, there is no DFX selection tool available to aid the designer in concurrent machine design applications. In this research, these challenges are addressed through a comprehensive qualitative literature review of DFX techniques with their implementation in Stuart Pugh: Total Design Activity Model (Pugh,1991). Various DFX techniques are mapped and clustered in a collaborative scheme, interactions and links between them are identified, and the relative importance weight of each is calculated. A description of a functional DFX scheme is proposed in this research that can aid designers in establishing lean design processes for machine development and reveals its potential application in Multi-DFX fuzzy multi-criteria decision-support system.

1.1.2 Simulating the concurrent interdependencies between Multi-DFX Techniques in Machine Design Conflict Resolution

The overall performance of a life-cycle phase under investigation can be improved if Multi-Design for X (MDFX) technique's design guidelines are applied concurrently. However, the complexity of selecting MDFX techniques at the conceptual and detailed design stages during machine development can increase by uncertain and imprecise knowledge about the MDFX interdependencies. For many industrial companies, alleviating the design decision complexity at these stages can have a positive impact on the industry's competitive market. Therefore, it becomes crucial to have a robust MDFX tool embedded with conflict resolution in valuing potential applications to justify their cohesion. Some limitations on the compatibility between MDFX remain a challenge. The unresolved challenge is how the information contained within MDFX can be organized such that the implications of design decisions are proactively evaluated and implemented. To address this challenge, an efficient decision tool for applying MDFX in the conceptual and detailed machine design development phases is proposed. In this research, the relative importance of DFXs guidelines and the essence of the interactions that arise between them are also studied. Also, a matrix model with multi-layers to simulate the interactions between MDFX is suggested to resolve the conflict of experts' opinion and aggregates the decision criteria layers into a single output. The proposed decision tool shows its effectiveness in the decision-making process by eliminating MDFX negative interactions and aiding the designer in shaping the optimal machine design with less development cost and time.

1.1.3 Hybrid FEAM-TOPSIS decision support model for MDFX techniques

Machine design development is critical to designers because most of the design decisions that can impact the downstream design activities are made in the conceptual and detailed design stages. Multi-DFX techniques have been developed over the years to boost up the machine design development efficiency and reduce its total cost and time. The dilemma addressed in this research is that by applying these techniques concurrently to support design decisions, they can generate a propagation effect that spans multiple life phases of the machine and influence their performance. However, selecting MDFX can be difficult due to imprecise and ambiguous machine design requirements. MDFX application is challenging for two reasons: (1) they have been developed to work independently and with a different focus; (2) it is challenging to determine how they complement and correlate between each other, in what arrangement, and where they should be implemented. Thus, this study proposes a structured hybrid Fuzzy Extent Analysis model (FEAM) aided with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) model to illustrate the inter-dependencies relations and the interactions among these techniques which till date remains absent. The proposed hybrid model is implemented on a real-world case study, and the results validated its feasibility, applicability, and effectiveness in a machine development process.

1.1.4 Decision support approach for Multi-DFX trade-off optimization in machine design: Hybrid genetic and Pareto optimality algorithm

Finding optimal Multi-DFX (MDFX) sets is challenging and time-consuming considering the vast number of feasible permutations involved (Huang, 1996). To overcome this challenging task, designers are required to implement effective searching and optimizing methods in conceptual and detailed phases of machine development (Andreasen and Olesen, 1993). These emerging methods create an opportunity for the designers in the design and manufacturing industry to find an optimal MDFX utilization solutions that minimizes machine design development cost and time while it maximizes the quality. A practical multi-objective optimization model for MDFX (cost, time, and quality) trade-off analysis with robust optimization searching algorithms such as genetic algorithms and Pareto optimality is highly crucial in machine design development.

Furthermore, the generated search solutions from a financial perspective based on the net present value and internal rate of return, as concluded by Bendeković (1993), aggregated performance metrics and accounts for machine design specific constraints. Thus, a hybrid model is proposed in this research to find and visualize the optimal solutions for MDFX. The developments made here provide the designers with an effective hybrid automated intelligent searching and optimizing tool that can aid them in selecting the desired utilization solutions for MDFX. This is achieved by maximizing the design development quality and minimizing the cost and time associated with these options while coupling their engineering-financial terms.

1.2 Research Objectives

This research is built on the following hypothesis:

"Implementing the developed MDFX multi-stage decision-making framework in prefab production machine design will support designers in selecting the best DFX techniques for a particular application, in order to minimize design development cost and time, while maximizing the design quality, thereby allowing for accurate design decisions and shaping the best optimized design plan."

To validate this hypothesis, the following research objectives are investigated and pursued:

(1) Development of a functional DFX scheme mitigated with Stuart Pugh: Total Design Activity Model where various DFX techniques are grouped and allocated to different phases of the machine development lifecycle.

(2) Development of aggregated matrix model to analyze and simulate the conflict arising from the application of MDFX in a machine design problem and

automatically resolve the conflict of experts' opinion by simulating the MDFX interactions with the decision design criteria multi-layers.

(3) Development of a generic multi-objective hybrid optimization model to balance the allocation and control the integration of MDFX techniques in each design criterion with a global goal to reduce the design development time and cost.

(4) Development of a hybrid robust optimization search model that analyses the MDFX searched solutions and generates the optimal trade-off metrics utilization options for MDFX.

1.3 Thesis Organization

The organization and structure of this thesis are illustrated in Figure 1.2 and consists of six chapters. Chapter 1 provides a brief background on the current application of DFX techniques in CE machine design and discusses its trade-off existing limitations followed by the research motivation and objectives. Chapter 2 presents an extensive qualitative literature review on DFX techniques in the product total design activity model and propose a collaborative DFX scheme. Chapter 3 describes a simulating tool that can locate and resolve the conflict arises from the application of MDFX in a problem context. Chapter 4 formulate the selection and ranking hybrid model for MDFX based on the fuzzy set theory and TOPSIS method. Chapter 5 propose the trade-off analysis model for MDFX performance metrics and calculate its relative economic values. Finally, Chapter 6 summarizes the general conclusions and presents the research contributions, limitations, and future research roadmap.

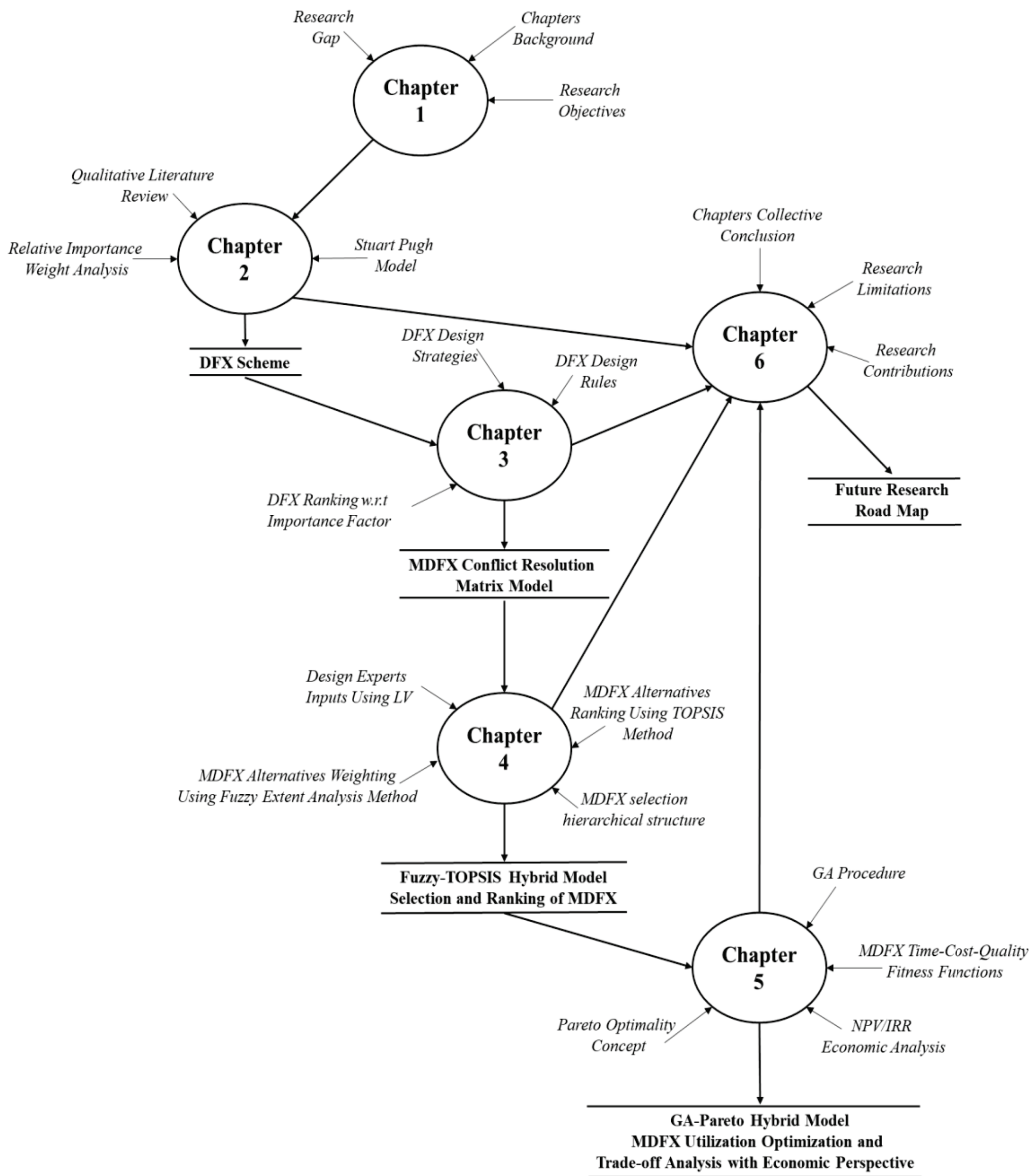

Figure 1.2 Thesis Organization Data Flow Diagram

Chapter 2 : A collaborative scheme for DFX techniques mitigated with total design activity model [1]

2.1 Introduction

Research conducted by Guangleng and Yuyun (1996) has concluded that the early design stages of the machine development process are the most influential determinant of machine total cost. By contrast, prototyping, production, manufacturing, and maintenance considerations contribute to a higher percentage of the total machine cost. Concurrent engineering (CE) aims to exploit opportunities for machine design improvements at each phase of the machine lifecycle by integrating machine design and their related process development so that the percentage of the redesign is minimized. The success of the machine design depends on the accuracy of design decision making. Also, in the early phases of machine development, the production cost is minimized when accurate decisions are implemented. CE offers the designer the ability to select multiple design decision tools spanning all production processes, which can widen the designer's technical overview of the machine development stage. However, poor tool selection may lead to deficiencies in machine development time, quality, and cost (Ahmad et al., 2014). The main difference between traditional and CE is that the latter regard machine development as an integrated, systematic, and the concurrent process of continuous improvement. A significant challenge of CE is to make correct decisions at the early stages of machine development when committed costs are still low, and design information is vague. Therefore, in CE the design

[1] The manuscript presented as Chapter 2 of this thesis was submitted to the 2019 Modular and Offsite Construction Summit, at the time of publication of this thesis.

activities costs are higher in the early stages of machine development. However, compared with traditional sequential engineering, development times are shorter, and thus the total cost is lower. Figure 2.1 Machine Development Stages illustrates the cost impact of CE, as explained by Veryzer (2005), of the machine value of design throughout each product development stage. Although the shortcomings of traditional sequential engineering and the advantages of CE in machine development are well established in the literature, though, as discussed by Fujimoto and Clark (1991) and by Clausing (1993), the transformation from a problem-prone sequential engineering paradigm to a problem-free CE environment remains a challenge.

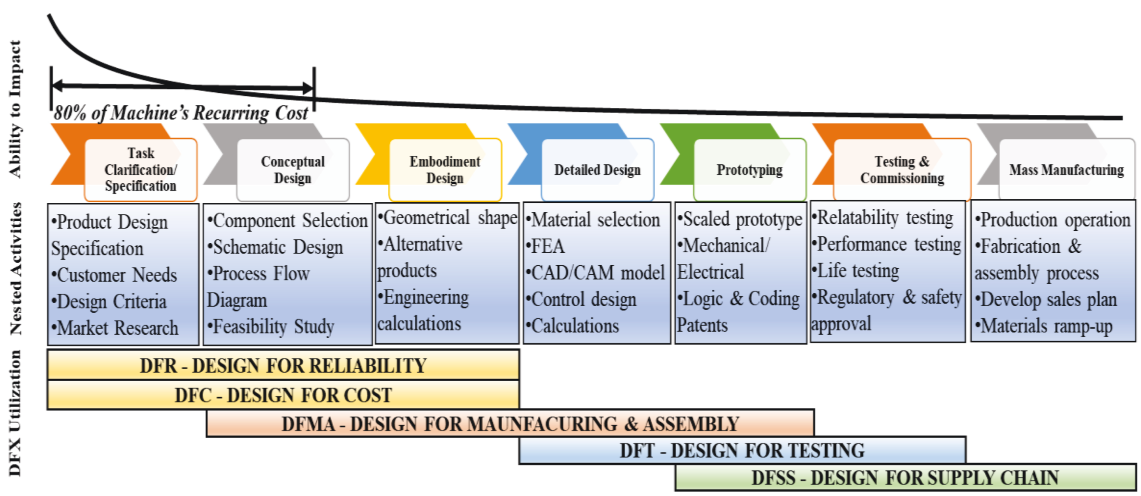

Figure 2.1 Machine Development Stages

The general purpose of implementing CE as explained by Guangleng and Yuyun (1996) in the machine design development is to improve quality, reduce cost and cycle time, and increase flexibility, productivity, and efficiency. It is intended to stimulate designers to consider all elements of the machine lifecycle in the early stages of the design. Figure 2.2 Machine Design Model in CE represents the machine design model in CE and explain the link between the design elements and the process. Numerous methods and tools have been developed to ease the implementation of CE in machine design. Among these methods is Design for X (DFX) techniques, where X stands for a specific life phase (e.g., manufacture, assembly) or virtue that the machine should possess (e.g., quality). However, these methods are usually not standardized, and in most cases, they have contradicting rules and results between them if applied in a design problem. Designers can achieve design goals, explore constraints, overcome difficulties, and consider the ramifications of their decisions early in the machine lifecycle when DFX techniques are implemented (Ahmad et al., 2014). The main DFX functionality accomplished by DFX techniques and their users' "designers" is summarized in Figure 2.3 where the first four functions and the second five functions are carried out mainly by designers, although few of these functions are achieved by them to some extent.

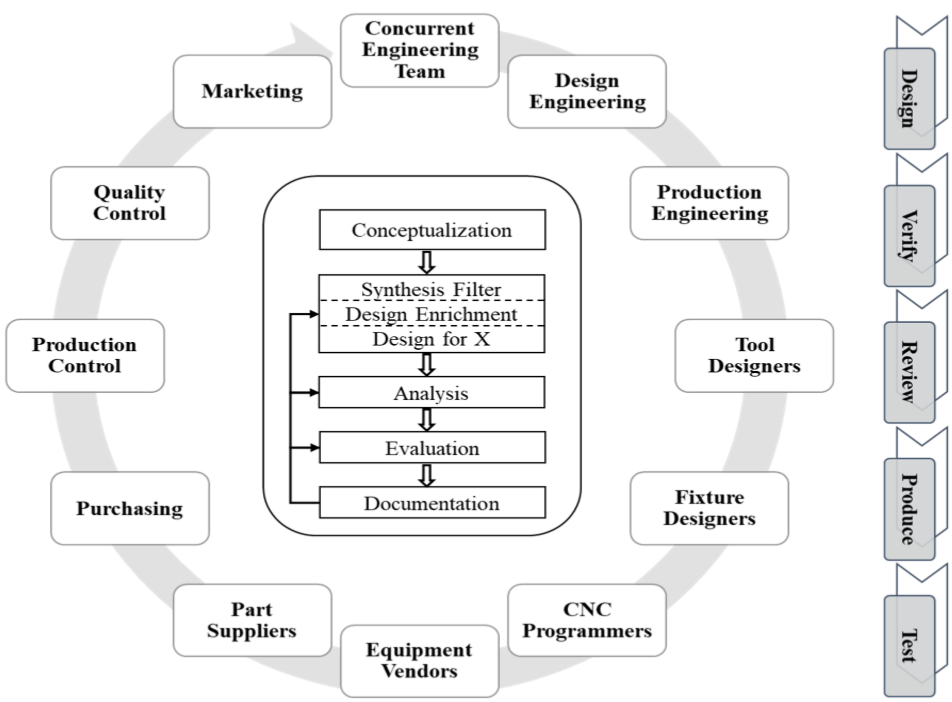

Figure 2.2 Machine Design Model in CE

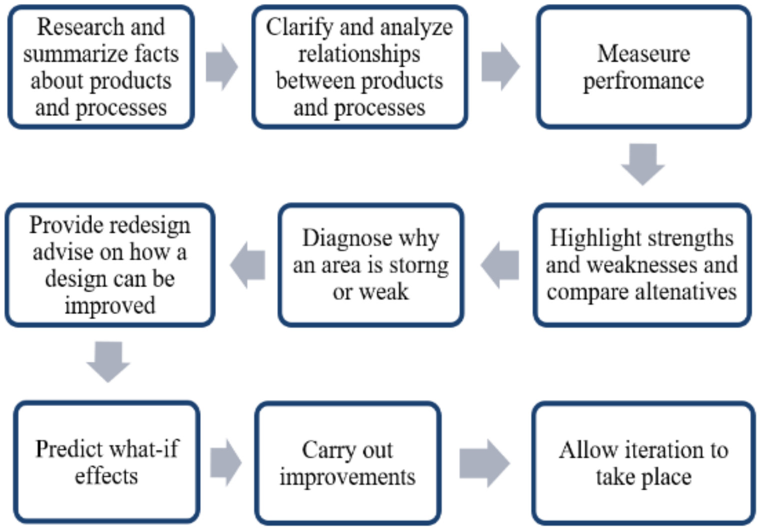

Figure 2.3 Main DFX functionality

2.2 Methodology

CE requires a holistic and systematic view of the machine design development process, so DFX techniques should be integrated and applied with a broader perspective and not applied in isolation. However, the relationships and interdependencies between DFX techniques and their links to the design process have garnered little attention in the literature. In this research these challenges are addressed through a review of various existing DFX techniques with potential applications at different stages in the total product design activity model is conducted. Based on the conducted literature review, the research work includes: (1) Mapping and clustering of the DFX methods utilized in Stuart Pugh Model, (2) a scheme which describes the interactions, links and interdependencies among DFXs tools, and (3) the relative importance weight calculations of different DFX techniques to guide/aid designers in selecting the most applicable ones for implementation in machine design.

2.2.1 Mapping existing DFX techniques

The various DFX techniques related to this study are presented in this research, and they are interrelated to various degrees. Research results are filtered and grouped with the main objective of generating a list of the most applicable DFX techniques related to machine design development and their characteristics from the literature. DFX techniques can be classified and arranged based on their: (1) purpose or goal, (2) scope, (3) character, and (4) focus. Figure 2.4 DFX categorization maprepresents the DFX categorization map developed during this research to facilitate the literature review findings.

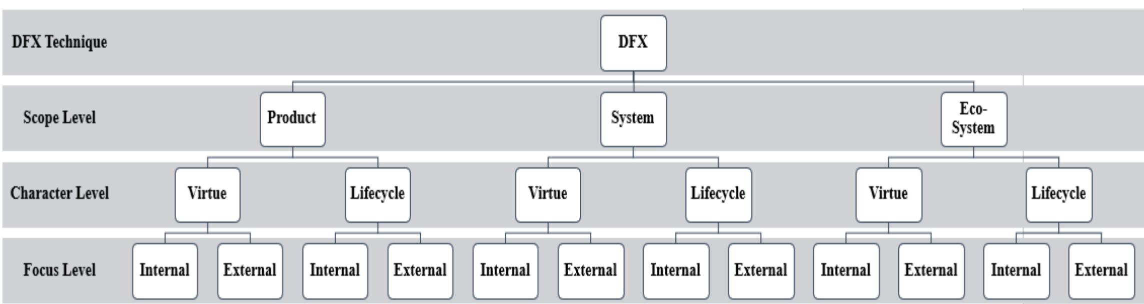

Figure 2.4 DFX categorization map

The scope of DFX implementation can span the product, system, ecosystem level, or a combination thereof (Chiu and Kremer, 2001). The product scope level focuses on the machine aspects which is an approach to designing a product such that the product design is instantly transitioned into production, manufactured at minimum cost with the highest quality (Chiu and Okudan, 2010). Fabricius (1994) proposed a set of general machine design guidelines to enhance the link between the design and manufacturing stages using a three-dimensional model. Different from the guidelines above, which are metric-based, Stoll (1988) described thirteen DFM guidelines that are strategy-based and practice-oriented. The system scope level focuses on the integration and manages the degree of coordination between different aspects of the machine value chain. The eco-system scope level referred to as green design, meanwhile, entails applying machine design engineering methodologies with the embodiment of a natural system to promote the effort in reducing greenhouse gases emissions.

Table 2.1 DFX techniques categorization

History and Overview of Design for X (DfX) Techniques											
DFX Application		**Stuart Pugh: Total Design Activity Model**					**Scope**	**Character**	**Focus**	**References**
Design For	**Main Objective**	**Specs.**	**Concpet**	**Detailed**	**Manufacture**	**Sell**				
Cost (DFC)	Minimize lifecycle costs	1,3	3,4,5	3,4,5	1,3,4,5	3	A,B,C	X	I	Unal & Dean (1992)
Manufacturing (DFM)	Minimize production costs	1,.3	1,2,3	1,3,4	1,3		A	Y	I	Stoll (1988)
Assembly (DFA)	Minimize production costs		3	3,4		3	A	Y	I	Nof et al. (1997)
Manufacturing & Assembly (DFMA)	Minimize production costs	1,3	1,3,4	1,3,4	1,3		A	Y	I	Boothroyd (1994)
Variety (DFV)	Minimize obstacles for inovation	3	3	3,5	3,5		A	X,Y	I	Martin (1999)
Quality (DFQ)	Maximize product quality	1	1,3,4	1,3,4,5	1,3,4,5	3	A	X	I,E	Franceschini & Rossetto (1997)
Six Sigma (DFSS)	Minimize variations and defects		1,3	1,3,5			A	X,Y	I	Harry & Schroeder (2000)
Quality Manufacturability (DFQM)	Improve product quality	1			1	3	A	X,Y	I	Das et al. (2000)
Reusability (DFRE)	Minimize obstacles for inovation			3		3	A	X	I	Cowan & Lucena (1995); Torroja et al. (1997)
Disassembly (DFDA)	Minimize environmental impact		1,3	1,3,5			A	Y	I	Zussman et al. (1994); Zhang & Kuo (1996)
Reliability (DFR)	Minimize failure percentage		1,5	1,5			A	X	I	Lalli & Packard (1994); Pecht (2007)
Testability (DFT)	Minimize failure percentage			1,3,4,5	1,3,4,5		A	X	I	Williams & Parker (1982); Pettichord (2002)
Obsolescence (DFO)	Minimize supply chain costs			3		3	A	Y	I	Singh & Sandborn (2006); Sandborn (2013)
Maintainability (DFMAI)	Minimize cost of ownership		2	2			A	X	I	Tortorella (2015)
Serviceability (DFSE)	Minimize cost of ownership		2	2			A	X	I	Dewhurst (1996)
Robustness (DFRO)	Minimize cost of production			1,3	1,3		A	X	I	Yu & Ishii (1998); Knoll & Vogel (2009)
End-Of-Life (DFEL)	Minimize environmental impact		1,3	1,3,4	1,3,4		A	Y	E	Allenby & Graedel (1993)
Remanufacture (DFRem)	Minimize obstacles for inovation			1,3	1,3		A	Y	I	Hatcher et al. (2011)
Failure Modes (DFMEA)	Minimize failure percentage	1,2	1,2,3				A	Y	I	Cutuli et al. (2006)
Material Substitution (DFMS)	Maximize resilience		1,3			4	A	X	I	Ljungberg (2005)
Modularity (DFMO)	Minimize obstacles for inovation			1,3		3	A	X	I	Erixon (1996)
Affordances (DFAF)	Maximize customer satisfaction	1,3,4	1,3			4	A	X	I	Maier & Fadel (2001)
User Empowerment (DFEM)	Maximize customer satisfaction	1,3,4	3,4				A	X	E	Ladner, R. E. (2015)
Lifecycle (DFLC)	Minimize lifecycle costs	1	1,3,4	1,3,4	1,3,4	1,3,4	B	Y	E	Chiu & Okusan (2010)
Transportability (DFTR)	Minimize supply chain costs			1,3,4		3	B	Y	E	Dowlatshahi (1999)
Mass Customization (DFMC)	Minimize obstacles for inovation	1,3,4		4,5	3,4,5	3	B	Y	E	Tseng & Jiao (1998)
Adaptability (DFAD)	Minimize obstacles for inovation			1,3,4			B	X	I	Gu et al. (2016)
Lean Six Sigma (DFLSS)	Minimize environmental impact		1,3	1,3,5	1,3		B,C	Y	E	Jugulum & Samuel (2010)
Sustainability (DFS)	Minimize environmental impact	1	1,3	1,3,4	1,3,4		C	X	E	Bhamra & Lofthouse (2007)
Recyclability (DFREC)	Minimize environmental impact		1,3	1,3,5			C	Y	E	Gaustad et al. (2010)
Energy Recovery (DFER)	Minimize environmental impact			1,3			C	X	E	Ljungberg (2005) ;Desmet (2015)
Logistics (DFL)	Minimize supply chain costs			1	4	4	B	Y	E	Mather (1992)
Network (DFN)	Minimize supply chain costs	3	3	3	3	4	B	Y	E	Maltzman et al. (2005)
Supply Chain (DFSC)	Minimize supply chain costs		1,5	1,3,5	1,3,5	4	B	Y	E	Lee & Sasser (1995)
Environment (DFE)	Minimize environmental impact	1,2,3,4,5	1,2,3,4	1,2,3,4	1,2,3,4		C	X	E	Fiksel & Wapman (1994), O'Shea (2004)
Classifications: 1= Guidelines, 2= Checklist, 3= Method, 4=Metrics, 5= Math Model										
Scope: A= Product, B= System, C= Ecosystem										
Character: X= Virtue, Y= Lifecycle										
Focus: I= Internal, E= External										

According to Holt and Barnes (2010), "character" in this context refers to the framework of reference that a DFX technique requires: whether the development is centered on a certain virtue of the product, or a certain characteristic of the functional system in which it is embedded. In this respect, DFX techniques are divided into two groups: those that optimize the machine with respect to a virtue (cost, quality, etc.), and those that optimize the machine with respect to a lifecycle phase (manufacture, assembly, etc.) (Van Hemel and Keldmann, 1996). These are labeled as DFXvirtue and DFXlifephase, respectively. Radziwill and Benton (2017) note that DFXvirtue techniques do not represent which virtues a machine should have but provide methods to check how well a design satisfies a given virtue. DFXlifephase techniques, meanwhile, help in ensuring that the influence of the whole machine lifecycle phases on the targeted performance is considered. They also explain that the focus is on the degree to which the DFX assimilates the stakeholder's requirements and preferences. Externally-focused DFX methods target supply chain needs, while internally-focused methods target machine specifications, production process requirements, and the type of service.

DFX methods are categorized into five main groups arranged in increasing level of complexity and importance: guidelines, checklists, metrics, mathematical models, and methods (Becker and Wits, 2013). Guidelines provide the guidance and advise required at each design phase. Checklists provide a list of items that need a "Yes"/"No" response and make judgments to verify designs. Metrics may involve both guidelines and checklists but can be presented in quantitative terms. Mathematics models include computational equations and scientific formulas that have been validated. Finally, the methods provide users with the design of systematic hierarchy structures and implementation procedures. Table 2.1 summarizes the clustering and categorization of 36 DFX techniques considered in this research based on the proposed methodology.

2.2.2 DFX relative importance weight analysis

The research is focused on two stages from the machine development lifecycle: the conceptual and detailed design stages listed under the Stuart Pugh: Total Design Activity Model. The reason for selecting this model among the various design methodologies is that it covers the entire lifecycle of machine development. A scientific database of contributions in the field of DFX and machine design is extracted from various repositories such as "Web of Science" and "Science Direct." The assumption is that the greater the number of publications focused on a given DFX technique in the field of machine development phase is, the higher the influence of that technique is. A CiteSpace II software is used to carry out the systematic mapping studies from the scientific database (Chen et al., 2010). It takes the input of the selected publication list and gives the systematic bibliographic analysis of keywords, citations, and publication. In the below-presented method to evaluate the importance weights, the focus is on the number of contributions published during a specific time interval for a given DFX technique. The analysis of the resulting data helps to derive importance weightings of a given DFX technique relative to other techniques published in the same period. For this purpose, the weighted average method is deployed to convert these numbers into weightings and to generate a ranked list. A weight is computed by the frequency of occurrence in a dataset, where the frequency is the number of publications multiplied by the importance weight associated with each period in the dataset from Table 2.2. The assumption here is that the importance of weight will increase as the period progresses toward the present year. This practice allows for more recent publications to receive more weight relative to older publications. The weighted average of publications is calculated by the following standard equation (2.2.1.1).

$$Weighted\ Average = \frac{Importance\ Weight * Frequency}{\Sigma Frequencies} \tag{2.2.1.1}$$

where: P_{DFX} = Frequency of publications related to DFX technique in a specific time period; n= Total numbers of DFX techniques; i= Lower year interval; j= Higher year interval.

The weighted average of the DFX for a specific time interval is calculated as follows:

$$W_{PDFX} = \prod_{i}^{j} P_{DFX}\ x \text{ Importance Weight} \tag{2.2.1.2}$$

The total weighted average of the DFX for a specific time interval is calculated as follows:

$$W_{PDFX} = \sum_{i}^{j} W_{P_{DFX}} \tag{2.2.1.3}$$

The percentage relative total weight of a specific DFX with reference to all other DFXs is calculated as follows:

$$W_{PDFX} = \frac{W_{PDFX}}{\sum_{i=1}^{n} W_{PDFX}} \tag{2.2.1.4}$$

Table 2.2 Importance weight associated with each period

Importance Weight (0-1)	**Papers Period (Years)**
0.05	≤ 1995
0.075	1996 ≤ Y ≤ 2000
0.1	2001 ≤ Y ≤ 2005
0.15	2006 ≤ Y ≤ 2010
0.225	2011 ≤ Y ≤ 2015
0.4	Y ≥ 2016

Table 2.3 DFX techniques with their relative importance weight index

Historical Distribution of the Research Effort of DfX tools								Weighted Average Calculation							
Design For / Time Period	Before 1995	1996-2000	2001-2005	2006-2010	2011-2015	After 2016	Total	Wpdfx≤ 1995 (2)	1995≤Wpdfx ≤2000 (2)	2001≤Wpdfx ≤2005 (2)	2006≤Wpdfx ≤2010 (2)	2011≤Wpdfx ≤2015 (2)	Wpdfx≥ 2016 (2)	Total Weight (3)	% Relative Total Weight (4)
Cost (DFC)	12	7	14	18	23	8	82	0.60	0.53	1.40	2.70	5.18	3.20	13.6	1.7
Manufacturing (DFM)	53	76	119	205	187	113	753	2.65	5.70	11.90	30.75	42.08	45.20	138.3	17.5
Assembly (DFA)	63	77	71	15	11	2	239	3.15	5.78	7.10	2.25	2.48	0.80	21.6	2.7
Manufacturing & Assembly (DFMA)	0	0	0	3	2	3	8	0.00	0.00	0.00	0.45	0.45	1.20	2.1	0.3
Variety (DFV)	0	0	5	16	13	1	35	0.00	0.00	0.50	2.40	2.93	0.40	6.2	0.8
Quality (DFQ)	25	26	21	30	37	12	151	1.25	1.95	2.10	4.50	8.33	4.80	22.9	2.9
Six Sigma (DFSS)	0	6	39	60	68	15	188	0.00	0.45	3.90	9.00	15.30	6.00	34.7	4.4
Quality Manufacturability (DFQM)	1	2	0	0	0	0	3	0.05	0.15	0.00	0.00	0.00	0.00	0.2	0.0
Reusability (DFRE)	0	3	5	1	2	0	11	0.00	0.23	0.50	0.15	0.45	0.00	1.3	0.2
Disassembly (DFDA)	13	37	52	45	48	32	227	0.65	2.78	5.20	6.75	10.80	12.80	39.0	4.9
Reliability (DFR)	47	32	69	123	176	65	512	2.35	2.40	6.90	18.45	39.60	26.00	95.7	12.1
Testability (DFT)	218	261	228	293	264	101	1365	10.90	19.58	22.80	43.95	59.40	40.40	197.0	24.9
Obsolescence (DFO)	0	0	1	0	3	0	4	0.00	0.00	0.10	0.00	0.68	0.00	0.8	0.1
Maintainability (DFMAI)	17	5	5	7	9	10	53	0.85	0.38	0.50	1.05	2.03	4.00	8.8	1.1
Serviceability (DFSE)	1	1	2	3	2	5	14	0.05	0.08	0.20	0.45	0.45	2.00	3.2	0.4
Robustness (DFRO)	1	3	9	8	18	8	47	0.05	0.23	0.90	1.20	4.05	3.20	9.6	1.2
End-Of-Life (DFEL)	0	2	8	7	5	9	31	0.00	0.15	0.80	1.05	1.13	3.60	6.7	0.8
Remanufacture (DFRem)	0	7	3	2	8	1	21	0.00	0.53	0.30	0.30	1.80	0.40	3.3	0.4
Failure Modes (DFMEA)	1	0	0	0	0	0	1	0.05	0.00	0.00	0.00	0.00	0.00	0.1	0.0
Material Substitution (DFMS)	4	0	1	5	10	3	23	0.20	0.00	0.10	0.75	2.25	1.20	4.5	0.6
Modularity (DFMO)	0	1	6	3	4	1	15	0.00	0.08	0.60	0.45	0.90	0.40	2.4	0.3
Affordances (DFAF)	0	0	0	0	3	0	3	0.00	0.00	0.00	0.00	0.68	0.00	0.7	0.1
Empowerment (DFEM)	3	1	1	1	2	0	8	0.15	0.08	0.10	0.15	0.45	0.00	0.9	0.1
Lifecycle (DFLC)	0	2	1	3	2	1	9	0.00	0.15	0.10	0.45	0.45	0.40	1.6	0.2
Transportability (DFTR)	1	2	0	0	0	0	3	0.05	0.15	0.00	0.00	0.00	0.00	0.2	0.0
Mass Customization (DFMC)	0	4	6	11	10	2	33	0.00	0.30	0.60	1.65	2.25	0.80	5.6	0.7
Adaptability (DFAD)	1	0	0	5	7	4	17	0.05	0.00	0.00	0.75	1.58	1.60	4.0	0.5
Lean Six Sigma (DFLSS)	0	0	0	1	2	0	3	0.00	0.00	0.00	0.15	0.45	0.00	0.6	0.1
Sustainability (DFS)	2	6	20	35	104	83	250	0.10	0.45	2.00	5.25	23.40	33.20	64.4	8.1
Recyclability (DFREC)	5	4	5	2	2	1	19	0.25	0.30	0.50	0.30	0.45	0.40	2.2	0.3
Energy Recovery (DFER)	0	0	1	1	0	1	3	0.00	0.00	0.10	0.15	0.00	0.40	0.7	0.1
Logistics (DFL)	1	3	1	3	5	1	14	0.05	0.23	0.10	0.45	1.13	0.40	2.4	0.3
Network (DFN)	3	5	8	16	33	11	76	0.15	0.38	0.80	2.40	7.43	4.40	15.6	2.0
Supply Chain (DFSC)	1	0	2	7	9	5	24	0.05	0.00	0.20	1.05	2.03	2.00	5.3	0.7
Environment (DFE)	26	109	153	112	85	39	524	1.30	8.18	15.30	16.80	19.13	15.60	76.3	9.6

2.3 Results and Discussions

From Table 2.1 it can be observed that comparably few techniques have been developed over the years for the early machine design stages relative to the later stages. This can be related to the fact that the physical variables of the machine being designed in the present case are still undefined. On the other hand, most of the machine-related DFX techniques are focused on the conceptual and detailed design phases, while system-related techniques concentrate on detailed design. Moreover, ecosystem-related concepts apply to all five design phases. The machine design environmental factor is becoming one of the main requirements in the conceptual and detailed design stages, and, because of environmental considerations, some machines are redesigned. Also, it can be concluded that the detailed methodologies for DFM, DFA, DFQ, and DFV have been proposed, while, for DFS and DFSC, there are only applicable guidelines and mathematical models available. The proposed categorization describes and specify the different structures type in a DFX technique; however, it fails to explicitly express which design activities should be addressed first and which of the techniques nor their implementation order so that they fulfill the machine design intent.

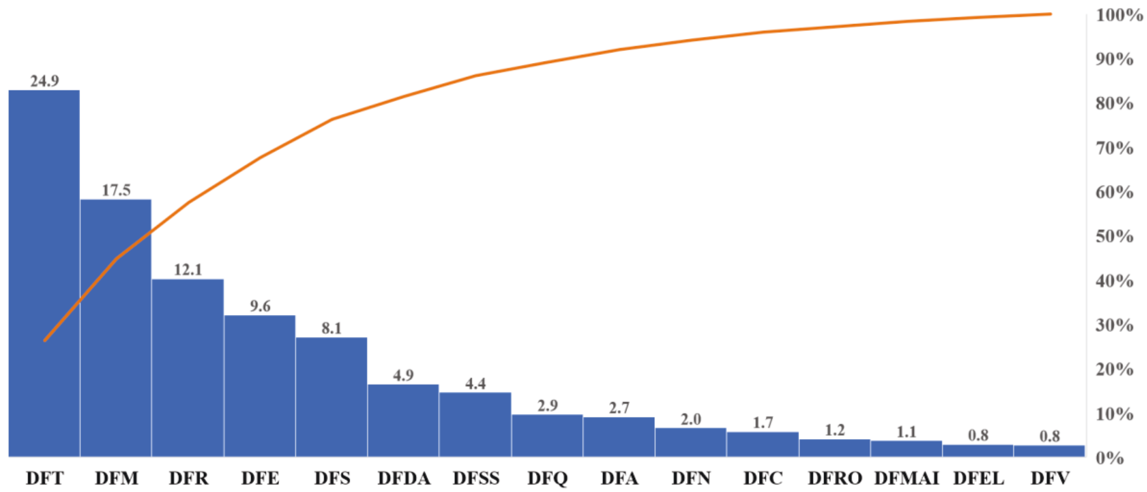

Figure 2.5 DFXs relative importance weight distribution percentage

In this research, a relative importance weight index is proposed to indicate the amount of effort spent by the researchers on a given DFX technique. In the left pane of Table 2.3, the number of published papers for each DFX technique in 5-year increments is tabulated. From the resultant table, it can be concluded that the interest rises for Assembly in 1996-2000. Then, Environment emerges as a vital DFX technique for the 2001-2005 interval. After 2005, Testability and Manufacturing garner increasing attention. Furthermore, the focus of research work is found to shift from the product scope to the system and then ecosystem after 1995. Also, a misleading conclusion could be drawn from the matrix if a weighting system is not implemented for the published papers. Figure 2.5 represents the generated ranked list, where DFT and DFM have recorded higher levels of importance (24.9%, 17.5%) in comparison to DFEL and DFV (0.8%), respectively.

2.4 Conclusion

This research summarizes findings based on a comprehensive literature review of various DFX techniques in the broad area of machine development. A clustered collaborative scheme was proposed housing thirty-six DFX techniques, revealing their links and interdependencies across five machine design phases. Moreover, the quantitative research on the maturity of DFXs across the years shows that the combined relative importance percentage allocated with top-ranked 15 DFXs (e.g., DFT, DFM, DFR, DFE, etc.) is 94.7%, which signals an increased level of importance and preparedness of these most effective, efficient, and versatile DFX techniques for machine design development.

Chapter 3 : Simulating the concurrent interdependencies between Multi-DFX Techniques in Machine Design Conflict Resolution[2]

3.1 Introduction

The implementation of MDFX in concurrent engineering machine design can result in contradictory and conflicting conclusions and recommendations for the designer's design-making process. Several independent studies have started to investigate and analyze these contradicting interactions by using various frameworks developed by Watson that can quantify the MDFX usefulness by design phase (Watson et al., 1996). They concluded that MDFX, depending on where they are implemented during the machine development process, have a varying impact threshold. Whereas Willcox and Sheldon realized that the implementation of Design for Assembly methodology is most useful at the conceptual stage (WILCOX and Sheldon, 1993). Because the tool component analysis is the main part of the methodology, it is preferred during the machine detailed design stage. The DFA analysis tool is an unreliable tool to be utilized during the conceptual machine stage because the design details required to undergo the analysis are not available at this stage. Hence, if the analysis tool is not effective at the conceptual design stage, then the alternative will be the benefits that the design guidelines of a specific DFX provide. So, to minimize the machine redesign possibilities and reduce the cost/time of this activity, the analysis tool should consider the importance of DFX guidelines.

[2] The manuscript presented as Chapter 3 of this thesis was submitted to the 2019 International Symposium on Automation and Robotics in Construction and Mining (ISARC), at the time of publication of this thesis.

Some research was undertaken to investigate how to tackle the conflicting implementation guidelines of MDFX. Thurston suggests a methodology to model the design decision results on the interval of a machine life-cycle (Thurston, 1991). A framework was developed to facilitate the decision-making process through ranking the design alternatives and calculating design trade-offs. In engineering design, it is a powerful analysis tool for decision making where multiple criteria and objectives exist. Unfortunately, for most applications, this method is very complicated and extensively time-consuming for designers in small to medium-sized organizations. If this ranking method is adopted to classify the design guidelines, it would be unnecessarily tedious because the model used by Thurston is to some extent more complicated to implement than what is required for this application. A simpler and faster method for trade-off analysis between MDFX is to implement a matrix approach. Meerkamm concludes that if MDFX techniques are to be utilized in a problem context, then their design guidelines will often contradict and constrain the design output (Meerkamm, 1994). Consequently, as explained by Watson et al., finding an optimal solution is becoming a difficult task for designers (Watson, 1996). As the design guidelines tend to be the DFX toolbox's most flexible aspect, they accurately indicate the nature of the DFX interactions and links between them and their concurrent interdependencies in ultimately finding an optimal design solution.

It is important to evaluate the application of MDFX in machine design development comprehensively. But due to the absence of information in the conceptual machine stage, problems and conflicts can arise when MDFX techniques are employed. This is because of a lack of information and vague objectives, which interfere with the designer's ability to evaluate design decision alternatives precisely. Decisions that emerge from applying one

DFX technique seem to be good for one phase of the machine life cycle but can conflict with other life cycle phases. The designer should oversee the concurrent effects of the decision-making process in machine design. If the previous decisions are based on inaccurate information, the following design stages will be affected significantly. The application of MDFX techniques in machine design development requires effective decision support systems. Given this, a decision support tool that simulates the concurrent interdependencies between MDFX techniques during the conceptual machine design stage is proposed in this research.

3.2 Methodology

The methodology presented in this section is based on Watson et al.'s model that uses a weighted matrix method to exploit the interactions between MDFX (Watson, 1996). The matrix method is extended to simulate the concurrent interdependencies between MDFX. The model output provides three useful indices. The first one indicates major areas of potential conflict occurring between the compared MDFX. The second illustrates how the value of a specific guideline is modified when interacting with the competing DFX guidelines. And the third is measuring the DFX techniques in terms of time metrics to estimate and reliably verify DFX interactions and design decisions comprehensively.

3.2.1 Procedure of the matrix

The methodology for assessing and ranking the DFX's competing design guidelines requires six distinct tasks to be undertaken. These tasks are described in the flowchart presented in Figure 3.1.

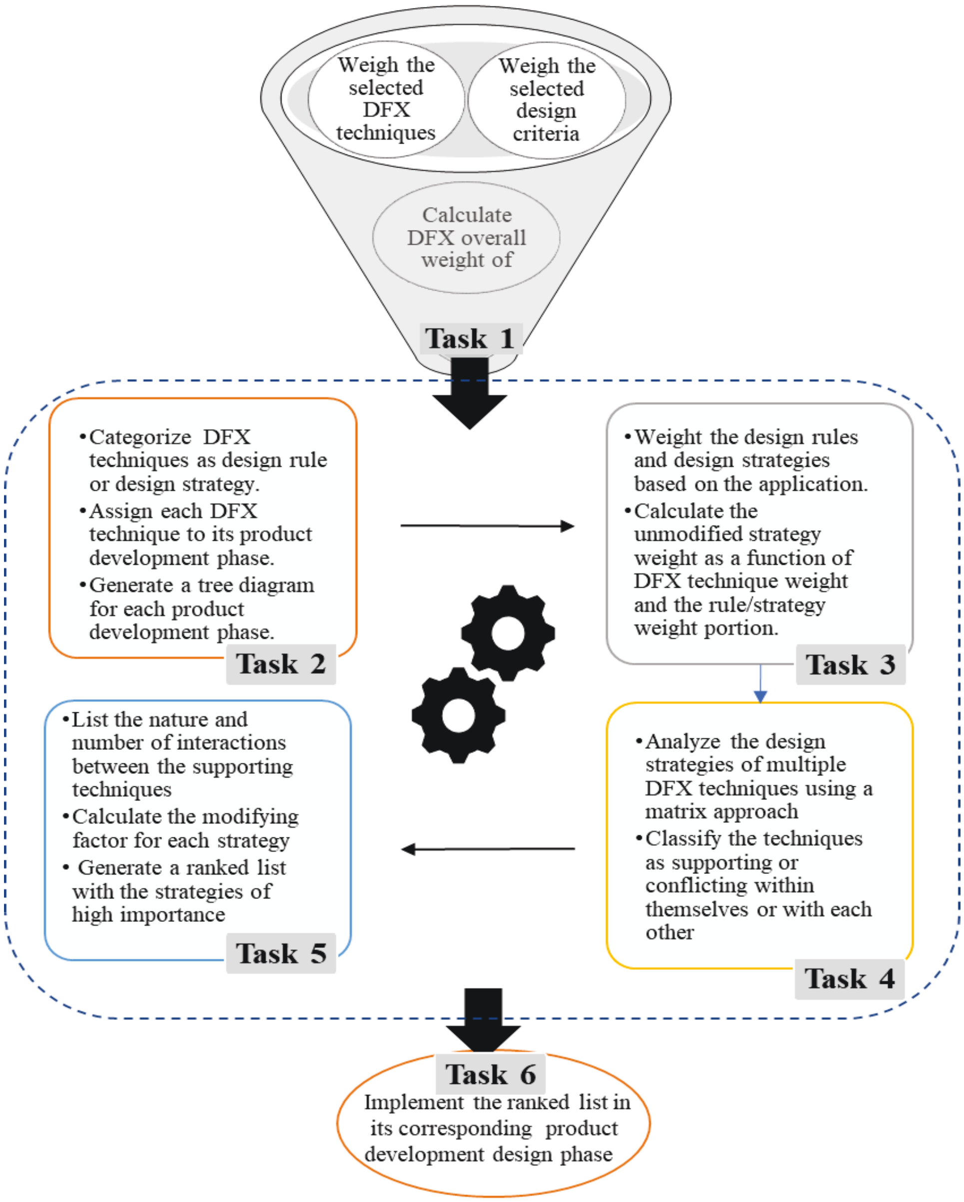

Figure 3.1 Multi-DFX techniques matrix model flow chart

3.2.2 Task 1: Determine DFX overall weight using the analytical hierarchy process (AHP) method

The first task involves selecting and calculating the overall relative importance (weight) of the chosen DFX techniques. This can be achieved by calculating the weight of each DFX technique separately with respect to the design criteria, and then by combining them in an

AHP model developed by Saaty to determine their relative importance in machine conceptual and detailed design stages (Saaty, 2008). In general, the relative importance of a DFX technique varies as to where and when it can be applied during the machine development process (Ahmad et al., 2014). He concludes that the area where a DFX technique can be utilized is defined by company and customer requirements, production capabilities, and industry orientations, in addition to other considerations. The product design specification (PDS) must be formulated at the beginning of the project based on the statement of needs before any design activity, as shown in Figure 3.2. Thus, it acts as the governor for the total design activity model, because it revolves around the boundaries of each design stage for any machine.

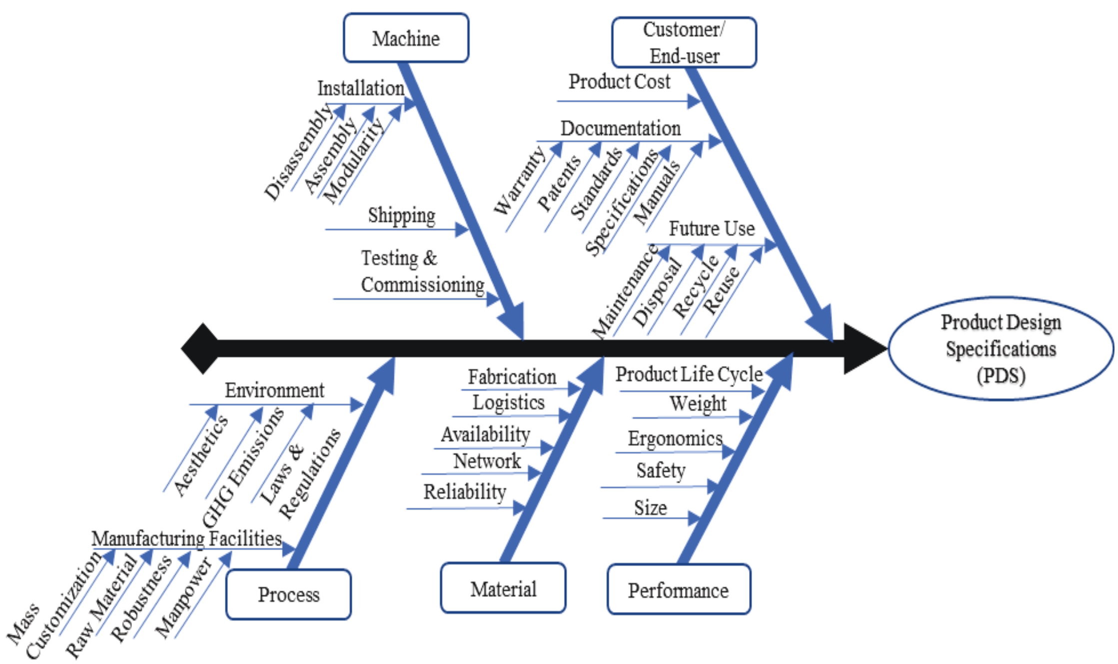

Figure 3.2 Product design specification (PDS)

The PDS forms a progressive, evolutionary, and extensive written document that evolves in consideration of the final machine characteristics. The PDS is then translated into design criteria that are followed by the design team, and as such, each design criterion will be associated with one or multiple DFX techniques that can satisfy its requirements. By adapting the total life-cycle cost/time method developed by Lukasz and Tomasz, the design team can successfully estimate each DFX technique's effect with respect to the other, and those values will be an indicator as to how much each DFX can reduce the development life-cycle overall cost and time (Lukasz and Tomasz, 2007).

DFX techniques are weighted with respect to each design criterion to generate an overall general normalized importance weight W_{DFXG} with a total value of 1. From that, the time required for each design activity T_{DFXG} can be derived under a certain DFX. This weighting factor will then be adopted in the general model for conceptual and detailed design stages. The weighting in the AHP model must rely on the designer's experience and intuition. W_{DFXG} and T_{DFXG} are calculated using Equation (3.2.2.1) and (3.2.2.2), respectively, as follows:

$$W_{DFX} = \frac{Cost_X}{Cost_T} \tag{3.2.2.1}$$

where $Cost_x$= The cost of life-cycle area x; $Cost_T$= The combined cost of the life-cycle.

$$T_{DFXG} = W_{DFXG}\ x\ T_t \tag{3.2.2.2}$$

where T_{DFXG}= The allocated time for a specific DFX in days; T_t = The total time for the design activity in days.

3.2.3 Task 2: Generate tree diagram to classify DFX design guidelines

In this section, the machine development process is categorized, and the hierarchical level of the DFX technique design guidelines is established. Watson, Radcliffe et al. proved that if DFX decision analysis tools are utilized during conceptual and detailed machine design stages, they could improve the design performance significantly (Watson et al., 1996). They also concluded that most DFX techniques fail to give what is expected because they merely provide the designer with directions on how and when the design rules can be implemented.

Pugh's Total Design Activity Model is used to describe the machine development process (Pugh, 1991). The model phases are 1) user need; 2) machine specification; 3) conceptual design; 4) detail design; 5) manufacture; and 6) and sales. Though design activities might not always have to occur concurrently in the sequence outlined by Pugh, his machine development model provides a detailed structured procedure of all the stages required. Table 3.1 contains some design guidelines examples which are the most applicable for machine design development process extracted from the Design for Assembly (DFA) methodology (Boothroyd and Dewhurst, 1989).

Table 3.1 DFA guidelines per design stage

Specification	• Standardize a machine's style. • Establish the machine design specification.
Concept Design	• Reduce the number of parts and components. • Eliminate machine features that do not have any tangible value to the customer. • Standardize a machine's style. • Using new materials and technologies. • Rational machine design by modules and product families.
Detailed Design	• Design multi-functional parts. • Developing the machine features that facilitate the positioning.

	• Avoid costly clamping systems.
Manufacture	• Simplicity. • Adapted tolerances. • Consideration of process-related design guidelines.

The second task in constructing the model is to organize the DFX technique design guidelines into a decision tree using a hierarchical structure. Each DFX technique consists of primary and secondary design guidelines called design rules and design strategies, respectively. The tree diagram consists of three levels where the first level is associated with the general DFX tool under study, the second level is associated with DFX design rules, and the third level is associated with DFX design strategies. Table 3.2 contains an example of the hierarchical tree using the DFA guidelines during the detailed design phase (Boothroyd and Dewhurst, 1989).

Table 3.2 DFA detailed design stage guidelines

Design Rules	Design Strategies
Reduce the number of parts and their types	Reduce unstandardized fasteners. Eliminate parts that function as connectors and conduits. Design multi-function parts. Do not follow piece-part producibility guidelines.
Eliminate physical adjustments	Reduce the number of physical parts between the machine input and output functions. Relocate critically related part surfaces close together. Implement kinematic design procedures and principles.
Ensure adequate clearance and unrestricted vision	Ensure adequate clearance for hands, tools, and subsequent process. Ensure that the vision of the operation is not restricted or compromised.
Minimize re-orientations	Minimize the necessity for reorientations during and after parts installation.

3.2.4 Task 3: Determining the weightings levels of the guidelines

The third task requires that the DFX technique design rules and strategies be weighted. Regarding the weighting levels, they are determined in each phase, which gives the designer a general design overview of the machine development process. The design rules weighting, W_{TR}, is determined independently, regardless of the design strategies number (on a scale of 1 to 10). While the design strategies weighting, W_{PS}, is determined in proportion to the design rule it corresponds to on a scale of 1 to 10, such that the total weight summation under design rules is equal to 1. The total weight of each design strategy, W_{TS}, is calculated using Equation (3.2.4.1) by multiplying the DFX technique overall weight, the design rule total weight, and the design strategy proportional weight. Thus, the total weight of each design strategy can fluctuate between 0 and 1. While the time required for each design strategy, T_{TS}, is calculated in days using Equation (3.2.4.2) by multiplying the strategy calculated weight from Equation (3.2.4.1) by the allocated time for the selected DFX divided by the summation of strategies weight for the selected design phase.

$$W_{TS} = W_{DFXG} \; x \; W_{TR} \; x \; W_{PS} \tag{3.2.4.1}$$

$$T_{TS} = \frac{T_{DFXG} \; x \; W_{TS}}{\sum_{i=0}^{n} W_{TS}} \quad where \; i=0,1,2 \ldots . \; n. \tag{3.2.4.2}$$

3.2.5 Task 4: Identifying interactions and links between guidelines

The fourth task involves determining the interactions and links between the strategies and reporting them inside the matrix model. The severity of any conflicts can be measured from these interactions. The matrix model can be utilized to compare multiple numbers of strategies from MDFX techniques. However, the process of finding each relationship between strategies can become tedious and time consuming for MDFX guidelines. It is assumed that not more than four DFX tools and a maximum number of ten strategies per phase should be adopted in the model.

Table 3.3 Strategies comparison values

R Values	Description
+ 10	Two or more strategies interact positively.
+5	One strategy supports positively the other in a broader scope.
0	No interaction occurs between the design strategies.
-5	One strategy supports negatively the other in a broader scope.
-10	Two or more strategies interact negatively.

From the matrix model, it is possible to pinpoint any conflict between two strategies to alert the designer that special consideration should be in place when dealing with them. This is done using the conflict index, CI, which quantifies the severity of the conflict. When a negative interaction occurs, the equation to calculate the conflict index is employed. The conflict index constant is calculated using Equation (3.2.5.1) as follows:

$$CI = W_{TS} \times W_{TS'} \times R \qquad (3.2.5.1)$$

if $CI < -10$ then conflict must be examined.

where $W_{TS'}$= Total weight of compared strategy; R= The comparison value for the two strategies, as shown in Table 3.3.

3.2.6 Tasks 5 & 6: Generating the ranked list of DFX strategies

The fifth task involves calculating the overall value ($\forall_{TS}$) of a design strategy considering strategies weight and their interactions with each other. The main process is based on the assumption that each design strategy has a total weighted value (W_{TS}) and interactions with other strategies adjust this. The prime factor is a function of the comparison index and the compared guideline weight. By summing the prime value over all the DFX interactions, a global scaler is determined. Equations (3.2.6.1) & (3.2.6.2) calculate the overall value ($\forall_{TS}$) as follows:

$$\forall_{TS} = W_{TS}\ (1 + \delta\ \forall) \tag{3.2.6.1}$$

$$\forall_{TS} = W_{TS}(1 + \sum \frac{(W_{TS'}\ x\ R\ x\ S\ )}{100}) \tag{3.2.6.2}$$

where $S = \frac{15}{W_{TS}}\ \ if\ W_{TS'} > W_{TS}\ and\ R < 0$ (3.2.6.3)

S=1 else

where $\delta\forall$=the total prime factor overall strategies and DFX techniques; S= the scaler; 15= Number of DFX techniques being researched; 100=scaling factor.

In Equation (3.2.6.3), the scaler considers the instances when a low weight design strategy conflicts with a high weight one. Having determined the total strategy value, a ranked list can be configured to be implemented in machine development. Any design strategies that have a negative total value should be ignored because if adopted, then it may lead to a life-cycle performance reduction due to its conflicting correlations with other strategies. After generating the ranked list, the redundant design strategies within the competing DFX will be removed to save time and to eliminate design repetition. However, if both design strategies match each other in the core objective, then the lesser time duration will be selected.

3.3 Validation Case Study

In this section, the focus of the case study will revolve around a part of the multi-function bridge machine prototype which is the nailing carriage in its conceptual design stage, as shown in Figure 3.3 and Figure 3.4. As the carriage at this stage is primarily a research tool, it is assumed that there would be a maximum amount of flexibility and testability within the variability of the experimental parameters. It also meant that a simple and unique machine would be designed. As the carriage will be operating in a large area with extreme precision at a controlled speed, it is apparent that the geometry and versatility of the carriage are considered as a major design criterion. It is also apparent that because the vertical force loads are so small, any part stresses would be negligible.

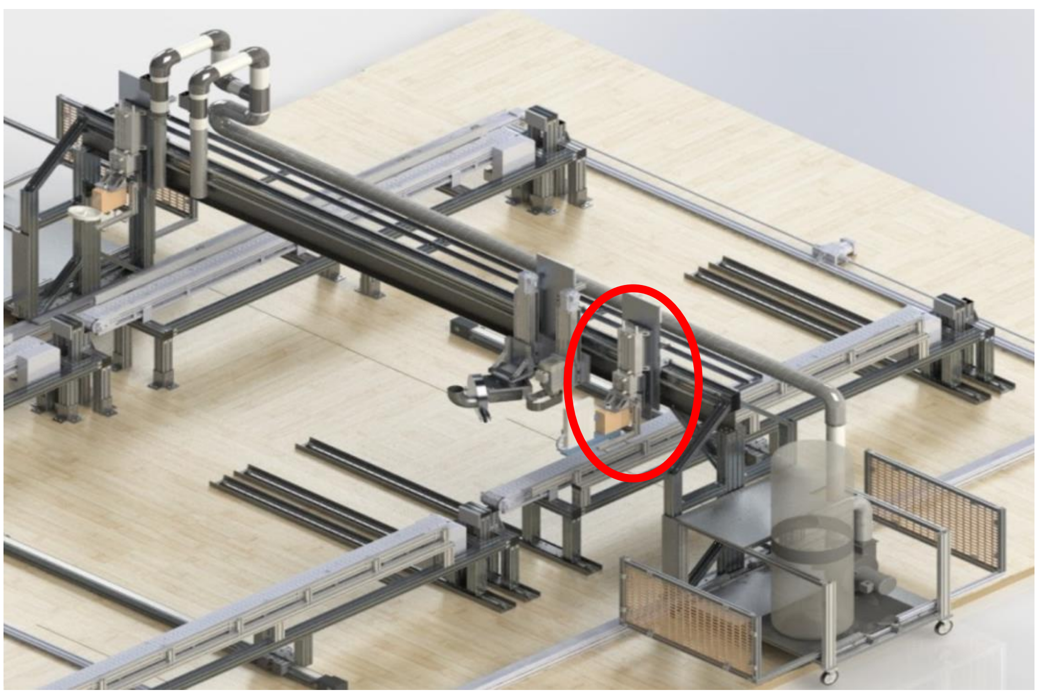

Figure 3.3 3D model of multi-function bridge prototype

From the PDS, the carriage to be designed is to accommodate multiple configurations of interchangeable tools, such as a nailer, stapler, and screwdriver. This operational requirement results in the device being partially disassembled and re-assembled after each operation and for different sheathing configurations. Regarding parts service life, it is expected that no major parts should fail throughout the device's life. The final requirement is that the device is to be designed and manufactured within a very limited budget. The detailed technical information of the machine development is excluded from this research for patentability and commerciality of the machine. Instead, some of the case study design related issues are discussed in broad terms. The timeline to complete the carriage conceptual design was 60 calendar days. These days are distributed on all 15 DFX techniques in accordance with their global weighting results.

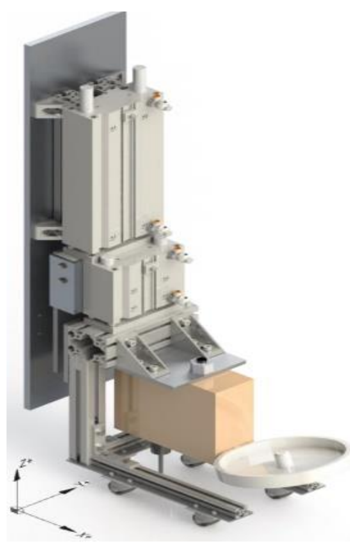

Figure 3.4 Nailer carriage detailed view

DFA Design rules and strategy weights by product development phase

Product Development Phase	Design Rules	W_{DFXG}	W_{TR}	Design Strategies	W_{PS}	W_{TS}	T_{TS}
Concept Design	1- Minimize the number of parts (Types & Count).	0.08	10	1- Minimize the number of parts and levels of assembly.	0.3	0.24	0.39
				2- Minimize the number of components and subassemblies.	0.3	0.24	0.39
				3- Reduce product complexity.	0.2	0.16	0.26
				4- Eliminate any product features that do not add value to the customer.	0.1	0.08	0.13
				5- Design mult-function parts.	0.1	0.08	0.13
	2- Increase product modularity.		8	1- Design products from modular subassemblies so that modules can be scheduled, built and tested independently.	0.4	0.26	0.42
				2- Standardize by common components, processes and methods to reduce costs across the whole system.	0.6	0.38	0.63
	3- Ensure base part design.		10	1- The product must has a suitable base part on which the rest of the assembly can be built.	0.6	0.48	0.78
				2- Maximize process yields between base and at each workstation for the whole assembly system.	0.4	0.32	0.52
	4- Aim for sequential assembly design.		8	1- Design the product to be built up in layers.	0.4	0.26	0.42
				2- Components can be added from above and located positively.	0.4	0.26	0.42
				3- Reduce the tendency to move during subsequent motions or steps.	0.2	0.13	0.21
	5- Minimize the need for reorientations during assembly.		2	1- Minimize the need for reorientations during assembly.	1	0.16	0.26

Figure 3.5 Design for assembly design rules and strategies for the conceptual stage

DFDA Design rules and strategy weights by product development phase

Product Development Phase	Design Rules	W_{DFXG}	W_{TR}	Design Strategies	W_{PS}	W_{TS}	T_{TS}
Concept Design	1- Improve the products structure for disassembly.	0.05	10	1- Subdivide the product into manageable subassemblies.	0.5	0.25	1.19
				2- Minimize the number of components and subassemblies.	0.5	0.25	1.19
				3- Standardize the products style.	0	0.00	0.00
	2- Improve the disassembly planning.		2	1- A void long disassembly paths.	1	0.10	0.48

Figure 3.6 Design for disassembly design rules and strategies for the conceptual stage

This to allocate time for each DFX technique and to study the effect of utilizing the proposed methodology in the time management of design activities.

Table 3.4 DFX global weighting results with their time allocations in the conceptual design stage

Global Weighting Associated with DFX in relation to each design criterion in Conceptual Design Phase	W_{DFXG}	T_{DFXG}
Design for Cost (DFC)	0.228	13.66
Design for Manufacturing (DFM)	0.125	7.49
Design for Assembly (DFA)	0.083	4.96
Design for Variety (DFV)	0.087	5.20
Design for Quality (DFQ)	0.087	5.23
Design for Six Sigma (DFSS)	0.051	3.06
Design for Disassembly (DFDA)	0.048	2.86
Design for Reliability (DFR)	0.058	3.51
Design for Testability (DFT)	0.038	2.29
Design for Maintainability (DFMAI)	0.033	1.96
Design for Robustness (DFRO)	0.036	2.14

Design for Mass Customization (DFMC)	0.025	1.51
Design for Sustainability (DFS)	0.044	2.66
Design for Network (DFN)	0.033	2.00
Design for Environment (DFE)	0.024	1.46

In this case, 15 DFX techniques fall under the scope of the conceptual design stage with their global weighting associated with the PDS that was calculated by adopting the AHP model. Table 3.4 summarizes the results where the total summation of all DFX weighting is equal to 1 and where each DFX has a time allocation associated with it. In this research, two DFX techniques were selected from the list to demonstrate the model functionality: Design for Assembly (DFA) and Design for Disassembly (DFDA). The DFA technique selected was developed by Boothroyd and Dewhurst (1989). The methodology has been refined and upgraded to provide a realistic and reliable design analysis tool with set of guidelines that are presented in a structured format. The tool follows the same basic procedures to analyze for manual, automatic and robotic assembly with different input data tables for the various processes. For this project, the manual assembly method is adequate. The designed machine would encounter assembly and re-assembly process on a regular basis. This process has a substantial effect on how the design guidelines are interpreted and rated. A team of researchers developed the DFDA technique adopted in this case study at the Manchester Metropolitan University (Simon et al., 1992; Zhang et al., 1993). The developed technique purpose is focused on the disassembling process to facilitate reconfiguration. Figure 3.5 and Figure 3.6 contain the list of design rules and strategies for conceptual design machine development phases for both DFA and DFDA techniques. Since two DFX techniques are being investigated, only one decision matrix for the conceptual machine development phase is selected for the demonstration of the comparison and ranking process. Figure 3.7 shows the conceptual design comparison matrix for DFA versus DFDA highlighting the guidelines interactions.

Conceptual Design	**DFDA Strategies**	Subdivide the product into manageable subassemblies.	Minimize the number of components and subassemblies.	Standardize the products style.	Avoid long disassembly paths.			
DFA Strategies	W_{TS}	0.25	0.25	0.00	0.10			
Minimize the number of parts and levels of assembly.	0.24	5	10	0	0	0.0375	0.25	9
Minimize the number of components and subassemblies.	0.24	5	10	0	0	0.0375	0.25	9
Reduce product complexity.	0.16	0	0	5	0	-	0.16	11
Eliminate any product features that do not add value to the customer	0.08	0	0	0	0	-	0.08	16
Design mult-function parts	0.08	0	0	0	5	0.0050	0.08	15
Design products from modular subassemblies so that modules can be scheduled, built and tested independently.	0.26	10	0	0	0	0.0250	0.26	5
Standardize by common components, processes and methods to reduce costs across the whole system.	0.38	0	0	5	0	-	0.38	2
The product must has a suitable base part on which the rest of the assembly can be built.	0.48	0	0	-5	0	-	0.48	1
Maximize process yields between base and at each workstation for the whole assembly system.	0.32	0	0	0	5	0.0050	0.32	3
Design the product to be built up in layers.	0.26	5	0	0	5	0.0175	0.26	7
Components can be added from above and located positively.	0.26	0	0	0	5	0.0050	0.26	8
Reduce the tendency to move during subsequent motions or steps.	0.13	0	0	0	5	0.0050	0.13	13
Minimize the need for reorientations during assembly.	0.16	0	0	-5	0	-	0.16	11
		0.0624	0.0480	- 0.0048	0.0520	δV		
		0.27	0.26	-	0.11		**VT**	
		4	6	17	14			**Ranking**

Figure 3.7 DFA vs DFDA comparison matrix

3.4 Results and Discussions

As highlighted in the matrix shown above in Figure 3.7, two design strategies have conflicted, so special consideration must be in place to resolve this conflict before the ranking procedure starts. However, the conflict occurs, in this case, is when the designer simultaneously attempts to minimize the need for reorientation during assembly while attempting to standardize the machine during disassembly. It is assumed that the arising conflict could be ignored, subject to further investigation, as the conflict index slightly exceeds the threshold value of ten.

Table 3.5 summarizes the ranking of the strategies in descending order based on their respective total value. After analyzing the results, the designer can eliminate from the ranked list the strategies that are repeated or have the same core objective, while the strategies with the same ranking order can be implemented concurrently in the design process to emphasize their relatively equal importance.

Table 3.6 summarizes the modifications after the designer has conducted the analysis. If both selected DFX techniques were to be applied in standalone mode, then after several design iterations they will conflict, which would lead to a machine redesign. The redesign process is a costly and time-consuming activity, and by applying this methodology, the designer can avoid the pitfall of such activity.

Table 3.5 DFA vs DFDA strategies ranking list in the conceptual design stage (before analyzing)

DFA and DFDA Strategies in Conceptual Design Stage Ranking List Summary	$\forall_{TS}$	Ranked List	T_{TS}
The product must has a suitable base part on which the rest of the assembly can be built.	0.48	1	0.78
Standardize by common components, processes and methods to reduce costs across the whole system.	0.38	2	0.63
Maximize process yields between base and at each workstation for the whole assembly system.	0.32	3	0.52
Design products from modular subassemblies so thatmodules can be scheduled, built and tested independently	0.26	5	0.42
Design the product to be built up in layers.	0.26	7	0.42
Components can be added from above and located positively.	0.26	8	0.42
Subdivide the product into manageable subassemblies.	0.25	4	1.19
Minimize the number of components and subassemblies.	0.25	6	0.39
Minimize the number of parts and levels of assembly.	0.24	9	0.39
Minimize the number of components and subassemblies.	0.24	9	1.19
Reduce product complexity.	0.16	11	0.26
Minimize the need for reorientations during assembly.	0.16	11	0.26
Reduce the tendency to move during subsequent motions or steps.	0.13	13	0.21
Avoid long disassembly paths.	0.10	14	0.48
Design mult-function parts.	0.08	15	0.13
Eliminate any product features that do not add value to the customer.	0.08	16	0.13
Standardize the products style.	0.00	17	0.00

Table 3.6 DFA vs DFDA strategies ranking list in the conceptual design stage (after analyzing)

DFA and DFDA Strategies in Conceptual Design Stage Ranking List Summary	$\forall_{TS}$	Ranked List	T_{TS}
The product must has a suitable base part on which the rest of the assembly can be built.	0.48	1	0.78
Standardize by common components, processes and methods to reduce costs across the whole system.	0.38	2	0.63
Maximize process yields between base and at each workstation for the whole assembly system.	0.32	3	0.52
Design products from modular subassemblies so thatmodules can be scheduled, built and tested independently.	0.26	4	0.42
Design the product to be built up in layers.	0.26	5	0.42
Components can be added from above and located positively.	0.26	6	0.42
Subdivide the product into manageable subassemblies.	0.25	7	1.19
Minimize the number of components and subassemblies.	0.25	8	0.39
Minimize the number of parts and levels of assembly.	0.24	9	0.39
Reduce product complexity.	0.16	10	0.26
Minimize the need for reorientations during assembly.	0.16	10	0.26
Reduce the tendency to move during subsequent motions or steps.	0.13	12	0.21
Avoid long disassembly paths.	0.10	13	0.48
Design mult-function parts.	0.08	14	0.13
Eliminate any product features that do not add value to the customer.	0.08	15	0.13

If the designer is to apply DFA with 5 days and DFDA with 3 days independently then the total time required for both will be 8 days. However, if they are applied together, the redundant design strategies between the two and the conflicted area will be removed and adjusted before initiating the design activity. Thus, reducing the total time to 6 days with a difference of 2 days.

Some observations were concluded after applying the matrix model in the case study mentioned above such as if the value of the conflict index constant exceeds a value of negative ten, then it can be declared that a conflict of substantial consequences has occurred, and some considerations are required to resolve it. This conflict can be resolved and avoided by implementing some tactics as follows:

(1) If the conflict index constant is close to ten, then the resulted conflict could be ignored and eliminated on the basis that it will create a down weight effect on the other design strategies in the ranked list.

(2) Develop and integrate a design methodology after examining the conflict-specific details to decrease the negative interaction areas between strategies—this is very useful in areas where partial conflict has been spotted (CI $\leq$ -10).

(3) The matrix model ranking function will eliminate any two design strategies that have a large total value difference, and it will eliminate negative values too.

The weighting procedure of any parameter may sometimes be a subjective process, as two different designers may weigh the same guideline differently. This difference comes from the usage circumstances, the experience, and interpretation of the designers as to what the guideline means. However, these differences will not give the user a misleading result because the guidelines are interpreted according to the designer's understanding.

3.5 Conclusion

Engineering design is an iterative process of solution generation and evaluation. It requires a designer to take a forward-thinking and a look ahead approach when finalizing a solution. In a dynamic environment, a concurrent application of MDFX techniques during the design process can be organized into multiple stages in which both evaluation and decision are needed. The main theme of this research was to present the need for a tool that can reliably estimate and verify the time/benefits of applying MDFX in a harmonized way in machine design. As a result, a decision support tool that can aid the designer in the decision-making process when MDFX are utilized will be required. The main feature of a design decision simulation tool is to enable designers to foresee and explore lifecycle consequences during the machine design. Also, to provide a structured workflow specifying how and when MDFX techniques can be applied with the ability to quantify the arising conflict that may occur between them. The tool's fundamental core is based on the information contained within the DFX guidelines, which may be classified as either a design strategy or rule so their interactions can be examined explicitly. Thus, the generation of a ranked list can be integrated in a time-effective and strategic manner, thereby shrinking the machine design time by at least 15%. As demonstrated, the MDFX decision tool can be implemented to serve as a generative decision system that proactively aids the designer in the decision-making process.

Chapter 4 : Hybrid FEAM-TOPSIS decision support model for MDFX techniques[3]

4.1 Introduction

In the last few years, the residential and non-residential off-site panelized construction in the wood manufacturing industry has experienced a rather dramatic transition from manual assembly to automatic production line assembly using automated robotic machines. The rise of new technologies for manufacturing and the worldwide competition between industry sectors are the two main contributors to this evolution in the off-site panelized construction manufacturing industry (Ahmad et al., 2014; Malik et al., 2019). The evolution has stimulated innovation in these manufacturing industries, causing a major shift in how production machines are designed and manufactured. Customers are interested in the acquisition of machines that are of high quality, low cost, and superior performance in a shorter deployment time. The recent marketplace competition for newer production machines is imposing a transformation in the way designers develop and design machines. These circumstances generate pressure on companies' engineering operations to boost the overall productivity. Also, Farr (2011) stated that approximate up to 75% of the machine lifecycle cost design decisions are decided in the conceptual and detailed design phases. One method to fulfill this demand is to increase the efficiency of engineering design activities, for example, by using computer-aided technologies (CAX) in machine design. Another method is to apply the concurrent engineering (CE) approach to enhance coordination amongst machine design development activities.

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[3] The manuscript presented as Chapter 4 of this thesis is ready to be submitted to the Journal of Engineering Design.

During the 1990s, CE emerged as a leading methodology with the aim to improve designed machine quality and reduce design development time and cost by eliminating or resolving the problems between product, process, and organization at the early design stages (Gadh, 1996). In this context, the implementation of the Design for X (DFX) philosophy is the best to be applied because DFX is considered a methodological and proactive technique for designing machines that focuses on optimizing the benefits over the machine's lifecycle. Thus, it is crucial to comprehensively assess the implementation of Multi-DFX (MDFX) techniques in machine design development. Decisions that emerge from the application of one DFX technique may have a positive impact on one phase of the product lifecycle but can conflict negatively with others making the design's technical feasibility and the machine business profitability evaluation more challenging for designers (Meerkamm, 1994). Because multiple DFX techniques operate on different measures for machine design (e.g., DFA cuts assembly time, while DFM cuts manufacturing time), it is not evident how the designer can judge and compare these diverse metrics. For every machine development activity, many design aspects, such as manufacturing, assembly, quality, ergonomics, robustness, functionality, and modularity have to be considered by the designer (Meerkamm, 1994), which leads the designer to deal with an increasing amount of information at the design stage. Thus, it is challenging for the designer to identify the relevant information to form a decision when MDFX techniques are utilized. Stober et al. (2009) identifies the fundamental requirements that can be key prerequisites for the designer to target and focus on during the development process with respect to machine development cost and time. Design decision-making tools must be developed to assess the designer decisions across the whole machine lifecycle as proposed by Hubka and Eder

(1988). Olesen (1992) discuss that performance of lifecycle phases in terms of cost and time could be influenced by the designer decisions made at the machine's early design stages. The majority of design decisions have positive and negative consequences on the machine development irrespective of whether the designer is knowledgeable or not concerning these ramifications (Borg and MacCallum, 1996). As a result, Olesen (1992) suggests that instead of focusing only on the machine function, the designer is invited to adopt the look-ahead strategy, which focuses on a total life-oriented machine design approach, to foresee and examine possible improvements in the designer decisions related to total life issues. This means that designers are forced to consider multiple issues, of which many of these are outside their domain when dealing with machine development. Designers are therefore expected to develop solutions that cater to multiple lifecycle issues when MDFX techniques are implemented.

During the machine development, the designer's main task is to find and adopt the right decision-making method and calculate its related process. In a dynamic design environment, a multiple-criteria decision-making system enables the designer to tackle complicated design decision problems effectively. A typical multi-stage decision-making procedure comprises some milestones, as detailed in Figure 4.1. Peilin et al. (2000) suggest that careful evaluation for appropriate design decisions should be conducted at each design stage when MDFX techniques are implemented. From a system perspective, MDFX application in product design is expressed as a process that is characterized by design-evaluation-re-design (Li and Ling, 2000; Xu et al., 2007). This evaluation process is considered complicated for many reasons: (1) it is crucial to consider all the design criteria objectives when designing a machine; however, some of these objectives conflict with one another, such as material quality versus material cost, or mass production versus customization, (2) it is difficult for the designer to quantify and weigh the design objectives in the machine early design stages due to the absence of information or ambiguous objectives, and (3) the designer's inclination towards being subjective makes the evaluation process more complex.

Figure 4.1 Generic multi-stage decision-making support system stages

To cope with this, fuzzy set theory can be implemented to assess and select MDFX alternatives. However, Haque et al. (2000) stated that the information available for the designer in the machine design early stages is most likely to be unreliable and fuzzy. With this said, the design decision problem is now difficult to characterize and structure when CE methodology is implemented. A design decision-making process can be organized into several stages in which both evaluation and decision are required. In this research, Fuzzy Extent Analysis Model (FEAM) aided with Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) is used to evaluate systematically the MDFX alternatives and facilitate decision making. With a comprehensive evaluation hybrid model based on FEAM and TOPSIS, a decision support framework is proposed in this study to facilitate the multi-stage decision making application for MDFX in conceptual and detailed machine design development stages. The model generates satisfactory solutions of MDFX combinations by optimizing their trade-off performance measures (Cost, Time) can be derived. The overall focus of this research is to establish a robust decision support system to aid designers in their design decision-making activities when MDFX techniques are applied to machine design development. The proposed methodology, developed in Microsoft Excel (software), is also tailored to model and eliminate the imprecision and linguistic vagueness when designers investigate their design decisions.

4.2 Literature Review

DFX technology has gone through rapid developments since the earliest research was published on the three-leading systematic DFA techniques (Boothroyd and Dewhurst, 1983). Youssef (1994) stated that hundreds of case studies on DFX techniques implementation in machine design have been released, reporting that a significant amount of benefit has been realized through their use. Another advancement is the important proliferation in the number and nature of developed DFX tools. Holbrook and Sackett (1988) listed dozens of research and commercial DFA tools. Huang)1996 (investigated and listed a wide variation of DFX tools that cover the whole product lifecycle. Such exponential expansion of DFX techniques in both number and nature is a concrete indication that interest from industry and academia in DFX is growing. More recent progress was made in identifying the need for an essential DFX pattern that can be utilized by the designer to clarify how DFX techniques can be implemented in a design problem and how they can be altered to create new ones. Andreasen and Olesen (1993) concluded that a unified DFX framework would overcome multiple design problems and can aid the designers in their quest to optimize the machine design by facilitating the selection process of the most applicable DFX techniques for a design problem. Researchers argued that if

MDFX tools are applied to reach the overall optimum solution, then the design activities could be optimized. However, without a unified framework, the MDFX integration, trade-off analysis, and their concurrent interface will be challenging for the designer to achieve. Various trials have been pursued in the exploration of a generic DFX framework. Andreasen and Olesen (1990) have investigated the Theory of Dispositions as an analytical and methodological approach for a generic DFX pattern. Another attempt was manifested in the formulation of the MFK system, which provides the designer with a workbench for MDFX integration (Meerkamm, 1993).

There are significant changes taking place in today's world market due to the advancement of technologies. Industrial and construction companies are forced to create new machines for the off-site panelized fabrication industry; therefore, the necessity for a decision-making tool that can determine the best optimal solution is becoming of high importance for designers (Martinez et al., 2019; Sarfaraz and Jenab, 2012, 2012). Zhao et al. (2003) stated that, when designers apply the concurrent machine development process, they will be forced to make complex design decisions. However, given the essence of these problems, the research emphasis is on developing support decision tools that focus on modeling issues (Chang et al., 1993). These tools are utilized by the designer to evaluate design decision alternatives and facilitate the decision-making process through the assessment of criteria, sub-criteria, preferences, and alternatives that can be classified into (1) single-objective decision-making (SODM), (2) multiple criteria decision-making (MCDM), and (3) other multiple attribute decision-making (MADM) methods. For this research, the MCDM methods identified by Steuer and Na (2003) will be implemented as a preferred course of action for the decision-maker. Figure 4.2 represents the heretical structure of the most used MCDM methods in various decision-making areas. In this research, the FEAM and TOPSIS are discussed in detail.

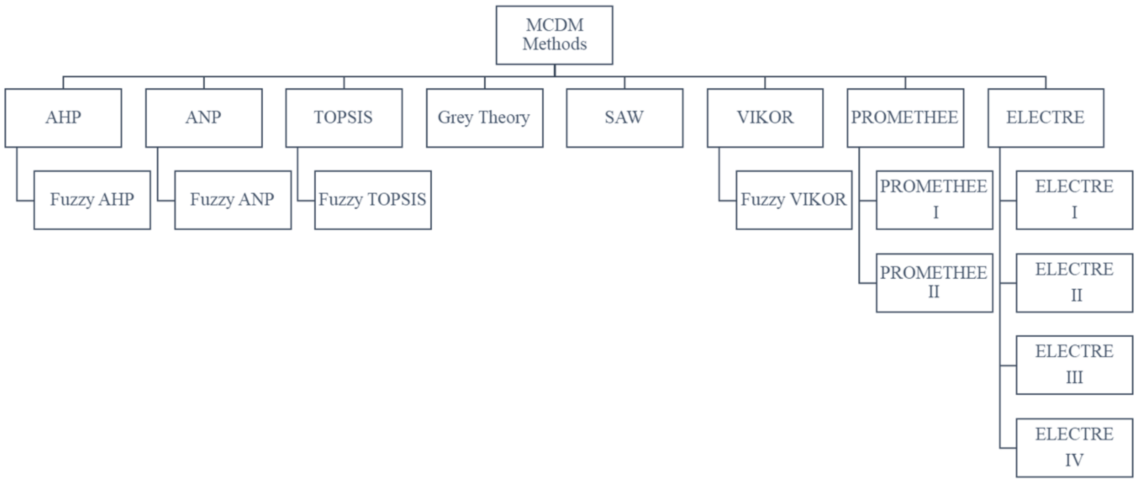


Figure 4.2 Hierarchical structure of MCDM methods

To solve complicated design decision issues, designers usually select the Analytic Hierarchy Process (AHP), which is a dynamic MCDM method. Saaty (1980) pinpoints that the prominent characteristic of the AHP method is its application limitations such as ambiguity and uncertainty of the design expert's opinion, which can be tracked down to the impressiveness of the designer's judgment. To overcome these problems and to improve the uncertainty of the AHP method, several researchers integrate it with the fuzzy set theory. Klir and Yuan (1996) reported that Zadeh developed the foundation of the fuzzy set theory through eliminating the vagueness and imprecision in designer's judgment by representing the approximate information in mathematical formulas. Thus, the unquantifiable and uncertain design information can be integrated into a fuzzy decision model.

Table 4.1 summarizes the most used types of the fuzzy set theory in design decision problem-solving. The fuzzy theory can be differentiated from the AHP method by its ability to track the knowledge vagueness when dealing with qualitative and quantitative design criteria and in eliminating the designer's biases and uncertainty when pairwise comparison judgments' precise numerical values are difficult to integrate. The fuzzy set theory operation revolves around its logic, arithmetic, mathematical programming, data analysis, and graph theory fuzziness. Cheng and Li (1997) resolve the design decision selection problem by systematically modeling it in a hierarchical structure and by applying the fuzzy set theory concept to analyze it. Basically, fuzzy methods represent the fuzzy domain of a problem by using the triangular fuzzy numbers (TFNs) for importance weight calculation instead of crisp numbers (Petkovic, 2012). However, the main disadvantage of the fuzzy theory is that the decision model input data, expressed by design experts in linguistic terms, depends only on the experts' point of view and technical experience and thus it can be associated with subjectivity. Tanaka (1982) and Tan et al. (2007) describe an analog approach to calculate the variation of the expert's judgment degree of confidence for quantitative and qualitative pairwise comparison that can be consistent with the fuzzy degree, λ, where a perfect consistency is denoted by $\lambda = 1$ and deficient inconsistency is denoted by $\lambda = 0$. Van Laarhoven and Pedrycz (1983) were some of the first researchers to implement Fuzzy AHP in a design problem application. They formulated the triangular membership functions that can be effective for the criteria and alternatives pairwise comparisons. Afterward, Buckley (1985) has expanded the research by determining the comparison ratios of the fuzzy priority's triangular membership functions. Chang (1996) also introduced the fuzzy extent analysis method that maximizes the usage of TFNs and eliminates the inconsistency and fuzziness in the input data.

Table 4.1 Fuzzy set theory types of information

Groups	Information	Appearance	Process	Property	Methodology	Attitude	Solutions
Linguistic	Verbal	Quantitative	Adapted	Complexity	Quantitative	Tolerance	Adapted
Fuzzy	Fuzzy	Dark	Replacement	Complexity	Transition	Indulgence	Complex
White	Known	Bright	Old	Order	Positive	Seriousness	Unique
Grey	Incomplete	Grey	Replacement	Complexity	Transition	Tolerance	Multiple
Black	Unknown	Dark	New	Chaos	Negative	Indulgence	Null

Fuzzy set theory becomes difficult and complicated to cope with when many pairwise comparisons are integrated into the design decision matrix. Thus, TOPSIS method is usually employed to aid and facilitate the ranking of alternatives, as concluded by Hwang and Yoon (1981). TOPSIS concept is explained by Wang et al. (2009) where they describe that the best alternative can be selected by the designer such that it has the shortest distance from the positive ideal solution (PIS) and concurrently it has the farthest distance from the negative ideal solution (NIS) (Seçme at al., 2009). By definition, PIS is the solution where benefits are maximized, but the cost is minimized. While the NIS is the solution where the benefits are minimized, but the cost is maximized. Opricovic and Tzeng (2004) stated that the TOPSIS method converts the qualitative and quantitative design criteria dimensions into non-dimensional ones. The main assumption of this method is that to determine the PISs and the NISs of each alternative, each design criteria must have the tendency to monotonically increase or decrease its utility function importance weight, which is referred later to be the alternative similarity index (or relative closeness coefficient, RCC). The RCC is calculated for each alternative by sub-calculating its relative distance to the PIS and its remoteness from the NIS using the Euclidean distance approach. TOPSIS method provides the designer with the alternatives order preference by computing their relative RCC values. After that, the alternative that has the maximum RCC value is considered the optimal alternative because it takes in to account the similarity to the PIS as well as the NIS. A proposed machine decision hierarchical structure featuring Fuzzy-TOPSIS, where the goal, product criteria, data criteria and the available DFX alternatives are represented in Figure 4.3.

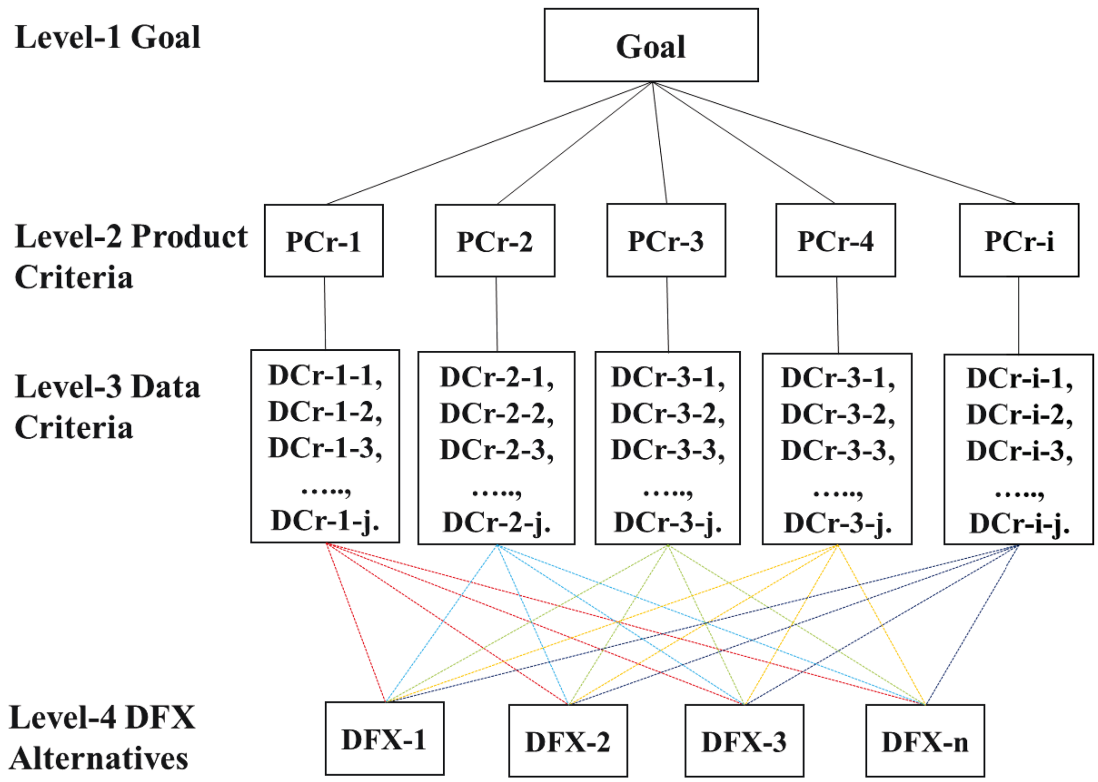


Figure 4.3 Proposed Fuzzy-TOPSIS machine DFX decision hierarchy

In the past years, DFX techniques have undergone an intensive investigation by researchers; therefore, many methods and application tools were developed to support the implementation of these techniques from basic checklists to complex mathematical models. Boothroyd et al. (1988) concluded that designers nowadays implement DFX in a design problem in the following ways: (1) by cross-functional multidisciplinary design teams, (2) by utilizing specialized design manuals that include do's/don'ts design rules, and (3) by applying automated design software. There are advantages and disadvantages to each of these methods when it is implemented in a design problem, but none of these methods offer a quantitative measure of MDFX trade-off analysis since payoffs and profits in a design problem are not easy to model and quantify. However, if MDFX alternatives are not assessed accurately, the evaluation process can provide the designer with wrong deductions and hence wrong design decisions (Zhao, 2002). Gupta et al. (1994) proposed a solution to evaluate MDFX techniques by constructing their multiple critiquing modules (e.g., fabrication, assembly, modeling, testing) and calculating their total development cost and time. In their proposed method, the model can detect that a DFX is inexpensive to implement, but time-consuming, or vice-versa. Maropoulos et al. (2003) also described an evaluation model to this problem called AMD architecture, in which MDFX techniques are integrated as one and their development cost and time assessment is calculated. The generalized framework for MDFX analysis is proposed by Tharakan et al. (2003) which enables the designer to select the design criterion that best fits the current design stage and its relative DFX technique. Hazelrigg (1996) concluded in his book that the sole goal of engineering design in general is to generate profit. The other design objectives are to (1) minimize design and manufacturing cost, (2) optimize machine quality, and (3) reduce development time. Thus, the main problem in this research was the development of a model that can reliably estimate and quantify the metrics of MDFX at the machine conceptual and detailed design phases. The function of this model is to provide a systematic procedure for the MDFX techniques trade-off analysis specifying their impact from development cost and time perspectives when they are applied in a design problem.

4.3 Problem Description and General Methodology

Which, when, and where a DFX tool should be used remain the unanswered questions for machine designers. The selection of DFX techniques is not solely linked to their availability but is linked to the current design problem and the designer's end goal. The importance of the application of MDFX techniques is due to their effectiveness in analyzing the design problem from different aspects. In this case, the research problem is not which DFX technique to utilize in the design, but rather which DFX technique to begin with and in what sequence should it be implemented with reference to other DFX techniques. Logically speaking, the DFX tools that are centered around the machine main assembly structure should be implemented before those that focus on components and sub-assemblies (e.g., Boothroyd and Dewhurst (1983)) suggest that DFA should be introduced to the design problem followed by DFM). The research gap is narrowed to address the two main problems when introducing MDFX techniques in machine design. The first one is the design changes that occurs when the designer separately applies a single DFX technique within each lifecycle of the machine development. If those changes, generated from the application of this single DFX, are applied in the machine design, they may conflict by the consecutive DFX techniques changes. The second one occurs when the application of MDFX enables the designer to foresee all design problems related to one phase of the machine development process at once and then generates a redesign order based on suggestions that must be dealt with before even starting the design process.

Based on these two problems, the intent of this research is to find and extract the best combination of MDFX techniques for a certain design criterion, which remains a major challenge for designers as they must examine all MDFX criteria associated with predefined weights. Therefore, having a hybrid model to incorporate all design experts' assessments, design criteria, and DFX alternatives into the decision matrix is becoming crucial. The model should find the best combination of MDFX techniques without needing to elicit the subjective and objective design criteria of the utility function. The hybrid model must also resolve the conflict of design experts' evaluation with respect to each design criterion. The main purpose of this research is to develop an intelligent decision process to support the integration of MDFX techniques in conceptual and detailed machine design concurrent engineering that not only assesses MDFX interactions and inter-dependencies but also provides optimized alternatives for designers. The qualitative and quantitative design criteria are implemented into an MDFX design decision matrix combining the FEAM and TOPSIS methods in an integrated decision support system. These methods unite the MDFX aspects and product design specification (PDS) needs for conceptual and detailed machine design activities systematically. Also, these methods optimize the trade-off analysis of MDFX integration based on development cost and time metrics. The FEAM is employed to calculate the PDS qualitative and quantitative criteria weights for MDFX selection process. This method is meant to present the linguistically ambiguous and incomplete knowledge. Additionally, TOPSIS is used to rank the MDFX alternatives based on overall evaluation score. MDFX combinations are generated by implementing a novel hybrid approach combining FEAM and TOPSIS. The proposed hybrid approach is a strategic decision-making tool providing the optimal combination of MDFX with reference to the design criterion taking into consideration the trade-offs performance metrics covering the machine's whole lifecycle. In this research, a machine development multi-stage decision-making support system framework is proposed, as illustrated in Figure 4.4 and explained in section 4.4. The focus of this research is on the conceptual and detailed design stage of the machine development, specifically on the MDFX hybrid engine, and trade-off analysis which is illustrated in section 4.4.

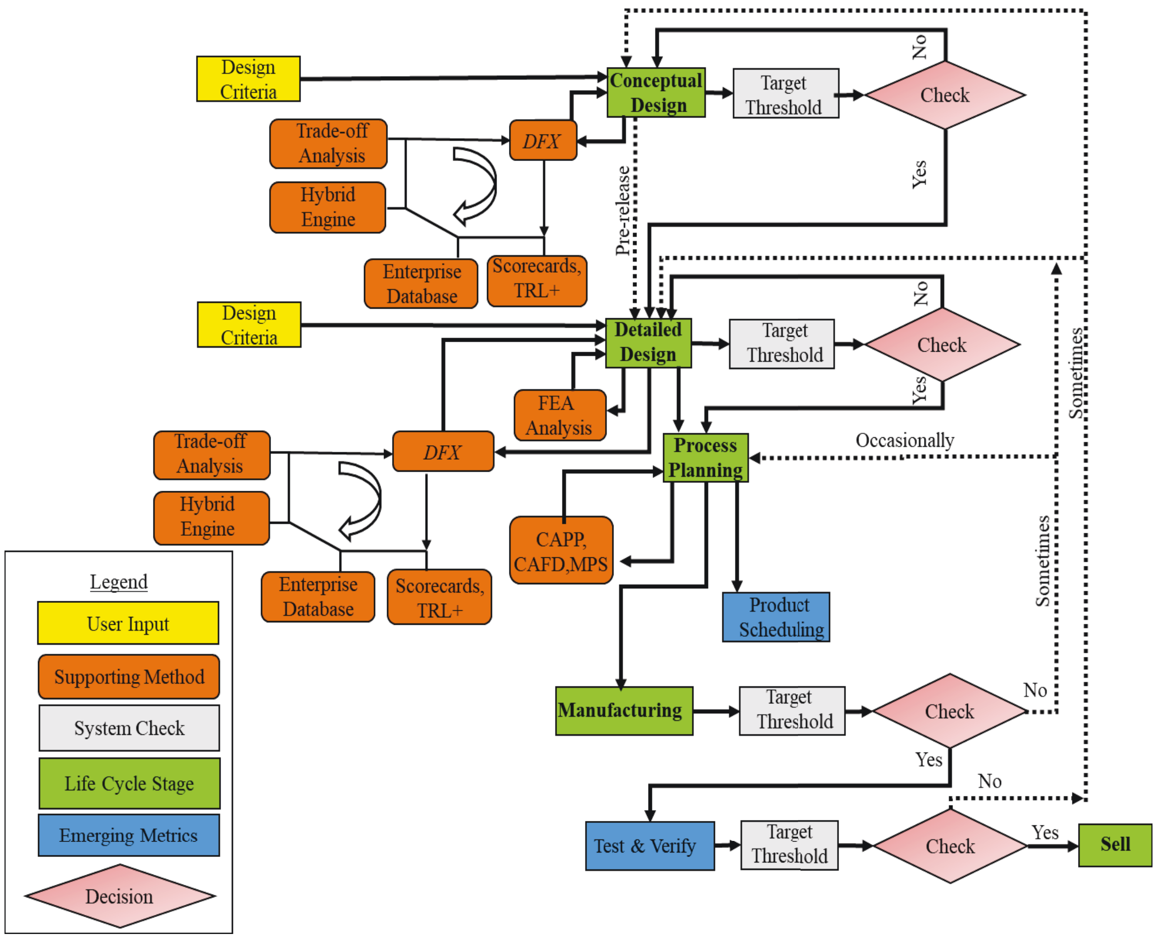


Figure 4.4 Machine development multi-stage decision-making support system framework

4.4 Hybrid FEAM-TOPSIS Model

The proposed framework composed of three parts: FEAM model, TOPSIS model, and the trade-off analysis model, as shown in Figure 4.5. The designer implements FEAM-TOPSIS methodology to weigh and rank MDFX alternatives based on experts input during the conceptual and detailed machine design phases of development. Trade-off model is then applied to search for satisfactory and optimal solutions of MDFX combinations by analyzing and optimizing their cost and time metrics. The proposed hybrid approach would be a strategic decision-making procedure providing insights for implementing MDFX techniques that aid the designer in the machine development process, while resolving MDFX conflicts, optimizing their trade-off analysis, and presenting their optimal combination with reference to the product development phase and its corresponding PDS.

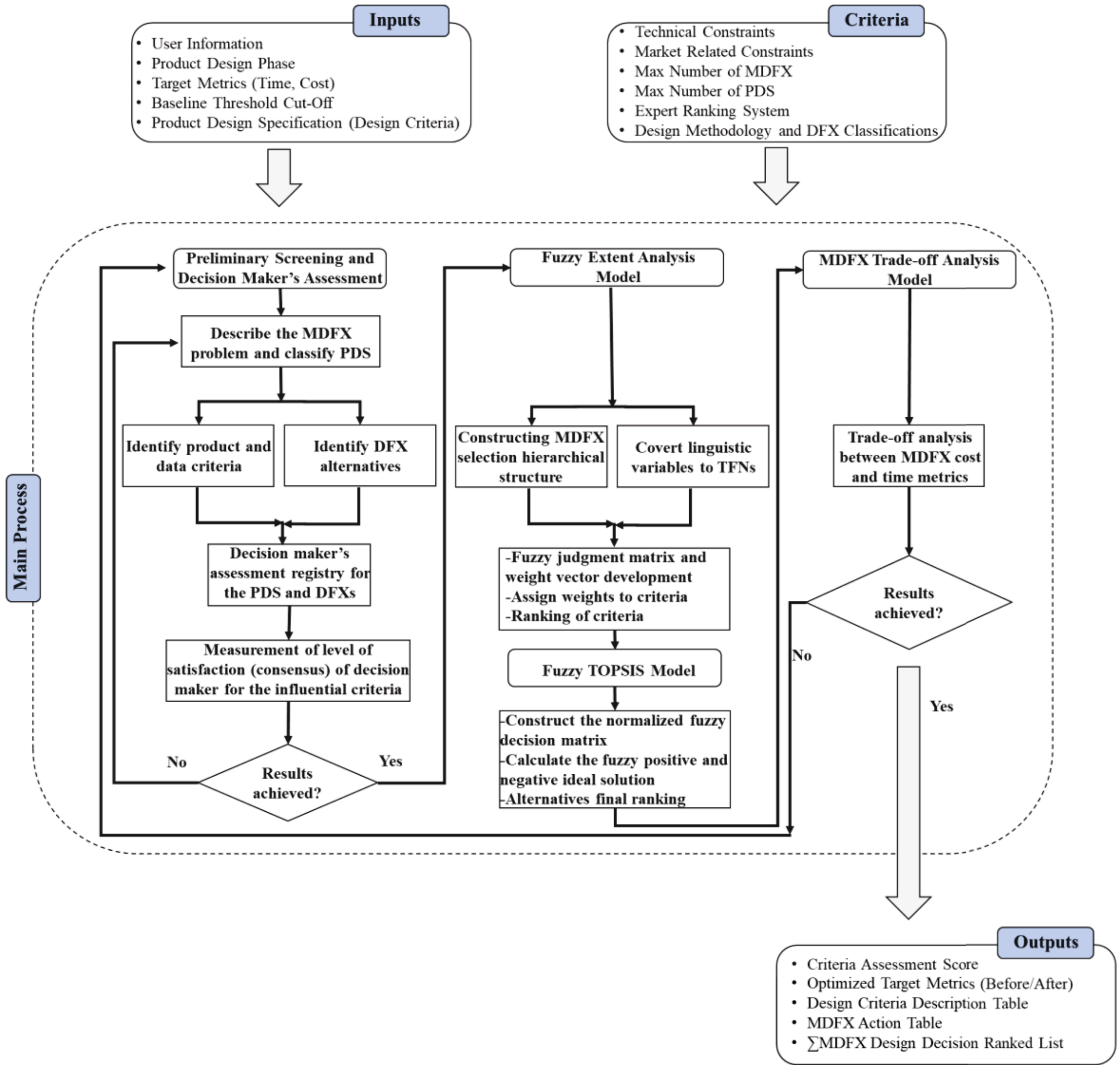


Figure 4.5 Architecture process diagram of the hybrid model

The aim of this study is to develop a design decision support framework for selecting the most applicable MDFX combination for conceptual and detailed machine design activities based on the qualitative and quantitative design criteria under cost and time factors. The FEAM-TOPSIS evaluation model, which is a combination of the fuzzy extent analysis method and TOPSIS method, is proposed to evaluate the MDFX alternatives and to represents the design experts' preferences. The evaluation model is described in Figure 4.5

and explained in sections 4.4.2 and 4.4.3. Each model has a distinctive set of steps to be executed and performed simultaneously.

4.4.1 Preliminary screening and decision maker's assessment

To establish the preliminary screening process and expert assessment weighted scores, a structured MDFX selection process model based on PDS or design criteria arise proposed and illustrated in Figure 4.6. The model registers all design experts' assessments and ratings into a final design decision matrix. In order to resolve the conflict of design experts' opinions with respect to each design criterion, a specific equation need to be derived. A design expert *x* has the weight represented by w_{ex} which is related to the designer experience and skill levels listed in Table 4.2. In this study, the weights are the years of technical experience in machine design and manufacturing for each design expert.

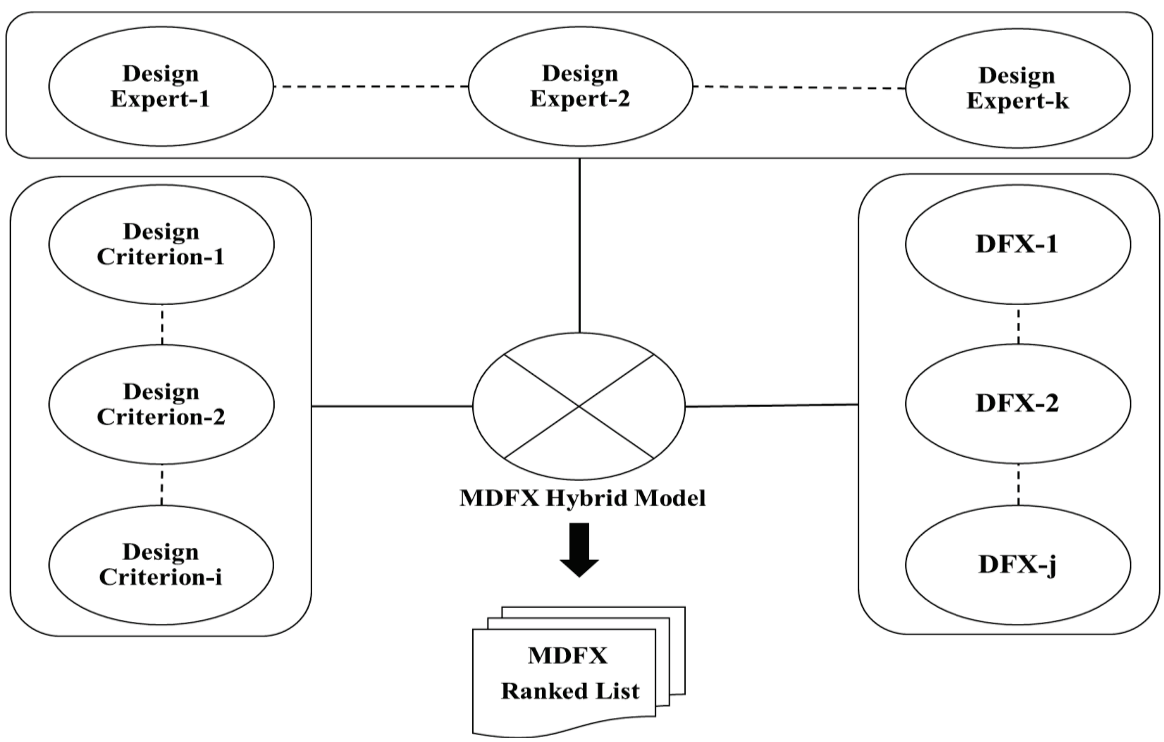


Figure 4.6 MDFX selection process structure

Task 1: Determine PDS set

Task 2: Using linguistic variables in Table 4.3, obtain the k^{th} design expert's opinion (e_{ij}^{k}) to establish the pairwise comparison between design criterion (DC) (*i*) and DFX technique (*j*) represented by Equation (4.4.1.1).

$$e_{ij}^{k} = \{DFX_i \overset{e_k}{\rightarrow} DFX_j \ \vdots \ i = 1,2,\ldots..,n; j = 1,2,\ldots..,m, k = 1,2,\ldots.K\} \tag{4.4.1.1}$$

Task 3: Using Equation (4.4.1.2), multiply the kth design expert's opinion (e_{ij}^{k}) by its corresponding weight based on the number of years of technical experience extracted from Table 4.2.

$$e_{ij}^{\prime k} = e_{ij}^{k} \ x \ w_x^e \tag{4.4.1.2}$$

where w_x^e = weight of expert *x* and $\sum w_x^e = 10$.

Table 4.2 Design expert's weight (w_x^e)

Experts Weight (0-10)	Expert Design Experience (Years)
0.8	0
1.7	$5 \leq Y \leq 10$
2	$10 \leq Y \leq 15$
2.5	$15 \leq Y \leq 20$
3	$20 \leq Y$

Task 4: The design experts' opinions can differ substantially; therefore, the conflict must be resolved by using the maximum aggregation function expressed in Equation (4.4.1.3).

$$DC - DFX_{agg}^{i \rightarrow j} = max\ (e_{ij}^{k}) \tag{4.4.1.3}$$

Task 5: Using Table 4.3, convert the linguistic variables (LV) to triangular fuzzy numbers (TFNs).

Table 4.3 The equivalent of linguistic variables to triangular fuzzy numbers (TFNs)

Saaty Nine Point Scale		Definition of Linguistic Term	Triangular Fuzzy Numbers (TFN)	
Reciprocal Intensity of Importance	**Intensity of Importance**		**TFN Scale**	**Reciprocal TFN Scale**
1	1	Equally Important (Eq. Imp.)	(1,1,1)	(1,1,1)
1/3	3	Weakly Important (W. Imp.)	(2,3,4)	(1/4,1/3,1/2)
1/5	5	Fairly Important (F. Imp.)	(4,5,6)	(1/6,1/5,1/4)
1/7	7	Strongly Important (S. Imp.)	(6,7,8)	(1/8,1/7,1/6)
1/9	9	Absolutely Important (A. Imp.)	(8,9,10)	(1/10,1/9,1/8)
1/2	2	Intermediate	(1,2,3)	(1/3,1/2,1)
1/3	4	values between	(3,4,5)	(1/5,1/4,1/3)
1/6	6	two adjacent	(5,6,7)	(1/7,1/6,1/5)
1/8	8	scales	(7,8,9)	(1/9,1/8,1/7)

4.4.2 Fuzzy extent analysis model (FEAM)

In this research, a Fuzzy Extent Analysis Model (FEAM) for MDFX techniques selection that involves multiple machine design criteria is investigated. The design criteria importance weights are determined through design experts' pairwise comparisons subjective judgment. The latter is represented as TFNs that can eliminate the expert's judgment where lack of confidence or ambiguity is noticed. In effect, the FEAM invests in the expert's judgments where more coherence or a high degree of confidence can be spotted. Furthermore, the fuzzy synthetic extent analysis method is adopted to determine the priority of each decision criterion, alternative, and finally optimize the overall goal.

The implementation steps are detailed in Figure 4.7 (explained later in details). In the simplified FEAM method, TFNs are used to register the design experts' judgments as represented in Figure 4.8.

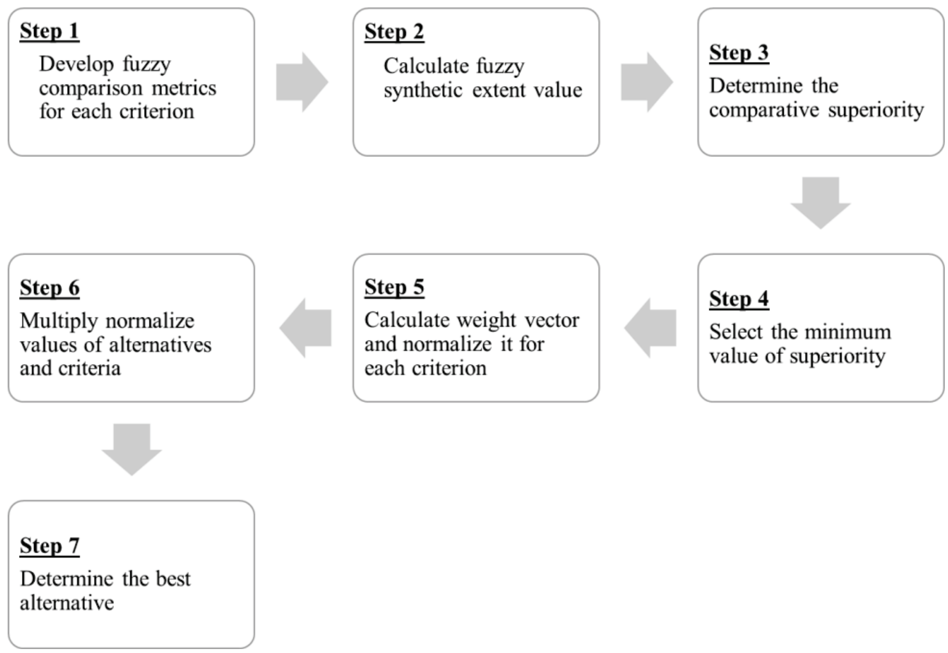


Figure 4.7 FEAM Approach Flow Map

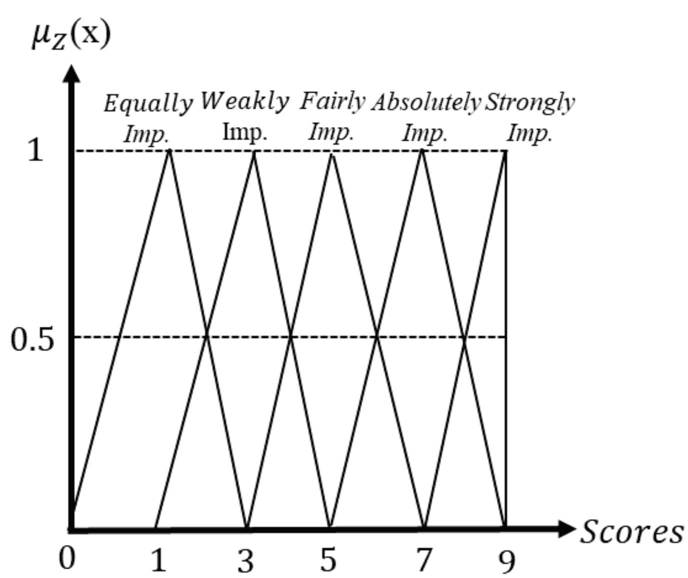


Figure 4.8 Membership Functions Evaluation Scores

Normally, the fuzzy set theory uses the TFNs to represent the design expert's assessment on alternatives with reference to each criterion. If a certain value resides within the triangular fuzzy boundaries, then that value is represented by a membership function. This concept facilitates the elimination of the model uncertainty that is sourced to design experts' technical judgments in the pairwise comparison matrix. The fuzzy boundaries are defined by three parameters: l is the minimum value, m is the mode value and u is the maximum value. The parameters can be expressed using Equation (4.4.2.1) (Chang, 1992; Chang, 1996) for extent analysis method on FEAM:

$$\mu_Z(x) = \begin{cases} \frac{x}{m-l} - \frac{l}{m-l}, x \in [l, m] \\ \frac{x}{m-u} - \frac{u}{m-u}, x \in [m, u] \\ 0, \qquad otherwise \end{cases} \tag{4.4.2.1}$$

In this research, the Chang (1996) fuzzy extent analysis method is used. The method states the following assumptions: Let $X\{x_1, x_2, x_3, \ldots\ldots, x_n\}$= a DFX design criterion set, and G $\{g_1, g_2, g_3, \ldots\ldots, g_n\}$ = goal set. Based on Chang's extent analysis method, each design criterion is investigated and the extent analysis method for each alternative/goal is performed. The extent analysis values *(m)* for each design criterion can be expressed by M_{gi}^{j} for *i=1, 2…….,n and j=1,2, ……., m* which are TFNs. After defining the signs and variables meaning, Chang's extent analysis model can be further explained in the following seven steps:

Step 1: Develop a fuzzy comparison matrix

It is challenging for the designer to map qualitative design criteria preferences to numerical estimates; therefore, a degree of uncertainty could exist in one or more pairwise comparison values in a FEAM model (Yu, 2002). By using TFNs in the pairwise comparisons matrix, a fuzzy design decision matrix $A = (a_{ij})_{n\,x\,m}$ can be derived (Tang and Beynon, 2005). Matrix $A = (a_{ij})_{n\,x\,m}$ is initiated by the designer, given that $a_{ij} = (l_{ij}, m_{ij}, u_{ij})$ and $a_{ij}^{-1} = (1/u_{ij}, 1/m_{ij}, 1/l_{ij})$, Equation (4.4.2.2).

In this step, the design expert is tasked to express the judgment of one design criterion over the another in linguistics terms while focusing on the overall goal. Each fuzzy membership function is expressed by three parameters of the symmetric TFN, the low point, mode point, and high point over which the membership function is defined. The comparison matrix is developed from the user input TFNs as illustrated in Equation (4.4.2.2).

$$A = (a_{ij}) = \begin{bmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) & \cdots & (l_{1n}, m_{1n}, u_{1n}) \\ (l_{21}, m_{21}, u_{21}) & \vdots & \ddots & \vdots \\ (l_{n1}, m_{n1}, u_{n1}) & (l_{n2}, m_{n2}, u_{n2}) & \cdots & (1,1,1) \end{bmatrix} \quad (4.4.2.2)$$

<u>*Step 2:*</u> Determine fuzzy synthetic extent value

This can be calculated using Equation (4.4.2.3).

$$S_c = \sum_{j=1}^{m} Z_{gi}^{j} \,\Theta [\sum_{i=1}^{n} \sum_{j=1}^{m} Z_{gi}^{j}]^{-1} \quad (4.4.2.3)$$

where TFNs are denoted by Z_c^i (i=1, 2…, n). The value for i^{th} criterion of $\sum_{i=1}^{n} Z_c^i$ is calculated by adding the *n* extent analysis fuzzy values by using fuzzy addition operation illustrated in Equation (4.4.2.4).

$$\sum_{i=1}^{n} Z_c^i = (\sum_{i=1}^{n} Z_{i1}, \sum_{i=1}^{n} Z_{i2}, \sum_{i=1}^{n} Z_{i3}) \quad (4.4.2.4)$$

<u>*Step 3:*</u> Calculate the comparative superiority

The comparative superiority of one TFN over the other is formulated as follows:

To find the DFX degree of possibility, two TFNs $Z_1 = (l_1, m_1, u_1)$ and $Z_2 = (l_2, m_2, u_2)$ are selected. The DFX degree of possibility declares that $Z_2 \geq Z_1$ as described in Equations (4.4.2.5) and (4.4.2.6).

$$V\,(Z_2 \geq Z_1) = sup\,[\,min\,(\mu_{Z_1}(x), \mu_{Z_2}(y))] \tag{4.4.2.5}$$

and can be equivalently expressed as explained by Chang (1992) as follows:

$$V\,(Z_2 \geq Z_1) = hgt\,(\,[\,Z_1 \cap Z_2\,] = \mu_{Z_1}(d) = \begin{cases} 1, & if\ m_2 \geq m_1 \\ 0, & if\ l_2 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & otherwise \end{cases} \tag{4.4.2.6}$$

where d denoted as the ordinate of D which is Z1 and Z2 intersection point (refer to Figure 4.9).

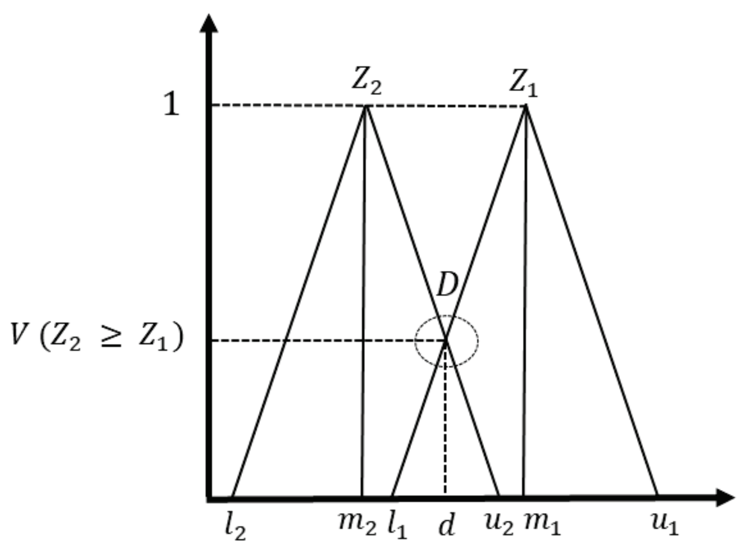


Figure 4.9 The intersection point between Z_1 and Z_2

<u>*Step 4:*</u> Select the superiority minimum value

The degree of probability for a fuzzy number *i* that is greater than *j* fuzzy numbers Z_i *(i=1, 2……., j)* can be represented by Equation (4.4.2.7).

$$V\ (Z \geq\ Z_{1,}Z_{2,}\ldots\ldots,Z_k\ )\ =\ V\ [\ Z \geq\ \ and \ldots. and\ (Z \geq\ Z_k)] = min\ V\ (Z \geq Z_i\ )\ , i = 1{,}2{,}3, \ldots\ldots. k \qquad (4.4.2.7)$$

Assuming that

$$d\ (\ \mathrm{DFX}A_i\ )\ =\ min\ V(S_i \geq\ S_k)]\ for\ k = 1{,}2{,}3, \ldots\ldots. n;\ k \neq i \qquad (4.4.2.8)$$

where DFXA is the DFX alternatives for *i* selected fuzzy number

<u>*Step 5:*</u> For each design criterion, calculate the weight vector and then normalize it

After that, the weight vector can be calculated by using Equation (4.4.2.9).

$$W\ '\ =\ (d\ '(\mathrm{DFX}A_1), d\ '(\mathrm{DFX}A_2), \ldots\ldots.,\ d\ '(DFXA_n))^T \qquad (4.4.2.9)$$

where $DFXA_i\ \ (i = 1{,}2, \ldots\ldots n) =\ are\ n\ elements.$

while the normalized weighted vectors are calculated using Equation (4.4.2.10).

$$W\ =\ (d(DFXA_1), d(\mathrm{DFX}A_2), \ldots\ldots., d(\mathrm{DFX}A_n))^T \qquad (4.4.2.10)$$

<u>*Step 6:*</u> Multiply normalize values of DFX alternatives and design criteria

After finding the design criteria and the DFX alternatives normalized weights in step 5, the final scores for each DFX alternative are calculated by multiplying each DFX alternative weight with its related design criterion.

<u>*Step 7:*</u> Determine the best DFX alternative

Based on these results, the DFX alternative with the highest final score is presented to the designer and a list of MDFX is generated.

4.4.3 TOPSIS model

In this study, TOPSIS method was proposed to evaluate the rankings obtained from the FEAM model and its procedure is illustrated in Figure 4.5. TOPSIS analyzes a multiple criteria decision-making (MCDM) problem as a geometric complex system. The output results obtained from FEAM model are imported as input weights in TOPSIS model. The TOPSIS model provides the designer with consistent and systematic criteria assessment, which can be related to the selection preference of the best DFX alternative that have the shortest relative distance from the PIS and the farthest relative distance from NIS. TOPSIS, by considering an ideal and a non-ideal solution, the model can help the designer in evaluating the MDFX ranking list and in selecting the best combination. Therefore, TOPSIS assumes that there are *m* DFX alternatives and *n* design criterion where the corresponding score of each DFX alternative with respect to each design criterion can be determined by following the six-step method as described by Wang et al. (2009) and explained below.

<u>*Step 1:*</u> Normalize the decision matrix values (Y_{ij}) extracted from Table 4.4 are converted to normalized values (N_{ij}) using Equation (4.4.3.1):

$$N_{ij} = \frac{Y_{ij}}{\sqrt{\sum_i^m Y_{ij}^2}}, \ i=1, 2, \ldots\ldots, m; \ j=1,2, \ldots\ldots n \qquad (4.4.3.1)$$

Table 4.4 Alternative assessment fuzzy ratings for linguistic variables

Definition of Linguistic Term	Triangular Fuzzy Numbers (TFN)
Very Poor (VP)	(1,1,3)

Poor (P)	(1,3,5)
Fair (F)	(3,5,7)
Good (G)	(5,7,9)
Very Good (VG)	(7,9,9)

Step 2: Determine the normalized weighted value (v_{ij}), using Equation (4.4.3.2):

$$v_{ij} = w_j N_{ij},\ i=1, 2, \ldots, m;\ j=1, 2, \ldots n \quad (4.4.3.2)$$

where w_j can be defined as the j^{th} design criterion and $\sum_{j=1}^{n} w_j = 1$

Step 3: Find the PIS denoted as DFXA$^+$ and NIS denoted as DFXA$^-$ using Equations (4.4.3.3) and (4.4.3.4), where v_i^+ is the maximum values of v_{ij} and v_i^- is the minimum values of v_{ij}.

$$DFXA^+ = \{v_1^+, \ldots, v_n^+\} = \left\{(\max_j v_{ij} | i \in I), (\min_j v_{ij} | i \in J\right\} \quad (4.4.3.3)$$

$$DFXA^- = \{v_1^-, \ldots, v_n^-\} = \left\{(\min_j v_{ij} | i \in J), (\max_j v_{ij} | i \in I\right\} \quad (4.4.3.4)$$

where *I* and *J* are correlated with the benefit and the cost criteria respectively.

Step 4: Calculate the PIS ($DFXd_i^+$) using the displacement differentiation function from Equation (4.4.3.5).

$$DFXd_i^+ = \left\{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2\right\}^{\frac{1}{2}},\ i=1, 2, \ldots m. \quad (4.4.3.5)$$

While, the NIS ($DFXd_i^-$) distance is given as Equation (4.4.3.6).

$$DFXd_i^- = \left\{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2\right\}^{\frac{1}{2}},\ i = 1, 2, \ldots m. \quad (4.4.3.6)$$

Step 5: Calculate the relative closeness coefficient RCC_i using Equation (4.4.3.7) which is the proximal relationship to the DFX alternatives considering the proximity from alternative $DFXA_i$ to $DFXA^+$ and from alternative $DFXA_i$ to $DFXA^-$ simultaneously.

$$RCC_i = \frac{DFXd_i^-}{(DFXd_i^+ + DFXd_i^-)}, \; i = 1, 2, \ldots\ldots m. \tag{4.4.3.7}$$

where RCC_i stands for the final performance score.

Step 6: Rank the calculated values, then select the PIS and NIS shortest distance which is the best solution and select the maximum value of RCC_i.

If the main objective is to maximize the design criteria, then relative closeness to PIS and distance from NIS is preferable. But if the main objective is to minimize design criteria, then relative closeness to NIS and distance from PIS is preferable. Figure 4.10 represents an illustration of the PIS and NIS. Two DFX alternatives, DFX_1 and DFX_2, are being interpreted with respect to their relative distances from PIS and NIS, respectively. The main objective is to minimize design criteria DC_1 and DC_2. However, alternative DFX_2 is closer to NIS (d_2^-) and farther from PIS (d_2^+) than DFX_1 (d_1^-, d_1^+), DFX_2 is better alternative over DFX_1.

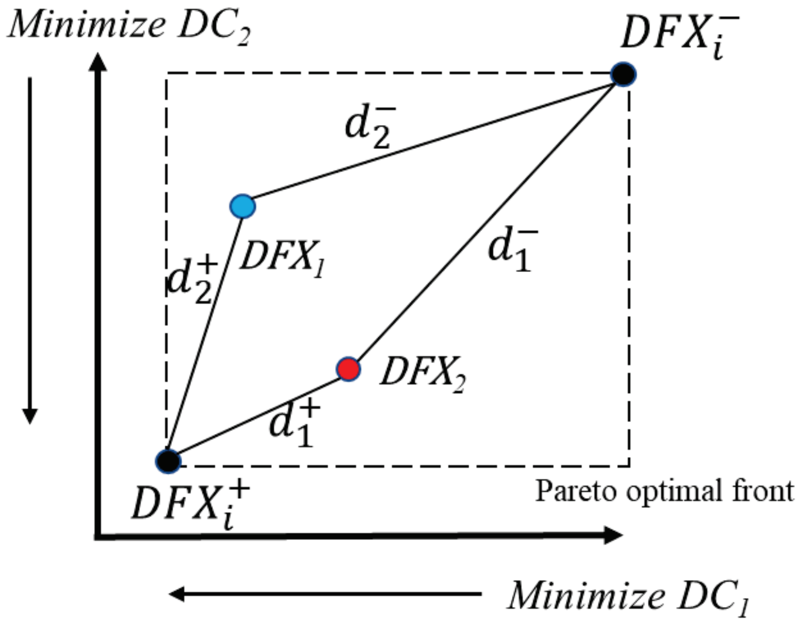


Figure 4.10 Illustrations of the notion of the ideal (PIS) and anti-ideal solutions (NIS)

4.5 Case Study

The objective of this section, as explained before, is to investigate the ranking and selection of MDFX combination in detailed machine design and optimizing their trade-off metrics. The proposed hybrid FEAM -TOPSIS model is implemented in the detailed design of automated wood framing machine-V2 for wood off-site prefabrication construction industry, as shown in Figure 4.11. The purpose of this machine is to fabricate wood wall frames of various dimensions that can later be used in construction projects. Before proceeding to the detailed design phase, the MDFX selection hierarchical structure for this case study, as represented in Figure 4.12, is formed from three levels: level 1 is the goal, which is represented by a ranked list of MDFX combinations for each design criterion; level 2 is the product criteria, which is composed of five sections (end-user (A), materials (B), machine (C), performance (D), and process (E)); level 3, which is a sub-section of level 2, where each product criteria is further declassified in to data criteria; and level 4, which consists of the five DFX alternatives that represent the proposed selection model. For this case study, fifteen DFX techniques were chosen and distributed on the product criteria, as indicated in Table 4.5, which are most relative to the current machine being designed, and twenty design experts with various years of design experience were interviewed to evaluate the design matrix. The experts' feedback and opinions were registered in a design decision matrix for product criteria, data criteria, and alternatives: Table 4.6 represents the comparative judgment of design experts for the product criteria in linguistic terms. After that, the linguistic terms are translated to TFNs from Table 4.3 and then the weighted average is calculated based on the design experts' weight from Table 4.2. Finally, the aggregated fuzzy comparison matrix is constructed for the product criteria level and for the end-user data criterion as shown in Table 4.7 and Table 4.8, respectively. The same procedure is repeated on the data criteria and alternatives levels. However, for the MDFX alternatives, a different fuzzy rating assessment is utilized for the linguistic terms, as shown in Table 4.4.

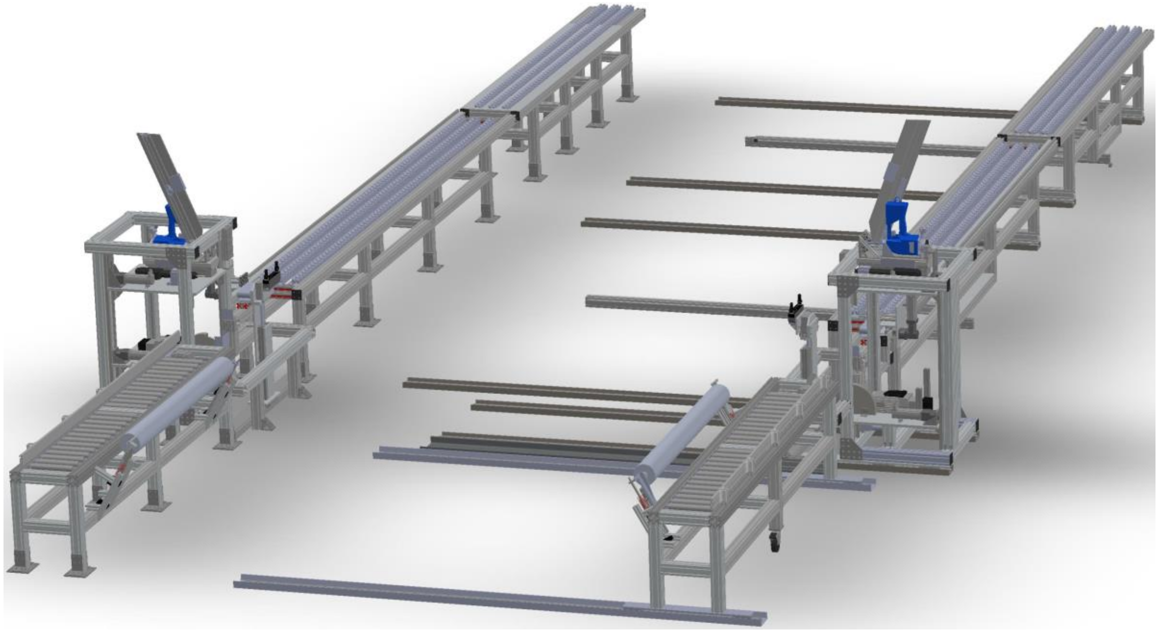


Figure 4.11 Automated wood framing machine-v2 CAD model

From Table 4.9, the calculated fuzzy synthetic extent values of five product criteria are extracted from the pairwise comparisons of the design experts' judgments. After the process of normalization, the weight vector of the product criteria, which are end-user, material, machine, performance, and process, are calculated using and found to be W= (0.184,0.035,0.017,0.394,0.370). The calculated value of the consistency ratio (CR) is equal to 0.09 which is less than 0.1. This is an indication that the calcuated weights have a high confidence degree. The same calculations procedure is applied to the data criterion pairwise comparison matrices and their priority weights can be found in Table 4.10-4.14. Table 4.15 summarizes the calculated results of product and data criteria where they are ranked. For example, in Table 4.16, the calculated normalized value (n_{ij}) for the end-user data criterion against its relative set of MDFX alternatives is represented. Then the weighted normalized value (v_{ij}) is calculated as shown in Table 4.17. From Table 4.18 the PIS (DFX^+) and NIS (DFX^-) are determined respectively. Next, the ideal solution distance is calculated by using the displacement differentiation function. Finally, the relative closeness coefficient to the ideal solution (RRC_i) is computed as shown in Table 4.19. Repeat the same calculation procedure for other product criteria as shown in Table 4.20-4.23, where the data criteria are rated against their respective set of MDFX alternatives.

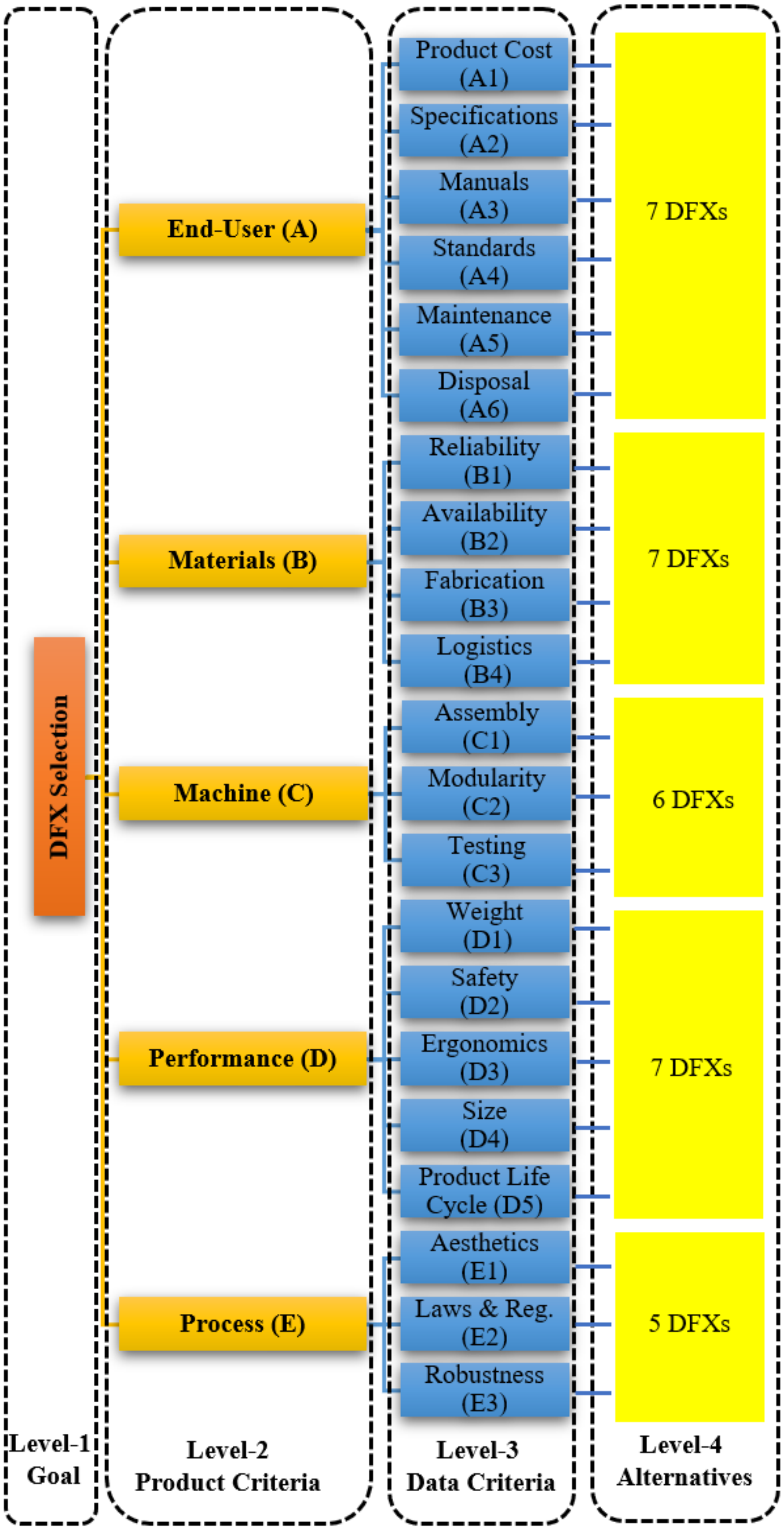


Figure 4.12 MDFX selection hierarchical representation

Table 4.5 DFX list (Alternatives) implemented in this case study with respect to each product criteria

DFX #	Design for	Product Criteria
1	Cost (DFC)	A, B, C, D, E
2	Manufacturing (DFM)	B, C, D, E
3	Assembly (DFA)	B, C, D
4	Variety (DFV)	B, E
5	Quality (DFQ)	A
6	Six Sigma (DFSS)	A, E
7	Disassembly (DFDA)	B, C, D
8	Reliability (DFR)	A, B
9	Testability (DFT)	C
10	Maintainability (DFMAI)	A, D
11	Robustness (DFRO)	C, E
12	End-Of-Life (DFEL)	A, D
13	Sustainability (DFS)	D
14	Network (DFN)	B
15	Environment (DFE)	A, E

Table 4.6 Comparative judgments of decision design experts for product criteria using linguistic terms

Product Criteria	**The left measure is greater**				**Neutral**	**The right measure is greater**				**Product Criteria**
	A. Imp	S. Imp	F. Imp	W. Imp	Eq. Imp	W. Imp	F. Imp	S. Imp	A. Imp	
A	4	4		1	2	4		4	1	A
A	4	4		2	6	3	1			A
A		2		1	8			3	6	A
A	1	2	1	4	2	4	1	2	4	A
B	2	3	2	2			3	3	5	B
B			2	3	2			5	8	B
B		3	2	3	4		2	3	3	B
C	1	2	3	1	3			2	8	B
C		4	2		1	2	6	5		C
D	3	4	1	2		2	3	3	2	C

Table 4.7 Aggregated fuzzy matrices at the product criteria (P.C) level using TFNs

P.C	A	B	C	D	E
A	(1,1,1)	(1,1.18,1.41)	(1.73,2,2.32)	(0.45,0.50,0.54)	(0.58,0.72,0.89)
B	(0.81,0.85,0.87)	(1,1,1)	(0.62,0.74,0.87)	(0.30,0.35,0.41)	(0.72,0.85,0.98)
C	(0.51,0.50,0.49)	(1.37,1.35,1.34)	(1,1,1)	(0.55,0.62,0.70)	(0.50,0.59,0.71)
D	(1.97,2.02,2.07)	(2.82,2.83,2.87)	(1.62,1.60,1.60)	(1,1,1)	(0.85,1.05,1.27)
E	(1.37,1.39,1.41)	(1.23,1.18,1.15)	(1.55,1.70,1.82)	(0.99,0.95,0.96)	(1,1,1)

Table 4.8 Aggregated fuzzy matrices at the end-user data criteria level using TFNs

A	A1	A2	A3	A4	A5	A6
A1	(1,1,1)	(3.2,3.8,4.4)	(6.48,7.54, 8.58)	(5.34,6.29, 7.20)	(2.13,2.56, 3.01)	(6.54,7.61, 8.65)
A2	(0.30,0.26,0.24)	(1,1,1)	(5.61,6.56, 7.47)	(5.23,6.03, 6.80)	(0.96,1.19, 1.48)	(7.11,8.14, 9.16)
A3	(0.15,0.13,0.12)	(0.18,0.15, 0.13)	(1,1,1)	(0.67,0.80, 0.95)	(0.32,0.39, 0.47)	(0.73,0.94, 1.20)
A4	(0.19,0.16,0.14)	(0.19,0.17, 0.15)	(1.25,1.26, 1.27)	(1,1,1)	(0.51,0.58, 0.67)	(0.79,0.96, 1.16)
A5	(0.43,0.39,0.36)	(0.85,0.84, 0.82)	(2.42,2.58, 2.72)	(1.91,2.13, 2.29)	(1,1,1)	(3.67,4.30, 5.05)
A6	(0.15,0.13,0.12)	(0.14,0.12, 0.11)	(1.08,1.06, 1.05)	(1.40,1.46, 1.51)	(0.25,0.23, 0.28)	(1,1,1)

Table 4.9 Fuzzy extent analysis model output at the product criteria level

Product Criteria	Fuzzy Synthetic Extent Value S_c	Weight Vector W'	Min Superiority Value $d\,(A_i)$	Normalized Weight Vector W
A	(4.76,5.39,6.17)	(0.16,0.19,0.23)	0.46	0.184
B	(3.46,3.79,4.13)	(0.11,0.13,0.15)	0.08	0.035
C	(3.92,4.06,4.25)	(0.13,0.14,0.16)	0.004	0.017
D	(8.27,8.50,8.80)	(0.27,0.30,0.33)	1	0.394
E	(6.13,6.22,6.34)	(0.20,0.22,0.23)	0.93	0.370

Table 4.10 Fuzzy extent analysis model output at the end-user (A) data criteria level

A	Fuzzy Synthetic Extent Value S_c	Weight Vector W'	Min Superiority Value $d\,(A_i)$	Normalized Weight Vector W
A1	(24.69,28.80,32.85)	(0.29,0.38,0.49)	1	0.219
A2	(20.21,23.19,26.15)	(0.24,0.31,0.39)	0.57	0.127
A3	(3.05,3.41,3.88)	(0.03,0.04,0.05)	0.55	0.120
A4	(3.92,4.12,4.39)	(0.04,0.05,0.06)	1	0.215
A5	(10.29,11.24,12.25)	(0.12,0.15,0.18)	0.55	0.121
A6	(4.02,4.01,4.06)	(0.048,0.054,0.061)	0.90	0.143

Table 4.11 Fuzzy extent analysis model output at the materials (B) data criteria level

B	Fuzzy Synthetic Extent Value S_c	Weight Vector W'	Min Superiority Value $d\,(A_i)$	Normalized Weight Vector W
B1	(4.18,4.68,5.27)	(0.19,0.231,0.26)	1	0.408
B2	(3.02,3.31,3.64)	(0.14,0.16,0.18)	0.21	0.086
B3	(3.48,2.92,2.91)	(0.16,0.144,0.147)	0.23	0.097
B4	(9.14,9.35,9.59)	(0.42,0.46,0.48)	1	0.410

Table 4.12 Fuzzy extent analysis model output at the machine (C) data criteria level

C	**Fuzzy Synthetic Extent Value S_c**	**Weight Vector W'**	**Min Superiority Value $d\,(A_i)$**	**Normalized Weight Vector W**
C1	(3.61,4.06,4.63)	(0.31,0.39,0.48)	0.88	0.296
C2	(3.80,4.28,4.87)	(0.33,0.41,0.51)	1	0.335
C3	(2.11,2.05,2.02)	(0.18,0.19,0.21)	1.09	0.368

Table 4.13 Fuzzy extent analysis model output at the performance (D) data criteria level

D	**Fuzzy Synthetic Extent Value S_c**	**Weight Vector W'**	**Min Superiority Value $d\,(A_i)$**	**Normalized Weight Vector W**
D1	(5.26,5.95,6.70)	(0.17,0.21,0.26)	0.35	0.136
D2	(5.36,5.97,6.74)	(0.17,0.21,0.25)	0.36	0.142
D3	(5.26,5.74,6.29)	(0.17,0.20,0.24)	0.16	0.064
D4	(3.13,3.27,3.44)	(0.10,0.11,0.13)	0.70	0.272
D5	(7.07,7.36,7.63)	(0.23,0.26,0.29)	1	0.385

Table 4.14 Fuzzy extent analysis model output at the process (E) data criteria level

E	**Fuzzy Synthetic Extent Value S_c**	**Weight Vector W'**	**Min Superiority Value $d\,(A_i)$**	**Normalized Weight Vector W**
E1	(2.16,2.40,2.69)	(0.21,0.24,0.29)	0.15	0.083
E2	(2.89,3.05,3.21)	(0.28,0.31,0.34)	0.68	0.373
E3	(4.14,4.29,4.41)	(0.40,0.44,0.48)	1	0.544

Table 4.15 Final evaluation results summary of data criteria importance weight with its relative ranking

Product criteria/Data Criteria	Normalized Weight	Overall Weight	Ranking Importance
End User	0.184	-	-
A1	0.219	0.03942	10
A2	0.127	0.02286	15
A3	0.120	0.0216	17
A4	0.215	0.0387	11
A5	0.121	0.02178	16
A6	0.143	0.02574	12
Materials	0.035	-	-
B1	0.408	0.07344	3
B2	0.086	0.01548	19
B3	0.097	0.01746	18
B4	0.410	0.0738	2
Machine	0.0017	-	-
C1	0.296	0.05328	8
C2	0.335	0.0603	7
C3	0.368	0.06624	6
Performance	0.394	-	-
D1	0.136	0.02448	14
D2	0.142	0.02556	13
D3	0.064	0.01152	21
D4	0.272	0.04896	9
D5	0.385	0.0693	4
Process	0.370	-	-
E1	0.083	0.01494	20
E2	0.373	0.06714	5
E3	0.544	0.09792	1

Table 4.16 Normalized fuzzy decision matrix between DFX alternatives and end-user data criteria (n_{ij})

DFX	A1	A2	A3	A4	A5	A6
DFX 1	(0.67,0.90, 0.98)	(0.49,0.77, 0.96)	(0.16,0.24, 0.56)	(0.40,0.66, 1)	(0.39,0.63, 0.93)	(0.18,0.29, 0.60)
DFX 5	(0.68,0.90, 1)	(0.57,0.78, 1)	(0.15,0.21, 0.52)	(0.38,0.62, 0.95)	(0.36,0.58, 0.89)	(0.17,0.25, 0.56)
DFX 6	(0.21,0.41, 0.65)	(0.21,0.36, 0.65)	(0.45,0.70, 1)	(0.46,0.64, 0.98)	(0.21,0.33, 0.65)	(0.14,0.20, 0.49)
DFX 8	(0.31,0.51, 0.75)	(0.28,0.36, 0.67)	(0.15,0.18, 0.49)	(0.15,0.23, 0.55)	(0.30,0.49, 0.81)	(0.14,0.18, 0.47)
DFX 10	(0.29,0.44, 0.69)	(0.28,0.49, 0.78)	(0.28,0.35, 0.70)	(0.20,0.30, 0.64)	(0.48,0.72, 1)	(0.14,0.16, 0.44)
DFX 12	(0.22,0.29, 0.55)	(0.22,0.33, 0.64)	(0.21,0.24, 0.58)	(0.19,0.23, 0.56)	(0.39,0.60, 0.91)	(0.47,0.72, 1)
DFX 15	(0.19,0.35, 0.60)	(0.20,0.28, 0.58)	(0.15,0.16, 0.46)	(0.15,0.19, 0.50)	(0.15,0.23, 0.53)	(0.49,0.7,0 .99)

Table 4.17 Weighted normalized fuzzy decision matrix between DFX alternatives and end-user data criteria (v_{ij})

DFX	A1	A2	A3	A4	A5	A6
	End-user (A) Data Criteria Fuzzy weights					
	(0.29,0.38, 0.49)	(0.24,0.31, 0.39)	(0.03,0.04, 0.05)	(0.04,0.05, 0.06)	(0.12,0.15, 0.18)	(0.048,0.0 54,0.061)
DFX 1	(0.19,0.34, 0.47)	(0.11,0.23, 0.37)	(0.005,0.0 1,0.02)	(0.01,0.03, 0.06)	(0.04,0.09, 0.16)	(0.04,0.01, 0.03)
DFX 5	(0.19,0.34, 0.49)	(0.13,0.24, 0.39)	(0.005,0.0 08,0.002)	(0.01,0.03, 0.05)	(0.04,0.08, 0.16)	(0.08,0.01, 0.03)
DFX 6	(0.06,0.15, 0.31)	(0.05,0.11, 0.25)	(0.013,0.0 28,0.05)	(0.01,0.03, 0.05)	(0.02,0.05, 0.11)	(0.007,0.0 1,0.03)
DFX 8	(0.09,0.19, 0.36)	(0.06,0.11, 0.26)	(0.004,0.0 07,0.02)	(0.006,0.0 01,0.03)	(0.03,0.07, 0.14)	(0.007,0.0 09,0.02)
DFX10	(0.08,0.16, 0.33)	(0.06,0.15, 0.30)	(0.008,0.0 01,0.03)	(0.008,0.0 01,0.03)	(0.05,0.10, 0.18)	(0.007,0.0 08,0.02)
DFX12	(0.06,0.11, 0.26)	(0.05,0.10, 0.24)	(0.006,0.0 01,0.002)	(0.007,0.0 11,0.03)	(0.04,0.09, 0.16)	(0.02,0.03, 0.06)
DFX15	(0.05,0.13, 0.29)	(0.04,0.08, 0.22)	(0.004,0.0 07,0.02)	(0.006,0.0 09,0.03)	(0.01,0.03, 0.09)	(0.02,0.03, 0.06)

Table 4.18 Fuzzy positive and negative ideal DFX solution

Ideal Solution	A1	A2	A3	A4	A5	A6
DFX^{+}	(0.19,0.34,0.49)	(0.13,0.24,0.39)	(0.01,0.02,0.05)	(0.01,0.03,0.06)	(0.05,0.10,0.18)	(0.02,0.03,0.06)
DFX^{-}	(0.05,0.10,0.26)	(0.04,0.08,0.22)	(0.004,0.006,0.02)	(0.006,0.009,0.03)	(0.01,0.03,0.09)	(0.006,0.008,0.02)

Table 4.19 The related relative closeness coefficient (RCC_i) and final DFX alternatives ranking for end-user (A)

DFX Alternatives	d_i^+	d_i^-	RCC_i	Final Ranking
DFX 1	0.074	0.417	0.849	2
DFX 5	0.064	0.422	0.869	1
DFX 6	0.367	0.122	0.250	5
DFX 8	0.339	0.148	0.304	4
DFX 10	0.290	0.199	0.407	3
DFX 12	0.380	0.110	0.224	6
DFX 15	0.441	0.046	0.094	7

Table 4.20 The related relative closeness coefficient (RCC_i) and final DFX alternatives ranking for materials (B)

DFX Alternatives	d_i^+	d_i^-	RCC_i	Final Ranking
DFX 1	0.110	0.432	0.797	1
DFX 2	0.221	0.320	0.592	2
DFX 3	0.334	0.206	0.382	4
DFX 4	0.516	0.021	0.039	7
DFX 7	0.511	0.026	0.049	6
DFX 8	0.401	0.135	0.252	5
DFX 14	0.246	0.292	0.542	3

Table 4.21 The related relative closeness coefficient (RCC_i) and final DFX alternatives ranking for machine (C)

DFX Alternatives	d_i^+	d_i^-	RCC_i	Final Ranking
DFX 1	0.129	0.420	0.765	2
DFX 2	0.227	0.322	0.587	5
DFX 3	0.124	0.426	0.775	1
DFX 7	0.141	0.406	0.743	3
DFX 9	0.443	0.104	0.190	6
DFX 11	0.164	0.387	0.703	4

Table 4.22 The related relative closeness coefficient (RCC_i) and final DFX alternatives ranking for performance (D)

DFX Alternatives	d_i^+	d_i^-	RCC_i	Final Ranking
DFX 1	0.014	0.414	0.967	1
DFX 2	0.237	0.192	0.448	4
DFX 3	0.225	0.204	0.477	2
DFX 7	0.224	0.204	0.476	3
DFX 9	0.258	0.173	0.402	5
DFX 11	0.333	0.096	0.224	6
DFX 13	0.342	0.086	0.201	7

Table 4.23 The related relative closeness coefficient (RCC_i) and final DFX alternatives ranking for process (E)

DFX Alternatives	d_i^+	d_i^-	RCC_i	Final Ranking
DFX 1	0.107	0.362	0.772	1
DFX 2	0.343	0.128	0.272	4
DFX 4	0.435	0.034	0.074	5
DFX 6	0.326	0.142	0.304	3
DFX 11	0.177	0.291	0.621	2

After calculating and ranking the MDFX techniques for each product criterion and in order to effectively estimate and verify which of these techniques in the detailed design of the automated wood framing machine-V2 would be the best fit, the cost/time analysis is pursued. The planned cost and time for the detailed design of the machine were completed after the concept design was approved by the designer. The planned design cost is $300,000 and the planned design time (schedule) is 120 calendar days to finish the machine detailed design. The cost and time are distributed equally over the product criteria. However, the assumption that the product criteria are equally weighted is wrong and each product criterion must be represented using its calculated final weight. Thus, the actual cost and time metrics of each product criterion can be concluded and the variance between planned and actual metrics can be calculated as shown in Table 4.24.

Table 4.24 Planned versus actual cost and time allocation per product criterion

Total Planned Cost			$300,000.00		
Total Planned Time			120 days		
Product Criteria	**A**	**B**	**C**	**D**	**E**
Planned Cost %	20.0%	20.0%	20.0%	20.0%	20.0%
Planned Time %	20.0%	20.0%	20.0%	20.0%	20.0%
Final Weight	0.18	0.04	0.02	0.39	0.37
Actual Cost %	18.4%	3.5%	1.7%	39.4%	37.0%
Actual Time %	18.4%	3.5%	1.7%	39.4%	37.0%
Variance %	−1.6%	−16.5%	−18.3%	19.4%	17.0%
Actual Allocated Cost	$55,200.00	$10,500.00	$5,100.00	$118,200.00	$111,000.00
Actual Allocated Time	22.08	4.20	2.04	47.28	44.40

By using the actual allocated cost and time for each product criterion as an input for the MDFX trade-off analysis model, the distributed cost and time for each DFX relative to its product criterion can be calculated as shown in Table 4.25 to Table 4.29. Each DFX can be represented by its actual cost and time required to complete the machine's detailed design.

Table 4.25 DFX alternatives projected cost and time allocation for end-user

Actual Allocated Cost	$55,200.00			
Actual Allocated Time	22.08 days			
DFX Alternatives	**Cci Results**	**Normalized Cci Results**	**Actual Cost per DFX**	**Actual Time per DFX**
DFX 1	0.84	0.28	$15,590.07	6.24
DFX 5	0.86	0.29	$15,952.27	6.38
DFX 6	0.26	0.09	$4,760.74	1.90
DFX 8	0.30	0.10	$5,567.41	2.23
DFX 10	0.41	0.14	$7,501.30	3.00
DFX 12	0.22	0.07	$4,124.00	1.65
DFX 15	0.09	0.03	$1,704.20	0.68

Table 4.26 DFX alternatives projected cost and time allocation for materials

Actual Allocated Cost	$10,500.00			
Actual Allocated Time	4.20 days			
DFX Alternatives	**Cci Results**	**Normalized Cci Results**	**Actual Cost per DFX**	**Actual Time per DFX**
DFX 1	0.80	0.30	$3,157.50	1.26
DFX 2	0.59	0.22	$2,337.57	0.94
DFX 3	0.38	0.14	$1,509.79	0.60
DFX 4	0.04	0.01	$154.84	0.06
DFX 7	0.05	0.02	$191.90	0.08
DFX 8	0.25	0.10	$1,004.19	0.40
DFX 14	0.54	0.20	$2,144.21	0.86

Table 4.27 DFX alternatives projected cost and time allocation for machine

Actual Allocated Cost	$5,100.00			
Actual Allocated Time	2.04 days			
DFX Alternatives	**Cci Results**	**Normalized Cci Results**	**Actual Cost per DFX**	**Actual Time per DFX**
DFX 1	0.76	0.20	$1,037.96	0.42
DFX 2	0.58	0.16	$794.31	0.32
DFX 3	0.77	0.21	$1,048.73	0.42
DFX 7	0.74	0.20	$1,005.26	0.40
DFX 9	0.19	0.05	$261.60	0.10
DFX 11	0.70	0.19	$952.14	0.38

Table 4.28 DFX alternatives projected cost and time allocation for performance

Actual Allocated Cost	$118,200.00			
Actual Allocated Time	47.28 days			
DFX Alternatives	**Cci Results**	**Normalized Cci Results**	**Actual Cost per DFX**	**Actual Time per DFX**
DFX 1	0.97	0.30	$35,840.23	14.34
DFX 2	0.45	0.14	$16,554.87	6.62
DFX 3	0.48	0.15	$17,653.04	7.06
DFX 7	0.48	0.15	$17,640.84	7.06
DFX 10	0.40	0.13	$14,835.21	5.93
DFX 12	0.22	0.07	$8,240.53	3.30
DFX 13	0.20	0.06	$7,435.28	2.97

Table 4.29 DFX alternatives projected cost and time allocation for process

Actual Allocated Cost	$111,000.00			
Actual Allocated Time	44.40 days			
DFX Alternatives	**Cci Results**	**Normalized Cci Results**	**Actual Cost per DFX**	**Actual Time per DFX**
DFX 1	0.77	0.38	$41,924.68	16.77
DFX 2	0.27	0.13	$14,807.28	5.92
DFX 4	0.07	0.04	$4,012.49	1.60
DFX 6	0.31	0.15	$16,666.42	6.67
DFX 11	0.62	0.30	$33,589.13	13.44

4.6 Results and Discussions

In this study, the proposed fuzzy extent analysis model based on Chang's method [48] suggests that product criterion D has the highest importance weight between the other four product criteria. Product criterion E is the second largest one followed by and criterion A. The results of this model are compared with the results of other fuzzy set theory methods. The results comparison summary of the product criteria level is shown in Table 4.30. As concluded in Table 4.30, the results of the proposed method are close to some extent to that of the other fuzzy methods. Chang's method results show that the importance weight of product criterion B is larger than that of C. Although the other methods calculation procedures are different from the proposed one, the results are very similar regarding the first three product criteria. The advantages of the hybrid decision support system compared to the other methods are: (1) a weight can be allocated to each design expert based on the number of years of experience; (2) it uses basic mathematical formulas to calculate the importance weights; (3) it incorporates an effective and easy scale to compare factors; and

(4) design experts can easily relate the linguistic terms to the TFNs scale in order to establish the design decision comparison matrix.

Table 4.30 Comparison of fuzzy set theory methods on the product criteria level

Method	Weight of A	Weight of B	Weight of C	Weight of D	Weight of E	Ranking
AHP (1980)	0.19	0.14	0.15	0.30	0.23	D>E>A>C>B
Buckley's (1985)	(0.15,0.18,0.22)	(0.12,0.14,0.16)	(0.13,0.14,0.16)	(0.27,0.30,0.33)	(0.22,0.23,0.25)	D>E>A>C>B
Chang's (1996)	0.184	0.035	0.017	0.394	0.370	D>E>A>B>C

By comparing the relative closeness coefficient (*RRCi*) values of the product criteria against its MDFX set of alternatives, multiple observations can be made. On the end-user level, DFC and DFQ represent 57% of the final rating, while DFEL and DFE represent 11% of the final rating, as shown in Figure 4.13. On the other hand, DFC and DFM correspond to 52% of the final rating, while DFV and DFDA correspond to 4% of the final rating on the materials level, as shown in Figure 4.13. As concluded from Figure 4.13, DFC, DFA, DFDA, and DFRO each represent approximately 20% from the final rating on the machine level. This can be translated to mean that each of these DFXs is of equal importance in the detailed machine design with respect to the machine product criteria. However, as indicated in Figure 4.13, only DFM, DFA, and DFDA are of equal importance on the performance product criteria level and each represents approximately 15% of the final rating, as seen in Figure 4.13. On the process level, DFC and DFRO combined to form 68% of the final rating; therefore, the techniques can be considered of high importance when applied in the machine detailed design.

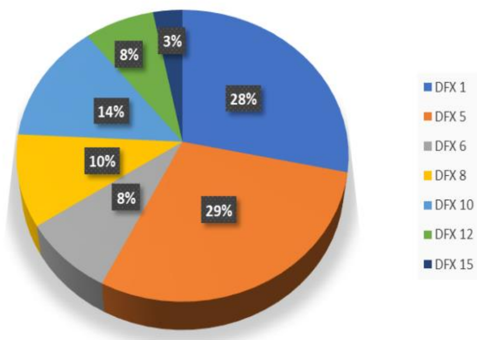


Figure 4.13 The final ranking of end-user product criteria alternatives

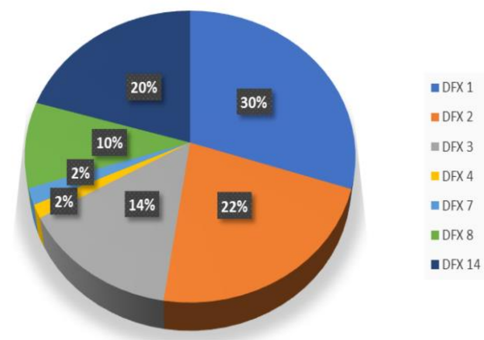


Figure 4.14 The final ranking of materials product criteria alternatives

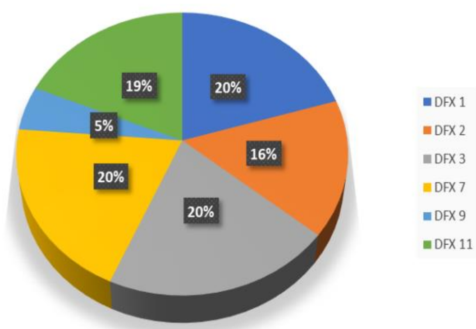


Figure 4.15 The final ranking of machine product criteria alternatives

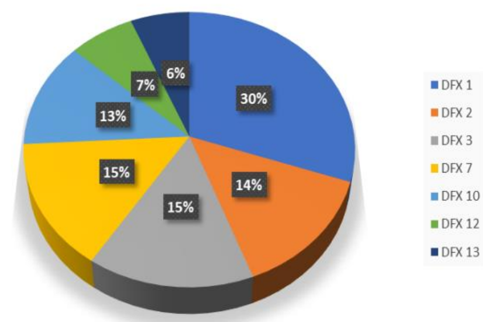


Figure 4.16 The final ranking of performance product criteria alternatives

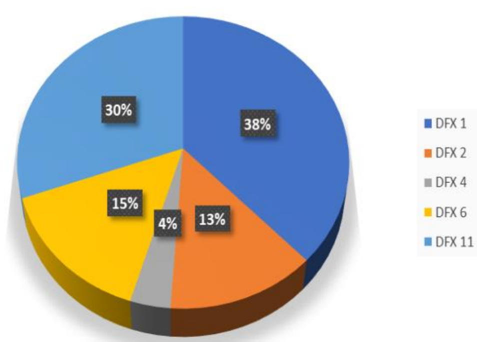


Figure 4.17 The final ranking of process product criteria alternatives

From Table 4.31, the cumulative RRC_i for MDFX alternatives with their respective ranking is summarized for all the product criteria combined. It shows that DFC, DFM, and DFA are the most important DFX techniques to be utilized in detailed machine design, whereas the DFT, DFV, and DFE are the least important DFX techniques to be utilized in detailed machine design.

Table 4.31 Commutative RCC_i for MDFX with their respective ranking on all product criteria level.

DFX Alternatives	$\sum RCC_i$	Final Ranking
DFX 1	4.145	1
DFX 2	1.894	2
DFX 3	1.629	3
DFX 4	0.113	14
DFX 5	0.865	6
DFX 6	0.565	8
DFX 7	1.264	5
DFX 8	0.555	9
DFX 9	0.193	13
DFX 10	0.807	7
DFX 11	1.319	4
DFX 12	0.446	11
DFX 13	0.201	12
DFX 14	0.541	10
DFX 15	0.092	15

Table 4.32 summarizes the actual cost and time required for each DFX to be utilized in the machine detailed design. As shown in Table 4.32, DFC has the highest cost to be utilized in the design of $97,550 and the highest time to be completed of 39 calendar days. On the other hand, DFEL has the lowest cost of $261 and the associated time can be negligible. The main observation that can be derived from Table 4.32 and Table 4.32 is that the ranking of DFX changes after the trade-off analysis model is implemented. For example, in Table 4.31 the top three DFX techniques were DFC, DFA, and DFM, whereas, in Table 4.32, this

result partially changed to DFC, DFM, and DFRO. This can be traced back to the importance of MDFX trade-off analysis in machine design to support the designer's decisions and to evaluate the impact of MDFX techniques on machine design development cost and schedule.

Table 4.32 MDFX ranking based on actual cost and time combining all product criteria

Combined DFX Alternatives for All Product Criteria		**Actual Allocated Cost Per DFX ($)**	**Actual Allocated Time Per DFX (days)**	**Ranking based on cost and time priority**
Cost (DFC)	DFX 1	$97,550.45	39	1
Manufacturing (DFM)	DFX 2	$34,494.03	14	3
Assembly (DFA)	DFX 3	$20,211.57	8	6
Variety (DFV)	DFX 4	$4,167.33	2	12
Quality (DFQ)	DFX 5	$15,952.27	6	8
Six Sigma (DFSS)	DFX 6	$21,427.17	9	5
Disassembly (DFDA)	DFX 7	$18,837.99	8	7
Reliability (DFR)	DFX 8	$6,571.60	3	11
Testability (DFT)	DFX 9	$261.60	0	15
Maintainability (DFMAI)	DFX 10	$22,336.51	9	4
Robustness (DFRO)	DFX 11	$34,541.26	14	2
End-Of-Life (DFEL)	DFX 12	$12,364.54	5	9
Sustainability (DFS)	DFX 13	$7,435.28	3	10
Network (DFN)	DFX 14	$2,144.21	1	13
Environment (DFE)	DFX 15	$1,704.20	1	14

In Figure 4.18, the optimized MDFX are represented with their cost and time metrics. It can be observed that DFC alone represents 32.5% of design cost and time when implemented in machine design, followed by DFM and DFRO, where each represents 11.5%. The DFT has the lowest optimization percentage of 0.1% followed by DFE with 0.6%. This result aids the designer in understanding and estimating the effect of applying MDFX in machine detailed design. By integrating MDFX in the machine development, the designer is able to utilize, optimize, and visualize their respective trade-offs before design development commence, leading to accurate forecast and reaching the design development planned cost and time.

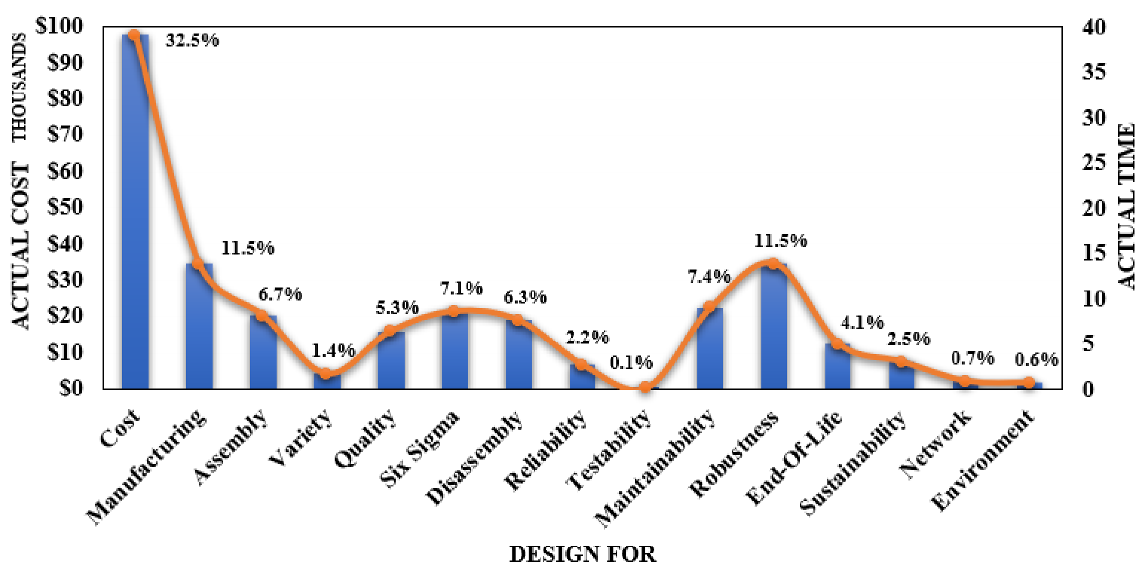


Figure 4.18 Optimized MDFX cost and time

4.7 Conclusion

A decisive decision support system has been proposed for integrating MDFX with PDS. In this research, a hybrid FEAM-TOPSIS model together with trade-off analysis model was implemented using conflict resolution, TFNs, and ranking methods to evaluate MDFX combinations. The hybrid model employs the fuzzy extent analysis method (FEAM) to calculate the importance weights of the PDS and to identify the best MDFX combinations while taking in to consideration the weights for experts, product criteria, data criteria, and MDFX alternatives. This model aids the designer in the selection of optimal MDFX alternatives based on the design criteria on the judgment of design experts. However, the disadvantage of this model is that the input data depends on the design experts' opinions and technical experience, and thus involves subjectivity and some biases. The evaluation of MDFX alternatives usually requires specified technical knowledge besides the design experience; however, design experts may display some bias in the judgments when providing a ranking preference of one design criterion over the another. For that reason, the TOPSIS model is the chosen method for the ranking of MDFX alternatives in terms of their total scoring. The importance of the criteria is evaluated by design experts, and the uncertainty of their assessment is considered in the fuzzy analysis model. Also, the experts' degree of confidence may be computed through the distribution of fuzzy numbers utilized for the pairwise comparison ratios in the proposed model. The proposed MDFX model based on trade-off analysis ensures the integration of design experts' assessment and evaluation in a decision-making system. Cost and time are utilized to compare MDFX alternatives so that lifecycle cost can be reduced. The weighing of the financial and economic impact of all MDFX selection design decisions provides a benchmark that can assists the designer in making decisions to best benefit the machine development. The hybrid model can be implemented in diverse range of machine design by adjusting the design experts' values, the structure of the problem's hierarchy, and their related design attributes. The conclusion from the case study is that DFC, DFM, and DFRO are the first three important DFX techniques for machine design with 55.5% of importance and cost/time optimization, while DFT, DFE, and DFN rank as last priorities among these techniques with 1.4%. Moreover, the performance (D) and the process (E) rank as the first two product criterion for these DFXs with 76% of importance.

The impetus for developing the hybrid decision support model was to ease the MDFX selection process by improving the designers' decision-making processes. The proposed decision support system model can evaluate and rank MDFX alternatives comprehensively using design weighted means absolute difference values. It provides benefits by improving design capability in terms of enabling designers to evaluate MDFX alternatives with interrelated design criteria. Also, it provides the designers with an automated decision support tool to aid them in capturing the features of different DFX techniques in conceptual and detailed machine design stages. The hybrid decision support system model also provides designers with a fuzzy relation point of view compared to the traditional performance evaluation model for dealing with imprecision and uncertainty. Finally, it enables designers to better interpret the whole evaluation process and provides a more precise, systematic, and effective decision support tool.

Chapter 5 : Hybrid Decision support approach for Multi-DFX trade-off optimization in machine design: Hybrid genetic and Pareto optimality algorithm[4]

5.1 Introduction

Designers tend to express the design decision optimality problem as a single objective function approach that requires continues optimization to maximize the overall machine lifecycle. However, this approach cannot guarantee that the designer can control multiple design decision variables where their formulation is based various design decision optimality criteria (Ahmad et al., 2014; Malik et al., 2019). Hence, multi-objective optimization design decision problems can be formed where the designer can determine the Multi-DFX (MDFX) techniques trade-off optima that represent the combined impact of these techniques on design decision activities. Bendeković (1993) proposes a framework featuring the Net Present Value (NPV) and Internal Rate of Return (IRR) concepts to measure the effectiveness of a set of design decisions through evaluating their financial parameters in terms of time. In design decision-making optimization, the pertinent measures of MDFX excellence are not the only criteria that control the problem constraints. In many cases, design decision objective functions are expressed based on a single criterion (e.g., machine weight), which does not correspond to the designer's notion of applying MDFX in machine design development. Thus, the impression of MDFX excellence is more holistic and includes the designer vision throughout the entire lifecycle of the machine from design to operation including performance measures. The designer's notion of the machine

[4] The manuscript presented in Chapter 5 of this thesis is ready to be submitted to the International Journal of Production Economics.

design development excellence would be composed of multiple qualitative and quantitative criteria in most cases including adaptivity, versatility, reliability, safety, acquisition terms, intangible and subjective design functionality expectations, etc. Therefore, a design decision support system (DDSS) framework is required to model the excellence of MDFX in the objective functions and generates a list of best fit MDFX techniques that maximize the machine overall lifecycle performance related to the designer's design conditions. This can be formulated as best-compromise multi-objective value-based optimization function where all equivalent economic values of partial objectives are represented as described in this research.

Many real-world design decision problems involve concurrent optimization of multiple incommensurable and conflicting objectives where no single optimal solution exists. But instead there is a set of various alternative solutions that are optimal when all design decision objectives are investigated making them superior solutions in the search space where no other solutions can match them. These solutions are known as Pareto-optimality solutions. To illustrate the power and importance of this approach in a brief example, consider the design of a pick and place robot clamping system. An optimal design solution for a designer might be to minizine the total cost of the clamping system while maximizing the system overall performance metrics. However, these objectives are generally from a designer's perspective conflicting to each other: one designer may achieve the high-performance objective but on the expense of high cost while other designers may fulfill the low-cost objective but on the expense of reducing performance metrics. But none of these solutions can be considered to be superior to the other solutions in the search space if designers do not implement the preference information methodology (e.g., a ranking system of the design decision objectives). Thus, a design decision tool that can aid the designer in exploring and assessing the design space for Pareto-optimality solutions will reduce search time and present the best set of solutions that can optimize MDFX trade-off metrics (e.g., Cost, Time, and Quality, as shown in Figure 5.1) at the same time.

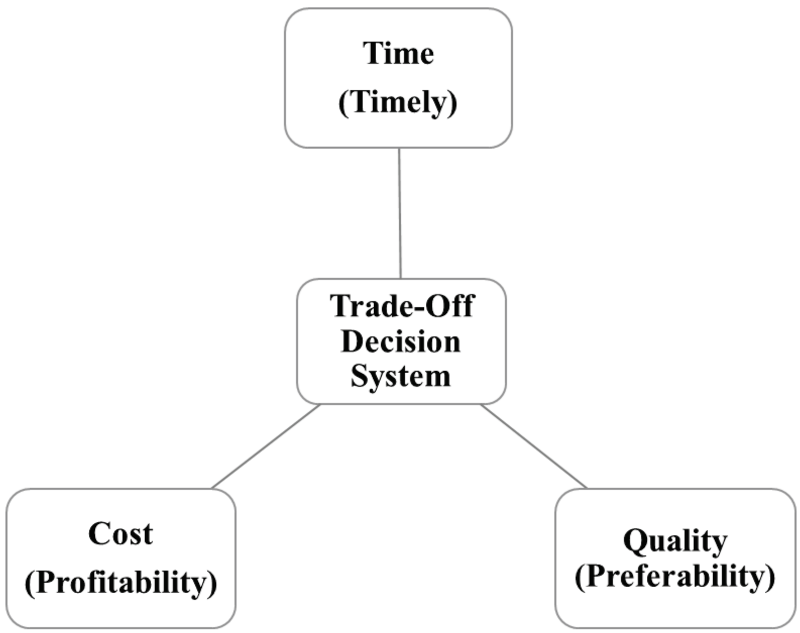


Figure 5.1 MDFX cost-time-quality trade-off pillars

Since the early 1970s, mathematical programming models and heuristic methods have been adapted as two main categories in solution finding (Feng et al., 1997), as shown in Figure 5.2 . Feng et al. (1997); Li and Love (1997) have developed various models of these categories and have compared their performance in multi-objective optimization problems. However, there are main disadvantages for both categories. The mathematical programming models' disadvantages are well-known in their arithmetic complexity, time-consuming computational nature, and small-size optimization problems applicability (Feng et al., 1997; Li and Love, 1997). On the other hand, they summarized the heuristic methods disadvantages by statin their disability in providing optimum solutions for the optimization problem and in their mathematical representations' deficiency. With modern advances in the artificial intelligence (AI) and computer technology research fields (Martinez et al., 2019), superior genetic algorithms (GAs) has emerged as the best optimization techniques for a design decision problem (Goldberg, 1989). GAs find the optimal solution of a design development problem through simulating natural evolution random search methodology and adopting the mechanisms of best fittest survival (Mitchell, 1998). Li and Love) 1997(; Goldberg (1989) reported the GAs methodology robustness and how they can search and locate the best optimal solution for a design decision problem efficiently. However, Feng et al. (1997); Li and Love (1997) discussed that the main disadvantage of adopting GAs is that they are time-consuming in searching for the best solution. Thus, in this study, some modifications are applied to the original GA methodology to reduce search computational time and to optimize MDFX trade-off metrics.

Heuristic Methods

- Easy to apply, provide acceptable solutions, utilized in large scale problems.
- Lack of mathematical representations, no optimal solution, variables are represented in linear relationship form instead of discrete one.

Mathematical Programming Methods

- Possibility of optimal solution.
- Difficult to represent the problem in mathematical formulas and adapted in small scale problems.

Genetic Algorithms

- Robust optimization algorithm, problem variables are represented in discrete relationship form, and can be utilized in large scale problems.
- Time consuming search, optimal solution can vary from one random search to other.

Figure 5.2 Existing optimization methods for MDFX trade-off

Little research has been conducted in the field of optimizing and utilizing MDFX techniques in machine design development. Few optimization models were developed by researchers such as linear programming and goal programming. However, none of them adapt GAs toward the problem. These models, as shown in Figure 5.3 can be grouped based on their optimization objectives into MDFX trade-off models that aim to: (1) minimize design cost by adopting MDFX (Gatzen et al., 2013); (2) optimize cost and time Design for X (DFX) trade-off analysis (Lukasz and Tomasz, 2007); and (3) minimize cost and/or time DFX metrics (Wulan and Deng, 2000). While the above-listed research studies have established the basic concept of optimizing MDFX in design development, there have been no reported studies related to multi-objective trade-off models for optimizing MDFX metrics such as cost (C), time (T), and quality (Q). Therefore, the purpose of this study is to develop the DDSS framework for selecting the optimal MDFX solutions for machine design development based upon the product design specifications (PDS) qualitative and quantitative criteria while optimizing the MDFX trade-off metrics. The genetic algorithm and Pareto optimality are combined in a hybrid search engine to generate the MDFX optimized solutions based on the fitness functions where design development cost and time is minimized, and design development quality is maximized. After that, these solutions are evaluated from an economic perspective by calculating their NPV and IRR values based on the design problem parameters.

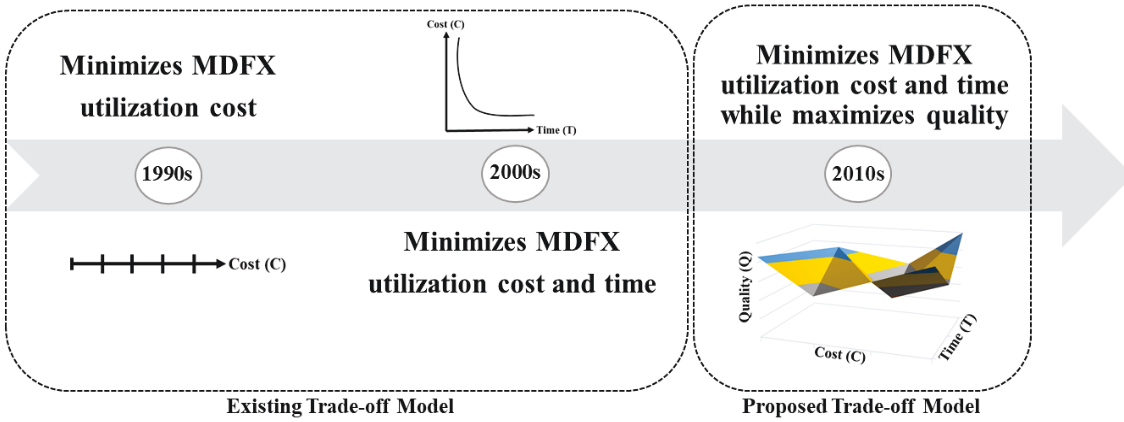


Figure 5.3 MDFX trade-off analysis model's progression evolution over time

5.2 Literature Review

In general, the more experience gained by the designer in the application of MDFX techniques, the earlier the conceptual and detailed design decision can be made and the higher the impact on overall life-cycle cost. Anderson (2000) and Coello (1999) discussed the complex and challenging problem in design decision making when trying to optimize constrained multiple objectives. The designer usually analyzes the optimized design decisions in terms of economic benefits over the entire machine lifecycle phases, and this is done by applying the concept of NPV and IRR aggerate metrics (Bendeković, 1993; Behrens and Hawranek, 1991). Significant research effort during the recent years was dedicated to the integration of business objectives early in the machine design stages. Saitou et al. (2005) established a survey of optimization techniques that can be implemented towards machine development problems, more specifically in excellence criteria (e.g., weight versus cost). Several researchers (Gu et al., 2002; Marston and Mistree, 1998; Wassenaar and Chen, 2001) have combined the engineering-related PDS and market-related attributes of machine design into a single excellence criterion that formulates the overall economic benefits of the decision-based-design (DBD) framework discussed by Hazelrigg (1998). However, the design decision problem utility functions formulation is still a topic for ongoing research. Michalek et al. (2006) proposed the framework for the overall utility function that coordinate, combine, and balance the machine design, manufacture and market problems. The design decision problem modeling and optimization of the objective functions receives little attention in MDFX research. Vucina et al. (2010) multi-criteria decision-making financial analysis model is described where the machine operational expenses and investment terms are embedded as main elements in the design decision objective functions during the conceptual and detailed machine development. Otto and Antonsson (1991) proposed an overall design preferences framework where trade-offs analysis and MDFX design strategies are investigated. A similar framework for flexible decision support system was also proposed by Olewnik and Lewis (2006). An elaboration of cost/performance trade-off analysis and optimization that can be adapted in the aircraft design decision feasibility evaluation was discussed by several researchers (Markish and Willcox, 2003; Harris, 2002). This reveals the importance of the trade-off analysis in the design decision-making process. Peoples and Willcox (2006) compared the performance versus the value-based design decisions by measuring the NPV metrics and by adopting the probabilistic and deterministic concepts to account for risk and uncertainty in the decision- making process. The NPV was also utilized as a design decision-making tool in the hydropower station conceptual design to maximize the return profits (Elíasson, 2000). Also, Georgiopoulos et al. (2002) described the model in which the expected value of NPV denoted by “the objective function” was calculated for an automotive design firm based on machine design variables and taking into account the trade-off metrics uncertainty.

DDSS are effective analytical models that aid designers in product cost estimation; hence, improved designer judgments at different levels of the design development estimation process) Kingsman and De Souza, 1997). They developed cost estimation model incorporating expert rules in the machines manufacturing companies that adapt make-to-order (MTO) systems which focus on customer needs and emphasize the application of design cost estimation rules. In this research and to incorporate the design experts' technical experience, AI philosophy is adopted to represent the designer's knowledge as input to the design decision-making model. Shehab and Abdalla (2002) proposed a knowledge-based cost estimation model for machines in the early design development stages. Similarly, Luong and Spedding (1999) described a knowledge-based model that integrate cost estimation into process planning. Thus, to represent DDSS more effectively and to eliminate the uncertainty in the trade-off heuristic data, designers are encouraged to represent the MDFX design decision-making problem by taking advantage of the expert system (ES) in the optimization algorithm.

Evolutionary algorithms are considered the best fit for solving multiple conflicting objectives in design design-making MDFX optimization problems (Kinnear et al., 1999). Since 1985, researchers developed various evolutionary methodologies to solve multi-objective optimization problems by concurrently searching for multiple solutions sets in a single run. One branch of evolutionary algorithms is genetic algorithms. The latter is superior searching algorithms that can be adapted in a variety of optimization mechanism where the survival-of-the-fittest strategy and genetic operators abstracted from nature are combined (Goldberg, 1989). The early discovery of GAs was made by Holland in the 1960s and further described in detail by Goldberg (Feng et al., 1997). Nowadays, GAs is applied in many engineering fields especially in machine design optimization problems (Michalewicz, 1996; Osman et al., 2006). Srinivas and Deb (1994) concluded that GAs are efficient and powerful searching algorithms that require a little information about the optimization problem which grants them the superiority over other optimization methods which lack features such as continuity, linearity, derivatives, etc. Also, GAs is an effective analytic tool mitigated with stochastic search technique that is applied to solve complicated and large problems using evolutionary and genetic principles (2007). Lee and Kim (2007) concluded that GAs, which follows the principles of evolution, demonstrates great potential in combinatorial optimization and this can be achieved when better chromosomes trade their properties with next genes in the generation and this is improved progressively over computational time (Li et al., 1998). As any other optimization method, GAs have some disadvantages that can be summarized by several researchers (Preechakul and Kheawhom, 2009; Zhang et al., 2009) in their papers, where they list some drawbacks such as initial parent's populations are generated randomly, the optimal solution is not guaranteed, and search efficiency becomes low after each mutation process. In his book, Goldberg (1989) described the main GAs theory where a randomly evolved population of certain species will begin to adapt to its environment after many generations in a well-known concept of the survival of the fittest. In the genetic game, the winner of applying different parameters is the optimal solution. These parameters are genes of chromosomes represented by binary strings where the better chromosome is the nearest one the optimal solution. Each solution is represented by a single chromosome which can be better or worse in the initial population. This population represents a part of the problem solution space defined as a search space where each feasible solution can be related to a distinct chromosome that is randomly chosen to form the initial parent populations. Next, solutions are selected based on their competitiveness rate through intensive computations measured by an objective fitness function. To simulate the continues process of offspring generations, best parent chromosomes mate to produce the best child or offspring genes that replace the least fit members in the parent population. Man et al. (1997) proposed some hints when users select the number of populations. After that, the genetic algorithm continues its searching process by applying the next stages such as such as selection, crossover, and mutation sequentially to acquire the new generation which is expected to be better in quality than its previous. The process mentioned above keeps evolving in which better solution take over unfit solution until the termination criteria are met and the final solution is generated. Figure 5.4 illustrates the main flowchart of the universal GAs operations.

In general, any multi-objective GA framework must have five main components (Goldberg, 1989):

(1) a genetic representation of solutions to the problem,

(2) initial population of solutions,

(3) an evaluation fitness function to rate solutions,

(4) reproduction genetic operators and definition of the GA parameters (max population size, string size, crossover probabilities, termination set point, etc.),

(5) a method to continuously update the latest Pareto solutions.

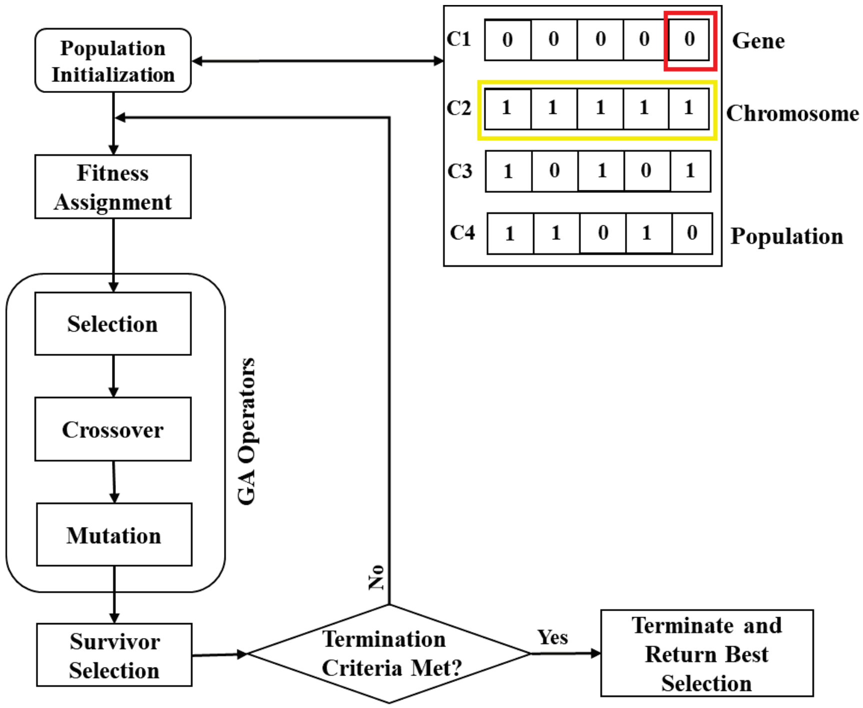


Figure 5.4 Genetic algorithm universal structure

New chromosomes are generated for the solution by implementing the crossover and mutation mechanisms. During the crossover operation, the genetic patrimony of each parent chromosome is mitigated followed by a random mutation. The new gene or chromosome, which can be referred to as child or offspring, exchange superior characteristics from the parent chromosome then its survival probability increases, and it is pushed forward to the next iteration. This process continues over the search running time until the algorithm hits the termination criteria and the solution will be considered the optimal solution due to its relative closeness. It is crucial in crossover operation to mate the parent's chromosomes pairs to generate child genes. Therefore, to accomplish this task, the user must specify the type of crossover operation required such as multi-point, single-point, uniform, half uniform, cut and slice, etc. In this research, the single-point crossover operation type is implemented with the probability of crossover (*Pc*) where two chromosomes break out from the randomly selected point and trade their information with the exchanged chromosomes. This will result in two chromosomes where the initial one referred as parent chromosome and the second one resulted from the exchange referred as offspring chromosome as illustrated in Figure 5.5. If *Pc*=0, then crossover operation will not occur and thus offspring's traits will be like that of parents. As mentioned before, mutation is the successive operation in GAs, where a gene is replaced with a randomly selected binary number (*RN*) between (0, 1) and within the limits of the parameter (Gen, and Cheng, 2000). User inputs the mutation probability (P_m) constant which creates the mutation process only if it is less than *RN*. The crossover and mutation operations are followed by evaluation step, in which solutions are validated against the user's expectations and selection criteria. At last, the algorithm terminates itself by activating one of the sets of conditions as described below:

(1) Terminate the algorithm after a max number of generations is reached;

(2) No significant improvement in the objective function output;

(3) Objective function reached a predetermined value.

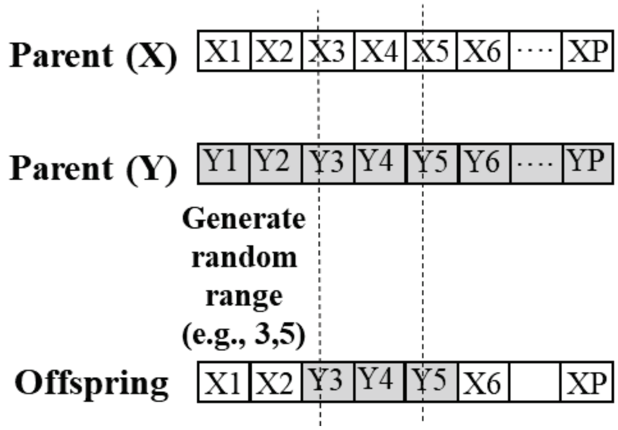


Figure 5.5 GA crossover operation

GAs optimization model starts its process by randomly generating genes from the parent population, but this takes place after GA parameters are defined, chromosome structure is formed, and fitness functions are set up. Population size (P_{size}) is the number of chromosomes in a solution set which is an important constant that influences the solution processing time and the optimum solution itself. In norm, the larger P_{size}, the larger the processing time and the probability of finding the optimal solution. Usually, the user specifies P_{size} which is an input to the GAs model and where each chromosome is evaluated against the fitness function.

A general multi-objective optimization problem (MOOP) can be defined as a vector function that connects *m* decision variables to *o* objectives as formulated in Equation (5.2.1) (Fonseca and Fleming, 1995; Steuer, 1986).

$$\text{MOOP:} Min/Max\ F(y) = \left(f_1(x), f_2(x), \ldots\ldots, f_o(x)\right) \tag{5.2.1}$$

Such that x=$(x_1, x_{2,\ldots\ldots}, x_n)$ $\in$ PS

y=$(y_1, y_{2,\ldots\ldots}, y_n)$ $\in$ OS where x is the decision vector, PS is the parameter space, y is the objective vector, OS is the objective space, $\left(f_1(x), f_2(x), \ldots\ldots, f_o(x)\right)$ are the o objective functions, $(x_1, x_{2,\ldots\ldots}, x_n)$ are the n optimization parameters, and PS,OS $\in R^n$ is the solution space.

All decision vectors (x) that are assigned to objective vectors where no slight improvement can be noticed without degradation of one of them are referred to as the MOOP solutions set. The previously mentioned vectors are known to be the Pareto optimality vectors. Mathematically, Pareto optimality concept can be explained as follows: Assume a maximization problem with two decision vectors $x,y \in PS$. Then, x is said to dominate over y or $x > y$ iff

$$\forall i \in \{1,2, \ldots\ldots, n\}: f_i(x) \geq f_i(y)$$

$$\exists j \in \{1,2, \ldots\ldots, n\}: f_j(x) > f_j(y)$$

Moreover, in this study x is considered to overcome y $(x \geq y)$ iff $x > y$ or $f_i(x) = f_i(y)$. All decision vectors (x) that are not dominated by any other ones of a given solution set are referred to as non-dominated points. The non-dominated decision vectors within the search space are referred to as Pareto optimal and together they form the Pareto-optimal set or Pareto-optimal front. The below interpretations regarding Pareto-optimal front are extracted from Ringuest and Rinks (1987); Laumanns et al., 2002.

Interpretation 1 (feasible solution): A feasible solution is one that satisfies all optimization problem constraints, known as, the set of all x that satisfy $x \in S$ which frame the feasible space.

Interpretation 2 (Pareto optimal solution): x^* is considered to be a Pareto optimal solution of MOOP if no another feasible x exists such that, $f_i(x) \leq f_i(x^*)$ for all i = 1, 2, . . . , n and $f_o(x) \neq f_o(x^*)$ for a min of one objective function f_o.

To optimize the multiple objectives from the MDFX trade-off model concurrently, a Pareto front (PF) approach is implemented in this research. PF can be different from traditional optimization methods by its tendency to eliminate conflicts between MDFX trade-off objectives (T, C, Q). In this research, an optimization model is described to optimize MDFX trade-off analysis between three main objective functions (C, T, Q) under different scenarios. Juan et al. (2006) concluded that Pareto optimality concept is the best to utilize in this problem if mixed with GAs. The main concept behind PF is that no solution is known to be totally dominated over the other solutions in all performance measurements aspects because these solutions have a higher probability to be in the next generation due to their relatively high fitness values. Laumanns et al. (2002) describes that as population evolution progress, its Pareto optimal zone converges. The solutions within the search space that cannot improve their vector components simultaneously are donated as non-dominated solutions. Figure 5.6 illustrates the acceptable Pareto optimal solutions. In literature, there are several methods approaches to rank and select the Multi-Objective Genetic Algorithms (MOGAs) such as Aggregating functions, Population-based, and Pareto-based. Furthermore, Coello et al. (2007) stated that extensive research has been undertaken in the past few years for the Pareto-based MOGAs (e.g., VEGA model proposed by Schaffer and Grefenstette (1985), PAES model proposed by Knowles and Corne (2000) and SPEA model proposed by Zitzler and Thiele (1999) etc..

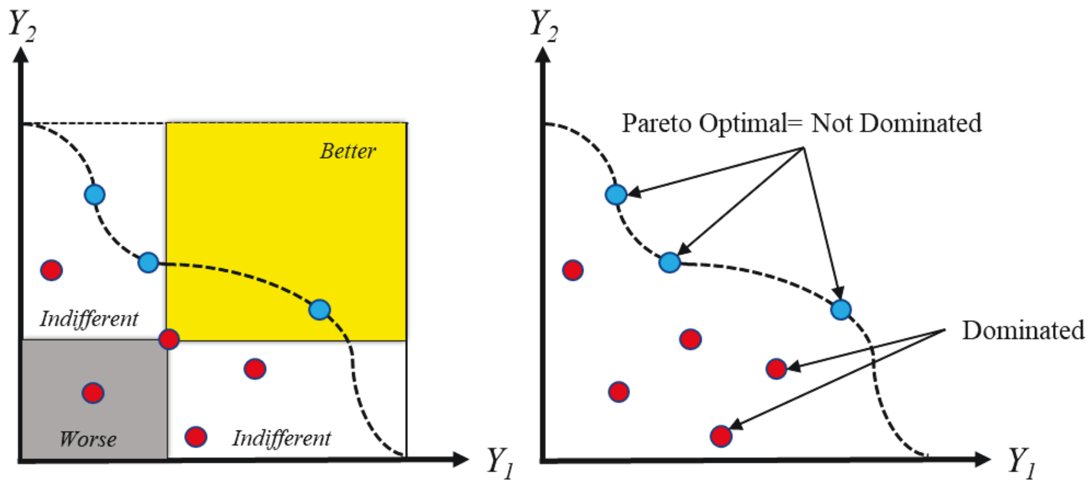
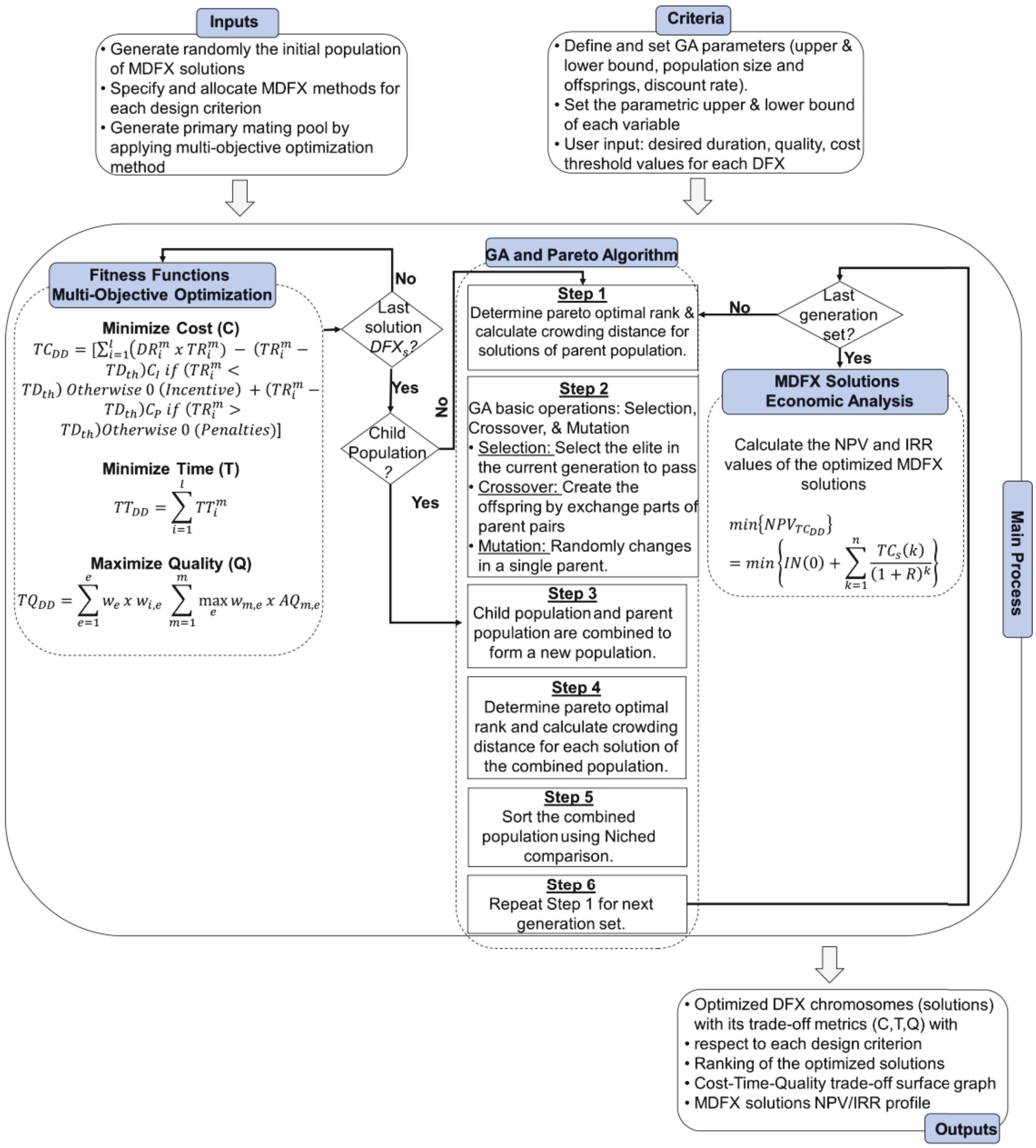


Figure 5.6 Illustration of Pareto optimally concept

5.3 Problem Description

To solve the MDFX decision-making problem with *i* design criteria and *m* DFX methods, the matrix-based (*i* x *m*) requires large space memory and more computational time during the evolution process to generate the optimal solutions. For this purpose, GAs is implemented with Pareto optimality concept in a hybrid model to generate the best fit MDFX techniques that pass the trade-off fitness functions evaluation and deemed to be non-dominated solutions represented as PF. Chromosomes structure was altered to preserve the feasibility of crossover and mutation operations in the proposed iterative process. Moreover, to eliminate the large solution space, the GAs is constrained by a finite-sized solution boundary. Thus, the main objective of this research is to propose an MDFX trade-off optimization model based on the hybridization concept of GAs and PF which in return supports the machine design development by reducing time and cost metrics while increasing the quality performance metrics as illustrated in Figure 5.7. This model will aid designers in the machine design industry sector in: (1) generating optimal MDFX utilization solutions that optimize the trade-off metrics; (2) financial evaluation of the generated solution set based on NPV and IRR concepts; and (3) representing the trade-off metrics in a visualized graphical form to support designers in the evaluation process of multiple utilization solutions on machine development.



$$TC_{DD} = [\sum_{i=1}^{l}(DR_i^m \ x \ TR_i^m) - (TR_i^m - TD_{th})C_I \ if \ (TR_i^m < TD_{th}) \ Otherwise \ 0 \ (Incentive) + (TR_i^m - TD_{th})C_P \ if \ (TR_i^m > TD_{th}) Otherwise \ 0 \ (Penalties)]$$

$$TT_{DD} = \sum_{i=1}^{l} TT_i^m$$

$$TQ_{DD} = \sum_{e=1}^{e} w_e \ x \ w_{i,e} \sum_{m=1}^{m} \max_e w_{m,e} \ x \ AQ_{m,e}$$

$$min\{NPV_{TC_{DD}}\} = min\left\{IN(0) + \sum_{k=1}^{n} \frac{TC_s(k)}{(1+R)^k}\right\}$$

Figure 5.7 Proposed MDFX trade-off analysis model implementation framework

5.4 Proposed Hybrid Genetic and Pareto Optimality Algorithm

In this section, an intelligent hybrid algorithm combining GA and Pareto concepts to solve the MDFX selection problem based on trade-off analysis followed by financial evaluation for the solution set based on NPV/IRR concepts is developed. For each chromosome of the GA algorithm, three objective functions are required to be evaluated, and the Pareto optimality selecting approach is utilized to evaluate different combinations of the three evaluated objective functions. The DDSS proposed flowchart for the MDFX trade-off analysis model is represented in Figure 5.8 and will be further explained in the next sections.

The main procedure for the hybrid model that is used in this research can be summarized below:

(1) Defining GAs parameters: Pc, Pm, and RN.

(2) Randomly initializing and generating the initial parent population composed of DFX techniques and design criteria.

(3) Evaluating the multi-objective fitness functions for each chromosome (DFX) based on T, C, and Q performance metrics.

(4) Grouping and sorting solution sets then ranking them based on the Pareto non-dominated selecting approach to form the initial chromosomes mating pool.

(5) Initiating the crossover operation mechanism for each pair of chromosomes with Pc.

(6) Initiating the mutation operation mechanism for each chromosome with Pm.

(7) The current population is replaced by the solution mating pool.

(8) Designer evaluates the solutions based on the objective function.

(9) If the termination criterion is reached, then finish. Otherwise, go to step 5 and repeat.

(10) After the final solution set is generated, financial evolution takes place and NPV/IRR metrics are calculated for each solution in the final set.

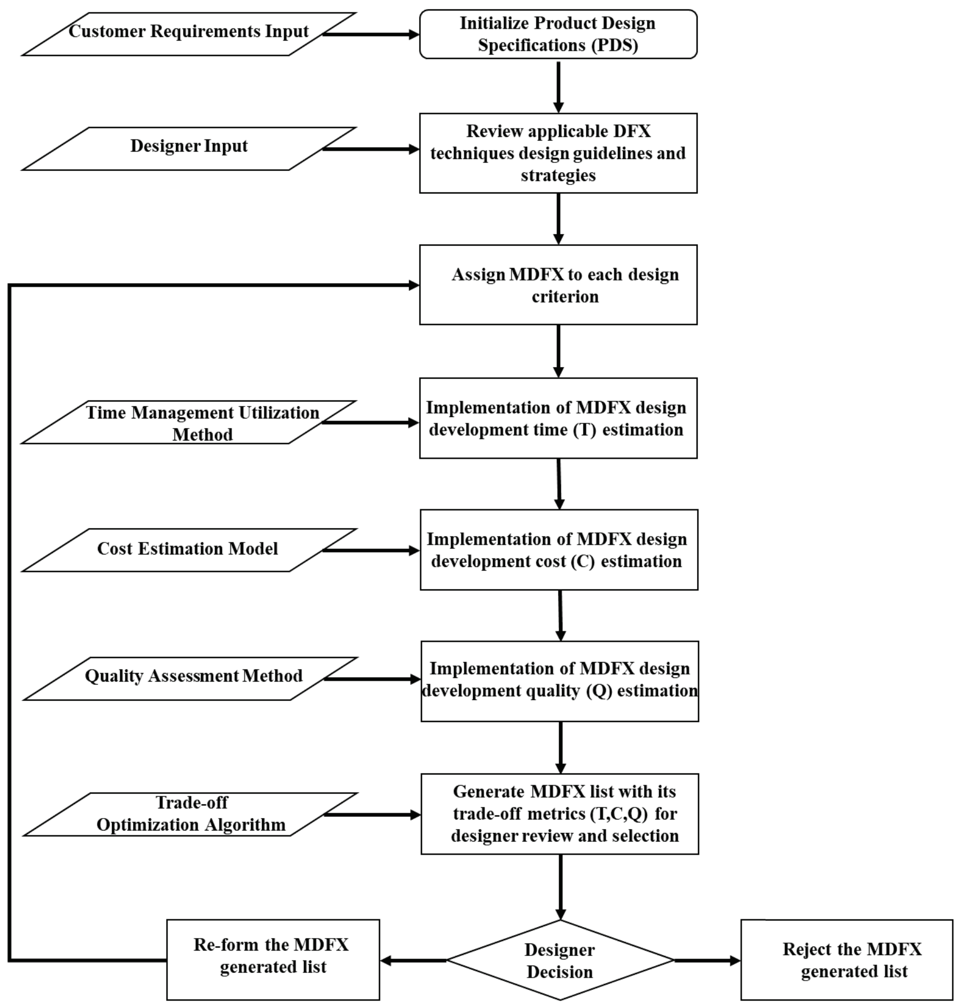


Figure 5.8 Proposed DDSS flowchart to MDFX trade-off analysis

5.4.1 Phase 1: GA algorithm model formation

The data structure of a genetic algorithm that represents the problem solution in coding space is composed of chromosomes which can be further broken-down to multiple genes each representing a variable. The content of the chromosome is exchanged with the value of the variable. In order to represent the appropriate structured design of the chromosome, the proposed approach is considered. Where each chromosome consists of a sequence of *i* sub chromosome (*i* is the number of PDS) and a matching set of *m* sub-chromosome (*m* is the number of DFX). All chromosomes are randomly generated such that their total summation is equal to $\sum_{m=1}^{m} C_{im}$ for each sub-chromosome *i*. Therefore, the generated chromosomes are randomly extracted illustrated in Figure 5.9, such that:

$x_{11} + x_{11} + \ldots.. + x_{1m} = DC_1$;

$x_{21} + x_{21} + \ldots.. + x_{2m} = DC_2$;

$x_{i1} + x_{i2} + \ldots.. + x_{im} = DC_m$.

where,

DC = design criterion.

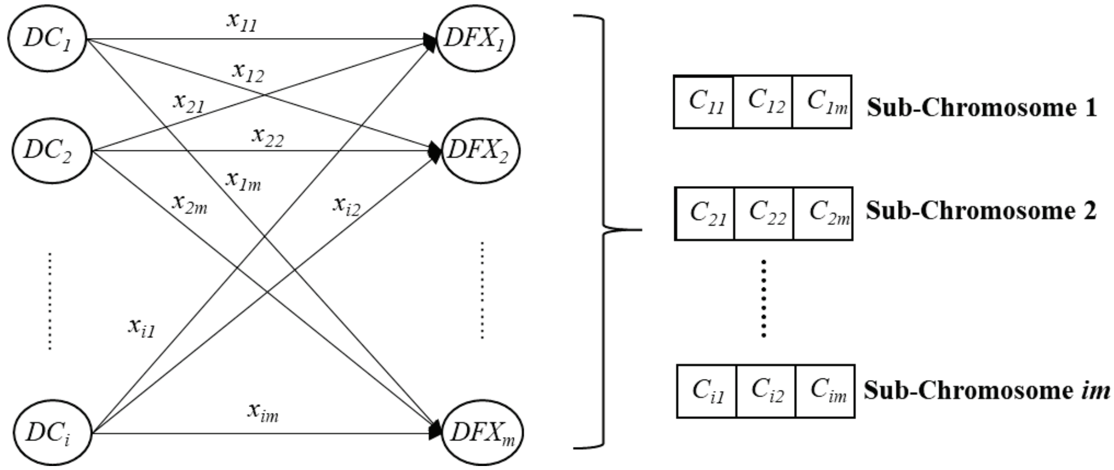


Figure 5.9 Illustration of MDFX chromosome's representation

All generated chromosome are feasible solutions and the chromosome length is = *m x i* as represented in (5.4.1.1).

$$\sum_{i=1}^{i} \sum_{m=1}^{m} C_{im} = \sum_{i=1}^{i} DC_i = \sum_{m=1}^{m} DFX_m \tag{5.4.1.1}$$

A standard population size $P_{size} = N$ can be evaluated based on non-dominated Pareto concept where a set of parent population chromosomes having o ($o > 1$) objective function values. Steuer (1986) described the procedure of the Pareto algorithm in five steps that can determine the non-dominated set of the solution as follows:

Step 0: Start with $i = 1$.

Step 1: For all $m = 1, 2, \ldots, N$ and $m \neq i$, compare the generated solutions x^i and x^m for domination.

Step 2: If for any m, x^i is dominated by x^m, mark x^i as 'dominated'.

Step 3: If $i = N$ is reached, then all other solutions in the set are acceptable, return to *Step 4*, else increment i by one and begin again from *Step 1*.

Step 4: All generated solutions that are not marked 'dominated' are tagged as non-dominated solutions.

Step 5: Generate a list of non-dominated final solutions.

In GAs, the reproduction or selection stage of chromosomes can be related to the survival of the fittest meaning that the chromosomes with the high value relative to the objective function are preserved and propagate from generation to another in the search for an optimal utilization solution. The main function of the selection operator is to maintain and improve the population quality by enabling the highest value chromosomes to mate and get cloned into the next generation. Selection directs the algorithm search operation to discover more regions with high-quality chromosomes in the search space. Laumanns et al. (2002) and Osman, et al. (2006) proposed a random-weighted method to generate a random search direction towards PF. Assume that the designer would like to maximize an objective function (*o*), then the weighted objective sum can be represented in Equation (5.4.1.2).

$$f(r) = w_1 f_1(r) + \cdots + w_o f_o(r) = \sum_{i=1}^{o} w_i f_i(r) \qquad (5.4.1.2)$$

where r= a string (i.e. individual), $f(r)$= combined fitness functions, $f_i(r)$= i^{th} objective function, and $\{w_i| \sum_{i=1}^{o} w_i = 1\}$ = constant weight for $f_i(r)$.

In this research, the roulette wheel selection mechanism in the reproduction operation is utilized (Goldberg, 1989). This method is based on the probability value of variable selection which is proportional to the population individual over total fitness ratio. This ratio is calculated using Equation (5.4.1.3).

$$P(r) = \frac{f(r) - f_{min}(\Phi)}{\sum_{x \in \Phi}\{f(r) - f_{min}(\Phi)\}} \tag{5.4.1.3}$$

Where,

P(r)=is the selection probability of a string *r* in a population $\boldsymbol{\Phi}$ and $f_{min}(\Phi) = Min\,\{f(r) |\, r \in \Phi\}$.

Unlike other searching techniques, GAs follows a searching protocol where the parameters are coded, and the transition rules are probabilistic. In the beginning, designers define the main four GA parameters: (1) Crossover probability parameter (P_c); (2) Mutation probability parameter (P_m); (3) Population size parameter (P_{size}); (4) Maximum number of generations (T_{max}). In this research, the arithmetic crossover mechanism is implemented, and the application of a crossover operation is limited to its P_c. If P_c is too small then the searching efficiency will be low; however, if P_c is too big then the structure destruction of a high-quality solution will be inevitable. The main objective of the crossover stage in GA is to trade information and properties between dual parents' chromosomes in order to produce dual child chromosomes for the next population set. In this research, a modified uniform crossover with P_c = 0.5 (P_c value is generally between 0.5 and 0.8, Goldberg (1989)) is used in either parents' populations. Usually, the mutation operator value is variable because the process of replacing one genotype by another one is random. The process starts with the selection of random gene from i^{th} sub-chromosome set and then replaced by a random integer within the interval [0, DC_i] such that the sum of all genes in the same set is equal to the i^{th} *DFX* $\sum_{m=1}^{m} Gene_{im} = DC_i$. P_m is considered an important factor in the process of extending population diversity. If P_m is too low then the induction of new gene will not be possible; however, if P_m is too high then the genetic evolution decayed into local random search. In this research, a modified uniform mutation with P_m = 0.02 (P_m value is generally between 0.001 and 0.1, Goldberg (1989)) is utilized. The efficiency and quality of the generated solution is directly linked with the parameter P_{size}. If P_{size} is too low then there are not enough sample and useful results cannot be concluded; however, if P_{size} is too high then searching computation time will exceed its limit. In this research, P_{size} = 50 (P_m value is generally between 10 and 100, Goldberg (1989)) is considered and T_{max}= 500.

First, the model initiates the GAs searching and optimizing operation after GA parameters (defined above) are defined by the user. The machine design development parameters include: (1) upper and lower bonds (constraints) of fitness functions; (2) design development completion desired duration; (3) design development quality and cost cut-threshold values; and (4) available DFX techniques for each design criteria and their expected impact on the design development quality, time, and cost. Note that the string size is equal to the total number of design criteria included in the analysis of MDFX. After that, the GA algorithm starts in generating random solutions DFX_s=1 to S DFX_s for the initial population PP_1 in the first generation (gs=1). These solutions represent an initial MDFX utilization set that can be allocated to each design criterion in the PDS. Then this set is further evolved to output the optimal MDFX utilization set for each design criterion in the PDS where the trade-off among MDFX cost, time, and quality metrics are optimized.

5.4.2 Phase 2: Multi-objective optimization fitness function

In this section, the model development stage is explained to formulate an intelligent, automated, and robust MDFX optimization trade-off model that supports advanced cost-time-quality performance metrics analysis. The robust optimization model is structured to cover the following main objectives: (1) Identifying the primary decision variables in the MDFX utilization problem; and (2) formulating the MDFX trade-off objectives into fitness functions to optimize the cost, time, and quality metrics.

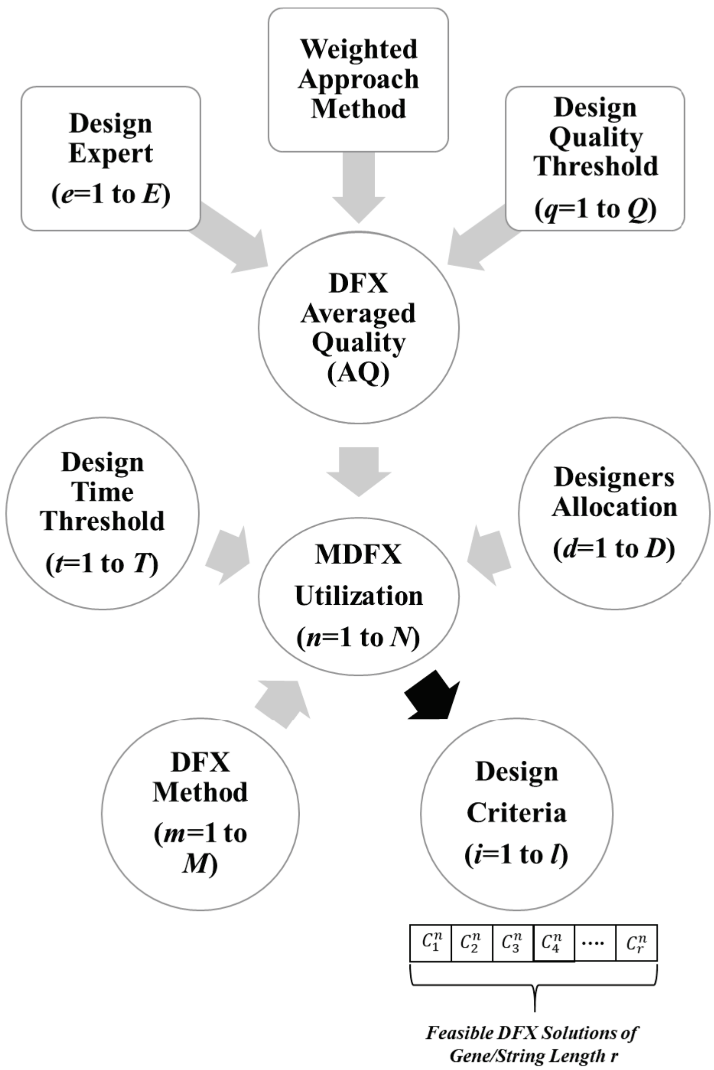


Figure 5.10 MDFX trade-off metrics optimization model

The proposed model is designed to include all the previous determined decision variables that may affect the machine design development cost, time, or quality. These variables are:

(1) DFX method (m), which indicates the different DFX techniques available; (2) designers' allocation (d), which represents designers' team based on their relative technical expertise per DFX; and (3) design time threshold (T_{th}), which represents allowable design time per DFX as shown in Figure 5.10. The proposed model mixes these decision variables (m, d, T_{th}) into a prime decision variable referred to as MDFX utilization (n), as illustrated in Figure 5.10. However, designers are faced by two major obstacles if they want to utilize this model in searching for the optimal MDFX utilization set which are: (1) how much is the computational time for this model; (2) the vast possible sets of MDFX make the solution space large (N^l) to search in. Thus, to overcome these challenges, the model dictates three objective functions to execute the evaluation process of MDFX trade-off metrics in machine design development. In this research, the formulation of a simplified design development total cost (TC_{DD}) is proposed to optimize the MDFX decision-support hybrid model, which considers only the design costs and neglects some variables of the economic analysis model as shown later. The main purpose here is to effectively evaluate the cost, time, and quality metrics of each feasible solution DFX_s in generation gs in order to determine the fitness of the MDFX solution. This fitness determines the chromosome likelihood of survival and probability of reproduction for each solution in following generations. The fitness functions (C, T, Q) for each solution is described below.

<u>*Step 1:*</u> Calculate the total design development cost (TC_{gs}^{s}) for solution (s) in generation set (gs) where gs = generation set from gs=1 to Gs, which consists of design costs as shown in Equation (5.4.2.1).

Minimize total design development cost:

$$TC_{DD} = \sum_{m=0}^{m} TC_i^m = [\sum_{i=1}^{l}(DR_i^m \, x \, TR_i^m) - (TR_i^m - TD_{th})C_I \; if \; (TR_i^m < TD_{th}) \; Otherwise \; 0 \; (Incentive) + (TR_i^m - TD_{th})C_P \; if \; (TR_i^m > TD_{th}) Otherwise \; 0 \; (Penalties)] \quad (5.4.2.1)$$

where TR_i^m= required development time in days of a design criterion (*i*) using DFX method (*m*); DR_i^m= daily cost rate for designer in $/day of DFX method for a design criterion. Also, TR_i^m is the total development time of a design criterion under DFX method while TD_{th}, C_I, and C_P, are denoted as the total design time threshold, incentive value, and penalty value, respectively and they are user-defined constants. Therefore, to determine if the selected chromosome is the best fit, it fitness value must be smaller then other chromosomes in the same set where the smaller value represent less design development total cost.

<u>*Step 2:*</u> Calculate design development time (TT_{gs}^s) for solution (*s*) in generation set (*gs*), which is the summation of the total design development time of all MDFX assigned to the generated solution as represented in Equation (5.4.2.2).

Minimize total design development time:

$$TT_{DD} = \sum_{i=1}^{l} TT_i^m \quad (5.4.2.2)$$

where TT_i^m=duration of design criterion (*i*) using DFX method (*m*).

<u>*Step 3:*</u> Calculate design development quality (TQ_{gs}^s) for solution (*s*) in generation set (*gs*) as shown in Equation (5.4.2.3) using the weighted approach method.

Maximize total design development quality:

$$TQ_{DD} = \sum_{m=1}^{m} TQ_i^m = \sum_{i=1}^{l} wv_i \sum_{m=1}^{m} \max_e w_{m,e}\ x\ AQ_{m,e} =$$

$$\sum_{e=1}^{e} w_e\ x\ w_{i,e}\ \sum_{m=1}^{m} \max_e w_{m,e}\ x\ AQ_{m,e} \tag{5.4.2.3}$$

where w_e =weight of design expert (e) based on the number of years of technical experience as shown in Table 5.1, $w_{i,e}$=weight of design criterion (i) by design expert compared to other design criterion in the PDS, wv_i =product weighted value of w_e and $w_{i,e}$, $w_{m,e}$=max weight of DFX method (m) by design expert relative to other DFXs, and $AQ_{m,e}$ = design experts averaged quality percentage with respect to DFX method relative to its effectiveness in reducing machine design lifecycle when using MDFX utilization (n).

Table 5.1 Design expert's weight (w_e)

Experts Weight (0-1)	Expert Design Experience (Years)
0.2	$5 \leq Y \leq 10$
0.3	$10 \leq Y \leq 15$
0.5	$15 \leq Y \leq 20$

5.4.3 Phase 3: MDFX population generation based on Pareto-GA concept

Based on the hybridization between GAs and Pareto optimality, the model can solve and optimize the C, T, and Q performance metrics of MDFX trade-off analysis. Consider that many feasible solutions points are located and plotted graphically on the visualization graph to form the final trade-off curve as shown in Figure 5.11. After plotting the initial versus the final trade-off curve, the algorithm can calculate using Equations (5.4.3.1, 5.4.3.2, and 5.4.3.3) the following: minimum distance (d_{min}) between the curve segments and parent points, the fitness values (f_i), and the selection probability (P_s) for each (x,y,z) point in the parent population set (Goldberg, 1989).

$$f_i = d_{max} - d_{min} \quad P_s = \frac{f_i}{\sum_{i=1}^{n} f_i} \tag{5.4.3.1}$$

$$d_{max} = \sqrt{(T_i - T_n)^2 + (C_i - C_n)^2 + (Q_i - Q_n)^2} \quad (5.4.3.2)$$

$$d_{min} = \sqrt{(T_i - T_j)^2 + \left(C_i - C_j\right)^2 + \left(Q_i - Q_j\right)^2} \quad (5.4.3.3)$$

Where d_{max} is the maximum d_{min} in the generation. The closer the distance to the tradeoff curve, the more fit the chromosome will be.

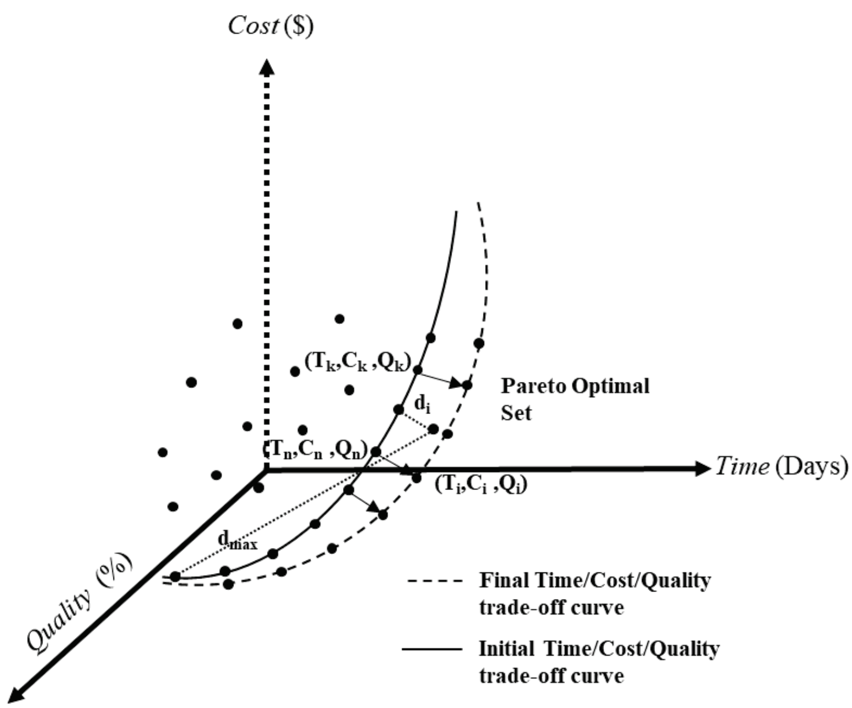


Figure 5.11 Pareto set for multi-objective optimization

The only difference of fitness function between cost, time, and quality priorities is the limitation function. The cost fitness function is constrained under the design development cost range of designers' decision, which can be represented in Equation (5.4.3.4).

$$LC_{min} \leq TC_{DD} \leq LC_{max} \quad (5.4.3.4)$$

Where LC_{min}, LC_{max} are lower and upper boundaries of cost, respectively.

Whereas, the time fitness function must be constrained over the design development time target (TD_t) of the designer's decision and the design development time threshold (TD_{th}) determined by the system, as shown in Equation (5.4.3.5).

$$TD_{th} \leq TT_{DD} \leq TD_t \tag{5.4.3.5}$$

While, the quality fitness function must be constrained over the design development averaged quality ($AQ_{m,e}$) of the designer's decision and the design development quality threshold (Q_{th}) determined by the system, as shown in Equation (5.4.3.6).

$$AQ_{m,e} \leq TQ_{DD} \leq Q_{th} \tag{5.4.3.6}$$

There are three types of the population that are considered in each generation: (1) parent population; (2) child population; and (3) combined population. For each generation set (*gs*), two-parent populations (PP_{gs}) are mated together to produce a child population (CP_{gs}). Child population will then present new solutions set by reordering and randomly allocating fractions of the generated solutions from the parent population. After that, the newly formed child population is mitigated with the parent population to form an expanded solution set for current generation referred to as combined population (N_{gs}). The traits of the combined population are compared, and a list of best-fit solutions is generated and forwarded to the next iteration as a parent population (Laumanns et al., 2002).

The computational procedure of GA can be described in six steps (Mitchell, 1998; El-Rayes and Kandil, 2005).

Step 1: Determine the Pareto optimal rank and calculate the crowding distance for each solution (DFX_s =1 to DFX_s S) by grouping and ranking the solutions from the parent population according to their PF dominance on other solutions, where the best-fit solution can be tagged ‘dominated’ if it shows its superiority over other solutions considering all optimization functions simultaneously.

Step 2: Create new child population using the basic GA operations of selection, crossover, and mutation. The purpose of the selection operation is to selects the chromosomes that will pass the reproduction process, by distinguishing the chromosomes that have higher optimal ranks and larger crowding distances. While, the crossover operation at a randomly predetermined point switch each pair of the selected chromosomes and exchange the variables embedded in its strings, resulting in two new chromosomes as illustrated in Figure 5.5 and described in Figure 5.12. Finally, the mutation operation changes randomly one of the variables values in the coded string to trigger deviation and to eliminate the existence of the premature convergence to the local optima (Golberg, 1989).

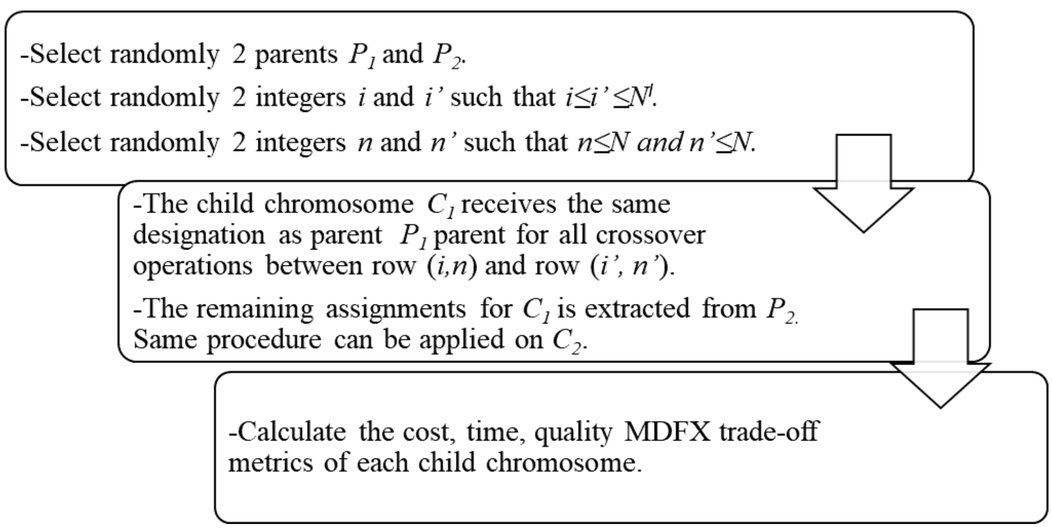


Figure 5.12 GA crossover operation algorithm

Step 3: Child population and parent population are combined to generate a new combined population of size 2*S* DFX_s which acts as a vessel for the selected elite best-fit solutions.

These solutions are passed on to the consecutive generation so that the loss of their good qualities can be avoided (Laumanns et al., 2002).

Step 4: Repeat *Step 2* by determining the Pareto optimal rank and calculating the crowding distance for each solution (DFX_s =1 to 2S DFX_s) of the latest combined population.

Step 5: Using the niched comparison rule, the algorithm sorts the new generated combined population. This rule helps in selecting the solutions that have a higher Pareto optimal rank and in sorting up the solutions with the same rank. Finally, it selects the solutions with larger crowding distances.

Step 6: Retain the top DFX_s solutions to form the new parent population (PP_{gs+1}) of the next generation then repeat *Step 1*.

This iterative computation of the second and third steps of the algorithm progress until the algorithm reaches its termination set point. In this research, the termination set point is the max predetermined number of generations.

5.4.4 Phase 4: MDFX solutions economic analysis

In this research, the economic analysis model is developed based on MDFX trade-off total impact valuation as implemented in feasibility assessments and selection (Bendeković, 1993). The economic analysis of the generated solutions provides the designer by the MDFX aggregated metrics where all economic variables are considered in the decision-making process over the total lifecycle performance of the machine and where designer subjective judgment is eliminated. Therefore, the system adopts the NPV/IRR concept developed by Vucina et al. (2010) to highlight the economic value of implementing MDFX in the machine design development.

The design development net profit or loss (P_s) of each solution for a successive time period *(k)* can be expressed as in Equation (5.4.4.1).

$$P_s(k) = I(k) - A(k) - TC_s(k) - F(k) - T(k) \quad (5.4.4.1)$$

where I can be denoted as the design initial total allocated budget, A the corresponding amortization rate, TC_s the total cost of design development solution, F the design financial expenses, and T the relatives taxes. The design development net economic flows *(E_s),* which presents an integral measure of the design decision economic value relative to the solution, can be calculated by using Equation (5.4.4.2).

$$E_s(k) = I(k) - IN(k) - TC_s(k) - T(k) \quad (5.4.4.2)$$

where IN is the incremental investment into design activities. The net economic flows are related to the net financial (profit or loss) flows excluding the financial properties (such as F) and some net economic flow properties that may have a neutral impact in altering the economic potential of a specific solution. Alternatively, Equation (5.4.4.1 and 5.4.4.2) can be combined in Equation (5.4.4.3) to facilitate the economic analysis in this study.

$$E_s(k) = P_s(k) + A(k) - IN(k) \quad (5.4.4.3)$$

The NPV computation rule is illustrated in Equation (5.4.4.4).

$$NPV = \sum_{k=o}^{k} \frac{E_S(k)}{(1+R)^k} \quad (5.4.4.4)$$

where R denoted as the discount rate and k the number of successive time periods. The IRR indicator is the rate of discounting (R^*) that if applied, it turns the NPV value (Equation (5.4.4.4) to zero, which is computed iteratively in Equation (5.4.4.5).

$$IRR = R^* \Rightarrow NPV(R^*) = \sum_{k=o}^{n} \frac{E_S(k)}{(1+R^*)^k} = 0 \qquad (5.4.4.5)$$

The *NPV* interpretation is as whether the MDFX solution is good or bad to be applied in the machine design development. If NPV>0 then the cost of design spent in the early stages of the machine development will return its value in the future at later stages; therefore, it is a good solution. Contrary to NPV>0, NPV<0 is considered a bad solution and designers should be aware of implementing it since it will create conflicts and negative profit in the future. While NPV=0 can be interpreted as there is no difference in the value of the design cost spent now and the profit generated later.

The proposed hybrid decision support model uses the economic analysis as the last checkpoint for the generated solutions, Equations (5.4.4.4 and 5.4.4.5) imply that the design decision model depends on several parameters other than technical design variables. This can be related to the interactive relation between the designer and the financial environment (e.g., design development lifespan, discounting rate, taxation schemes, etc.) that can affect the optimization model. In general, to apply the NPV/IRR as a cost indicator towards the economic analysis of design decision, a unified cost objective function must be derived taking into consideration all the economic factors. Where the designer can oversee if the decision is economically trustworthy by measuring its optimality value with reference to C, T, and Q objective functions. Therefore, by combining Equations (5.4.3.

and 5.4.4.4), a resultant NPV/IRR objective function is formulated as shown in Equation (5.4.4.6).

$$min\{NPV_{TC_s}\} = min\left\{-I + IN(0) + \sum_{k=1}^{k} \frac{TC_{DD}}{(1+R)^k}\right\} \tag{5.4.4.6}$$

The main assumptions in Equation (5.4.4.6) for this research are as follows:

(1) no relative taxes and amortization terms are considered

(2) *I(k)*= the initial budget allocated for the design development

(3) *IN(0)*=investment, typically cost of design development usually between 0.05 and 0.2 from the solution total design cost.

where TC_s=total cost of design development solution.

5.5 Case Study

A preliminary analysis is performed to select and input the GA parameters values as shown in Table 5.1. Accordingly, a population size of 50 and a max number of generations of 500 are found suitable for this case study in order to better compromise between computational time and solutions diversity from the literature study. The proposed optimization model is implemented in the conceptual design of the mass timber automated processing center machine, as shown in Figure 5.13, to illustrate and demonstrate its capabilities and accuracy. Here, the designer main objective, before starting the machine conceptual design, is to select the best fit MDFX techniques that can be utilized against the design criteria with minimum design development cost and time but with maximum quality. For this purpose, twenty design experts are interviewed, and their results are grouped based on their number of years of design experience in to three groups A, B, and C. In each group, the answers from the experts interviewed are combined and the average results are selected as input data for the hybrid engine model as shown in Table 5.1 and Table 5.1. The case study consists of six design criterions, which forms the case study PDS, and six DFX methods under investigation. Each design criterion has several possible utilization solutions that can be used towards it (refer Table 5.1 and Table 5.1).

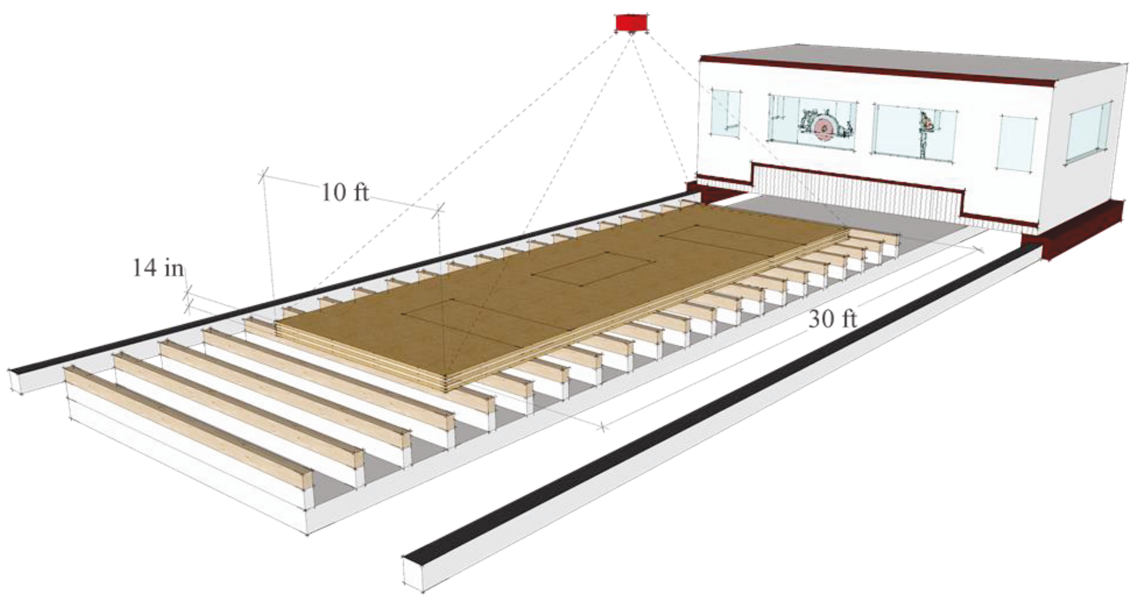


Figure 5.13 Mass timber automated processing center

For this case study, the preliminary estimation is an average of 4.4 MDFX utilization options to implement for each of the six design criterions in the conceptual machine design as shown in Table 5.1, which results in more than 1.2 billion (i.e., 3.2^{18}) possible MDFX combinations that can be implemented in machine design development. Each of these possible MDFX utilization solutions sets have a unique impact on machine design development; however, the main challenge in this study is how effective can the hybrid model search this large space of feasible solutions in order to find the optimal solutions sets and maintain the balance between MDFX trade-off performance metrics (cost, time, and quality). The daily incentive amount and the daily penalties amount of this case study are considered to be 100 \$/day and 50 \$/day respectively. While the expected lifespan (k) of the design decisions is 5 years, the design investment factor is 0.05, and the discounting rate is 0.2. The initial budget for the design development (I) was estimated to be \$7000.

The proposed GA-Pareto procedure is coded in the macro language of Solver, which is a Microsoft® Excel add-in program, that utilizes the evolutionary solving method analysis. The program is designed to find an optimal (maximum or minimum) value for multiple objective formulas or fitness functions subject to its constraints. The program adjusts the values in the decision variable cells to satisfy the limits on cost, time, and quality threshold constraints. After that, it produces the result that the designer requires for the objective function to make an informative decision. The use of Solver facilitates the implementation process since the search and optimization engine GA algorithms are built-in functions and are not programmed independently. The initial matrix for MDFX utilization options is created as shown in Table 5.1. The matrix first results regarding DFX trade-off performance metrics was listed in Table 5.1 where total design development cost, time, and quality for each DFX utilization option is calculated with relative to its design criterion. After running the hybrid engine, the search results come back as shown in Table 5.1 where the MDFX utilization solution was {1,6,5,4,3,2}. Meaning that if this solution was implemented by the designer in the machine design development towards the design criteria set, the cost of the design development will be \$6,900 with a duration of 30 days and quality of 61.73 %. However, the solution may not be the optimal one on the lifespan of the machine. Therefore, the solution is analyzed from an economic perspective based on

NPV/IRR financial concept to establish a money value understanding protocol to the designer to implement in the MDFX decision-making process as shown in Table 5.1. The IRR best compromise value is when NPV is equal to 0, for the first MDFX utilization option this was achieved at 0.7255%. The solution with the least NPV is the best solution that the designer should consider when maximizing the design decision value over the machine design development lifespan.

Table 5.2 GA case study initial parameters

Parameter	**Value**
r	5
P_c	0.5
P_m	0.02
RN	0,1
P_{size}	50
T_{max}	500
LC_{min}	\$6,000
LC_{max}	\$10,000
TD_t	28 days

Table 5.3 Design experts' details

Design Experts Group Data	**Design Experts Group A**	**Design Experts Group B**	**Design Experts Group C**
Weight of design expert (w_e)	0.5	0.2	0.3
Designer daily cost rate in \$/day (DR)	200	300	400
Required Design Time (R_{DT})	5	10	15

Table 5.4 Design criteria weights with respect to each design expert

	Design criterion weight with respect to each design expert $W_{i,e}$			**Weighted Value (wv_i) W_e x $W_{i,e}$**
Design Creation (i)	**Design Experts Group A**	**Design Experts Group B**	**Design Experts Group C**	

1	0.4	0.2	0.4	0.340
2	0.3	0.4	0.4	0.350
3	0.2	0.4	0.4	0.300
4	0.65	0.4	0.4	0.525
5	0.15	0.4	0.4	0.275
6	0.05	0.4	0.4	0.225

Table 5.5 Design for methods parent chromosomes

	#	**Design for method (*m*)**
Parent Chromosomes	1	Cost
	2	Assembly
	3	Manufacturing
	4	Maintainability
	5	Quality
	6	Robustness

Table 5.6 Design criteria parent chromosomes

	#	**Design Criteria (*i*)**
Parent Chromosomes	1	Product Cost
	2	Functionality
	3	Robustness
	4	Assembly
	5	Modularity
	6	Reliability

Table 5.7 DFX utilization options

								Design Experts Group -A		**Design Experts Group -B**		**Design Experts Group -C**				
i	***m***	***d***	**Effort (%)**	TD_{th}	Q_{th}	TR_{DT}	**DR $/day**	$w_{m,e}$	$Q_{m,e}$	$w_{m,e}$	$Q_{m,e}$	$w_{m,e}$	$Q_{m,e}$	wv_i	$tw_{m,e}$	$AQ_{m,e}$
1	1	A	100	8	95	5	$200	0.30	85	0.15	95	0.11	97	0.34	0.30	92
	2	B	100	10	90	10	$300	0.15	90	0.20	85	0.28	95		0.28	90
	3	C	100	12	85	15	$400	0.27	90	0.21	80	0.05	85		0.27	85
	4	A,B	50,50	14	80	7.5	$250	0.12	80	0.17	85	0.08	75		0.18	80
	5	A,C	50,50	16	75	12.5	$300	0.05	70	0.12	80	0.20	75		0.20	75
	6	B,C	50,50	18	70	15	$350	0.11	80	0.14	70	0.28	65		0.28	72
2	1	B	100	10	90	10	$300	0.15	90	0.20	85	0.28	95	0.35	0.28	90
	2	C	100	12	85	15	$400	0.27	90	0.21	80	0.05	85		0.27	85
	3	A,B	50,50	14	80	7.5	$250	0.12	80	0.17	85	0.08	75		0.18	80
	4	A,C	50,50	16	75	12.5	$300	0.05	70	0.12	80	0.20	75		0.20	75
	5	B,C	50,50	18	70	15	$350	0.11	80	0.14	70	0.28	65		0.28	72
	6	A	100	8	95	5	$200	0.30	85	0.15	95	0.11	97		0.30	92

3	1	C	100	12	85	15	$400	0.33	80	0.24	85	0.07	75	0.30	0.33	80
	2	A,B	50,50	14	80	7.5	$250	0.18	70	0.20	80	0.10	75		0.21	75
	3	A,C	50,50	16	75	12.5	$300	0.11	80	0.15	70	0.22	65		0.22	72
	4	B,C	50,50	18	70	15	$350	0.17	85	0.17	95	0.30	97		0.30	92
	6	A	100	8	95	5	$200	0.21	90	0.23	80	0.30	85		0.30	85
4	1	A,B	50,50	14	80	7.5	$250	0.18	70	0.20	80	0.10	75	0.52	0.21	75
	2	A,C	50,50	16	75	12.5	$300	0.11	80	0.15	70	0.22	65		0.22	72
	3	B,C	50,50	18	70	15	$350	0.17	85	0.17	95	0.30	97		0.30	92
	5	A	100	8	95	5	$200	0.21	90	0.23	80	0.30	85		0.30	85
	6	B	100	10	90	10	$300	0.33	80	0.24	85	0.07	75		0.33	80
5	1	A,C	50,50	16	75	12.5	$300	0.15	80	0.22	70	0.28	65	0.27	0.28	72
	2	B,C	50,50	18	70	15	$350	0.21	85	0.24	95	0.36	97		0.36	92
	3	A	100	8	95	5	$200	0.40	85	0.25	95	0.19	97		0.41	92
	6	B	100	10	90	10	$300	0.22	70	0.27	80	0.16	75		0.28	75
6	1	B,C	50,50	18	70	15	$350	0.19	85	0.20	95	0.35	97	0.22	0.36	92
	3	A	100	8	95	5	$200	0.23	90	0.26	80	0.35	85		0.36	85
	4	B	100	10	90	10	$300	0.35	80	0.27	85	0.12	75		0.36	80
	5	C	100	12	85	15	$400	0.20	70	0.24	80	0.15	75		0.24	75

Table 5.8 DFX trade-off metrics values

i	m	TC_i^m ($)	TT_i^m (days)	TQ_i^m (%)
1	1	$1,150	5	9.42
	2	$3,000	10	8.57
	3	$6,300	15	7.80
	4	$2,200	7.5	4.76
	5	$3,925	12.5	5.10
	6	$5,400	15	6.82
2	1	$3,000	10	8.57
	2	$6,300	15	7.80
	3	$2,200	7.5	4.76
	4	$3,925	12.5	5.10
	5	$5,400	15	6.82
	6	$1,150	5	9.42
3	1	$6,300	15	8.98
	2	$2,200	7.5	5.23
	3	$3,925	12.5	5.41
	4	$5,400	15	9.48
	6	$1,150	5	8.73
4	1	$2,200	7.5	5.23
	2	$3,925	12.5	5.41
	3	$5,400	15	9.48
	5	$1,150	5	8.73
	6	$3,000	10	8.98
5	1	$3,925	12.5	6.88
	2	$5,400	15	11.38
	3	$1,150	5	12.71

	6	\$3,000	10	7.08
6	1	\$5,400	15	11.22
	3	\$1,150	5	10.33
	4	\$3,000	10	9.72
	5	\$6,300	15	6.22

Table 5.9 DFX selection sample based on fitness functions

i	***Selected m***	***Min TC_{DD}* (\$)**	***Min TT_{DD}* (days)**	**Max *TQ_{DD}* (%)**
1	1	\$1,150	5	9.42
2	6	\$1,150	5	9.42
3	6	\$1,150	5	9.48
4	5	\$1,150	5	9.48
5	3	\$1,150	5	12.71
6	3	\$1,150	5	11.22
∑Trade-off Metrics		\$6,900	30	61.73

Table 5.10 Solutions NPV and IRR economic values

IRR	**Solutions NPV**					
	1	2	3	4	5	6
0%	\$245.00	\$303.86	\$2,807.27	\$1,403.56	\$824.28	\$4,517.76
5%	-\$1,248.67	-\$1,201.94	\$785.35	-\$328.96	-\$788.82	\$2,143.20
10%	-\$2,370.64	-\$2,333.03	-\$733.42	-\$1,630.35	-\$2,000.50	\$359.54
15%	-\$3,224.48	-\$3,193.81	-\$1,889.23	-\$2,620.73	-\$2,922.60	-\$997.86
20%	-\$3,882.04	-\$3,856.71	-\$2,779.35	-\$3,383.45	-\$3,632.75	-\$2,043.22
25%	-\$4,394.01	-\$4,372.84	-\$3,472.37	-\$3,977.28	-\$4,185.64	-\$2,857.12
30%	-\$4,796.63	-\$4,778.73	-\$4,017.38	-\$4,444.28	-\$4,620.46	-\$3,497.18
35%	-\$5,116.21	-\$5,100.90	-\$4,449.98	-\$4,814.97	-\$4,965.59	-\$4,005.23
40%	-\$5,372.05	-\$5,358.83	-\$4,796.31	-\$5,111.72	-\$5,241.89	-\$4,411.96
45%	-\$5,578.51	-\$5,566.96	-\$5,075.79	-\$5,351.20	-\$5,464.86	-\$4,740.19
50%	-\$5,746.36	-\$5,736.17	-\$5,302.99	-\$5,545.89	-\$5,646.12	-\$5,007.02
55%	-\$5,883.76	-\$5,874.69	-\$5,488.99	-\$5,705.26	-\$5,794.51	-\$5,225.45
60%	-\$5,996.96	-\$5,988.82	-\$5,642.23	-\$5,836.57	-\$5,916.77	-\$5,405.42
65%	-\$6,090.80	-\$6,083.42	-\$5,769.26	-\$5,945.41	-\$6,018.11	-\$5,554.60
70%	-\$6,169.04	-\$6,162.28	-\$5,875.16	-\$6,036.15	-\$6,102.59	-\$5,678.97
75%	-\$6,234.60	-\$6,228.39	-\$5,963.91	-\$6,112.21	-\$6,173.41	-\$5,783.21
80%	-\$6,289.84	-\$6,284.07	-\$6,038.68	-\$6,176.27	-\$6,233.06	-\$5,871.02
85%	-\$6,336.59	-\$6,331.20	-\$6,101.96	-\$6,230.50	-\$6,283.54	-\$5,945.34
90%	-\$6,376.34	-\$6,371.27	-\$6,155.77	-\$6,276.60	-\$6,326.47	-\$6,008.53
95%	-\$6,410.28	-\$6,405.49	-\$6,201.71	-\$6,315.97	-\$6,363.12	-\$6,062.48
100%	-\$6,439.38	-\$6,434.82	-\$6,241.10	-\$6,349.72	-\$6,394.55	-\$6,108.74

5.6 Results and Discussions

The developed MDFX hybrid model was implemented in the mass timber automated processing center and was used to navigate and search the possible solution large space. By adopting the Pareto optimality concept, the model was successful in reducing significantly the solutions large space and this was achieved by precluding the Pareto dominated solutions in the successive iterations of the GA parent population. The output of the hybrid engine generates 310 Pareto optimal non-dominated solutions for this case study where each solution signifies a possible optimal MDFX utilization solution for each of the six-design criterion in the PDS set. Accordingly, it presents to the designer a unique combination and optimal allocation of trade-off performance metrics. Table 5.1 shows a sample result of these solutions and summarize their cost, time, and quality impact on machine design development. It is noticed from Table 5.1 that solutions #1,2,3,4, and 5 could be considered as optimal solutions for this case study since their total design cost $6,900, $6,956, $9,340, $8,003, and $7,452 respectively, is between the lower and upper defined cost constraints. But, if the designer wants to emphasize on the design target time constraint, which is defined as 28 days or less, then the possible solutions, in this case, will be #2, 3, and 4. Finally, by choosing the highest quality percentage between the remaining solutions, the designer concludes that solution #3 is the optimal solution with the quality of 77%.

Table 5.11 MDFX pareto optimal utilization nondominated solutions with their trade-off metrics

Solution (*s*)	**MDFX utilization options (*n*)**	***TC*** TC_s (\$)	TT_s **(days)**	TQ_s **(%)**
1	{1,6,6,5,3,3}	$6,900.00	30.00	61.73
2	{1,5,3,4,2,6}	$6,956.06	27.58	60.88

3	{2,3,1,2,3,4}	$9,340.26	27.82	77.17
4	{2,5,1,3,2,1}	$8,003.39	26.37	66.02
5	{1,1,3,2,2,1}	$7,451.70	28.19	63.88
6	{1,4,2,5,1,3}	$10,969.30	25.16	81.46

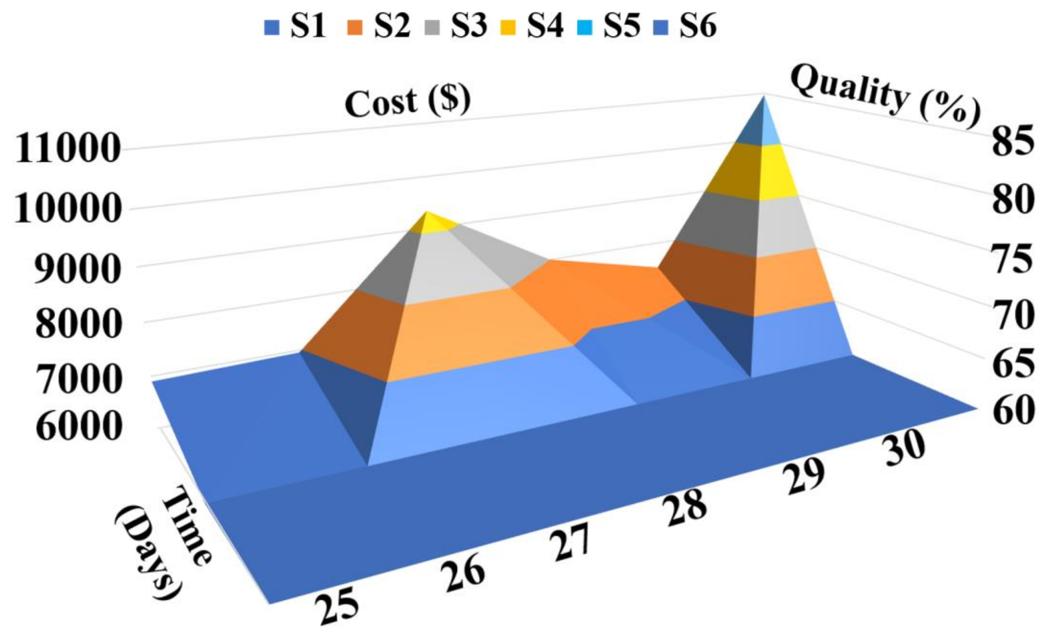


Figure 5.14 MDFX solutions cost-time-quality trade-off surface

The generated final list of Pareto optimal non-dominated solutions is plotted on a fitted visualizing surface to present the relation between MDFX trade-off performance metrics as illustrated in Figure 5.18. This graphical tool can be used by designers to visualize and evaluate the impact of various MDFX utilization solutions on machine design development. Besides, these trade-off performance metrics can also be represented in 2D slices where the trade-offs performance metrics between two design development objectives at a time are illustrated as shown in Figure 5.15, Figure 5.16, and Figure 5.17.

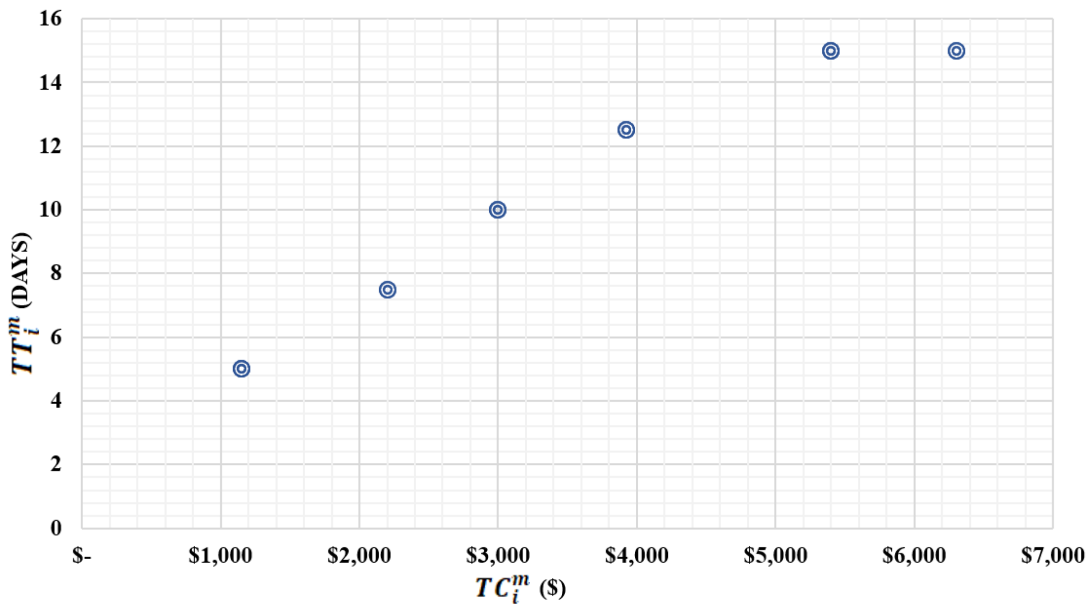


Figure 5.15 Cost-time DFX trade-off analysis with respect to each design criterion

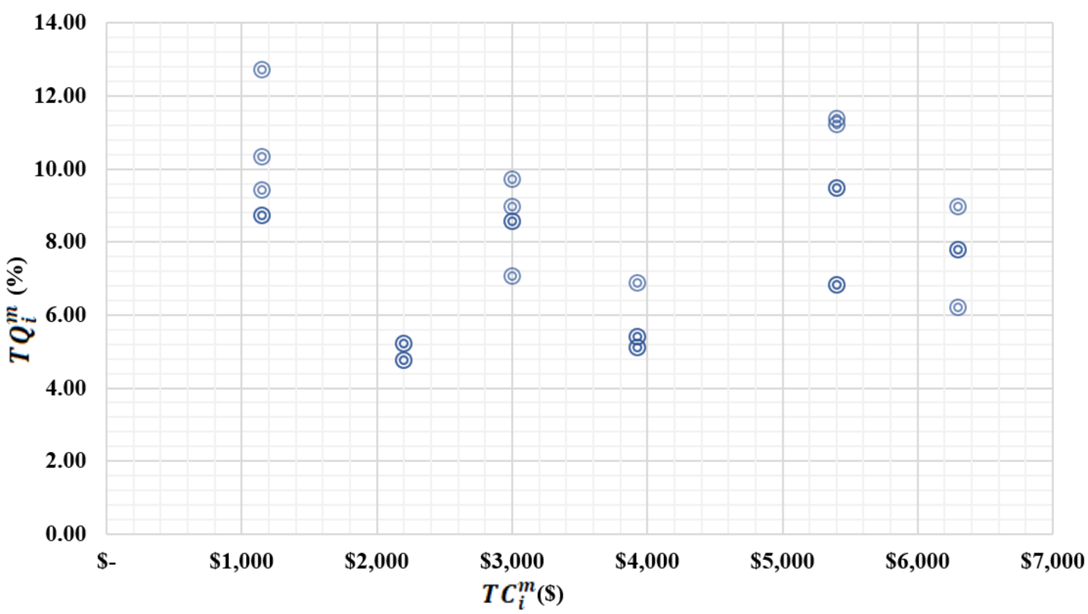


Figure 5.16 Cost-quality DFX trade-off analysis with respect to each design criterion

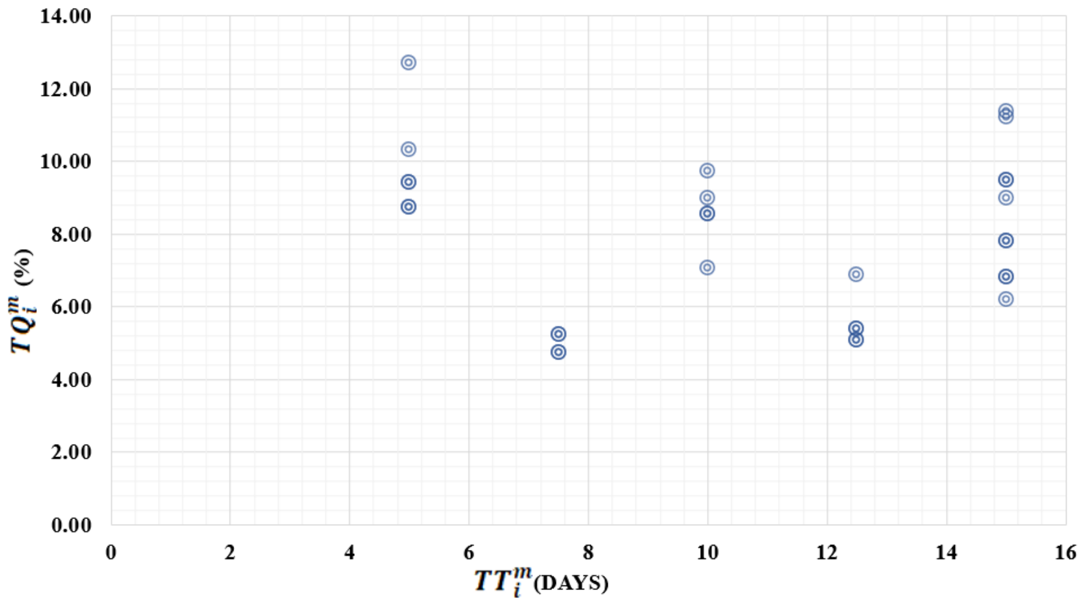


Figure 5.17 Time-quality DFX trade-off analysis with respect to each design criterion

From the previous discussion, the optimal solution was #3 but if the NPV/IRR economic model results were analyzed, then the conclusion will be altered. As observed in Figure 5.18, solution #2 has the second least NPV/IRR ratio from start to finish with values of \$303 and -\$6435 respectively. The optimum solution, if only the economic analysis results were taken into consideration during the decision-making process, will be solution #1. However, if cost, time, and quality constraints are applied, then this solution will change from #1 to #2 where it satisfies the optimization model objective functions, constraints, and least NPV/IRR ratio.

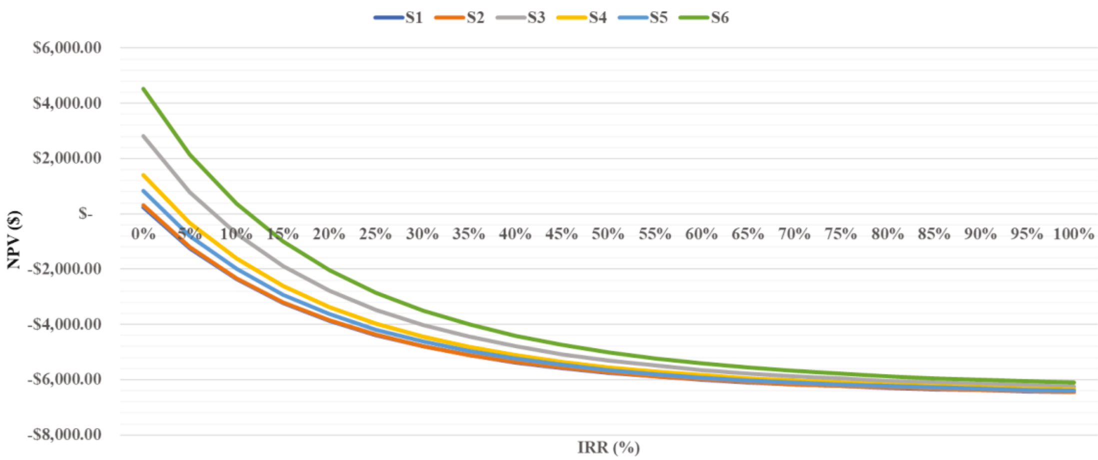


Figure 5.18 MDFX solutions NPV/IRR profile

The proposed optimization hybrid model outcome has been proven and demonstrated that it has several unique characteristics as follows:

(1) The model considers discrete cost-time-quality relationships within design criterions.

(2) GAs is efficient algorithm in finding optimal solutions by searching in a partial chunk of the total solution search space.

(3) The hybrid optimization engine takes into consideration the designer input such as machine design development target duration, upper and lower cost, daily incentive, and daily penalties into its formulation and uses total design development cost, time, and quality as the objective functions to optimize MDFX trade-off performance metrics.

(4) The hybrid model accounts for the economic analysis of the hybrid model output to aid the designer in the decision-making process and to present a money value for the solution over the machine design lifespan.

5.7 Conclusion

A multi-objective optimization hybrid model was developed in this research to support the cost-time-quality trade-off analysis of MDFX. It is designed and structured to search for optimal MDFX utilization solutions to minimize machine design development cost and time while maximizing its quality. The main process of proposed model can be broken-down in to four parts: (1) GA algorithm model formation part where all primary decision variables and objective functions are incorporated; (2) multi-objective optimization part where MDFX performance metrics are optimized based on the fitness functions; (3) population generation based on Pareto-GA concept part that implements a multi-objective GA parameters for MDFX utilization solutions to facilitate the simultaneous trade-off metrics optimization operation of MDFX; (4) economic analysis part to assess the generated solutions from a financial perspective. A real machine design development case study is presented and analyzed to illustrate the effectiveness of the hybrid model and demonstrate its capabilities in developing optimal trade-offs among MDFX cost, time, and quality with some limitation in handing higher-dimensional problems. The proposed model proved to be useful to designers in machine design development activities. The economic analysis model leads to couple the engineering–financial fields and decision-making process. This is also adaptable with the optimization decision support system and the results interpretation are made based on the integral economic perspective of design for excellence and Pareto optimality; therefore, the application of NPV/IRR concept as best-compromise analytical formulations can be shown as pragmatic measures in this problem.

Also, to the proposed hybrid approach for solving MDFX optimization problem, there are two important characteristic features need to be highlighted. First, the introduction of a new chromosome's structure which can represent all possible non-dominated feasible solutions. Also, in order to preserve the feasibility and traits of the chromosome, a criterion was developed. Based on this criterion, the GAs crossover and mutation operations were modified and implemented to generate a higher set of feasible chromosomes. Secondly, the hybrid engine is an iterative multi-objective GA algorithm with the ability to avoid an overwhelming number of solutions by utilizing the Pareto optimality concept which can retain the best fit solutions and update them iteratively during the searching operation. Moreover, to help the designer extracts the best compromise solution from a finite set of alternatives an economic model is adopted featuring NPV/IRR financial concepts in the decision-making process.

The superiority and applicability of the hybrid GA-Pareto concept in machine design development has been proven in this research. Furthermore, the implementation of GA-Pareto model in integration with Microsoft® Excel Solver Add-in program has been proven to be effective to be used in the machine design development problem and in decision-making process. While large MDFX utilization problem still require large computational time, series and continuous packages of improvements in the GA procedure. The developed model provides a practical decision-making tool which utilized by designers to implement MDFX in machine design development.

Chapter 6 : Conclusion

6.1 General Conclusion

Engineering design is an iterative process of solution generation and evaluation. It requires a designer to take a forward-thinking and a look ahead approach when finalizing a solution. In a dynamic environment, a concurrent application of MDFX techniques during the design process can be organized into multiple stages in which both evaluation and decision are needed. The main theme of this research was to present the need for a tool that can reliably estimate and verify the time/benefits of applying MDFX in a harmonized way in machine design. As a result, a decision support tool that can aid the designer in the decision-making process when MDFX are utilized will be required.

In this research, a collaborative DFX scheme was developed based on a comprehensive literature review of various DFX tools in the broad area of machine development. The scheme proposed contains thirty-six DFX techniques where their links and interdependencies across five machine design phases are revealed. Moreover, the quantitative research on the maturity of DFXs across the years shows that the combined relative importance percentage allocated with top-ranked DFX techniques which signal an increased level of preparedness of these most effective, efficient, and versatile DFX tools for machine design deployment. Also, in this research, a design decision simulation tool was developed to enable designers to foresee and explore lifecycle consequences during the machine design. It provides a structured workflow specifying how and when MDFX techniques can be applied with the ability to quantify the arising conflict that may occur between them. The tool's fundamental core is based on the information contained within the DFX guidelines, which may be classified as either a design strategy or rule, so their interactions can be examined explicitly. Thus, the generation of a ranked list can be integrated in a time-effective and strategic manner, thereby shrinking the machine design time.

Furthermore, the research was directed to develop a decisive decision support system for integrating MDFX with PDS. This was achieved by a hybrid FEAM-TOPSIS model embedded with trade-off analysis model using conflict resolution, TFNs, and ranking methods to evaluate MDFX combinations. The proposed MDFX model based on trade-off analysis ensures the integration of design experts' assessment and evaluation in a decision-making system. Cost and time are utilized to compare MDFX alternatives so that lifecycle cost can be reduced. The weighing of the financial and economic impact of all MDFX selection design decisions provides a benchmark that can assist the designer in making decisions to best benefit the machine development.

Also, the research targets the development of a multi-objective optimization model to support the cost-time-quality trade-off analysis of MDFX. It is designed and structured to search for optimal MDFX utilization solutions to minimize machine design development cost and time while maximizing its quality. The optimization model is developed by utilizing the GAs-Pareto optimality methods. Also, the hybrid model was integrated with the economic analysis model; thus, leading to the coupling of the engineering–financial fields and the decision-making process. This is also adaptable with the application of NPV/IRR concept as best-compromise analytical formulations can be shown as pragmatic measures to help the designer extracts the best compromise solution from a finite set of alternatives. The developed models provide practical decision-making tools which can be utilized by designers to implement MDFX in machine design development.

6.2 Research Contributions

The contributions of this research can be summarized as follows:

(1) Development of a structured DFX scheme that can be applied in Stuart Pugh model. This scheme can aid the designer in selecting and allocating DFX techniques for different phases of machine design development (Objective 1).

(2) Design decision simulation tool that can reliably estimate and verify the time/benefits of the application of MDFX in a harmonized way in machine design. Also, it resolves the conflict arising between MDFX by analyzing their interdependencies and simulating their interactions. It enables designers to foresee and explore lifecycle consequences during the machine design and serve as a strategic time-effective tool for the application of MDFX (Objective 2).

(3) A hybrid decision support model that features the integration of MDFX with PDS, evaluate and rank MDFX alternatives with interrelated design criteria, and achieve the desired reduction of design development cost and time over the whole machine lifecycle (Objective 3).

(4) A hybrid multi-objective optimization model that can search for optimal MDFX utilization plans to minimize machine design development time and cost while maximizing its quality (Objective 4).

6.3 Research Limitations

This research is subject to the following limitations:

(1) The functional scheme is limited to thirty-six DFX techniques distributed on the machine lifecycle phases related to Stuart Pugh model and subject to the proposed relative weighting system.

(2) The methodology behind the MDFX conflict resolution is only focused on the conceptual and detailed design development phases of the machine with a maximum number of DFX techniques equal to 15. Also, the analysis function in the model is limited to four DFX tools and a maximum number of ten strategies per phase.

(3) The hybrid decision support model is relatively depending on the design experts' values and assessment criteria which can have some degree subjectivity, bias, imprecision and uncertainty. Also, the structure of the problem's hierarchy and the design attributes are closely inter-related.

(4) In the hybrid multi-objective optimization model, the proposed algorithm has high tendency in performing a random search which requires longer computational processing time for large MDFX optimization problems. One solution to that is to code the search GA-Pareto procedure using a faster high-performance programming language other than the VBA programming language (e.g., Java, Python, C++, etc.).

(5) For both hybrid models, the analyzed sample of the data is limited to 20 design experts and the fuzzy ranking system.

6.4 Future Research

Future research can be oriented and focused on the upgradable options for these models and the possible extensions to this study as represented in Figure 6.1, including the following:

(1) Development efforts should be focused on bridging both scheme normative issues, concerned with the design decision-making theoretical logic, and descriptive issues, concerned with its practicalities together. Also, future research should be directed toward validating the proposed DFX scheme in other engineering domains, to widen and promote the applicability of DFX techniques.

(2) Extend the applicability of the decision tool in the DFX trade-off analysis with respect to cost and quality to provide a better understanding of client needs while controlling the machine lifecycle. Moreover, the future development of this methodology will be required to cover the other phases of the machine lifecycle (e.g., embodiment design, manufacturing, and sales).

(3) Explore how to reform the gaps between each criterion and its relative MDFX combination by applying the Interactive Network Relationship Map (INRM) methodology and recording the relationships complexity factor. The INRM could be used not only to search for the most crucial criterion for the single DFX, but also to calculate and asses the relationships and intercorrelation variables between them. The hybrid decision support model is relatively depending on the design experts' values and assessment criteria which can have some degree of subjectivity, bias,

imprecision and uncertainty. Moreover, the structure of the problem's hierarchy and the design attributes are closely inter-related.

(4) The Integration of the hybrid model with a design cost estimating system with historical database could provide a more realistic market evaluation of the cost, time, and quality associated with each DFX method. Also, the model can be altered to implement the dependency feature that enables the user to activate the crushing decision option to execute the design development in a faster time. Moreover, some formulation rectifications could be done on the basic GAs algorithm to boost up the computational procedure execution searching time in similar optimization problems.

(5) Development of a web-based centralized intelligent automated computerized design development decision-making environment for MDFX optimization problems to support designers during the conceptual and detailed machine design stages and by taking the machine lifecycle into consideration.

(6) For both hybrid models, a larger sample of data (> 20) must be collected to accurately verify the model effectiveness and these models must be extended to target different machines for different sectors other than prefab construction machines. Design an expert system database to capture the learned lessons from previous projects.

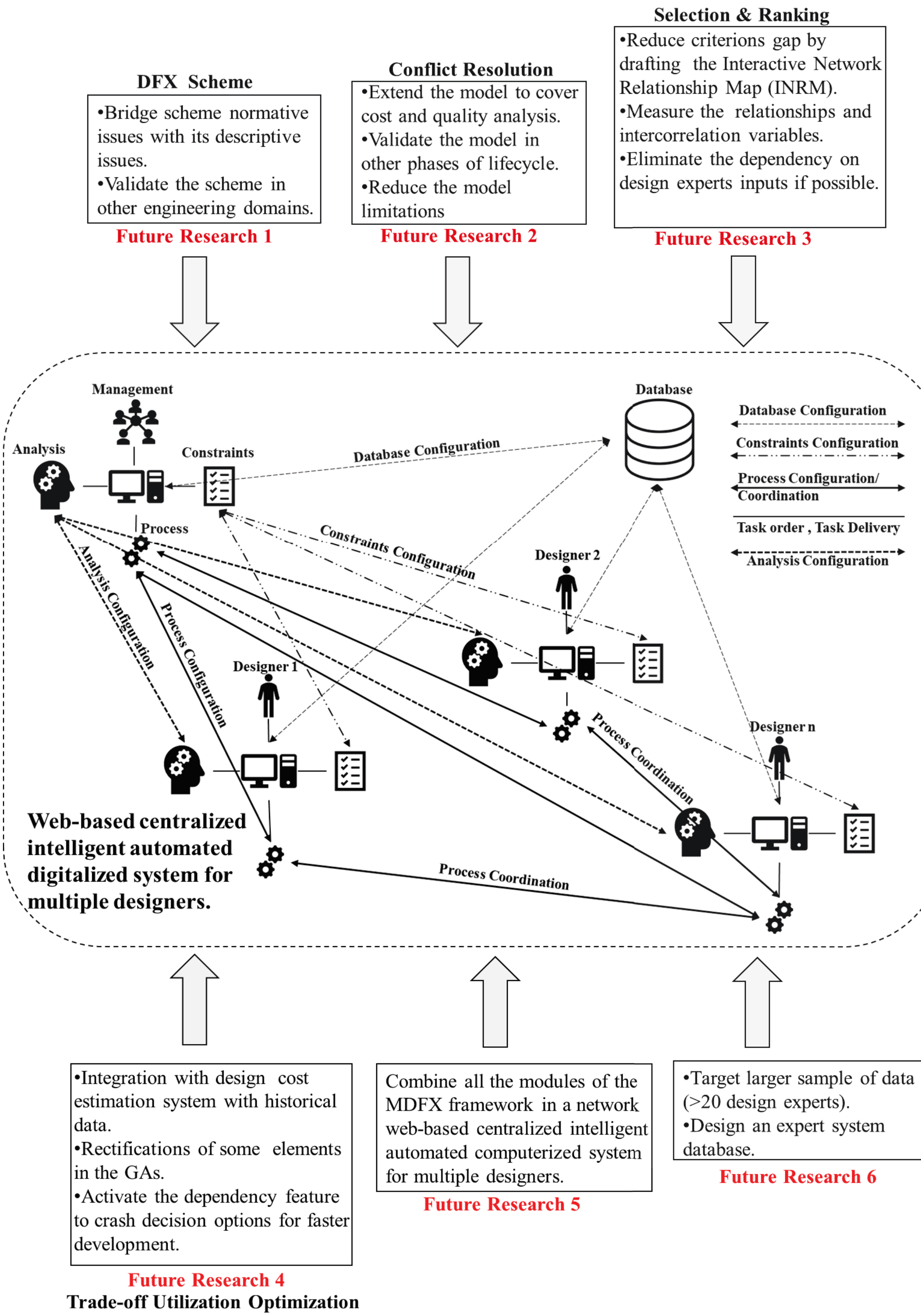


Figure 6.1 Future work road map

References

Ahmad, R., Lahonde, N., and Omhover, J. F. (2014). Game methodology for design methods and tools selection. Journal of Learning Design, 7(1), 1–9.

Andersson, J. (2000). A survey of multiobjective optimization in engineering design. Department of Mechanical Engineering, Linktjping University. Sweden.

Andreasen, M. M., & Olesen, J. (1990). The concept of dispositions. Journal of Engineering Design, 1(1), 17-36.

Andreasen, M. M., & Olesen, J. (1993). Minutes of WDK workshop on DFX research. Technical University of Denmark, Denmark, 17-36.

Aruldoss, M., Lakshmi, T. M., & Venkatesan, V. P. (2013). A survey on multi criteria decision making methods and its applications. American Journal of Information Systems, 1(1), 31-43.

Behrens, W., & Hawranek, P. M. (1991). Manual for the preparation of industrial feasibility studies. Vienna: United Nations Industrial Development Organization.

Becker, J. M. J., and Wits, W. W. (2013). A Template for Design for eXcellence (DfX) methods. In Smart Product Engineering (pp. 33-42). Springer, Berlin, Heidelberg.

Bendeković, J. (1993). Planning of investment projects. Ekonomski institut Zagreb.

Boothroyd, G. (1983). Design for Assembly. Boothroyd Dewhurst. Inc., Wakefield, RI.

Boothroyd, G., & Dewhurst, P. (1988). Product design for manufacture and assembly. Manufacturing Engineering, 100(4), 42-46.

Boothroyd, G. and Dewhurst, P. (1989). "Product design for assembly." Boothroyd Dewhurst Inc. Wakefield, USA.

Borg, J., & MacCallum, K. J. (1997). Structuring knowledge of life-cycle consequences for supporting concurrent design exploration. In Knowledge Intensive CAD (pp. 208-223). Springer, Boston, MA.

Buckley, J. J. (1985). Fuzzy hierarchical analysis. Fuzzy sets and systems, 17(3), 233-247.

Chang, A. M., Holsapple, C. W., & Whinston, A. B. (1993). Model management issues and directions. Decision Support Systems, 9(1), 19-37.

Chang, D. Y. (1992). Extent analysis and synthetic decision. Optimization techniques and applications, 1(1), 352-355.

Chang, D. Y. (1996). Applications of the extent analysis method on fuzzy AHP. European journal of operational research, 95(3), 649-655.

Chen, C., Ibekwe-SanJuan, F., and Hou, J. (2010). The structure and dynamics of cocitation clusters: A multiple-perspective cocitation analysis. Journal of the American Society for information Science and Technology, 61(7), 1386-1409.

Cheng, F. Y., & Li, D. (1997). Multiobjective optimization design with Pareto genetic algorithm. Journal of Structural Engineering, 123(9), 1252-1261.

Chiu, M. C., and Kremer, G. E. O. (2011). Investigation of the applicability of Design for X tools during design concept evolution: a literature review. International Journal of Product Development, 13(2), 132-167.

Chiu, M. C., and Okudan, G. E. (2010). "Evolution of design for X tools applicable to design stages: a literature review". In ASME 2010 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (pp. 171-182). American Society of Mechanical Engineers.

Clausing, D.P. (1993). World-class concurrent engineering. Concurrent Engineering: Tools and Technologies for Mechanical System Design, 108. Springer, Berlin, Heidelberg.

Coello, C. A. C., Lamont, G. B., & Van Veldhuizen, D. A. (2007). Evolutionary algorithms for solving multi-objective problems (Vol. 5). New York: Springer.

Coello, C. C. (1999, July). An updated survey of evolutionary multiobjective optimization techniques: State of the art and future trends. In Proceedings of the Congress on Evolutionary Computation (Vol. 1, pp. 3-13). Piscataway, NJ: IEEE Press.

Das, S. K., Datla, V., and Gami, S. (2000). DFQM-An approach for improving the quality of assembled products. International Journal of Production Research, 38(2), 457-477.

Elíasson, J. (2000). Maximization of the profit of hydropower stations used as a design tool. At: www2. verk. hi. is/vhi/vatnaverkfrstofa/greinar/Vienna2000lecture. pdf.

Fabricius, F. (1994). Seven-step procedure for design for manufacture. World Class Design for Manufacture, 1(2), 23–30.

Farr, J. V. (2011). Systems life cycle costing: economic analysis, estimation, and management. CRC Press.

Feng, C. W., Liu, L., & Burns, S. A. (1997). Using genetic algorithms to solve construction time-cost trade-off problems. Journal of computing in civil engineering, 11(3), 184-189.

Fonseca, C. M., & Fleming, P. J. (1995). An overview of evolutionary algorithms in multiobjective optimization. Evolutionary computation, 3(1), 1-16.

Fujimoto, T., & Clark, K. B. (1991). Product development performance: Strategy, organization, and management in the world auto industry. Harvard business school press, Boston, MA.

Gadh, R. (1996). Computer-aided concurrent design. Computer-Aided Design, 5(28), 319.

Gatzen, M. M., Pemberton, R. W., Peters, V., & Krueger, S. (2013). A holistic design for excellence model based on life cycle costing and design scorecards. In DS 75-5: Proceedings of the 19th International Conference on Engineering Design (ICED13) Design For Harmonies, Vol. 5: Design for X, Design to X, Seoul, Korea 19-22.08. 2013 (pp. 281-290).

Gen, M., & Cheng, R. (2000). Genetic algorithms and engineering optimization (Vol. 7). John Wiley & Sons.

Georgiopoulos, P., Fellini, R., Sasena, M., & Papalambros, P. Y. (2002, January). Optimal design decisions in product portfolio valuation. In ASME 2002 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (pp. 593-602). American Society of Mechanical Engineers.

Goldberg, D. E. (1989). Genetic Alogorithms in Search. Optimization & Machine Learning.

Gu, X., Renaud, J. E., Ashe, L. M., Batill, S. M., Budhiraja, A. S., & Krajewski, L. J. (2002). Decision-based collaborative optimization. Journal of Mechanical Design, 124(1), 1-13.

Guangleng, X. and Yuyun, Z. (1996). Concurrent engineering systematic approach and application. Tsinghua Science and Technology, 1(2), 185–192.

Gupta, S. K., Regli, W. C., & Nau, D. S. (1994). Integrating DFM with CAD through design critiquing. Concurrent Engineering, 2(2), 85-95.

Haque, B. U., Belecheanu, R. A., Barson, R. J., & Pawar, K. S. (2000). Towards the application of case based reasoning to decision-making in concurrent product development (concurrent engineering). In Applications and Innovations in Intelligent Systems VII (pp. 81-101). Springer, London.

Harris, J. A. C. (2002). The application of Pareto optimization to cost-performance trade-offs in the design of structural Components.

Hazelrigg, G. A. (1996). Systems engineering: an approach to information-based design. Upper Saddle River, NJ: Prentice Hall.

Hazelrigg, G. A. (1998). A framework for decision-based engineering design. Journal of mechanical design, 120(4), 653-658.

Holbrook, A. E. K., & Sackett, P. J. (1988). Design for assembly—guidelines for product design. Assembly Automation, 8, 202-211.

Holt, R. and Barnes, C. (2010). Towards an integrated approach to ‘design for X’: An agenda for decision-based DFX research. Research in Engineering Design, 21(2), 123–136.

Huang, G. Q. (1996). Introduction to design for X: concurrent engineering imperatives. Design for X-Concurrent Engineering Imperatives.

Hubka, V., & Eder, W. E. (2012). Theory of technical systems: a total concept theory for engineering design. Springer Science & Business Media.

Hwang, C. L., & Yoon, K. (1981). Methods for multiple attribute decision making. In Multiple attribute decision making (pp. 58-191). Springer, Berlin, Heidelberg.

Juan, Y. K., Shih, S. G., & Perng, Y. H. (2006). Decision support for housing customization: A hybrid approach using case-based reasoning and genetic algorithm. Expert Systems with Applications, 31(1), 83-93.

Kingsman, B. G., & de Souza, A. A. (1997). A knowledge-based decision support system for cost estimation and pricing decisions in versatile manufacturing companies. International Journal of Production Economics, 53(2), 119-139.

Kinnear, K. E., Langdon, W. B., Spector, L., Angeline, P. J., & O'Reilly, U. M. (Eds.). (1999). Advances in genetic programming (Vol. 3). MIT press.

Klir, G. J., & Yuan, B. (1996). Fuzzy sets, fuzzy logic, and fuzzy systems: selected papers by Lotfi A. Zadeh. World Scientific Publishing Co., Inc..

Knowles, J. D., & Corne, D. W. (2000). Approximating the nondominated front using the Pareto archived evolution strategy. Evolutionary computation, 8(2), 149-172.

Laumanns, M., Thiele, L., Deb, K., & Zitzler, E. (2002). Combining convergence and diversity in evolutionary multiobjective optimization. Evolutionary computation, 10(3), 263-282.

Lee, C. K., & Kim, S. K. (2007). GA-based algorithm for selecting optimal repair and rehabilitation methods for reinforced concrete (RC) bridge decks. Automation in Construction, 16(2), 153-164.

Leu, S. S., & Yang, C. H. (1999). GA-based multicriteria optimal model for construction scheduling. Journal of construction engineering and management, 125(6), 420-427.

Li, H., & Li, L. X. (2000). Integrating systems concepts into manufacturing information systems. Systems Research and Behavioral Science: The Official Journal of the International Federation for Systems Research, 17(2), 135-147.

Li, H., & Love, P. (1997). Using improved genetic algorithms to facilitate time-cost optimization. Journal of Construction Engineering and management, 123(3), 233-237.

Li, H., Love, P. E., & Ogunlana, S. (1998). Genetic algorithm compared to nonlinear optimization for labour and equipment assignment. Building Research & Information, 26(6), 322-329.

Li, X. (2016). “Process automation for flexible residential wall panel manufacturing.” University of Alberta.

Lukasz, M. and Tomasz, N. (2007). Dfx platform-a holistic approach to design concepts evaluation. Guidelines for a Decision Support Method Adapted to NPD Processes, 21–22.

Luong, L. H. S., & Spedding, T. (1995). An integrated system for process planning and cost estimation in hole making. The International Journal of Advanced Manufacturing Technology, 10(6), 411-415.

Malik, N., Ahmad, R., & Al-Hussein, M. (2019). Generation of safe tool-paths for automatic manufacturing of light gauge steel panels in residential construction. Automation in Construction, 98, 46-60.

Man, K. F., & Tang, K. S. (1997, November). Genetic algorithms for control and signal processing. In Industrial Electronics, Control and Instrumentation, 1997. IECON 97. 23rd International Conference on (Vol. 4, pp. 1541-1555). IEEE.

Markish, J., & Willcox, K. (2003). Value-Based multidisciplinary techniques for commercial aircraft system design. AIAA journal, 41(10), 2004-2012.

Maropoulos, P. G., Bramall, D. G., & McKay, K. R. (2003). Assessing the manufacturability of early product designs using aggregate process models. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 217(9), 1203-1214.

Marston, M., & Mistree, F. (1998). An implementation of expected utility theory in decision based design. ASME DETC, Design Theory and Methodology.

Martinez, P., Ahmad, R., & Al-Hussein, M. (2019). A vision-based system for pre-inspection of steel frame manufacturing. Automation in Construction, 97, 151-163.

Meerkamm, H. (1993). Design system mfk—an important step towards an engineering workbench. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 207(2), 105-116.

Meerkamm, H. (1994). Design for X—A core area of design methodology. Journal of Engeering Design, 5(2), 165-181.

Michalek, J. J., Ceryan, O., Papalambros, P. Y., & Koren, Y. (2006). Balancing marketing and manufacturing objectives in product line design. Journal of mechanical design, 128(6), 1196-1204.

Michalewicz, Z. (1994). Evolution strategies and other methods. In Genetic Algorithms+ Data Structures= Evolution Programs (pp. 167-184). Springer, Berlin, Heidelberg.

Mitchell, M. (1998). An introduction to genetic algorithms. MIT press.

Olesen, J. (1992). Concurrent development in manufacturing. Institute for Engineering Design, Technical University of Denmark (DTH).

Olewnik, A., & Lewis, K. (2006). A decision support framework for flexible system design. Journal of Engineering Design, 17(1), 75-97.

Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European journal of operational research, 156(2), 445-455.

Osman, M. S., Abo-Sinna, M. A., & Mousa, A. A. (2006). IT-CEMOP: An iterative co-evolutionary algorithm for multiobjective optimization problem with nonlinear constraints. Applied mathematics and computation, 183(1), 373-389.

Otto, K. N., & Antonsson, E. K. (1991). Trade-off strategies in engineering design. Research in Engineering Design, 3(2), 87-103.

Peilin, Y., Jun, Z., & Yonghong, W. (2000). Decision-making of product design for concurrent engineering. JOURNAL-XIAN JIAOTONG UNIVERSITY, 34(2), 85-88.

Peoples, R. E., & Willcox, K. E. (2006). Value-based multidisciplinary optimization for commercial aircraft design and business risk assessment. Journal of Aircraft, 43(4), 913-921.

Petkovic, J., Sevarac, Z., Jaksic, M. L., & Marinkovic, S. (2012). Application of fuzzy AHP method for choosing a technology within service company. Technics Technologies Education Management-Ttem, 7(1), 332-341.

Preechakul, C., & Kheawhom, S. (2009). Modified genetic algorithm with sampling techniques for chemical engineering optimization. Journal of Industrial and Engineering Chemistry, 15(1), 110-118.

Pugh, S. (1991). Total design: Integrated methods for successful product engineering.

Radziwill, N. M. and Benton, M. C. (2017). Design for X (DfX) in the internet of things (IoT). arXiv preprint arXiv:1707.06208.

El-Rayes, K., & Kandil, A. (2005). Time-cost-quality trade-off analysis for highway construction. Journal of construction Engineering and Management, 131(4), 477-486.

Ringuest, J. L., & Rinks, D. B. (1987). Interactive solutions for the linear multiobjective transportation problem. European Journal of Operational Research, 32(1), 96-106.

Saaty, T. L. (1980). Analytical Hierarchy Process McGraw Hill Company. New York.

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. International journal of services sciences, 1(1), 83–98.

Saitou, K., Izui, K., Nishiwaki, S., & Papalambros, P. (2005). A survey of structural optimization in mechanical product development. Journal of computing and information science in engineering, 5(3), 214-226.

Sarfaraz, A., & Jenab, K. (2012). A fuzzy conceptual design selection model considering conflict resolution. International Journal of Engineering and Technology, 4(1), 38.

Schaffer, J. D., & Grefenstette, J. J. (1985, August). Multi-objective learning via genetic algorithms. In Ijcai (Vol. 85, pp. 593-595).

Seçme, N. Y., Bayrakdaroğlu, A., & Kahraman, C. (2009). Fuzzy performance evaluation in Turkish banking sector using analytic hierarchy process and TOPSIS. Expert Systems with Applications, 36(9), 11699-11709.

Shehab, E., & Abdalla, H. (2002). An intelligent knowledge-based system for product cost modelling. The international journal of advanced manufacturing technology, 19(1), 49-65.

Simon, M., Fogg, B., and Chambellant, F. (1992). Design for cost-effective disassembly. Technical Report DDRnRl.

Srinivas, N., & Deb, K. (1994). Muiltiobjective optimization using nondominated sorting in genetic algorithms. Evolutionary computation, 2(3), 221-248.

Steuer, R. E. (1986). Multiple criteria optimization. Theory, Computation and Applications.

Stöber, C., Gruber, G., Krehmer, H., Stuppy, J., & Westphal, C. (2009). Herausforderung Design for X (DfX). In DFX 2009: Proceedings of the 20th Symposium on Design for X, Neukirchen/Erlangen, Germany, 24.09. 2009.

Stoll, H.W. (1988). Design for manufacture. Manufacturing Engineering, 100(1), 67–73.

Tamošaitienė, J., & Zavadskas, E. K. (2013). The multi-stage decision making system for complicated problems. Procedia-Social and Behavioral Sciences, 82, 215-219.

Tan, R. R., Briones, L. M. A., & Culaba, A. B. (2007). Fuzzy data reconciliation in reacting and non-reacting process data for life cycle inventory analysis. Journal of Cleaner Production, 15(10), 944-949.

Tanaka, H. (1982). Linear regression analysis with fuzzy model. IEEE Trans. Syst. Man. Cybern., 12(6), 903-907.

Tang, Y. C., & Beynon, M. J. (2005). Application and development of a fuzzy analytic hierarchy process within a capital investment study. Journal of Economics and Management, 1(2), 207-230.

Tharakan, P. V., Zhao, Z., & Shah, J. (2003, January). Manufacturability evaluation shell: A re-configurable environment for technical and economic manufacturability evaluation. In ASME 2003 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (pp. 227-236). American Society of Mechanical Engineers.

Thurston, D. L. (1991). A formal method for subjective design evaluation with multiple attributes. Research in engineering Design, 3(2), 105-122.

van Hemel, C. G., and Keldmann, T. (1996). "Applying "design for X" experience in design for environment." In Design for X (pp. 72-95). Springer, Dordrecht.

Van Laarhoven, P. J., & Pedrycz, W. (1983). A fuzzy extension of Saaty's priority theory. Fuzzy sets and Systems, 11(1-3), 229-241.

Veryzer, R. W. and Borja de Mozota, B. (2005). The impact of user-oriented design on new product development: An examination of fundamental relationships. Journal of Product Innovation Management, 22, 128–143.

Vučina, D., Lozina, Ž., & Vlak, F. (2010). NPV-based decision support in multi-objective design using evolutionary algorithms. Engineering Applications of Artificial Intelligence, 23(1), 48-60.

Wang, J. W., Cheng, C. H., & Huang, K. C. (2009). Fuzzy hierarchical TOPSIS for supplier selection. Applied Soft Computing, 9(1), 377-386.

Wassenaar, H. J., & Chen, W. (2001). An approach to decision-based design. ASME Paper No. DETC01/DTM-21683.

Watson, B., Radcliffe, D., and Dale, P. (1996). A meta-methodology for the application of DFX design guidelines. In Design for X, Springer, Dordrecht, pp. 441–462.

WILCOX, M. and Sheldon, D. (1993). How the Design Team in management terms will handle the DFX tools. Proceedings of the 9th International Conference on Engineering Design, 2, 875–881.

Wulan, M. Q., & Deng, J. D. (2000). Intelligent mechanism to support DFX-abilities in automated designer's environment. Chinese Journal of Aeronautics, 13(4), 234-241.

Xu, L., Li, Z., Li, S., & Tang, F. (2007). A decision support system for product design in concurrent engineering. Decision support systems, 42(4), 2029-2042.

Youssef, M. A. (1994). Design for manufacturability and time-to-market, Part 1: theoretical foundations. International Journal of Operations & Production Management, 14(12), 6-21.

Yu, C. S. (2002). A GP-AHP method for solving group decision-making fuzzy AHP problems. Computers & Operations Research, 29(14), 1969-2001.

Zhang, 'B., Simon, M., and Dowie, T. (1993). Initial investigation of design guidelines and assessment of design for disassembly. Technical Report, DDRTR03, Aug (pp. 17–19).

Zhang, Y., Li, X., & Wang, Q. (2009). Hybrid genetic algorithm for permutation flowshop scheduling problems with total flowtime minimization. European Journal of Operational Research, 196(3), 869-876.

Zhao, H., Zhang, Y., Wang, Z., Lee, S. F., & Kwong, W. C. (2003). Research on group decision support system for concurrent product development process. Journal of Materials Processing Technology, 139(1-3), 619-623.

Zhao, Z. (2002). Design decision-making in global manufacturing enterprise in 2020. Student Design Contest Paper, NSF Travel Grant.

Zitzler, E., & Thiele, L. (1999). Multiobjective evolutionary algorithms: a comparative case study and the strength Pareto approach. IEEE transactions on Evolutionary Computation, 3(4), 257-271.

Appendix-A

A-1 Design experts interview questions

Name: _________________ **Date/Time: _______________**

Location: _____________________ **Specialty: _______________**

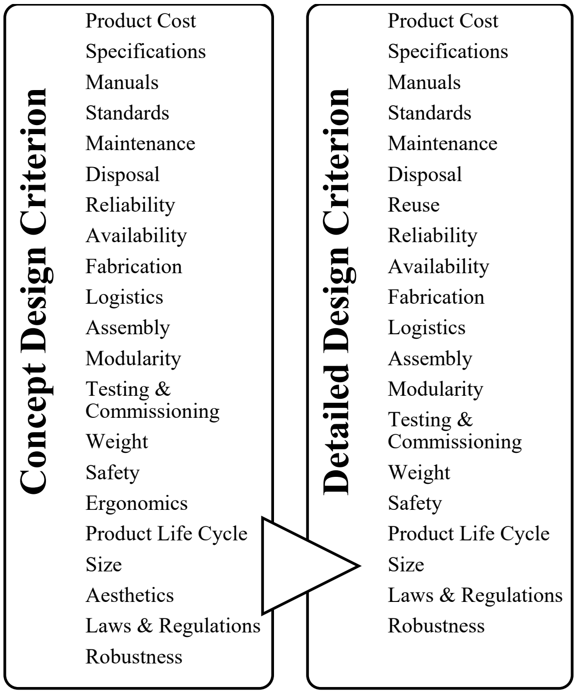
1- As an expert in design and manufacturing sector, what two phases of a product life cycle are the most important in your opinion:

A- Customer Needs/Specifications
B- Concept Design
C- Detailed Design
D- Manufacture
E- Sell

2- Select the **top 10** Design for X (DFX) techniques that are beneficial in your opinion for any product development regardless of which phase is the product life cycle at:

A- Design for Cost (DFC)
B- Design for Manufacturing (DFM)
C- Design for Assembly (DFA)
D- Design for Manufacturing & Assembly (DFMA)
E- Design for Variety (DFV)
F- Design for Quality (DFQ)
G- Design for Six Sigma (DFSS)
H- Design for Testability (DFT)
I- Design for Obsolescence (DFO)
J- Design for Reusability (DFRE)
K- Design for Disassembly (DFDA)
L- Design for Reliability (DFR)
M- Design for Environment (DFE)
N- Design for Sustainability (DFS)
O- Design for Network (DFN)
P- Design for Robustness (DFRO)
Q- Design for Maintainability (DFMAI)
R- Design for End-Of-Life (DFEL)
S- Design for Supply Chain (DFSC)
T- Design for Recyclability (DFREC)
U- Design for Remanufacture (DFRem)
V- Design for Modularity (DFMO)
W- Design for Affordances (DFAF)

3- The product design specifications (PDS) is an evolutionary, comprehensive written document, which must evolve to match the characteristics of the final product. Poor PDS leads to poor design that will fail in the market. Good PDS does not guarantee good design but make the goal more attainable. PDS set the design in context, which is a comprehensive set of constrains. Select the **top 10** from each design stage.



4- By implementing a pairwise comparisons method we will be able to rank a specific product criterion and its importance with respect to other criterions. Put a check mark where the interaction between these criteria is the best fit.

Absolutely Important (9, 9, 9)	Strongly Important (6, 7, 8)	Fairly Important (4, 5, 6)	Weakly Important (2, 3, 4)	Criterion	Equally Important (1, 1, 1)	Criterion	Weakly Important (2, 3, 4)	Fairly Important (4, 5, 6)	Strongly Important (6, 7, 8)	Absolutely Important (9, 9, 9)
				Product Cost		Specifications				
				Product Cost		Maintenance				
				Product Cost		Reliability				
				Product Cost		Assembly/Disassembly				
				Product Cost		Weight/Size				
				Product Cost		Safety/Ergonomics				
				Specifications		Maintenance				
				Specifications		Reliability				
				Specifications		Assembly/Disassembly				
				Specifications		Weight/Size				
				Specifications		Safety/Ergonomics				
				Maintenance		Reliability				
				Maintenance		Assembly/Disassembly				
				Maintenance		Weight/Size				
				Maintenance		Safety/Ergonomics				
				Reliability		Assembly/Disassembly				
				Reliability		Weight/Size				
				Reliability		Safety/Ergonomics				
				Assembly/Disassembly		Weight/Size				
				Assembly/Disassembly		Safety/Ergonomics				
				Weight/Size		Safety/Ergonomics				

5- Rate the Design for X in a pairwise comparison on a nine-point scale (1 to 9) as per the below table. Note: Disregard the shaded area.

Rating	Description
1	Equally preferred
3	Moderately preferred
5	Strongly preferred
7	Very strongly preferred
9	Extremely strongly preferred
2,4,6,8	Between two numbers above

Design for	Cost (DFC)	Manufacturing (DFM)	Assembly (DFA)	Robustness (DFRO)	Quality (DFQ)	Sustainability (DFS)	Reliability (DFR)	Testability (DFT)
Cost (DFC)	1							
Manufacturing (DFM)		1						
Assembly (DFA)			1					
Robustness (DFRO)				1				
Quality (DFQ)					1			
Sustainability (DFS)						1		
Reliability (DFR)							1	
Testability (DFT)								1

6- Each DFX technique consist of a number of high-level design guidelines, called design rules. Each rule contains a set of low-level design guidelines, called design strategies. In conceptual and detailed design stages, weight the below two DFX techniques (DFA and DFDA) design rules from (1 to 10) with 10 the highest.

Conceptual Design		Weight (1 to 10)
DFA	1- Minimize the number of parts (Types & Count)	
	2- Increase product modularity	
	3- Ensure base part design	
	4- Aim for sequential assembly design	
	5- Minimize the need for reorientations during assembly	
DFDA	1- Improve the products structure for disassembly	
	2- Improve the disassembly planning	

Detailed Design		Weight (1 to 10)
DFA	1- Minimize the number of parts (Types & Count)	
	2- Aim for the elimination of adjusments and parts asymmetry	
	3- Elimnate tangling, jamming	
	4- Design parts to be self-aligning and self-locating	
	5- Reduce number of fastening products	
	6- Ensure adequate access and unrestricted vision	
	7- Execute one-way assembly methodology	
DFDA	1- Improve the product structure for disassembly.	
	2- Improve access and vision for disassembly.	
	3- Improve disassembly planning.	
	4- Material compatibility.	
	5- Implementing component design rules.	
	6- Design and selection of connectors.	
	7- Maximize end of life value of the product.	

7- In conceptual and detailed design stages, assign a C value to each cross between two strategies. This to determine and gauge whether any number of strategies from any number of DFX techniques have conflicted so severely.

C Values	Interpretations
+ 10	Strategies interact very positively
+ 5	One strategy tends to support the other in a broad sense
0	No form of interacation exists between the strategies
- 5	Some conflict exists as to the direction the design should take
- 10	The strategies are almost completely contradictory in nature

Conceptual Design	DFDA Strategies	Subdivide the product into manageable subassemblies	Minimize the number of components and subassemblies	Standardize the products style	Avoid long disassembly paths
DFA Strategies					
Minimize the number of parts and levels of assembly					
Minimize the number of components and subassemblies					
Reduce product complexity					
Eliminate any product features that do not add value to the customer					
Design mult-function parts					
Design products from modular subassemblies so that modules can be scheduled, built and tested independently					
Standardize by common components, processes and methods to reduce costs across the whole system					

Detailed Design	DFDA Strategies	Subdivide the whole assembly into manageable subassemblie	Minimize the number of connections between subassemblies	Minimize the number of components and subassemblies	Standardize the products style	Make sure that components are accessible	Reduce the number of changes in direction required in a removal operation	Avoid long disassembly paths	Subassemblies that are difficult to disassemble should be made of the same or compatible material
DFA Strategies									
Reduce the number of parts between the input and output function									
Move critically related surfaces close together to facilitate tolerance control									
Follow kinematic design principles									
Eliminate or minimize the need for repositioning an assembly once it is fixtured									
Ensure adequate clearance for hands, tools, and subsequent processes									
Ensure that vision of the process is not restricted or compromised.									
Design simple assembly operations: parts can be assembled only one way; if misassembled, subsequent parts cannot be added									
Minimize motion distance, within practical limits, to reduce motion time and improve accuracy									

A-2 Design expert's participants list

Experts Weight (0-10)	Expert Design Experience (Years)	Number of design experts interviewed
0.8	0	2
1.7	$5 \leq Y \leq 10$	4
2	$10 \leq Y \leq 15$	3
2.5	$15 \leq Y \leq 20$	4

A-3 Design expert’s data collection for FEAM

Product Criteria- Fuzzy Numbers in Comparison Matrices

Product Criteria	The left measure is greater												Neutral			The right measure is greater												Product Criteria	Total number of design experts
	A. Imp.			S. Imp.			F. Imp.			W. Imp.			Eq. Imp.			W. Imp.			F. Imp.			S. Imp.			A. Imp.				
	(8,9,10)			(6,7,8)			(4,5,6)			(2,3,4)			(1,1,1)			(1/4,1/3,1/2)			(1/6,1/5,1/4)			(1/8,1/7,1/6)			(1/10,1/9,1/8)				
	8	9	10	6	7	8	4	5	6	2	3	4	1	1	1	0.25	0.33	0.50	0.17	0.20	0.25	0.13	0.14	0.17	0.10	0.11	0.13		
End-User (A)	4	4	4	4	4	4	0	0	0	1	1	1	2	2	2	4	4	4	0	0	0	4	4	4	1	1	1	Materials (B)	20
End-User (A)	4	4	4	4	4	4	0	0	0	2	2	2	6	6	6	3	3	3	1	1	1	0	0	0	0	0	0	Machine (C)	20
End-User (A)	0	0	0	2	2	2	0	0	0	1	1	1	8	8	8	0	0	0	0	0	0	3	3	3	6	6	6	Performance (D)	20
End-User (A)	1	1	1	2	2	2	1	1	1	4	4	4	1	1	1	4	4	4	1	1	1	2	2	2	4	4	4	Process (E)	20
Materials (B)	2	2	2	3	3	3	2	2	2	2	2	2	0	0	0	0	0	0	3	3	3	3	3	3	5	5	5	Machine (C)	20
Materials (B)	0	0	0	0	0	0	2	2	2	3	3	3	2	2	2	0	0	0	0	0	0	5	5	5	8	8	8	Performance (D)	20
Materials (B)	0	0	0	3	3	3	2	2	2	3	3	3	4	4	4	0	0	0	2	2	2	3	3	3	3	3	3	Process (E)	20
Machine (C)	1	1	1	2	2	2	3	3	3	1	1	1	3	3	3	0	0	0	0	0	0	2	2	2	8	8	8	Performance (D)	20
Machine (C)	0	0	0	4	4	4	2	2	2	0	0	0	1	1	1	2	2	2	6	6	6	5	5	5	0	0	0	Process (E)	20
Performance (D)	3	3	3	4	4	4	1	1	1	2	2	2	3	3	3	0	2	2	3	3	3	3	3	3	2	2	2	Process (E)	20

Data Criteria A- Fuzzy Numbers in Comparison Matrices

Product Criteria	The left measure is greater												Neutral			The right measure is greater												Product Criteria	Total number of design experts	Integration Power
	A. Imp.			S. Imp.			F. Imp.			W. Imp.			Eq. Imp.			W. Imp.			F. Imp.			S. Imp.			A. Imp.					
	(8,9,10)			(6,7,8)			(4,5,6)			(2,3,4)			(1,1,1)			(1/4,1/3,1/2)			(1/6,1/5,1/4)			(1/8,1/7,1/6)			(1/10,1/9,1/8)					
	8	9	10	6	7	8	4	5	6	2	3	4	1	1	1	0.25	0.33	0.50	0.17	0.20	0.25	0.13	0.14	0.17	0.10	0.11	0.13			
A1	8	8	8	3	3	3	2	2	2	3	3	3	2	2	2	0	0	0	2	2	2	0	0	0	0	0	0	A2	20	0.050
A1	12	12	12	5	5	5	2	2	2	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	A3	20	0.050
A1	10	10	10	4	4	4	3	3	3	2	2	2	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	A4	20	0.050
A1	6	6	6	5	5	5	1	1	1	3	3	3	0	0	0	0	0	0	2	2	2	3	3	3	0	0	0	A5	20	0.050
A1	14	14	14	2	2	2	3	3	3	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	A6	20	0.050
A2	12	12	12	3	3	3	2	2	2	2	2	2	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	A3	20	0.050
A2	11	11	11	3	3	3	3	3	3	1	1	1	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	A4	20	0.050
A2	0	0	0	2	2	2	5	5	5	3	3	3	2	2	2	3	3	3	4	4	4	1	1	1	0	0	0	A5	20	0.050
A2	16	16	16	1	1	1	3	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	A6	20	0.050
A3	0	0	0	0	0	0	5	5	5	2	2	2	4	4	4	2	2	2	3	3	3	4	4	4	0	0	0	A4	20	0.050
A3	0	0	0	0	0	0	3	3	3	2	2	2	1	1	1	3	3	3	0	0	0	6	6	6	5	5	5	A5	20	0.050
A3	0	0	0	0	0	0	6	6	6	4	4	4	0	0	0	3	3	3	5	5	5	2	2	2	0	0	0	A6	20	0.050
A4	0	0	0	2	2	2	4	4	4	0	0	0	3	3	3	0	0	0	4	4	4	3	3	3	4	4	4	A5	20	0.050
A4	0	0	0	0	0	0	5	5	5	3	3	3	4	4	4	2	2	2	5	5	5	1	1	1	0	0	0	A6	20	0.050
A5	8	8	8	6	6	6	2	2	2	0	0	0	1	1	1	3	3	3	0	0	0	0	0	0	0	0	0	A6	20	0.050

Data Criteria B- Fuzzy Numbers in Comparison Matrices

Product Criteria	The left measure is greater												Neutral			The right measure is greater												Product Criteria	Total number of design experts	Integration Power
	A. Imp.			S. Imp.			F. Imp.			W. Imp.			Eq. Imp.			W. Imp.			F. Imp.			S. Imp.			A. Imp.					
	(8,9,10)			(6,7,8)			(4,5,6)			(2,3,4)			(1,1,1)			(1/4,1/3,1/2)			(1/6,1/5,1/4)			(1/8,1/7,1/6)			(1/10,1/9,1/8)					
	8	9	10	6	7	8	4	5	6	2	3	4	1	1	1	0.25	0.33	0.50	0.17	0.20	0.25	0.13	0.14	0.17	0.10	0.11	0.13			
B1	4	4	4	4	4	4	0	0	0	1	1	1	2	2	2	4	4	4	0	0	0	4	4	4	1	1	1	B2	20	0.050
B1	4	4	4	4	4	4	0	0	0	2	2	2	6	6	6	3	3	3	1	1	1	0	0	0	0	0	0	B3	20	0.050
B1	0	0	0	2	2	2	0	0	0	1	1	1	8	8	8	0	0	0	0	0	0	3	3	3	6	6	6	B4	20	0.050
B2	1	1	1	2	2	2	1	1	1	4	4	4	1	1	1	4	4	4	1	1	1	2	2	2	4	4	4	B3	20	0.050
B2	2	2	2	3	3	3	2	2	2	2	2	2	0	0	0	0	0	0	3	3	3	3	3	3	5	5	5	B4	20	0.050
B3	0	0	0	0	0	0	2	2	2	3	3	3	2	2	2	0	0	0	0	0	0	5	5	5	8	8	8	B4	20	0.050

Data Criteria C- Fuzzy Numbers in Comparison Matrices

Product Criteria	The left measure is greater												Neutral			The right measure is greater												Product Criteria	Total number of design experts	Integration Power
	A. Imp.			S. Imp.			F. Imp.			W. Imp.			Eq. Imp.			W. Imp.			F. Imp.			S. Imp.			A. Imp.					
	(8,9,10)			(6,7,8)			(4,5,6)			(2,3,4)			(1,1,1)			(1/4,1/3,1/2)			(1/6,1/5,1/4)			(1/8,1/7,1/6)			(1/10,1/9,1/8)					
	8	9	10	6	7	8	4	5	6	2	3	4	1	1	1	0.25	0.33	0.50	0.17	0.20	0.25	0.13	0.14	0.17	0.10	0.11	0.13			
C1	4	4	4	2	2	2	2	2	2	1	1	1	4	4	4	2	2	2	0	0	0	3	3	3	2	2	2	C2	20	0.050
C1	6	6	6	3	3	3	3	3	3	0	0	0	0	0	0	3	3	3	3	3	3	2	2	2	0	0	0	C3	20	0.050
C2	7	7	7	2	2	2	2	2	2	3	3	3	0	0	0	4	4	4	2	2	2	0	0	0	0	0	0	C3	20	0.050

Data Criteria D-Fuzzy Numbers in Comparison Matrices

Product Criteria	The left measure is greater												Neutral			The right measure is greater												Product Criteria	Total number of design experts
	A. Imp.			S. Imp.			F. Imp.			W. Imp.			Eq. Imp.			W. Imp.			F. Imp.			S. Imp.			A. Imp.				
	(8,9,10)			(6,7,8)			(4,5,6)			(2,3,4)			(1,1,1)			(1/4,1/3,1/2)			(1/6,1/5,1/4)			(1/8,1/7,1/6)			(1/10,1/9,1/8)				
	8	9	10	6	7	8	4	5	6	2	3	4	1	1	1	0.25	0.33	0.50	0.17	0.20	0.25	0.13	0.14	0.17	0.10	0.11	0.13		
D1	2	2	2	4	4	4	2	2	2	0	0	0	4	4	4	0	0	0	2	2	2	2	2	2	4	4	4	D2	20
D1	3	3	3	2	2	2	0	0	0	1	1	1	2	2	2	3	3	3	0	0	0	3	3	3	6	6	6	D3	20
D1	8	8	8	3	3	3	0	0	0	3	3	3	3	3	3	0	0	0	3	3	3	0	0	0	0	0	0	D4	20
D1	0	0	0	2	2	2	3	3	3	0	0	0	0	0	0	2	2	2	4	4	4	6	6	6	3	3	3	D5	20
D2	6	6	6	3	3	3	0	0	0	2	2	2	1	1	1	3	3	3	0	0	0	3	3	3	2	2	2	D3	20
D2	8	8	8	2	2	2	1	1	1	0	0	0	0	0	0	4	4	4	3	3	3	2	2	2	0	0	0	D4	20
D2	4	4	4	0	0	0	0	0	0	3	3	3	4	4	4	0	0	0	5	5	5	4	4	4	0	0	0	D5	20
D3	5	5	5	3	3	3	2	2	2	1	1	1	0	0	0	3	3	3	4	4	4	2	2	2	0	0	0	D4	20
D3	0	0	0	4	4	4	4	4	4	0	0	0	3	3	3	2	2	2	0	0	0	4	4	4	3	3	3	D5	20
D4	0	0	0	0	0	0	6	6	6	2	2	2	0	0	0	3	3	3	2	2	2	5	5	5	2	2	2	D5	20

Data Criteira E- Fuzzy Numbers in Comparison Matrices

Product Criteria	The left measure is greater												Neutral			The right measure is greater												Product Criteria	Total number of design experts	Integration Power
	A. Imp.			S. Imp.			F. Imp.			W. Imp.			Eq. Imp.			W. Imp.			F. Imp.			S. Imp.			A. Imp.					
	(8,9,10)			(6,7,8)			(4,5,6)			(2,3,4)			(1,1,1)			(1/4,1/3,1/2)			(1/6,1/5,1/4)			(1/8,1/7,1/6)			(1/10,1/9,1/8)					
	8	9	10	6	7	8	4	5	6	2	3	4	1	1	1	0.25	0.33	0.50	0.17	0.20	0.25	0.13	0.14	0.17	0.10	0.11	0.13			
E1	2	2	2	3	3	3	1	1	1	2	2	2	2	2	2	3	3	3	0	0	0	4	4	4	3	3	3	E2	20	0.050
E1	0	0	0	4	4	4	0	0	0	3	3	3	0	0	0	2	2	2	4	4	4	6	6	6	1	1	1	E3	20	0.050
E2	0	0	0	2	2	2	5	5	5	1	1	1	3	3	3	0	0	0	5	5	5	2	2	2	2	2	2	E3	20	0.050

A-4 Design expert's data collection for TOSIS model (End-user DFX Alternatives)

	Legend
DFX	**Design for**
1	Cost (DFC)
2	Manufacturing
3	Assembly (DFA)
4	Variety (DFV)
5	Quality (DFQ)
6	Six Sigma (DFSS)
7	Disassembly
8	Reliability (DFR)
9	Testability (DFT)
10	Maintainability
11	Robustness
12	End-Of-Life (DFEL)
13	Sustainability (DFS)
14	Network (DFN)
15	Environment (DFE)

Fuzzy Numbers in Comparison Matrices																Total number of design experts	Integration Power
DFX	**VP** (1,1,3)			**P** (1,3,5)			**F** (3,5,7)			**G** (5,7,9)			**VG** (7,9,9)			Data Criteria		
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX1	0	0	0	0	0	0	2	2	2	4	4	4	14	14	14	**A1**	20	0.050
DFX5	0	0	0	0	0	0	0	0	0	8	8	8	12	12	12	**A1**	20	0.050
DFX6	2	2	2	8	8	8	7	7	7	3	3	3	0	0	0	**A1**	20	0.050
DFX8	2	2	2	4	4	4	5	5	5	7	7	7	2	2	2	**A1**	20	0.050
DFX10	4	4	4	3	3	3	5	5	5	6	6	6	2	2	2	**A1**	20	0.050
DFX12	9	9	9	2	2	2	4	4	4	2	2	2	3	3	3	**A1**	20	0.050
DFX15	4	4	4	8	8	8	5	5	5	3	3	3	0	0	0	**A1**	20	0.050

Fuzzy Numbers in Comparison Matrices																Total number of design experts	Integration Power
DFX	**VP** (1,1,3)			**P** (1,3,5)			**F** (3,5,7)			**G** (5,7,9)			**VG** (7,9,9)			Data Criteria		
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX1	1	1	1	4	4	4	2	2	2	3	3	3	10	10	10	**A2**	20	0.050
DFX5	2	2	2	0	0	0	4	4	4	6	6	6	8	8	8	**A2**	20	0.050
DFX6	6	6	6	8	8	8	2	2	2	1	1	1	3	3	3	**A2**	20	0.050
DFX8	9	9	9	2	2	2	1	1	1	4	4	4	4	4	4	**A2**	20	0.050
DFX10	3	3	3	6	6	6	5	5	5	6	6	6	0	0	0	**A2**	20	0.050
DFX12	8	8	8	5	5	5	2	2	2	5	5	5	0	0	0	**A2**	20	0.050
DFX15	10	10	10	4	4	4	3	3	3	3	3	3	0	0	0	**A2**	20	0.050

DFX	Fuzzy Numbers in Comparison Matrices															Data Criteria	Total number of design experts	Integration Power
	VP			**P**			**F**			**G**			**VG**					
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX1	12	12	12	6	6	6	2	2	2	0	0	0	0	0	0	**A3**	20	0.050
DFX5	14	14	14	5	5	5	1	1	1	0	0	0	0	0	0	**A3**	20	0.050
DFX6	2	2	2	3	3	3	6	6	6	5	5	5	4	4	4	**A3**	20	0.050
DFX8	16	16	16	4	4	4	0	0	0	0	0	0	0	0	0	**A3**	20	0.050
DFX10	10	10	10	0	0	0	6	6	6	4	4	4	0	0	0	**A3**	20	0.050
DFX12	14	14	14	0	0	0	4	4	4	2	2	2	0	0	0	**A3**	20	0.050
DFX15	18	18	18	2	2	2	0	0	0	0	0	0	0	0	0	**A3**	20	0.050

DFX	Fuzzy Numbers in Comparison Matrices															Data Criteria	Total number of design experts	Integration Power
	VP			**P**			**F**			**G**			**VG**					
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX1	2	2	2	4	4	4	6	6	6	8	8	8	0	0	0	**A4**	20	0.050
DFX5	3	3	3	5	5	5	3	3	3	7	7	7	2	2	2	**A4**	20	0.050
DFX6	4	4	4	0	0	0	8	8	8	6	6	6	2	2	2	**A4**	20	0.050
DFX8	12	12	12	8	8	8	0	0	0	0	0	0	0	0	0	**A4**	20	0.050
DFX10	10	10	10	6	6	6	2	2	2	2	2	2	0	0	0	**A4**	20	0.050
DFX12	14	14	14	2	2	2	4	4	4	0	0	0	0	0	0	**A4**	20	0.050
DFX15	16	16	16	4	4	4	0	0	0	0	0	0	0	0	0	**A4**	20	0.050

DFX	Fuzzy Numbers in Comparison Matrices															Data Criteria	Total number of design experts	Integration Power
	VP			**P**			**F**			**G**			**VG**					
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX1	2	2	2	4	4	4	5	5	5	7	7	7	2	2	2	**A5**	20	0.050
DFX5	3	3	3	5	5	5	2	2	2	8	8	8	2	2	2	**A5**	20	0.050
DFX6	8	8	8	6	6	6	3	3	3	2	2	2	1	1	1	**A5**	20	0.050
DFX8	4	4	4	4	4	4	7	7	7	5	5	5	0	0	0	**A5**	20	0.050
DFX10	2	2	2	2	2	2	4	4	4	8	8	8	4	4	4	**A5**	20	0.050
DFX12	3	3	3	3	3	3	5	5	5	7	7	7	2	2	2	**A5**	20	0.050
DFX15	12	12	12	6	6	6	2	2	2	0	0	0	0	0	0	**A5**	20	0.050

DFX	Fuzzy Numbers in Comparison Matrices															Data Criteria	Total number of design experts	Integration Power
	VP			**P**			**F**			**G**			**VG**					
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX1	9	9	9	7	7	7	4	4	4	0	0	0	0	0	0	**A6**	20	0.050
DFX5	11	11	11	6	6	6	3	3	3	0	0	0	0	0	0	**A6**	20	0.050
DFX6	14	14	14	6	6	6	0	0	0	0	0	0	0	0	0	**A6**	20	0.050
DFX8	16	16	16	4	4	4	0	0	0	0	0	0	0	0	0	**A6**	20	0.050
DFX10	18	18	18	2	2	2	0	0	0	0	0	0	0	0	0	**A6**	20	0.050
DFX12	2	2	2	3	3	3	3	3	3	7	7	7	5	5	5	**A6**	20	0.050
DFX15	3	3	3	2	2	2	2	2	2	8	8	8	5	5	5	**A6**	20	0.050

A-5 Design expert’s data collection for TOSIS model (Materials DFX Alternatives)

DFX	Fuzzy Numbers in Comparison Matrices															Data Criteria	Total number of design experts	Integration Power
	VP			**P**			**F**			**G**			**VG**					
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	2	2	2	3	3	3	4	4	4	8	8	8	3	3	3	**B1**	20	0.050
DFX 2	4	4	4	5	5	5	8	8	8	2	2	2	1	1	1	**B1**	20	0.050
DFX 3	8	8	8	6	6	6	3	3	3	2	2	2	1	1	1	**B1**	20	0.050
DFX 4	14	14	14	5	5	5	1	1	1	0	0	0	0	0	0	**B1**	20	0.050
DFX 7	18	18	18	2	2	2	0	0	0	0	0	0	0	0	0	**B1**	20	0.050
DFX 8	1	1	1	1	1	1	4	4	4	5	5	5	9	9	9	**B1**	20	0.050
DFX 14	12	12	12	8	8	8	0	0	0	0	0	0	0	0	0	**B1**	20	0.050

DFX	Fuzzy Numbers in Comparison Matrices															Data Criteria	Total number of design experts	Integration Power
	VP			**P**			**F**			**G**			**VG**					
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	2	2	2	4	4	4	11	11	11	3	3	3	0	0	0	**B2**	20	0.050
DFX 2	12	12	12	6	6	6	2	2	2	0	0	0	0	0	0	**B2**	20	0.050
DFX 3	15	15	15	5	5	5	0	0	0	0	0	0	0	0	0	**B2**	20	0.050
DFX 4	17	17	17	3	3	3	0	0	0	0	0	0	0	0	0	**B2**	20	0.050
DFX 7	18	18	18	2	2	2	0	0	0	0	0	0	0	0	0	**B2**	20	0.050
DFX 8	18	18	18	2	2	2	0	0	0	0	0	0	0	0	0	**B2**	20	0.050
DFX 14	10	10	10	2	2	2	4	4	4	4	4	4	0	0	0	**B2**	20	0.050

DFX	Fuzzy Numbers in Comparison Matrices															Data Criteria	Total number of design experts	Integration Power
	VP			**P**			**F**			**G**			**VG**					
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	0	0	0	3	3	3	2	2	2	8	8	8	7	7	7	**B3**	20	0.050
DFX 2	0	0	0	0	0	0	6	6	6	4	4	4	10	10	10	**B3**	20	0.050
DFX 3	0	0	0	2	2	2	4	4	4	8	8	8	6	6	6	**B3**	20	0.050
DFX 4	12	12	12	6	6	6	2	2	2	0	0	0	0	0	0	**B3**	20	0.050
DFX 7	10	10	10	4	4	4	4	4	4	2	2	2	0	0	0	**B3**	20	0.050
DFX 8	16	16	16	4	4	4	0	0	0	0	0	0	0	0	0	**B3**	20	0.050
DFX 14	12	12	12	6	6	6	2	2	2	0	0	0	0	0	0	**B3**	20	0.050

DFX	Fuzzy Numbers in Comparison Matrices															Data Criteria	Total number of design experts	Integration Power
	VP			**P**			**F**			**G**			**VG**					
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	2	2	2	4	4	4	8	8	8	6	6	6	0	0	0	**B4**	20	0.050
DFX 2	2	2	2	8	8	8	5	5	5	3	3	3	2	2	2	**B4**	20	0.050
DFX 3	8	8	8	4	4	4	6	6	6	2	2	2	0	0	0	**B4**	20	0.050
DFX 4	18	18	18	2	2	2	0	0	0	0	0	0	0	0	0	**B4**	20	0.050
DFX 7	16	16	16	4	4	4	0	0	0	0	0	0	0	0	0	**B4**	20	0.050
DFX 8	19	19	19	1	1	1	0	0	0	0	0	0	0	0	0	**B4**	20	0.050
DFX 14	1	1	1	3	3	3	5	5	5	6	6	6	5	5	5	**B4**	20	0.050

A-6 Design expert's data collection for TOSIS model (Machine DFX Alternatives)

Fuzzy Numbers in Comparison Matrices																	Total number of design experts	Integration Power
DFX	VP			P			F			G			VG			Data Criteria		
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	2	2	2	4	4	4	5	5	5	4	4	4	5	5	5	**C1**	20	0.050
DFX 2	3	3	3	2	2	2	8	8	8	6	6	6	1	1	1	**C1**	20	0.050
DFX 3	0	0	0	2	2	2	2	2	2	6	6	6	10	10	10	**C1**	20	0.050
DFX 7	0	0	0	0	0	0	4	4	4	8	8	8	8	8	8	**C1**	20	0.050
DFX 9	10	10	10	4	4	4	6	6	6	0	0	0	0	0	0	**C1**	20	0.050
DFX 11	0	0	0	2	2	2	4	4	4	6	6	6	8	8	8	**C1**	20	0.050

Fuzzy Numbers in Comparison Matrices																	Total number of design experts	Integration Power
DFX	VP			P			F			G			VG			Data Criteria		
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	0	0	0	0	0	0	6	6	6	8	8	8	6	6	6	**C2**	20	0.050
DFX 2	0	0	0	2	2	2	5	5	5	6	6	6	7	7	7	**C2**	20	0.050
DFX 3	0	0	0	3	3	3	2	2	2	7	7	7	8	8	8	**C2**	20	0.050
DFX 7	1	1	1	2	2	2	4	4	4	5	5	5	8	8	8	**C2**	20	0.050
DFX 9	12	12	12	6	6	6	2	2	2	0	0	0	0	0	0	**C2**	20	0.050
DFX 11	0	0	0	3	3	3	8	8	8	4	4	4	5	5	5	**C2**	20	0.050

Fuzzy Numbers in Comparison Matrices																	Total number of design experts	Integration Power
DFX	VP			P			F			G			VG			Data Criteria		
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	0	0	0	4	4	4	8	8	8	6	6	6	2	2	2	**C3**	20	0.050
DFX 2	8	8	8	7	7	7	5	5	5	0	0	0	0	0	0	**C3**	20	0.050
DFX 3	10	10	10	5	5	5	3	3	3	2	2	2	0	0	0	**C3**	20	0.050
DFX 7	12	12	12	6	6	6	2	2	2	0	0	0	0	0	0	**C3**	20	0.050
DFX 9	0	0	0	1	1	1	6	6	6	5	5	5	8	8	8	**C3**	20	0.050
DFX 11	6	6	6	8	8	8	4	4	4	2	2	2	0	0	0	**C3**	20	0.050

A-7 Design expert's data collection for TOSIS model (Performance DFX Alternatives)

Fuzzy Numbers in Comparison Matrices																	Total number of design experts	Integration Power
DFX	VP			P			F			G			VG			Data Criteria		
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	2	2	2	3	3	3	8	8	8	7	7	7	0	0	0	**D1**	20	0.050
DFX 2	3	3	3	5	5	5	6	6	6	6	6	6	0	0	0	**D1**	20	0.050
DFX 3	4	4	4	6	6	6	7	7	7	3	3	3	0	0	0	**D1**	20	0.050
DFX 7	2	2	2	4	4	4	5	5	5	6	6	6	3	3	3	**D1**	20	0.050
DFX 10	1	1	1	8	8	8	2	2	2	5	5	5	4	4	4	**D1**	20	0.050
DFX 12	10	10	10	8	8	8	2	2	2	0	0	0	0	0	0	**D1**	20	0.050
DFX 13	14	14	14	6	6	6	0	0	0	0	0	0	0	0	0	**D1**	20	0.050

DFX	Fuzzy Numbers in Comparison Matrices															Data Criteria	Total number of design experts	Integration Power
	VP			P			F			G			VG					
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	2	2	2	4	4	4	4	4	4	5	5	5	5	5	5	**D2**	20	0.050
DFX 2	12	12	12	5	5	5	3	3	3	0	0	0	0	0	0	**D2**	20	0.050
DFX 3	10	10	10	6	6	6	4	4	4	0	0	0	0	0	0	**D2**	20	0.050
DFX 7	14	14	14	2	2	2	4	4	4	0	0	0	0	0	0	**D2**	20	0.050
DFX 10	12	12	12	4	4	4	2	2	2	2	2	2	0	0	0	**D2**	20	0.050
DFX 12	16	16	16	4	4	4	0	0	0	0	0	0	0	0	0	**D2**	20	0.050
DFX 13	18	18	18	2	2	2	0	0	0	0	0	0	0	0	0	**D2**	20	0.050

DFX	Fuzzy Numbers in Comparison Matrices															Data Criteria	Total number of design experts	Integration Power
	VP			P			F			G			VG					
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	2	2	2	4	4	4	5	5	5	6	6	6	3	3	3	**D3**	20	0.050
DFX 2	12	12	12	4	4	4	4	4	4	0	0	0	0	0	0	**D3**	20	0.050
DFX 3	10	10	10	4	4	4	4	4	4	2	2	2	0	0	0	**D3**	20	0.050
DFX 7	8	8	8	6	6	6	3	3	3	3	3	3	0	0	0	**D3**	20	0.050
DFX 10	7	7	7	5	5	5	8	8	8	0	0	0	0	0	0	**D3**	20	0.050
DFX 12	15	15	15	5	5	5	0	0	0	0	0	0	0	0	0	**D3**	20	0.050
DFX 13	17	17	17	3	3	3	0	0	0	0	0	0	0	0	0	**D3**	20	0.050

DFX	Fuzzy Numbers in Comparison Matrices															Data Criteria	Total number of design experts	Integration Power
	VP			P			F			G			VG					
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	4	4	4	5	5	5	8	8	8	3	3	3	0	0	0	**D4**	20	0.050
DFX 2	5	5	5	6	6	6	9	9	9	0	0	0	0	0	0	**D4**	20	0.050
DFX 3	2	2	2	7	7	7	7	7	7	4	4	4	0	0	0	**D4**	20	0.050
DFX 7	3	3	3	5	5	5	12	12	12	0	0	0	0	0	0	**D4**	20	0.050
DFX 10	8	8	8	8	8	8	4	4	4	0	0	0	0	0	0	**D4**	20	0.050
DFX 12	18	18	18	2	2	2	0	0	0	0	0	0	0	0	0	**D4**	20	0.050
DFX 13	14	14	14	6	6	6	0	0	0	0	0	0	0	0	0	**D4**	20	0.050

DFX	Fuzzy Numbers in Comparison Matrices															Data Criteria	Total number of design experts	Integration Power
	VP			P			F			G			VG					
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	2	2	2	3	3	3	5	5	5	5	5	5	5	5	5	**D5**	20	0.050
DFX 2	4	4	4	2	2	2	6	6	6	8	8	8	0	0	0	**D5**	20	0.050
DFX 3	3	3	3	5	5	5	5	5	5	7	7	7	0	0	0	**D5**	20	0.050
DFX 7	5	5	5	6	6	6	6	6	6	3	3	3	0	0	0	**D5**	20	0.050
DFX 10	6	6	6	8	8	8	4	4	4	2	2	2	0	0	0	**D5**	20	0.050
DFX 12	2	2	2	4	4	4	3	3	3	8	8	8	3	3	3	**D5**	20	0.050
DFX 13	2	2	2	3	3	3	4	4	4	6	6	6	5	5	5	**D5**	20	0.050

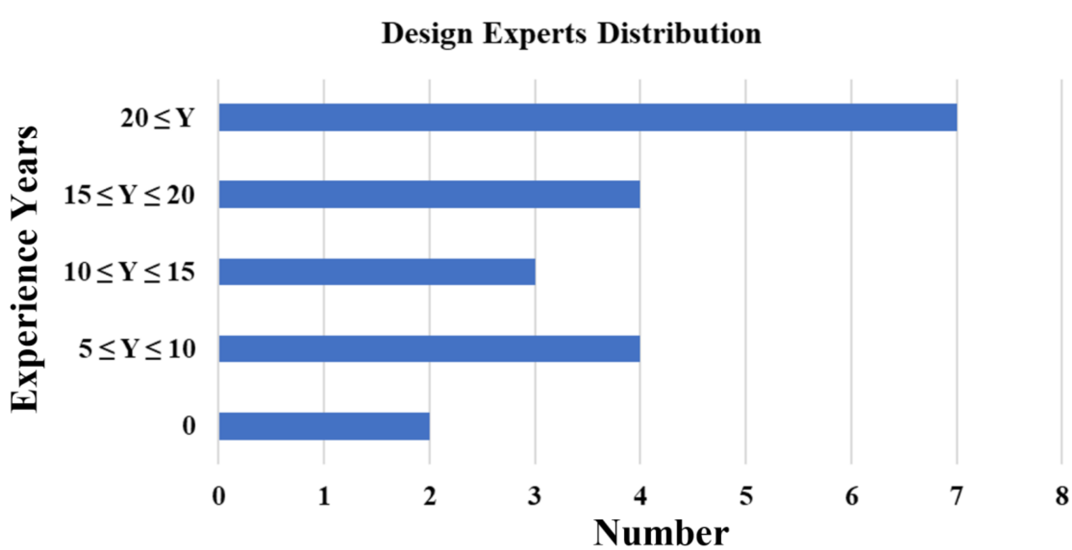
A-8 Design expert's data collection for TOSIS model (Process DFX Alternatives)

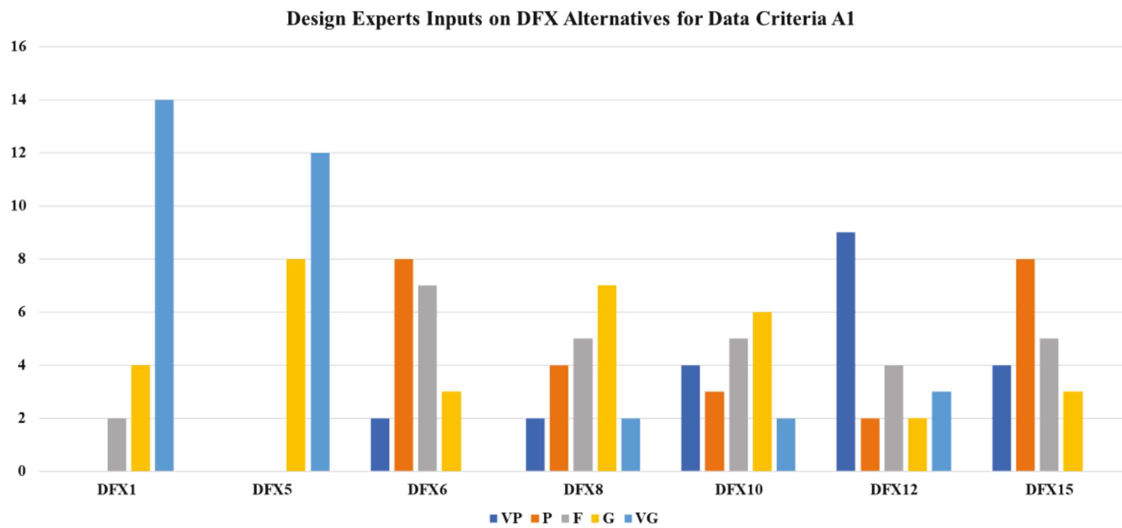
Fuzzy Numbers in Comparison Matrices																Total number of design experts	Integration Power
DFX	VP			P			F			G			VG			Data Criteria		
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	8	8	8	4	4	4	6	6	6	2	2	2	0	0	0	**E1**	20	0.050
DFX 2	12	12	12	6	6	6	2	2	2	0	0	0	0	0	0	**E1**	20	0.050
DFX 4	16	16	16	4	4	4	0	0	0	0	0	0	0	0	0	**E1**	20	0.050
DFX 6	18	18	18	2	2	2	0	0	0	0	0	0	0	0	0	**E1**	20	0.050
DFX 11	10	10	10	8	8	8	2	2	2	0	0	0	0	0	0	**E1**	20	0.050

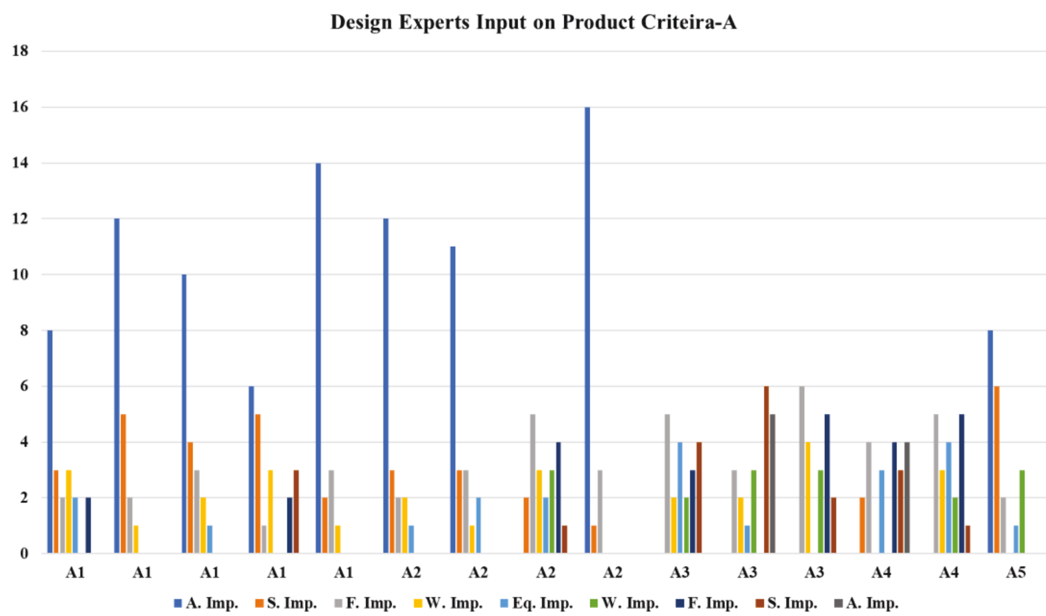
Fuzzy Numbers in Comparison Matrices																Total number of design experts	Integration Power
DFX	VP			P			F			G			VG			Data Criteria		
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	3	3	3	6	6	6	8	8	8	3	3	3	0	0	0	**E2**	20	0.050
DFX 2	8	8	8	8	8	8	4	4	4	0	0	0	0	0	0	**E2**	20	0.050
DFX 4	12	12	12	4	4	4	4	4	4	0	0	0	0	0	0	**E2**	20	0.050
DFX 6	2	2	2	3	3	3	5	5	5	6	6	6	4	4	4	**E2**	20	0.050
DFX 11	14	14	14	6	6	6	0	0	0	0	0	0	0	0	0	**E2**	20	0.050

Fuzzy Numbers in Comparison Matrices																Total number of design experts	Integration Power
DFX	VP			P			F			G			VG			Data Criteria		
	(1,1,3)			(1,3,5)			(3,5,7)			(5,7,9)			(7,9,9)					
	1	1	3	1	3	5	3	5	7	5	7	9	7	9	9			
DFX 1	2	2	2	1	1	1	6	6	6	5	5	5	6	6	6	**E3**	20	0.050
DFX 2	6	6	6	8	8	8	4	4	4	2	2	2	0	0	0	**E3**	20	0.050
DFX 4	13	13	13	7	7	7	0	0	0	0	0	0	0	0	0	**E3**	20	0.050
DFX 6	16	16	16	4	4	4	0	0	0	0	0	0	0	0	0	**E3**	20	0.050
DFX 11	0	0	0	2	2	2	4	4	4	6	6	6	8	8	8	**E3**	20	0.050

A-9 Data collection main trends




Design Experts Inputs on DFX Alternatives for Data Criteria A1
16
14
12
10
8
6
4
2
0
DFX1
DFX5
DFX6
DFX8
DFX10
DFX12
DFX15
VP P F G VG


Design Experts Input on Product Criteira-A
18
16
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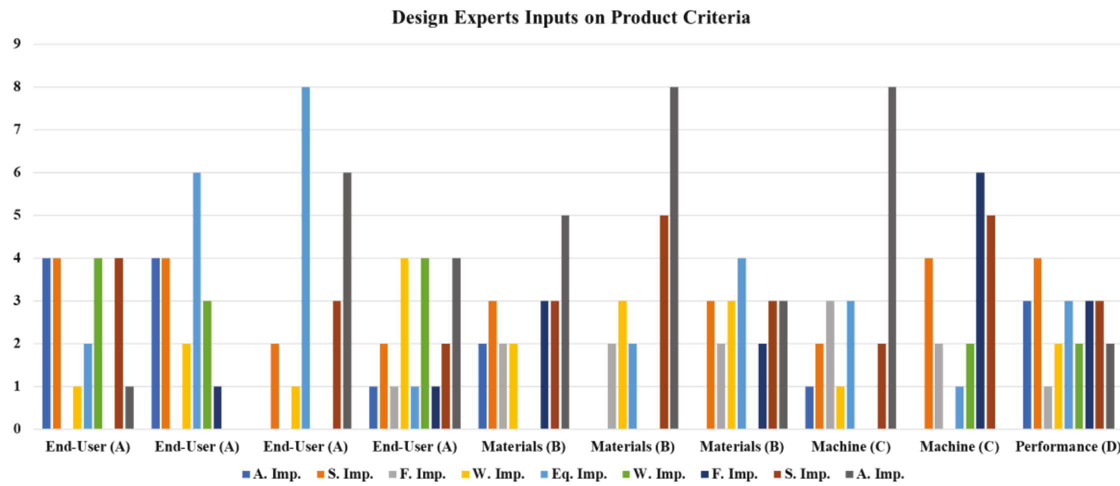
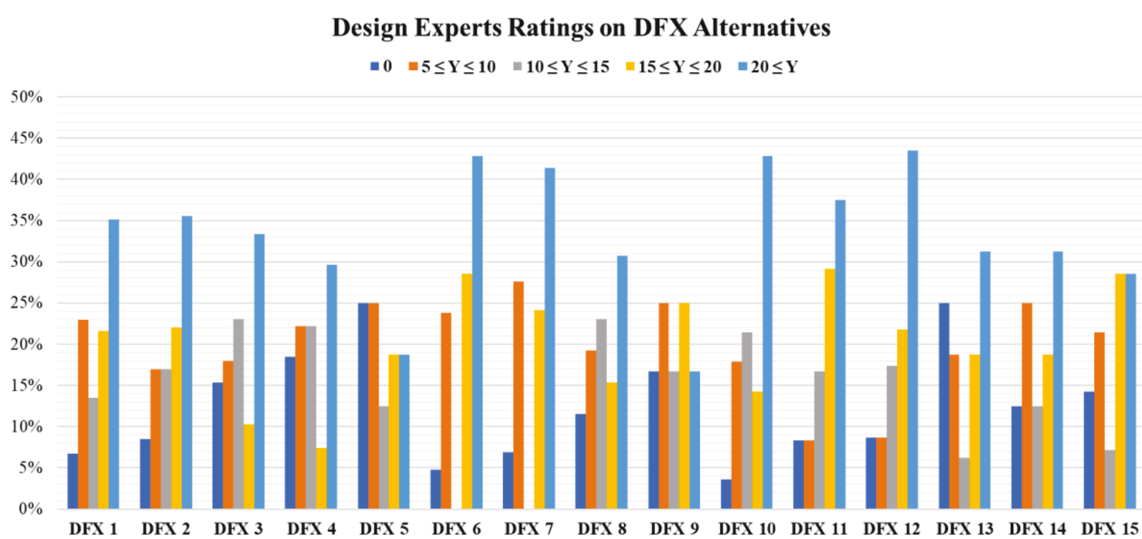
A1 A1 A1 A1 A1 A2 A2 A2 A2 A3 A3 A3 A4 A4 A5
A. Imp. S. Imp. F. Imp. W. Imp. Eq. Imp. W. Imp. F. Imp. S. Imp. A. Imp.



Experience Years	Designer	DFX 1	DFX 2	DFX 3	DFX 4	DFX 5	DFX 6	DFX 7	DFX 8	DFX 9	DFX 10	DFX 11	DFX 12	DFX 13	DFX 14	DFX 15
0	10	3	3	2	2	1	2	3	0	1	0	0	2	1	1	0
0	12	2	3	3	2	0	0	0	2	0	2	2	2	1	1	1
$5 \leq Y \leq 10$	11	5	2	2	0	1	2	3	0	1	2	0	0	1	1	1
$5 \leq Y \leq 10$	14	3	2	1	2	1	1	2	1	1	2	1	1	1	1	1
$5 \leq Y \leq 10$	17	5	3	3	2	1	0	3	2	1	0	0	0	0	1	0
$5 \leq Y \leq 10$	20	4	3	1	2	1	2	0	2	0	1	1	1	1	1	1
$10 \leq Y \leq 15$	3	3	3	3	2	1	0	0	2	1	2	2	2	0	0	0
$10 \leq Y \leq 15$	5	4	3	3	2	0	0	0	2	0	2	0	2	1	1	1
$10 \leq Y \leq 15$	9	3	4	3	2	1	0	0	2	1	2	2	0	0	1	0
$15 \leq Y \leq 20$	2	4	3	2	1	1	2	1	0	1	1	1	1	1	1	1
$15 \leq Y \leq 20$	6	4	3	0	0	1	2	3	2	1	0	2	0	1	1	1
$15 \leq Y \leq 20$	15	4	3	2	1	0	0	3	0	0	1	2	2	1	1	1
$15 \leq Y \leq 20$	16	4	4	0	0	1	2	0	2	1	2	2	2	0	0	1
$20 \leq Y$	1	5	2	3	2	0	1	2	1	0	2	1	0	0	1	1
$20 \leq Y$	4	5	2	2	1	0	2	3	2	0	2	1	1	0	0	0
$20 \leq Y$	7	5	2	2	1	1	2	0	1	0	2	0	2	1	1	1
$20 \leq Y$	8	3	3	2	1	0	1	2	1	0	1	2	2	1	1	1
$20 \leq Y$	13	1	4	2	0	0	2	0	2	1	2	2	2	1	1	1
$20 \leq Y$	18	2	4	2	2	1	0	3	0	0	2	2	2	1	0	0
$20 \leq Y$	19	5	4	0	1	1	1	2	1	1	1	1	1	1	1	0



From the design experts' ratings on DFX alternatives, it is apparent that the level of importance and ranking of DFX techniques has changed dramatically. For example, the conclusion derived from objective 1 state that design for testability was ranked first and design for manufacturing was ranked second among the top-ranked 15 DFX techniques. However, in objective 3 conclusion, some variations can be noticed. Where design for testability is ranked last and design for manufacturing remain in the second rank between the 15 DFX techniques. The results variation between objectives 1 and 3 can be linked to the increasing knowledge gap between research and industry design experts.

A-10 Data collection Analysis

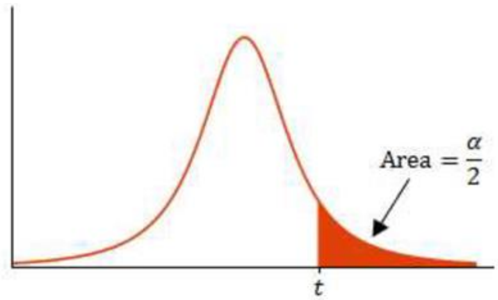
Since the number of samples are less than 30, then the t-distribution tables and equations are used to analysis the extracted data.

Description	Values	Equation
Normally distributed data	-	-
Experts interviewed (sample)	N=20	-
Confidence of interval	95%	-
Sample Mean	µ = 26.94 ± 2.09= [24.85, 29.03]	$\mu = \frac{\sum_{i=1}^{N} X}{N}$
Sample Standard Deviation	7.76	$\sigma = \sqrt{\frac{(X_i - \mu)^2}{N}}$

Sample Variance	60.36 [39.71, 102.71]	$S^2 = \frac{1}{N-1}\sum_{i=1}^{N}(X_i - \mu)^2$

Percentiles of the $t_{(1-\alpha/2),df}$ distribution (values of t such that $100(1-\alpha/2)\%$ of the distribution is less than t)

$$\bar{X} \pm t_{(1-\alpha/2),(n-1)} \frac{S}{\sqrt{n}}$$



df	$t_{0.600}$	$t_{0.700}$	$t_{0.800}$	$t_{0.900}$	$t_{0.950}$	$t_{0.975}$	$t_{0.990}$	$t_{0.995}$
1	0.3249	0.7265	1.3764	3.0777	6.3138	12.7062	31.8205	63.6567
2	0.2887	0.6172	1.0607	1.8856	2.9200	4.3027	6.9646	9.9248
3	0.2767	0.5844	0.9785	1.6377	2.3534	3.1824	4.5407	5.8409
4	0.2707	0.5686	0.9410	1.5332	2.1318	2.7764	3.7469	4.6041
5	0.2672	0.5594	0.9195	1.4759	2.0150	2.5706	3.3649	4.0321
6	0.2648	0.5534	0.9057	1.4398	1.9432	2.4469	3.1427	3.7074
7	0.2632	0.5491	0.8960	1.4149	1.8946	2.3646	2.9980	3.4995
8	0.2619	0.5459	0.8889	1.3968	1.8595	2.3060	2.8965	3.3554
9	0.2610	0.5435	0.8834	1.3830	1.8331	2.2622	2.8214	3.2498
10	0.2602	0.5415	0.8791	1.3722	1.8125	2.2281	2.7638	3.1693
11	0.2596	0.5399	0.8755	1.3634	1.7959	2.2010	2.7181	3.1058
12	0.2590	0.5386	0.8726	1.3562	1.7823	2.1788	2.6810	3.0545
13	0.2586	0.5375	0.8702	1.3502	1.7709	2.1604	2.6503	3.0123
14	0.2582	0.5366	0.8681	1.3450	1.7613	2.1448	2.6245	2.9768
15	0.2579	0.5357	0.8662	1.3406	1.7531	2.1314	2.6025	2.9467
16	0.2576	0.5350	0.8647	1.3368	1.7459	2.1199	2.5835	2.9208
17	0.2573	0.5344	0.8633	1.3334	1.7396	2.1098	2.5669	2.8982
18	0.2571	0.5338	0.8620	1.3304	1.7341	2.1009	2.5524	2.8784
19	0.2569	0.5333	0.8610	1.3277	1.7291	2.0930	2.5395	2.8609
20	0.2567	0.5329	0.8600	1.3253	1.7247	2.0860	2.5280	2.8453
21	0.2566	0.5325	0.8591	1.3232	1.7207	2.0796	2.5176	2.8314
22	0.2564	0.5321	0.8583	1.3212	1.7171	2.0739	2.5083	2.8188

A-11 Second case study for objective 2

This case study is related to objective 2 section where the nailer carriage is the main subject of this case study in its detailed design stage. Two DFX techniques (DFA and DFDA) are investigated and the results are shown in the later sections.

DFA Design rules and strategy weights by product development phase

Product Development Phase	Design Rules	W_{DFXG}	W_{TR}	Design Strategies	W_{PS}	W_{TS}	T_{TS}
Detailed Design	1- Minimize the number of parts (Types & Count).	0.11	7	1- Attempt to design symmetrical parts to avoid need for extra orienting devices or motions.	0.35	0.27	0.44
				2- Test each part's need for existence as a separate component.	0.1	0.08	0.13
				3- Eliminate parts that act as conduits and connectors.	0.2	0.15	0.25
				4- Design mult-function parts.	0.35	0.27	0.44
	2- Aim for the elimination of adjusments and parts asymmetry.		4	1- Reduce the number of parts between the input and output function.	0.6	0.26	0.43
				2- Move critically related surfaces close together to facilitate tolerance control.	0.1	0.04	0.07
				3-Follow kinematic design principles.	0.2	0.09	0.14
				4- Eliminate or minimize the need for repositioning an assembly once it is fixtured.	0.1	0.04	0.07
	3- Elimnate tangling, jamming.		2	1- A void projections, holes or slots that will cause tangling with other parts when placed in bulk, bin or feeder.	0.5	0.11	0.18
				2- Provide features to prevent jamming, such as nesting.	0.5	0.11	0.18
	4- Design parts to be self-aligning and self-locating.		4	1- Design parts with built in alignment.	0.4	0.18	0.29
				2- Avoid parts that require special grasping tools.	0.2	0.09	0.14
				3- Eliminate or minimize the number of electrical and mechanical adjustments.	0.3	0.13	0.22
				4- Facilitate assembly operations by providing chamfers or tapers to help guide and position fasteners.	0.1	0.04	0.07
	5- Reduce number of fastening products.		4	1- Reduce number of rivets, screws, bolts, special-purpose fasteners.	0.6	0.26	0.43
				2- Eliminate separate fasteners.	0.4	0.18	0.29
	6- Ensure adequate access and unrestricted vision.		8	1- Ensure adequate clearance for hands, tools, and subsequent processes.	0.3	0.26	0.43
				2- Ensure that vision of the process is not restricted or compromised.	0.7	0.62	1.01
	7- Execute one-way assembly methodology.		7	1- Design simple assembly operations: parts can be assembled only one way; if misassembled, subsequent parts cannot be added.	0.5	0.39	0.63
				2- Minimize motion distance, within practical limits, to reduce motion time and improve accuracy.	0.5	0.39	0.63

DFDA Design rules and strategy weights by product development phase

Product Development Phase	Design Rules	W_{DFXG}	W_{TR}	Design Strategies	W_{PS}	W_{TS}	T_{TS}
Detailed Design	1- Improve the product structure for disassembly.	0.05	10	1- Subdivide the whole assembly into manageable subassemblies.	0.25	0.13	0.60
				2- Minimize the number of connections between subassemblies.	0.35	0.18	0.83
				3- Minimize the number of components and subassemblies.	0.4	0.20	0.95
				4-Standardize the products style.	0	0.00	0.00
	2- Improve access and vision for disassembly.		2	1- Make sure that components are accessible.	1	0.10	0.48
	3- Improve disassembly planning.		3	1- Reduce the number of changes in direction required in a removal operation.	0.3	0.05	0.21
				2- Avoid long disassembly paths.	0.7	0.11	0.50
	4- Material compatibility.		0	1- Subassemblies that are difficult to disassemble should be made of the same or compatible material.	1	0.00	0.00
	5- Implementing component design rules.		1	1- Integrate components with the same material and avoid the combination of different materials.	0.4	0.02	0.10
				2- Mark materials permanently to assist sorting.	0.3	0.02	0.07
				3- Design in predetermined fracture points that allow rapid removal of components.	0.3	0.02	0.07
	6- Design and selection of connectors.		10	1- Make connectors of a compatible material to avoid the need for disassembly.	0	0.00	0.00
				2- Minimize the type and number of connection forms.	0.35	0.18	0.83
				3- Select easy to disassemble connectors.	0.25	0.13	0.60
				4- Use connectors with fracture points for difficult situations.	0	0.00	0.00
				5- Ensure connectors can be removed with standard tools.	0.4	0.20	0.95
	7- Maximize end of life value of the product.		1	1- Standardize components.	0.4	0.02	0.10
				2- Design for long life and reuse.	0.6	0.03	0.14

Detailed Design	DFDA Strategies	Subdivide the whole assembly into manageable subassemblies.	Minimize the number of connections between subassemblies.	Minimize the number of components and subassemblies.	Standardize the products style.	Make sure that components are accessible.	Reduce the number of changes in direction required in a removal operation	Avoid long disassembly paths.	Subassemblies that are difficult to disassemble should be made of the same or compatible material.	Integrate components with the same material and avoid the combination of different materials.	Mark materials permanently to assist sorting.	Design in predetermined fracture points that allow rapid removal of components.	Make connectors of a compatible material to avoid the need for disassembly.	Minimize the type and number of connection forms.	Select easy to disassemble connectors.	Use connectors with fracture points for difficult situations.	Ensure connectors can be removed with standard tools.	Standardize components.	Design for long life and reuse.			
DFA Strategies	W_{TS}	0.13	0.18	0.20	0.00	0.10	0.05	0.11	0.00	0.02	0.02	0.02	0.00	0.18	0.13	0.00	0.20	0.02	0.03			
Attempt to design symmetrical parts to avoid need for extra orienting devices or motions.	0.27	0	0	5	10	0	0	5	5	-5	0	0	5	5	0	0	0	5	0	0.008	0.27	4
Test each part's need for existence as a separate component.	0.08	0	-5	-10	0	0	5	5	10	0	5	0	0	0	10	0	0	0	0	- 0.003	0.08	25
Eliminate parts that act as conduits and connectors.	0.15	0	0	0	-5	0	0	0	5	5	10	0	0	0	0	0	0	0	0	0.001	0.15	15
Design mult-function parts.	0.27	0	0	0	0	0	0	0	-5	0	0	0	0	10	0	0	0	5	0	0.006	0.27	5
Reduce the number of parts between the input and output function.	0.26	0	0	0	0	-10	0	0	0	0	0	5	0	0	0	5	0	0	0	- 0.003	0.26	7
Move critically related surfaces close together to facilitate tolerance control.	0.04	0	0	0	0	0	0	0	0	-5	0	0	10	0	0	0	10	0	5	0.007	0.04	28
Follow kinematic design principles.	0.09	10	0	0	5	0	10	0	0	0	0	5	0	0	-5	0	0	-5	0	0.004	0.09	23
Eliminate or minimize the need for repositioning an assembly once it is fixtured.	0.04	0	0	10	0	5	0	-10	0	0	5	-5	0	5	0	0	0	10	0	0.008	0.04	27
A void projections, holes or slots that will cause tangling with other parts when placed in bulk, bin or feeder.	0.11	-5	5	0	0	0	0	0	0	0	10	0	5	0	0	5	0	0	0	0.001	0.11	19
Provide features to prevent jamming, such as nesting.	0.11	5	0	-5	0	0	-5	0	-10	0	-10	0	0	0	0	10	0	5	0	- 0.002	0.11	20
Design parts with built in alignment.	0.18	5	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0.010	0.18	11
Avoid parts that require special grasping tools.	0.09	0	0	0	0	0	0	0	0	0	10	0	5	0	10	0	-5	-10	5	0.001	0.09	24
Eliminate or minimize the number of electrical andmechanical adjustments.	0.13	5	0	0	0	0	0	10	0	-10	0	0	0	0	0	0	0	0	0	0.005	0.13	16
Facilitate assembly operations by providing chamfers or tapers to help guide and position fasteners.	0.04	0	0	0	0	0	5	5	5	0	5	5	-5	0	-5	5	0	0	5	0.001	0.04	29
Reduce number of rivets, screws, bolts, special-purpose fasteners.	0.26	-10	0	0	0	0	0	0	-5	0	0	0	0	0	0	0	0	0	0	- 0.004	0.26	8
Eliminate separate fasteners.	0.18	5	0	-5	0	-5	0	0	0	0	10	0	0	0	0	0	0	0	0	- 0.002	0.18	14
Ensure adequate clearance for hands, tools, and subsequent processes.	0.26	5	5	0	-5	0	0	-10	0	0	0	0	0	0	0	0	0	0	0	0.002	0.26	6
Ensure that vision of the process is not restricted or compromised.	0.62	0	5	0	5	0	5	0	0	5	0	0	5	0	0	5	0	0	10	0.005	0.62	1
Design simple assembly operations: parts can be assembled only one way; if misassembled, subsequent parts cannot be added.	0.39	5	0	5	0	10	0	0	0	0	0	0	0	0	-10	0	0	-5	0	0.004	0.39	2
Minimize motion distance, within practical limits, to reduce motion time and improve accuracy.	0.39	0	0	0	10	0	0	0	0	0	5	5	5	0	0	0	0	0	-5	-	0.39	3
		0.01	0.02	0.01	0.03	0.00	0.01	0.00	- 0.00	0.00	0.02	0.01	0.03	0.01	-0.01	0.02	-	0.00	0.02	δV		
		0.13	0.18	0.20	-	0.10	0.05	0.11	-	0.02	0.02	0.02	-	0.18	0.12	-	0.20	0.02	0.03		**Vtot**	
		17	12	9	35	22	26	21	35	31	33	34	35	13	18	35	10	32	30			**Ranking**

DFA and DFDA Strategies in Detailed Design Stage Ranking List Summary (Before Analysis)	$\forall_{TS}$	Ranked List	T_{TS}
Select easy to disassemble connectors.	0.62	1	0.44
A void projections, holes or slots that will cause tangling with other parts when placed in bulk, bin or feeder.	0.39	2	0.13
Provide features to prevent jamming, such as nesting.	0.39	3	0.25
Ensure that vision of the process is not restricted or compromised.	0.27	4	0.44
Attempt to design symmetrical parts to avoid need for extra orienting devices or motions.	0.27	5	0.43
Subdivide the whole assembly into manageable subassemblies.	0.26	6	0.07
Design mult-function parts.	0.26	7	0.14
Eliminate parts that act as conduits and connectors.	0.26	8	0.07
Follow kinematic design principles.	0.20	9	0.18
Subassemblies that are difficult to disassemble should be made of the same or compatible material.	0.20	10	0.18
Design parts with built in alignment.	0.18	11	0.29
Make sure that components are accessible.	0.18	12	0.14
Mark materials permanently to assist sorting.	0.18	13	0.22
Eliminate or minimize the number of electrical andmechanical adjustments.	0.18	14	0.07
Minimize motion distance, within practical limits, to reduce motion time and improve accuracy.	0.15	15	0.43
Minimize the type and number of connection forms.	0.13	16	0.29
Avoid long disassembly paths.	0.13	17	0.43
Design in predetermined fracture points that allow rapid removal of components.	0.12	18	1.01
Minimize the number of components and subassemblies.	0.11	19	0.63
Ensure connectors can be removed with standard tools.	0.11	20	0.63
Eliminate or minimize the need for repositioning an assembly once it is fixtured.	0.11	21	0.60
Test each part's need for existence as a separate component.	0.10	22	0.83
Reduce the number of parts between the input and output function.	0.09	23	0.95
Minimize the number of connections between subassemblies.	0.09	24	0.00
Design simple assembly operations: parts can be assembled only one way; if misassembled, subsequent parts cannot be added.	0.08	25	0.48
Reduce the number of changes in direction required in a removal operation	0.05	26	0.21
Reduce number of rivets, screws, bolts, special-purpose fasteners.	0.04	27	0.50
Ensure adequate clearance for hands, tools, and subsequent processes.	0.04	28	0.00
Eliminate separate fasteners.	0.04	29	0.10
Use connectors with fracture points for difficult situations.	0.03	30	0.07
Facilitate assembly operations by providing chamfers or tapers to help guide and position fasteners.	0.02	31	0.07
Make connectors of a compatible material to avoid the need for disassembly.	0.02	32	0.00
Design for long life and reuse.	0.02	33	0.83
Integrate components with the same material and avoid the combination of different materials.	0.02	34	0.60
Avoid parts that require special grasping tools.	0.00	35	0.00
Move critically related surfaces close together to facilitate tolerance control.	0.00	35	0.95
Standardize components.	0.00	35	0.10
Standardize the products style.	0.00	35	0.14

DFA and DFDA Strategies in Detailed Design Stage Ranking List Summary (After Analysis)	$\forall_{TS}$	Ranked List
Select easy to disassemble connectors.	0.619	1
Avoid projections, holes or slots that will cause tangling with other parts when placed in bulk, bin or feeder.	0.387	2
Provide features to prevent jamming, such as nesting.	0.385	3
Ensure that vision of the process is not restricted or compromised.	0.272	4
Attempt to design symmetrical parts to avoid need for extra orienting devices or motions.	0.271	5
Subdivide the whole assembly into manageable subassemblies.	0.264	6
Design mult-function parts.	0.263	7
Eliminate parts that act as conduits and connectors.	0.263	8
Follow kinematic design principles.	0.202	9
Subassemblies that are difficult to disassemble should be made of the same or compatible material.	0.200	10
Design parts with built in alignment.	0.178	11
Mark materials permanently to assist sorting.	0.177	12
Eliminate or minimize the number of electrical and mechanical adjustments.	0.176	13
Minimize motion distance, within practical limits, to reduce motion time and improve accuracy.	0.154	14
Minimize the type and number of connection forms.	0.133	15
Avoid long disassembly paths.	0.127	16
Design in predetermined fracture points that allow rapid removal of components.	0.124	17
Ensure connectors can be removed with standard tools.	0.110	18
Eliminate or minimize the need for repositioning an assembly once it is fixtured.	0.105	19
Test each part's need for existence as a separate component.	0.100	20
Reduce the number of parts between the input and output function.	0.088	21
Design simple assembly operations: parts can be assembled only one way; if misassembled, subsequent parts cannot be added.	0.077	22
Reduce number of rivets, screws, bolts, special-purpose fasteners.	0.044	23
Ensure adequate clearance for hands, tools, and subsequent processes.	0.044	24
Use connectors with fracture points for difficult situations.	0.031	25
Facilitate assembly operations by providing chamfers or tapers to help guide and position fasteners.	0.020	26
Make connectors of a compatible material to avoid the need for disassembly.	0.020	27
Design for long life and reuse.	0.015	28
Integrate components with the same material and avoid the combination of different materials.	0.015	29

In the detailed design phase of objective 2 case study, if the designer is to apply DFA with 7 days and DFDA with 7 days independently then the total time required for both will be 14 days. However, if they are applied together, the redundant design strategies between the two and the conflicted area will be removed and adjusted before initiating the design activity. Thus, reducing the total time to 13 days with a difference of 1 days. The strategies elimination process is conducted based on the following:

1- From the aggregated matrix between DFX techniques shows a CI ≤ -10, then conflict occurs, and special considerations must be in place before design process can be initiated.

2- Strategies with same ranking number must be eliminated if its core objective can be found in other strategies.

3- Strategies with an overall value ($\forall_{TS}$) equal to zero must be eliminated from the ranked list.