AN INTELLIGENT DESIGN APPROACH TRAINED BY FABRICATION TECHNIQUES

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

AYÇA SÖNMEZ

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
BUILDING SCIENCE IN ARCHITECTURE

FEBRUARY 2021

Approval of the thesis:

AN INTELLIGENT DESIGN APPROACH TRAINED BY FABRICATION TECHNIQUES

submitted by **AYÇA SÖNMEZ** in partial fulfillment of the requirements for the degree of **Master of Science** i**n Building Science in Architecture, Middle East Technical University** by,

Prof. Dr. Halil Kalıpçılar
Dean, Graduate School of **Natural and Applied Sciences** _____

Prof. Dr. F. Cânâ Bilsel
Head of the Department, **Architecture** _____

Prof. Dr. Arzu Gönenç Sorguç
Supervisor, **Architecture, METU** _____

Examining Committee Members:

Assoc. Prof. Dr. İpek Gürsel Dino
Architecture, METU _____

Prof. Dr. Arzu Gönenç Sorguç
Architecture, METU _____

Prof. Dr. Şebnem Yalınay Çinici
Architecture, Bilgi University _____

Assist. Prof. Dr. Mehmet Koray Pekeriçli
Architecture, METU _____

Assist. Prof. Dr. İlker Erkan
Architecture, Süleyman Demirel University _____

Date: 15.02.2021

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last name : Ayça Sönmez

Signature :

ABSTRACT

AN INTELLIGENT DESIGN APPROACH TRAINED BY FABRICATION TECHNIQUES

Sönmez, Ayça
Master of Science, Building Science in Architecture
Supervisor: Prof. Dr. Arzu Gönenç Sorguç

February 2021, 138 pages

The developments in recent technologies through Industry 4.0 lead to the integration of digital design and manufacturing processes. While manufacturing is becoming an essential input of the design, it is usually considered at the last stages of the design process. This misconception creates a gap between digital design and fabrication, resulting in fabricated outcome being different from initial design in the context of architectural tectonics.

This thesis aims to provide a basis to bridge digital design and fabrication processes by training the design process through fabrication constraints. In order to provide a holistic design approach, a case study is presented, in which a wall design is considered through two stages. In the first stage, a top-down design process is obtained without considering fabrication. In the second stage, an artificial intelligence (AI) based generative design method trained by material and fabrication data is followed. Through top-down approach, problems with fabrication techniques are observed. On the other hand, AI based approach is adopted to study form-finding using different technologies such as generative design and cloud computing. The results indicate that design space explorations and generative design simulations can provide a significant variety of manufacturable design alternatives. While the results

can be grouped based on their visual similarity, different aspects of design alternatives show that manufacturing has a large impact on transforming the initial design.

All of the obtained design alternatives are used to construct a dataset that includes different design parameters. The dataset from the AI based method is used to train a decision tree classifier learning algorithm in order to provide decision making tasks in choosing the manufacturing method. The data obtained from the top-down method is used as a test data set in order to compare real-life cases and algorithm-predicted outcomes.

Keywords: Generative Design, Computer-Aided Fabrication, Arcihtecture 4.0, Artificial Intelligence, Digital Tectonics

ÖZ

ÜRETİM TEKNİKLERİ İLE EĞİTİLEN AKILLI BİR TASARIM YAKLAŞIMI

Sönmez, Ayça
Yüksek Lisans, Yapı Bilimleri, Mimarlık
Tez Yöneticisi: Prof. Dr. Arzu Gönenç Sorguç

Şubat 2021, 138 sayfa

Endüstri 4.0 ile birlikte gelen teknolojik gelişmeler ile dijital tasarım ve üretim süreçleri bütünleşik bir hal almaya başlamıştır. Üretim, tasarım için en temel parametrelerden birine dönüşmüşken genellikle tasarım sürecinin en son aşamasında düşünülmektedir. Bu yaklaşım, üretim ve tasarım süreçleri arasında mimari tektonik bağlamında bir boşluk yaratmaktadır ve son ürünün ilk tasarımdan mimari tektonik bağlamında farklı olmasına neden olmaktadır.

Bu tez, dijital tasarım ve üretim süreçleri arasında bir bağlantı sağlamayı amaçlamaktadır. Bütünleşik bir tasarım yaklaşımı için bir duvar tasarımı iki aşama üzerinden çalışılmıştır. Birinci aşamada fabrikasyon düşünülmeden lineer bir tasarım yaklaşımı izlenmiştir. İkinci aşamada ise yapay zeka tabanlı ve üretim bilgisini içeren bir üretken tasarım yöntemi benimsenmiştir. Lineer tasarım yöntemi ile fabrikasyon tekniklerindeki problemler gözlemlenmiştir. Diğer yandan, yapay zeka tabanlı yöntem ile üretken tasarım ve bulut tabanlı teknolojiler ile form bulma çalışması yapılmıştır. Tasarım alanı keşfi ve üretken tasarım simülasyonlarının çok sayıda üretilebilir tasarım alternatifi sağladığı gözlemlenmiştir. Sonuçlardan elde edilen çeşitli tasarım alternatifleri üretimin ilk tasarımı dönüştürmede büyük bir etkisi olduğunu göstermektedir.

Elde edilen tasarım alternatifleri ile bir veri kümesi oluşturulnuştur. Yapay zeka tabanlı metod ile edinilen veri kümesi, bir karar ağacı öğrenmesi algoritmasını eğitmek için kullanılmıştır. Bu algoritmanın tasarlanan herhangi bir model için üretim tekniği seçimi yapması beklenmektedir. Lineer yöntemden elde edilen veri kümesi ile gerçek durum ve algoritmanın tahmin ettiği üretim tekniklerinin karşılaştırması yapılmıştır.

Anahtar Kelimeler : Üretken Tasarım, Bilgisayar Destekli Fabrikasyon, Mimari 4.0, Yapay Zeka, Dijital Tektonik

To my dearest family

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my supervisor and mentor Prof. Dr. Arzu Gönenç Sorguç not only for her guidance, support and advice, but also for her patience and understanding. It was a great journey to work with her, and this thesis would not be possible without her encouragement and challenging me to think outside the box.

I also want to express my appreciation and gratitude to the examining committee members, Assoc. Prof. Dr. İpek Gürsel Dino, Prof. Dr. Şebnem Yalınay Çinici, Assist. Prof. Dr. Mehmet Koray Pekeriçli and Assist. Prof. Dr. İlker Erkan for their valuable comments and contribution.

I want to thank to my parents Neslihan and Ertuğrul Sönmez for their continuous support and understanding from the day that I was born. Also, thanks to my dearest sister Deniz Sönmez Ünal and Erhan Ünal for their technical and motivational support.

I am very thankful to my friends for their support, and hospitality. Especially, my sincere blessings are to Sıla Efil, Ece Öztepe and Melda Erdinç for their friendship and trials to help me with the thesis discussion with their contributions. I also want to thank to Zeynep Öziş for her contribution, friendship and being the best companion during my graduate education.

I owe gratitude to my coworkers at Framaco and Debbas Architecture for their understanding and patience. I also want to thank to members of any bands I've been to during thesis process for their understanding.

I am very grateful to METU Design Factory team for their support, motivation and contributions. I especially want to thank to Dr. Müge Kruşa Yemişcioğlu for her comments and guidance during this process, as well as for her constant support and motivation.

I also want to thank to any architect or designer, who are not afraid of technology, but rather embrace it, and contribute to its development.

Last, but not least, I want to thank to my significant other Can Yıldırım for his both academic and emotional support, which I can’t express with words. Thank you for being the closest to me despite the distance and enabling me to achieve things that I cannot imagine.

TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

LIST OF ABBREVIATIONS

ABBREVIATIONS

3D	Three Dimensional
AI	Artificial Intelligence
Appx.	Approximately
BBOX	Bounding Box
CPS	Cyber-Physical Systems
CAD	Computer-Aided Drafting
CAF	Computer-Aided Fabrication
CAM	Computer-Aided Manufacturing
DSE	Design Space Explorations
FDM	Fused Deposition Modeling
Hr-Hrs	Hour-Hours
IT	Information Technologies
MDF	Medium Density Fiberboard
MFR	Manufacturing
ML	Machine Learning
PLA	Polylactic Acid
SLA	Stereolithography
XPS	Expanded Polystyrene

CHAPTER 1

INTRODUCTION

The way humans create always changed through technological developments of the time they live in. First Industrial Revolution brought steam-powered machines, Second Industrial revolution created machine dependent mass production and the Third Industrial Revolution introduced computerization and scripting. Today's technologies such as artificial intelligence, robotics, 3D printing and machine learning are introducing a Fourth Industrial Revolution (Industry 4.0.), which aims to provide intelligent products and production processes. Manufacturing systems are becoming smart through intelligent machines, which are defined as cyber-physical systems that enable interactions between humans and machines. (Brettel et al., 2014) These shifts in new technologies always effected the way people think, the tools they use and the products they created.

Manufacturing systems in Industry 4.0 are becoming self-organized, decentralized and always in communication with each other via a virtual network. Moreover, this virtual network is a part of an internet of things that enable integration of all smart processes. While being self-organized with their sensor and actuators, these systems can also have interfaces to communicate with its user and provide human-machine interactions.

This change in manufacturing led to change in products, and the integration of hardware and software. Combined with the digitalization in tools and manufacturing systems, Industry 4.0 leads to digitalized environments. In a digital environment as defined above, like every discipline, architecture of Industry 4.0 has also been reaching a new phase which is data-driven and performative. In this sense, it can be claimed that new technologies affect architectural types, form, construction

techniques, and how buildings are fabricated. Manufacturing systems are becoming smarter, and fabrication owns a critical role in architectural or construction practices. It can be said that digitalization in tools and fabrication principles are also influencing the design process, and fabrication is becoming one of the initial steps of design process, which also changes architectural tectonics.

Although file-to-factory approach and computational design tools are well-embraced in architectural practices, the implementation of intelligent systems in Industry 4.0 remains in building component scale. Also, while architecture is becoming to be produced in digitalized environments, the end product is not always what the designer expects or sees on the screen. Initial design can be altered through several iterations between file-to-factory and can even change completely in the final product. (Figure 1.1)

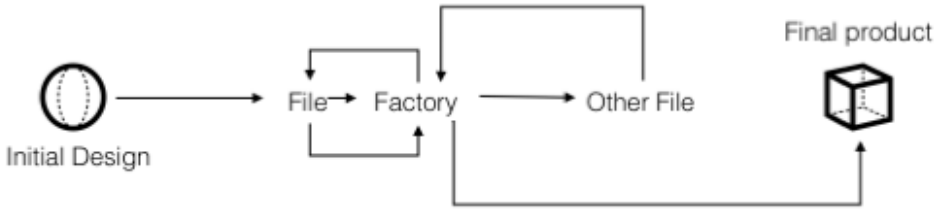


Figure 1.1 Dialogue between file to factory process and final product

This change occurs mostly due to not considering the physical aspects such as material and fabrication details, during the computational design process, which also causes time and material loss. In other words, it is due to the separation of computational design and fabrication processes. In this sense, integrating fabrication while exploring design alternatives can lead to more accurate design instances, and a controlled design process. Additionally, the use of systems based on artificial intelligence can help to connect digital design and fabrication processes, by minimizing the gap between, and it can provide efficiency in time and material use.

This thesis aims to provide an insight to this dilemma between digital and material, by providing an intelligent holistic design approach, in which the process is trained by manufacturing constraints. The research gives a brief background on effects of industrial revolutions and introduces main technologies that can connect these processes. Then, it is discussed in the context of architectural tectonics and accuracy between digital model and the physical outcome. The problem is studied with two different experiments, one is intuitive and the other one depends on AI based methods.

1.1 Problem Statement

Since digital design and fabrication processes have effects on architectural tectonics, the separation of these creates various problems between initial and fabricated designs. What is designed initially, can be subjected to several alterations and thus, it may not be the same with the fabricated outcome. As the dialogue between fabrication and computation has the ability to change the initial design, fabrication should be considered as one of the initial steps of the design process. Since fabrication process implicitly includes optimization tasks, design processes evolve into finding various instances of a design. With the recent improvements in AI and intelligent manufacturing, design processes can learn from manufacturing data to provide several manufacturable design instances, which can help connecting design and fabrication processes.

1.2 Aim and Objectives of the Research

This thesis aims to provide an exploration of the gap between digital and physical processes, by a bottom-up design approach with generating and evaluating design alternatives through AI based environments. Through this exploration, it is aimed to show the importance of a holistic design approach. The objectives of the thesis can be listed as below:

- To minimize time loss and iterative actions during fabrication process
- To integrate fabrication in developing the design alternatives
- To keep design accuracy by selecting the best fabrication method

In order to achieve these objectives, questions that will be answered in this research can be listed as below:

- What are the limitations of fabrication methods and materials?
- Which parameters can be used in selecting the manufacturing method?
- What is the relationship of mass, volume and tectonics with manufacturing method and materials?
- What is the accuracy of proposed approach?

1.3 Scope

This thesis is comprised of five chapters. This chapter introduces the problem statement and research objectives. Second chapter presents the background and earlier research on the field. Third chapter describes the material and method of research by introducing two phases of the experiments. Fourth chapter presents the results of this experiment. Fifth chapter continues with the discussion of the presented research by grouping and evaluating research outcomes, as well as introducing an assessment for design instances to show how design instances change according to different fabrication criteria. Last chapter summarizes the thesis, points out the highlights and present limitations. Recommendations for future work are also included in the last chapter.

The diagram given in Table 1.1 provides a summary of the thesis chapters, as a manual of the scope.

Table 1.1 Thesis structure

THESIS STRUCTURE					
CHAPTER 1 INTRODUCTION	CHAPTER 2 BACKGROUND	CHAPTER 2 RESEARCH DESIGN	CHAPTER 3 RESULTS AND ANALYSIS	CHAPTER 4 DISCUSSION	CHAPTER 5 CONCLUSION

Introduction to Problem
 	
Problem Statement
 	
Hypothesis
 	
Research Aim
 	
Research Questions
	Architecture in the context of Industrial Revolutions
	
	• Architecture 4.0
	
	Recent Technologies in Research Context
	
	• Generative Design
	• CPSs
	• Machine Learning
	• Cloud Computing
	
	Architectural Tectonics
	
	• Impact of CAF
	  ◦ Fabrication Principles
	  ◦ Fabrication Techniques
	• Impact of Algorithm
	  ◦ Digital Tectonics
	  ◦ Digital Materiality
	
	Problems in Translation between Digital and Analog
	
	Accuracy and Precision
	
	• Examples from Different Disciplines
	
	Holistic Design Approach
	
	• Top-down Approach
	• Bottom-up Approach
	• Digital Workflows and Ecosystems
		Introduction of Experimental Research
		
		Explorations on a Pre-designed Form
		
		• Description of Computational Model
		• Fabrication Techniques and Materials
		
		AI-Based Explorations
		
		• Design Space
		  ◦ Case I: Partial Model with Initial Shape
		  ◦ Case II: Full Model as Preserve Geometry
		  ◦ Case III: Partial Model - Smaller Size with Initial Shape
		• Structural Inputs
		• Generative Design Objectives
		• Manufacturing and Materials
		
		Implementation of ML
		
		• Decision Tree Classifier
		  ◦ Model Parameters
		  ◦ Description of Evaluation Metrics
			First Phase
			
			• Fabricated Outcomes
			• Fabrication and Optimization Process
			• Dataset for ML Prediction
			
			Second Phase
			
			• Generative Design Outcomes
			• Mass-Volume Graphs
			• Combined Graphs for Extreme Cases of Materials
			
			Decision Tree Classifier
			
			• Comparison of ML-Predicted Outcomes and Real-Life Cases
				Top-Down Approach
				
				• Problems during Fabrication Process
				• Design Changes
				
				AI-Based Approach
				
				• Grouping the Outcomes per Similarity
				• Change in Design Instances per Design and Fabrication Criteria
				• Advantages
				• Discussion of the Method within the Points in Chapter 1
				
				Re-designing the Process
				
				• Form-finding
				• Instance Assessment
				• Model Checking
					Summary of the Thesis
					
					General Conclusions
					
					Limitations
					
					Recommendations for Future Work

CHAPTER 2

LITERATURE REVIEW

This chapter presents the background of the research problem, and provides a review of literature based on earlier research. Firstly, an overview of development of architecture through industrial revolutions is presented and the architecture of Industry 4.0 is examined in order to understand the shift between the third and the fourth industrial revolutions. Secondly, since some recent technologies can overcome the struggle between file and factory, research based on these technologies are presented within the context of fabrication in order to see how they can be implemented.

Also, since one of the main research concerns is fabrication, architectural tectonics, and how it is effected by fabrication techniques and principles are examined. Additionally, how computational processes effect architectural tectonics is discussed, and how the dialogue between computation and fabrication impacts the final product is examined.

Lastly, an evaluation of top-down and bottom-up design processes, and integrated workflows are discussed as their implementations can provide different solutions to the gap discussed in the research problem by combining virtual and physical processes.

2.1 Development of Architecture through Industrial Revolutions

Industrial revolutions in history have always affected architecture and its different aspects. Like building materials were evolving through industrial revolutions, different types of buildings are constructed. With mass production, and following the developments in CAD/CAM systems, the process of architectural design and

fabrication has been changed. Additionally, research on robotics, electronics and biomimetics, affected not only design and fabrication processes, but also, form and operation of buildings. Forms, inspired by nature are scripted based on algorithms with non-conventional geometries, and buildings also started to interact digitally and physically with its user.

This development of architecture can also be considered as a tectonic change, which includes both materials and construction techniques.

Table 2.1 illustrates the summary of the development of architecture through industrial revolutions:

Table 2.1 Architecture through industrial revolutions

1		• Steam power • Mechanization	→	• Cast-iron structures • Early skyscrapers • Functional and slender buildings
2		• Mass production • Electricity	→	• Mass production of building components • Accelerated construction
3		• Computerization • Early discussions of cybernetics	→	• CAD/CAM developments • Freedom in complexity of forms • Mass customization • File-to-factory
4		• Cyber-physical systems • Internet of things • Smart automation	→	• Architecture 4.0 • Smart / interactive buildings • Distributed manufacturing • Robotic/AI-based fabrication

2.1.1 Architecture through Earlier Industrial Revolutions

Developments in first and second industrial revolutions changed buildings completely to industrial type and overcame Gothic style. Buildings are designed to be more functional and with slender elements. Cast iron structures such as bridges and railways; moreover, buildings like Eiffel Tower and Crystal Palace are

constructed. The change is significant because new materials provided new opportunities like buildings being lightweight and constructed in very short time with the invention of steam-powered machines. (n.a, 2018) Also, the use of iron and steel lead to the construction of early examples of skyscrapers in United States. With the second industrial revolution, mass production of this new type of buildings is enabled. (Fisher, 2014)

Third industrial revolution, which is also defined as the IT revolution made a huge impact on architectural styles, as well as the tools and the design process. Rather than "mass production" of second industrial age, the concept of "mass customization" emerged together with new developments in 3D printing, CNC manufacturing and laser cutting. These new technologies are not only used in products, but also in architecture, as in manufacturing the parts or the whole of a building. (Fisher, 2015) The drafting and design processes became more accurate, and instead of orthogonal geometries, more free-form geometries are experimented. Drafting and manufacturing can be handled computationally with one file, which means design processes also became a file-to-factory approach. This approach enabled direct data transfer between computational model and the machines that are used for manufacturing. (Oosterhuis, 2004)

2.1.2 Architecture in the Age of Industry 4.0

While architecture has adapted very well to first and second industrial revolution, after third, its development is rather slow compared to other disciplines. Shifting to a new industrial revolution, new technologies that are discussed such as smart automation and integrated cyber-physical systems, and through Industry 4.0 have been started to effect architecture and this change is assumed to be very drastic in the upcoming years. According to a survey by Microsoft and RIBA (2018), almost 90% of survey respondents claim that developments in digital technologies transform the way architects work, and over 80% of them believe that 10 years from now, operation of architectural practice will be very different. Through this

transformation, computational data becomes especially important in every phase of architectural design and construction. Through algorithm, architects have the freedom of designing the process with generative solutions which can provide different design instances of a single form, and the opportunity to experiment with non-Euclidean geometries. This change also affected how buildings are constructed and provided ease of optimization in fabrication in dealing with complex forms. Also, with today's new type of buildings such as smart, adaptive or interactive buildings, data continue to even influence the building in post-construction phase, which enables the operation of building by providing real-time interactions with user or environment. (Bier & Knight, 2014)

With Industry 4.0 discussions, as cyber-physical systems, which are combination of physical, electronic and biological systems, are introduced in manufacturing. Buildings can be considered as intelligent products, results of intelligent manufacturing systems, in which data-driven design and digital fabrication dominates the process. While shifting to an age of new industrial-digital revolution, architecture is also shifting from physical to digital and merged systems, which can be defined as so-called Architecture 4.0. (Sorguç et al., n.d.)

Differing from earlier architecture, artificial intelligence (AI) is becoming to have a major role in both fabrication and operation of architecture. AI is usually used in diagnostics and problem solving, but with the new developments in machine learning, it can also learn to construct form and models based on available data. In this sense, it can be said that in today's architecture, one of the most important notions is computational data and its interactivity. Still not being fully claimed Industry 4.0 concepts, architecture is started getting more involved with AI tools in two main areas. First one can be claimed as operation of buildings, as they are becoming smart or interactive. Buildings are designed to perform interaction tasks with their users through sensors and respond to the user's needs. (van Berkel, 2020) Second, and major role is through fabrication. As manufacturing becomes more automated, the sustainability of the end product, as well as the sustainability of the

construction process increases. This is due to minimizing time, material use and energy by automation. (Lojanica et al., 2018)

Although smart manufacturing technologies such as robotic fabrication and 3D printing have already been started to be used in construction area, such applications are not commonly used because they are still in the process of research. This might be due to architects' being late in adapting the new technologies (Carpo, 2017), and still being in adaptation process to 3rd industrial revolution. Mostly, digital processes and fabrication are conceived separately, which creates a gap between those.

2.2 Recent Technologies Connecting Digital Design and Fabrication Processes

Recent technologies that are introduced within the fourth industrial revolution such as smart factory, smart manufacturing, internet of things, and cyber physical systems, also effects the way how architecture is designed, and fabricated. While such applications enabled data exchange between machines, computer and its user, the process itself became more intelligent through machine learning algorithms.

Developments in artificial intelligence have always effected manufacturing tools and processes. Examples can be given as robotic construction with sensors, and the use of data analytics for decision-making. Moreover, improvements in data science have enabled machine learning algorithms to generate models that are acquired from earlier knowledge, which keeps manufacturing errors at minimum. In addition, with advanced automation, machines become self-controlled and self-organized systems that do not need human monitoring. (Kusiak, 2019) With this approach, the time and energy used for manufacturing is minimized, and manufacturing processes are becoming more sustainable.

While manufacturing is effected from this technologies, architectural design cannot be thought separate from these advancements. (Menges, 2015) Compared to earlier digital fabrication and drafting methods, in the age of Industry 4.0, digital 3D model

gains great importance. Being an earlier prototype of the physical artifact, a comprehensive analysis of buildings relation with its environment, or its structural or topology aspects can be solved. (Leal et al., 2018) Additionally, through generative design process, it is possible to simulate different design alternatives before fabrication and improve these alternatives through machine learning algorithms. So, recent technologies have the ability to close the gap between design and fabrication/manufacturing process. In this sense, within the scope of this thesis, technologies that can tie these processes can be reviewed in three main headings.

2.2.1 Topology Optimization-Based Generative Design

In an extended design process, which includes fabrication phase, manufacturing methods and material become important parameters starting from the very initial phase of the process. Consequently, generative design simulations including topology optimization, and design space explorations are helpful in providing such a holistic design process.

A topology optimization problem can be defined as the distribution of material in a determined design domain consisting of loads and other constrains, in order to achieve an objective, which might be structural performance, or cost, minimizing volume, etc. (Sigmund & Maute, 2013) While used widely in mechanical engineering with a variety of approaches, in architecture, the use of topology optimization is common in structural stability, stiffness, size and shape optimizations. (Beghini et al., 2014)

On the other hand, for manufacturing, optimization methods are used in product /process selection, resource acquisition, planning management, and quality control. Moreover, improving product performance and lowering production costs can be considered as objectives of topology optimization in manufacturing. (Giuseppe et al., 2014) In other words, it aims to increase the manufacturability of the initial design and to monitor the process.

Topology optimization tasks usually focus on the improvement of a single initial design alternative. Considering design alternatives of parametric design freedom, topology optimization should not be the problem to be focused, but a tool to find different design alternatives, containing structural and/or, fabrication data. This approach of optimization and design can be defined in the realm of generative design, which offers a variety of design alternatives under some constraints and design objectives. (Wu et al., 2019) In other words, a design space is constructed by the designer, and the algorithm handles the geometry creation. It may also be used to improve a single geometry, having diverse variations. While topology optimization is aimed to improve the alternative of concern, generative design creates new outputs based on topology optimization and increases the manufacturability of inputs. (Akella, 2018) The steps of generative design process are presented as below (Oh et al., 2019)

1- Design parameter and objective definition for topology optimization
2- Generating design outcomes with different parameters
3- Evaluating and iterating options, and selecting the best one
4- Manufacturing

As presented by Akella (2018), below image given in Figure 2.1 shows topology optimization based generative design results of redesigning a part of Airbus' A320 aircraft. This example shows that although the process aims to increase the efficiency of one particular design, by generative design there are many alternatives that designer can evaluate. The results show that weight of the aircraft is decreased 45 percent, which leads to efficiency in both material, construction and operation of the aircraft.

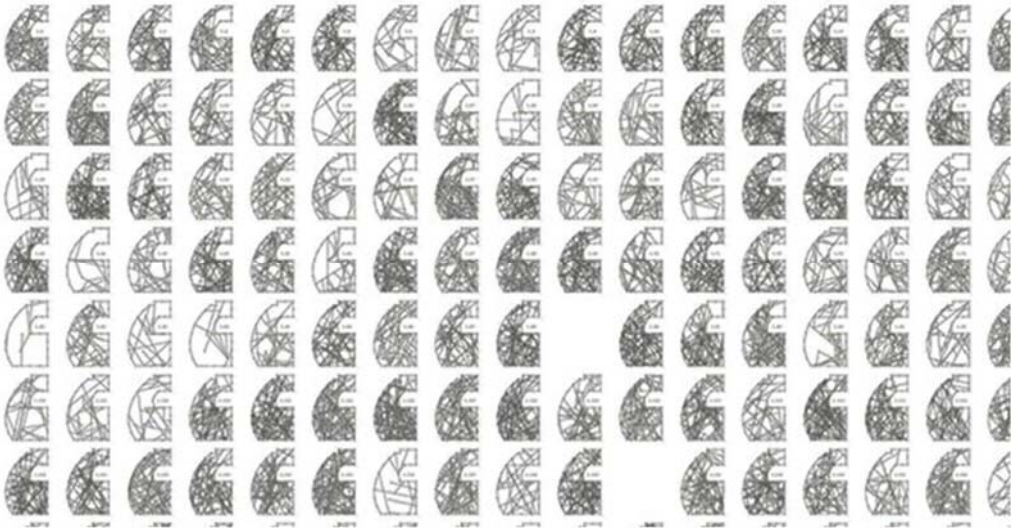


Figure 2.1 Generative design alternatives of Airbus A320 partition (Akella, 2018)

As the example given above shows, this technology provides several options to the designer, but also increases the manufacturability of the output by iterating all of the outcomes to find optimal solution. The most important part to be noted that this process is already complete without actually experimenting with fabrication and materials physically, which improves time consumption and material efficiency.

To sum up, considering digital design freedom and computational methods, any parametric software provides numerous generative solutions to one design problem. However, fabrication has certain constraints, which can set a design space with several objectives and limitations for a topology optimization task. So, combining generative design with topology optimization can improve the quality of manufactured models, and decrease the gap between initial design and the final product. This type of generative design is integrated with machine learning algorithms and cloud computing, which are explained in further paragraphs.

Since this type of generative design includes the use of a design space in form-finding, it can be claimed as a design space exploration (DSE) task, which is a complex process of finding the best design alternative that complies with the design requirements and objectives in a space of defined rules and constraints. (Cardoso et

al., 2017) Simulations based on design space explorations are used in embedded systems and computer architecture (Taghavi & Pimentel, 2010), and optimization, prototyping and system integration in engineering tasks (Kang et al., 2011), and multi-objective optimization methods are already used in architecture for performance, structural optimization and parametric design. (Fuchkina et al., 2018) Yet, the use of DSE in architecture can be extended to include fabrication and manufacturing concerns to provide manufacturable design instances.

2.2.2 Cyber-Physical Systems

A cyber-physical system is a system that is introduced with Industry 4.0, which is composed of both virtual data and physical mechanisms. In other words, such systems connect digital and analog through sensors and actuators and information processing. CPSs also allow interactions with user, other machines and smart products. CPSs are composed of sensing-actuating mechanisms, a network system and works through an algorithm to process information. These systems can detect physical data through sensors in real-time and can access and process computational data through their network system and provide automation of processes through this communication. In other words, they are composed of the interactions between physical and analog.

CPS has been used in smart buildings, or robotic construction in architecture. Cyber-physical production systems can be defined over its use in manufacturing field. Main characteristics of such production systems are listed as below: (Monostori et al., 2016)

- Smartness, to ability to detect, analyze and understand information from context and provide autonomous actions.
- Connectedness, the ability of providing different types of interactions, i.e. with user or with other machines and to use these interactions to perform. Also, can be defined as its connectivity to data and services on the Internet.

- Responsiveness, to provide feedback to real time changes or adaptability.

Implementation of cyber-physical systems in manufacturing can be investigated in five levels, proposed by Lee, Bagheri and Kao (2015) as smart connection (Level I), which implements acquiring data through sensors, conversion from data to information (Level II), includes selection of relevant information from gathered physical data, cyber level (Level III) a center information hub which analyzes data and its similar cases, cognition level (Level IV) includes synthesis, simulation of data and diagnostics for decision making, and finally configuration level (Level V), which are the applications of the decision and feedback to physical world.

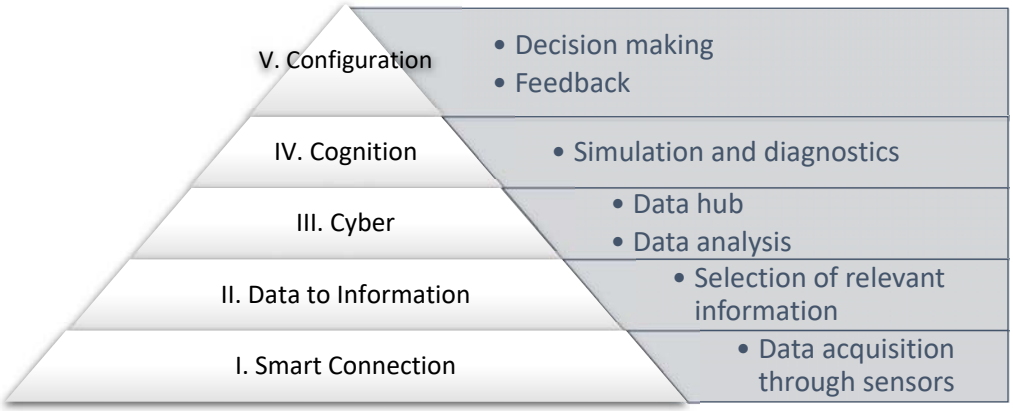


Figure 2.2 Levels of Cyber-Physical Systems (Lee, Bagheri & Kao, 2015), redrawn by author

Addition to cyber-physical systems, in computer-aided fabrication, Menges defines cyber-physical making, where machines can interact, and the process is improved with a continuous data flow. (2015) While similar systems like robotic fabrication, or embedded sensors are used in architectural fabrication, they are not totally integrated systems as they are not able to analyze the data or optimize the manufacturing process. Developing the cyber, cognition and configuration levels and their ability to analyze and interpreting data of such systems can improve

optimization of manufacturing process and can provide a better, integrated understanding of cyber-physical system-based manufacturing.

2.2.3 Machine Learning

Machine learning can be defined as computer's ability to learn without explicit programming. Its algorithms are usually investigated in three main categories as below:

- Supervised learning: There are inputs and output variables (Y=f(X)) and algorithm is used to learn mapping function from input to output. Learning process is provided by learning from training data set.
- Unsupervised learning: There is only input parameter. Learning is due to adopting and discovering based on input and output is predicted. Clustering algorithms are examples to this.
- Reinforcement learning: It is based on output and a reward is given for correct output and a penalty for incorrect output. Correct input/output pairs are not presented and there are no corrections of actions.

Although it has three main categories, machine learning has been differentiated in a more complex way considering algorithm variations as shown in the figure below (Wuest et al., 2016)

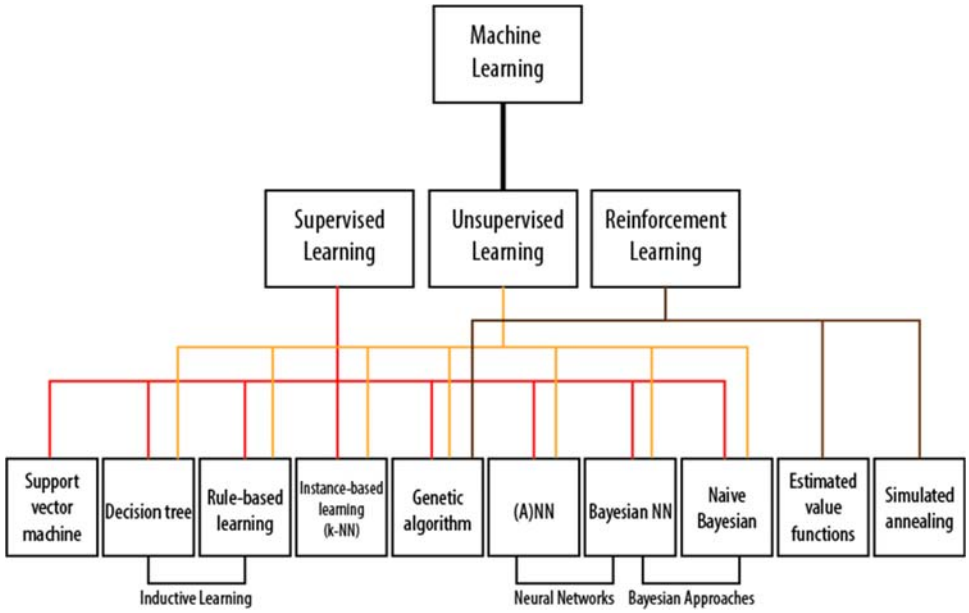


Figure 2.3 Machine Learning Algorithms (Wuest et al, 2016), redrawn by author

Learning from collected data and self-adapting are aspects of computational intelligence. As Monostori et al (1996) claim intelligence is deeply related with learning, and learning ability must be an essential feature of intelligent manufacturing systems, which are essential for Industry 4.0 applications.

Since there is feedback, supervised learning algorithms are considered as better fit for manufacturing approaches and they can be used in developing a framework, by employing combinations of different algorithms.

Implementation of machine learning in manufacturing can be accomplished with claiming patterns from existing datasets. Through this, it can provide a base for the improvement of predictions about future actions of the system. (Alpaydin, 2010) With this approach, manufacturing tasks might be completed with less errors, by learning from earlier applications, and eliminate them in predictions.

As manufacturing problems are highly complex and dependent on multiple variables, machine learning algorithms are suitable to solve these problems as they are able to

deal with multi-dimensional and changing data. Machine learning has been used in manufacturing in areas such as design, process planning and modeling, quality control and robotics. (Monostori et al., 1996) Integration of such algorithms in design and decision-making process before the manufacturing/fabrication processes can create a bridge between digital design and fabrication processes. Ramsgaard Thomsen et al. (2020), places machine learning between design and fabrication data, and between fabrication data and fabrication processes. (Figure 2.4) In between design and fabrication data, algorithms can provide the simulation of fabrication, or form-finding, and in the second placement it enables machine to learn from the fabrication process and give feedback. While this can be implemented for robotic fabrication or sensor-based machines easily, it may not be available for different techniques.

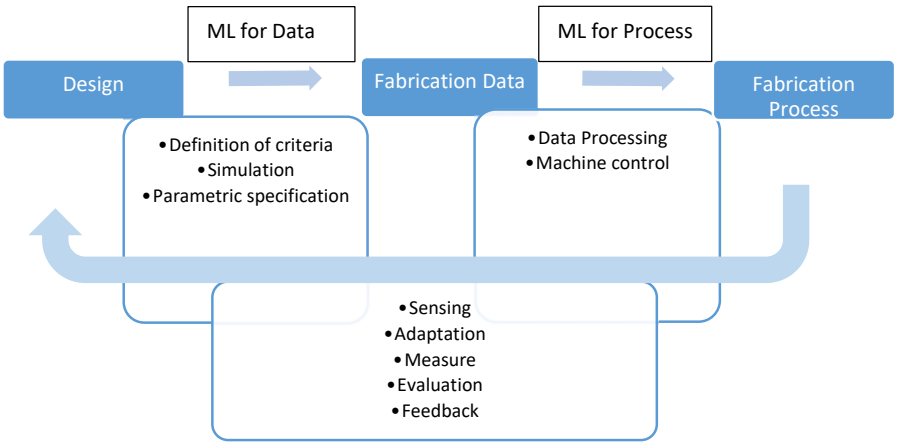


Figure 2.4 Placement of machine learning in digital fabrication process for Industry 4.0 based intelligent manufacturing (Ramsgaard Thomsen et al, 2020), redrawn by author

Additionally, as presented by Tamke, Nicholas and Zwierzycki (2018), both unsupervised regression-based approaches and supervised neural network-based algorithms can be used for digital fabrication. Unsupervised ML can be used in process learning, and providing adaptive fabrication, which is possible with sensing

through fabrication process. However, in such applications when a sensor is not available, supervised ML can provide a prediction for fabrication based on earlier model-based inputs and outputs.

Such algorithms and generative design processes can run through cloud computing, which is a technology that allows data storage, access, and computer-based applications to run independently of the computer's hardware. These operations are done with the data available through the Internet. (Kaur et al., 2014) With the developments in huge-data handling and storage, cloud computing is more efficient to use with such data. Such use of cloud computing combined with machine learning and topology optimization, is very efficient in providing generative design solutions.

Firstly, cloud computing allows different operations to run at the same time. Therefore, it accelerates the design process. For example, it can allow multiple machine learning and optimization tasks for different design alternatives in generative design process, and the results can be presented at the same time. (Buonamici et al., n.d.) Additionally, since learning tasks require large datasets, cloud computing can be a tool achieving this data. Also, the use of cloud computing is independent from any computer hardware, and makes the data available in anywhere and anytime, without any need of high computational power. (Carrillo et al., 2015)

To sum up, for improving digital design and fabrication, three main technologies can be used. Derived from above, these technologies can be very integrated with each other. However, since the research in those fields in relation with fabrication is rather new, the majority of the current implementations are mainly focused on robotic fabrication, or feedback-based approaches, or improving performance of the design.

2.3 Impacts of Fabrication and Algorithm on Architectural Tectonics

Computer-based architectural research is started in early 1960s, with the developments in digital manufacturing and advanced computerization in 3rd industrial revolution, which led to a shift in form and tectonic understanding in architecture, and experiments with non-Euclidean, topological surfaces. While the improvements in digital fabrication regarding architecture are rather slow, with the advents in additive manufacturing, and Computer Numerical Control (CNC) systems, more complex buildings and building assemblies/components can be produced accurately and fast. Shifting from cartesian geometries to topological freeform surfaces, architects are more involved with digital design and fabrication technologies.

Changing geometries also require different fabrication, and construction techniques, which creates a new type of tectonics that is combination of digital and physical. While digital design process effects the fabrication process and product, fabrication considerably effects the design outcome, as the last process of designing.

In this sense, it is important to understand the term "architectural tectonics". In traditional manner, architectural tectonics refer to the science and art of integration of form, material, structure, and the focus on how construction assemblies come together in a building or building component. Architectural tectonics includes components of buildings, method of construction and material, intersection details of different components, impact of context of building. Moreover, it includes the study of construction, aesthetics and representational qualities of a building. (Schwartz, 2017)

As explained earlier, being one of the most important notions in this age, data and algorithm effect form-finding, fabrication and assembly of building components, as well as optimization of performance and operation. Therefore, it can be claimed that data has its own architectural tectonics. In other words, the tools and algorithm they are produced through are reflecting themselves on building, form or construction

assemblies. Even it is possible to see that buildings which are produced with same parametric design software may have similar tectonic characteristics.

This can be seen also in different disciplines, to give an example, when Finite Element Method was introduced in automotive design, in most of the recent automotive of that time, same type of optimization algorithm is used and most of the cars ended up with very similar design and structure. Reconsidering this through buildings, on one hand, architects have the freedom of finding variations of generative forms and experiment, simulate with many different flexible materials through computerization. On the other hand, there are similarities between different forms and construction details. This can be defined as tectonics of algorithm, as they are assumed to be products of same data logic.

Additionally, fabrication technique and method emphasize the tectonics of algorithmically designed building. While algorithmic design gives a freedom to deal with non-conventional forms, fabrication technique puts constrains in design, and change the tectonics of initial design. In this sense, fabrication becomes very important, and it should be a part of form-finding algorithm. Also, in the age of cyber-physical revolution in manufacturing, fabrication is becoming more data-driven, and products are becoming smarter, and more modular. This approach is also started to be seen in buildings, as their fabrication process is becoming more data-driven, and building components started to act smarter, in which tools are reflected directly on building tectonics.

Since architecture is a discipline highly related to its tools, especially in the digital age, algorithms and developments in digital fabrication not only change the way that architects design, but also, combined with fabrication technique, they have their own reflections on building characteristics. In this sense, fabrication technique, and material have a huge impact on the design. While designing complex forms through computation, using conventional material and fabrication techniques creates a new type of tectonic approach which is the combination of digital, and physical.

2.3.1 Impact of Computer-Aided Fabrication

As the geometries, which architects deal with, become more complex, it is becoming more difficult to construct them with traditional construction methods. Improvements in CAD/CAM technologies combined with new materials are changing also how architects design. (Afify & Elmoghazy, 2007) This change makes computer-aided fabrication (CAF) as an essential step for architectural design process.

The impact of fabrication on tectonics can be explained with a simple example: To construct a dome, there are several fabrication methods that can be applied, and each one is different from each other in terms of detailing and tectonics.

Figure 2.5 Domes with different fabrication methods

While differences in construction and tectonics can be observed on even the simplest forms, these differences can occur in building or building component scale. For the example above in Figure 2.5, to elaborate the impact of CAF on tectonics, if the architect designed the dome as a monolithic dome, at the fabrication stage, it might be changed to a paneled dome depending on economical constrains and it won't be

perceived as it is initially designed. Also, each dome in the above example can also be constructed with different computational models using different algorithms. In other words, their physical structure can be included in the form of digital data. Therefore, even in a simple dome geometry, digital model can influence how it will be fabricated. In other words, while fabrication has an impact on changing design, algorithms can effect the fabrication starting from initial design phases. Therefore, it can be claimed that fabrication, effected by algorithm can change architectural tectonics.

Current digital fabrication technologies are divided into several principles and methods, which lead to different type of construction, and emphasis when applied to architecture.

2.3.1.1 Principles of Fabrication

With current technology of the digital age, fabrication techniques in construction and architecture varies in various ways from 3D printing, CNC applications to robotic fabrication and flexible formworks. Dunn (2012) emphasizes the principles of digital fabrication in four main headings, which are cutting, addition, subtraction, and forming. Each principle can be associated with different machines, detailing and construction techniques, with different requirements and materials, whereas some construction techniques also include hybrid principles.

2.3.1.1.1 Cutting

Cutting is the process of manufacturing by mechanically removing material through slicing. (Toenshoff, 2014) Machines in this process can be listed as a laser-cutter, a plasma-arc, or a waterjet. (Dunn, 2012) While 3D applications of cutting are available with multi-axis machining, cutting process is commonly used in 2D fabrication techniques, with planar assembly units, which are manufactured with 2-axis cutting. Most common uses of 2D fabrication can be listed as layering

(contouring), sectioning or waffle structures with joinery, folding and unfolding, and planar type of paneling such as triangulation or tessellations. As to be discussed in next sections of this thesis, what is mutual for these fabrication techniques is they enable building complex surfaces by planar elements, which can be structure of the form, or a skin creating the surface depending to the tectonics of the constructed building. (Kolarevic, 2001)

2.3.1.1.2 Additive Manufacturing

Additive manufacturing is producing solid geometries through building the material up in a layer-by-layer process. It is also referred to as rapid prototyping and 3D Printing by providing quick products, or mockups. (Gibson et al., 2014) In this technique, machines that are used differ in their use of material, whether if they produce supporting elements, and their curing process. Examples of technologies used are Selective Laser Sintering (SLS), 3D Printing and Fused Deposition Modelling (FDM). (Ozturk, 2018) This type of manufacturing provides file-to-factory fabrication, without the use of any intermediary elements, product can be manufactured directly as a monolithic object through a .stl file. Also, complex forms can be produced more accurately with relation to the computational model and layer thickness of the printer. (Dunn, 2012)

While used widely in industrial product design, the use of 3D printers in architecture is in its infancy stage in large scale use, but it is very promising considering construction time, cost and safety. (Mathur, 2016) Building components are 3D printed for pre-fabrication, such as custom designed masonry units, irregular panel assemblies, and steel trusses. Printers can also provide mold assemblies for casting. Additionally, researches on in-situ 3D printing of concrete buildings are conducted, and full-scale buildings are constructed. (Hager et al., 2016)

2.3.1.1.3 Subtractive Manufacturing

Subtractive manufacturing can be defined as the reverse of additive manufacturing. It is the subtraction of the volume of the reverse of the product from a solid material with chemical or mechanical multi axis milling process. (Wiertelarz, 2016) This process is provided by CNC milling machines with computer-controlled movement through sets of coded instructions.

Like additive manufacturing, file-to-factory approach can also be seen in here, since these machines work with 3D solid models. Use of subtractive methods in architecture is kind of similar to additive methods with creating monolithic complex forms. (Paoletti, 2018) While being an old technology, CNC milling is used in many computer-aided fabrication processes in architecture, such as fabricating building components like panels with complex curved geometry, also formwork or casting bed for curved concrete surfaces. (Ku & Chung, 2015)

2.3.1.1.4 Forming and Casting

Forming is the process of re-shaping or deforming the material through mechanical forces, like application of heat or steam. (Dunn, 2012) While moldings are used to obtain the required shape, those can be manufactured through traditional methods, 3D printing, or CNC manufacturing with materials vary from wood, steel, plastic and fabric. With right molding and material, intended form can be achieved with forming, and it is widely used in full scale reinforced concrete buildings, especially for monolithic buildings / building components. However, the process is a bit time consuming, compared to file-to-factory approaches, since it includes several steps. (Mahamood et al., 2014) Recent research includes robotic and adaptive formwork for flexible construction for complex surfaces. (Shaffer, 2017) Also, the use of robotics is getting involved in the fabrication, and placement of formworks.

2.3.1.2 Techniques in CAF

The techniques used in computer-aided fabrication are explained briefly as below (Iwamoto, 2013) Each technique can be achieved with different use of above-mentioned principles:

- Paneling/Tessellating: The surface is divided into subdivisions based on a repeating form, and each subdivision might form a panel.
- Contouring: Stacking of 2D layers of material, or creating layers by carving through solid
- Sectioning: The overall form is constructed with cross-sectional curves.
- Forming: Fabricating desired shape through forming a mold and casting, suitable for mass production
- Folding: The process of turning 2D surfaces to 3D forms, like origami.

Several examples can be given to above techniques, and some of them are so widely used that to an extent that they create their own architecture. In this sense, it can be claimed that fabrication has a big impact on changing the design tectonics. Below diagram shows different examples of fabrication techniques on different scales. (Figure 2.6) It can be observed that each fabrication system has different architectural language.

Figure 2.6 Examples of different fabrication techniques

While each fabrication system needs different requirements in computational model, they influence the building's material, detail and eventually form characteristics. As 3D printing provides great capabilities in formwork systems, CNC cutting and milling enables custom designed paneling available with very short time.

Figure 2.6 shows that each fabrication technique creates a different tectonic approach. Although they are presented in different scales, products of same fabrication techniques show similarities. While some of them highlights the

structural aspects such as sectioning or folding, some of them tend to highlight the surface rather than structure, due to fabrication method, and the use of material.

Moreover, before computational models are fabricated, they are prepared through computer processes. While each fabrication system is limited, any software used in this process also starts to create their own tectonics. For example, if a virtual model is manufactured through additive processes, it needs to be modeled solid, and if not designed as parts, the outcome product tends to be more monolithic. Similarly, for 2-axis cutting in order to fabricate with paneling, the 3D model needs to have surface subdivisions, and the outcome tends to be more modular with planar elements due to 2D fabrication process.

2.3.2 Impact of Algorithm

Developments in parametric design software and fabrication techniques, enabled architects to design and build the non-Cartesian spaces and geometries. In other words, they enabled the shift from flat geometries to elastic, topological surfaces which are dependent on various environmental/design parameters that can re-generate the surface itself without losing its geometric qualities. (Zavoleas & Taylor, 2019) In this approach, parametric functions define the space and geometry, instead of implicit equations, which can provide different possibilities of form. (Kolarevic, 2000) While this provides a freedom in form, by allowing shrinking, or expanding the form in different axes, any parametric design software can help to define the constraints and rules of the topological surface, based on certain parameters.

In early practices in CAD based architecture, computers were tools in architectural representation, to visualize conventionally designed buildings. However, with developing interest in digital, computers are not only tools of visualization, but they also become a part of the design process. (Leach, 2009) To elaborate, computer

algorithms and scripting become a part of form-finding, and structural and environmental control optimization, also fabrication.

In this process, determining steps and rules of design process, rather than the form itself, can be defined as the algorithm. Through algorithmic design approach, by defining decisions in design process, it can be claimed that algorithm actually designs the process, rather than the product. Computational models and software can be concluded as tools to design the algorithm, which is the logic and set of rules that creates the final product.

For example, in form-finding, as processes that form geometries can be defined with mathematical equations, scripting is a way to produce complex, advanced forms in architecture. In this sense it can be said that, while algorithm enables complexity and unpredictability, it also enables calculability at the same time. (Nilsson, 2007) Additionally, it breaks the randomness of any decision in architectural design process; therefore, it has its own limitations.

The calculability of algorithmic architecture is linked with computers' capacity to perform equations or optimization tasks for form-finding. Unpredictability is due to material nature of architecture, as it is designed for physical world, which has material characteristics that cannot be completely included in design phase of computation. The duality of digital and material, today, is defined as digital tectonics.

2.3.2.1 Digital Tectonics

> *The seemingly paradoxical use of the immaterial domain of the computer to understand the material properties of architecture has spawned a new term in architecture: 'digital tectonics. In other words, the old opposition between the highly material world of the tectonic and the immaterial world of the digital has broken down. What we have instead is new tectonics of the digital or 'digital tectonics'*
>
> Neal Leach, Digital Morphogenesis, 2009

As cited by Leach above (2009), digital tectonics is the use of virtual to produce physical architecture. According to Beesley & Seebohm (2000) it is an integral method in which software, and fabrication tools are used to construct a form. In other words, it is a combined virtual and physical systematic approach that comprehends virtual geometric formations, with details solved with physical construction methodologies. The most important elements of digital tectonics are algorithms and data structures which produce generative results dependent to its performance, environment and user requirements. More than that, algorithmically constructed buildings mostly represent its designer's ideas and they are in direct relation, with the tools they have been constructed. (Jabi, 2004) In this sense, these tools can be defined as the algorithm, software with fabrication technique and material. It is claimed that these outcomes of digital tectonics led architecture into a digital morphogenesis, where design methodologies change from "form-making" to "form-finding". In other words, architects do not design the form, but they design the generative system that creates the form. (Leach, 2009)

Another discussion in digital tectonics is the tectonics of the algorithm. In this sense, for digitally tectonic designs, it can be said that they are based on geometrical and computational rules, or steps which reflects themselves on form. Aranda & Lasch, (2006) define the algorithm as the rules that define the form's pre-material state and its transition to physical state, and algorithmic approaches are mainly derived from the nature such as packing, weaving, spiraling or flocking.

Additionally, tectonics of any parametric software that are used can be defined, as to form a design that is based on above algorithms, there are several commands in parametric design software that are used in. For example, to construct a spiral there are several mathematical steps that are formed through certain commands. Similarly, for weaving or blending, there are embedded commands that can run such computational models. Also, for packing, or tiling, several subdivisions can be made on surface. There are also software commands that can perform these actions. Due to limitations and possibilities of each software, and data logic, tectonics of outcome products may have similar qualities. It is possible to make an analogy between

commands in any software such as “paneling tools-paneled buildings”, “weaving-weaved buildings” (Figure 2.7) or “voronoi-packed or paneled buildings”. (Figure 2.8) This approach shows that, any software used in design process, with its commands, has a great impact on new typologies of buildings.

Figure 2.7 Weaving: 3D model (SketchUp) and Building (Argul Weave / BINAA + Smart-Architecture)

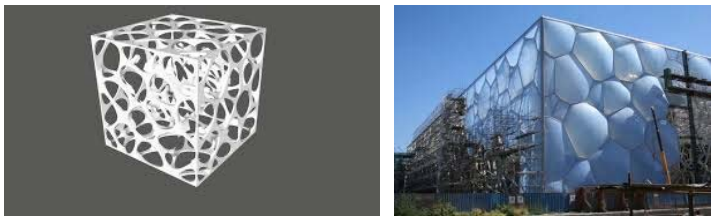


Figure 2.8 Voronoi: 3D model cube (SketchUp) and Beijing Water Cube (PTWArchitects)

While creating new types of tectonics, this approach may result in misconception that computational tools are used for pattern making for certain styles of architecture, for visual impression, which should not be the case. (van Berkel, 2020) Rather, it is a tool for finding different design alternatives based on parameters.

In addition, it can also be seen that analysis, and optimization method through software have certain effects on building tectonics. Software that performs topology, or structural optimizations, eventually re-shapes the initial design to a more constructable one. This is due to material nature of architecture, and limitations due to structure and material.

Lastly, considering new developments in sensor-actuator systems and machine to machine collaboration, new types of digital tectonics can be defined. One example to this is swarm tectonics due to swarm intelligence algorithm in which participants of swarm behavior are self-organized and decentralized themselves (Chen, 2015) This type of buildings consists of small assemblies that are intelligent and communicate with its context and with themselves. Swarm tectonics can be an example of an interactive architecture case, which can be a part of building operations as an interface, or an automata, which can communicate and respond/adapt itself to its users or environment. In such cases, data interactions create operations, so, it can be said that their behavior is defined digitally, and these behaviors have also effects on their material and construction.

Being an in-between state, notion of digital tectonics starts another discussion which can be claimed as digital materiality.

2.3.2.2 Digital Materiality

For today's architecture it can be said as quoted in Michael Fox's Interactive Architecture, architect Michael Weinstock states: "Material is no longer subservient to a form imposed upon it but is instead the very genesis of the form itself." (Fox, 2016) As digital fabrication processes are getting involved with design, the designer/architect should consider the limitations of material and fabrication system in the very initial stages of design in order to prevent time and material loss.

It is true when considering conventional definition of tectonics, material is the basis, and the design is poetically in harmony with its even smallest unit composed of any material. With today's technology, digital materiality can refer to different meanings. Firstly, for digital tectonics, as Menges describes combined "cyber-physical making", (Menges, 2015) we may mention two different type of making which are cyber and physical. Considering cyber part of the design, we cannot speak of any material, because data does not have material. Although, it can be material through

simulations, modeling or software, however still we cannot speak of materiality of software. (Leonardi, 2010) So, it can be claimed that digital tectonics actually become material when they are fabricated.

Secondly, even though digital tectonics is defined with the use of conventional materials and construction methods, with today's technology, they are not-so-conventional, including involvement of computation and algorithm. Digital tools can also be used in optimization of materials constructing form. For example, computer simulations become very useful in determining stress-strain forces and bending capacity of structure and material. During this process, according to results of simulations, materials like can be strengthened. An example might be fiberglass reinforced materials can be strengthened through a finite element analysis with computation. (Ahlquist, 2015; Martins et al., 2018) So, rather than ambiguity, between material and digital, it can also be defined as the digital process of optimizing the material, as material has characteristics that can be interpreted by computers.

Lastly, computation can directly influence material characteristics. For example, building components might be composed of bio-nanotechnological materials that are flexible in shape and have a high degree of resolution. In this sense, optimization of materials can also be data-driven or even material itself can be a cyber-physical system composed of sensor-actuator mechanisms. It is speculated that such materials can also have sensor-controller systems at a very small scale. There are materials developed that can shrink or expand in the area of fabrics and polymers. (Fox, 2010) In MIT, small interlocking composite material assemblies are produced, which are very lightweight and can be reassembled in order to be used in large scale structures. (Chandler, 2013) Experiments with 4D printing can also be added to these developments in flexible, digital materiality.

So, it can be claimed that although data does not have any material characteristics, its implementations on fabrication and material characteristics might be described as digital materiality. It can also be defined as a state between analog and digital, in

which digital processes are created with physical, material output. Since the concepts of digital tectonics and materiality are in-between situations, the process of translating digital to analog becomes very critical and cause problems between design and fabrication processes.

2.3.2.3 Translation Between Digital and Analog

Although computer-aided fabrication provides great opportunity in producing complex forms, in this process, there is a two-way situation, which creates challenges while providing this opportunity. Allowing digital, complex topologies to have physical properties and providing economic efficiency by re-using the computational data and construction drawings, in such fabrication processes, it becomes a challenge to translate between digital processes and analog products.

This dilemma can be explained in two main aspects. Firstly, the surface smoothness and the precision present on the computational model, when meets the limitations of materials and fabrication techniques, seems to be lost or can be provided with high cost and long time. Although it is possible to get smooth surfaces through additive manufacturing such as 3D printing, not every surface is suitable for 3D printing, and it costs a lot to achieve smooth and layerless appearance. Solution to this might be subtractive manufacturing or paneling. However, subtractive manufacturing such as CNC milling, same problem might continue again dependent on the manufacturing tolerance, and it causes a lot of material loss. On the other hand, surface divisions such as paneling change the surface characteristics and accuracy of final model to the initial design. Such problems can also occur with additive manufacturing. For example, if the initial design is composed of smooth surfaces that 3D printing can handle but also includes slender elements, it won't work because 3D printing does not support very slender elements (Seely, 2000) and the designer will need to change the slenderness of those elements, which eventually changes the initially designed computational model.

Another aspect is the optimization process of computational model for digital fabrication systems. Each digital fabrication system has its own interpretation of computational data, and sometimes, such systems cannot read the computational model or a part of it. This causes the repetition of whole detailing and modeling process. A common way of the computational design process is working with digital models and repeating the process of converting digital models to physical mockups. When it fails in the fabrication process, same actions are repeated in changing the computational model and fabricating it again until finding the right detail, which causes deficient use of time, and material loss.

Another dilemma in this translation issue can be claimed as, since the initial precision in computational model cannot be provided with current fabrication techniques or materials, or it is overly expensive in terms of time and cost, freedom of algorithmic design is lost. Also, software that are used in this area are specialized to fulfill requirements of certain fabrication techniques, which causes a standardization in detailing, which opposes the computational design freedom. Therefore, architects should design with considering the fabrication technique, and its computational requirements.

The precision issue regarding fabrication can also be discussed as the precision loss between different software. Any parametric design software provides "data precision" which results in smooth and complex forms. However, while preparing the parametric models for manufacturing, software that are used mostly include a graphic user interface, enabling visual interactions for ease of use. This leads the model to "geometric precision" which can be considered as freer in form-finding or editing, however more limited in manufacturing and precision compared to data precision.

The model prepared for fabrication can be called intermediary model. The problem starts with the loss of accuracy between parametric model and intermediary model, and when it is fabricated, final model may lose its precision due to material limitations. For example, in CNC applications, even though precision loss between

intermediary model and initial model is minimum, final model's surface roughness might affect its form and tectonics due to its material characteristics. Therefore, it becomes a real issue to lose minimum precision and accuracy before it becomes material. In this sense, virtual model should also contain fabrication data from the initial concept design phase, which provides more control in the design process.

2.4 Accuracy and Precision

Other than fabrication principles and the effects of computation, there are several concepts to be considered in the fabrication process such as accuracy, precision, cost, reliability, and durability. While shifting from virtual to physical environments, CAF does not always provide zero tolerance construction process due to material and economical limitations. (Loh, 2015) While zero tolerance might be achievable in industrial design, for architecture, buildings tend to be affected by loads and natural forces, human and material error, it cannot be the same, hence, it is more complicated. (Denari, 2012)

While this issue can be due to manufacturing tolerances, it may also occur because of the fabrication being the last step of design. What we see on the computer screen might not always be what we get. It may be in detail scale, or full model scale, some parts of the computational model may be revised, as it is pre-processed for digital fabrication. Also, due to limitations caused by material, cost or fabrication, the details in the final product may be different from what designer initially intended.

Regarding tolerance in fabrication within the context of tectonics; accuracy and precision stands out in this discussion. Accuracy is value's closeness to the true value, whereas precision refers to the consistency of this accuracy. For example, in 3D printing, we can get the digitally designed model in perfect accuracy, however if the same model is printed with the different machine, it is not certain that it will repeat the same action. Even if the same fabrication technique is used to produce the

same digital model, due to machine and material differences there might be accuracy differences.

Figure 2.9 Products of different 3D printers (Formlabs)

Above example in Figure 2.9 shows results from different 3D printers. The one on the left is printed with FDM (Fused Deposition Modeling), in which layers are extruded through a nozzle, whereas the one on the right is printed with SLA (Stereolithography), which includes a curing process with laser for each layer. Therefore, the one on right shows more accurate results. Even though what we see is a smooth surface on computer screen, the issue of layer thickness might show the stair-stepping effect on physical model (Gebhardt, 2011), which is commonly seen in 3D printed concrete applications as shown in the work presented in Figure 2.10 below (Gosselin et al., 2016):

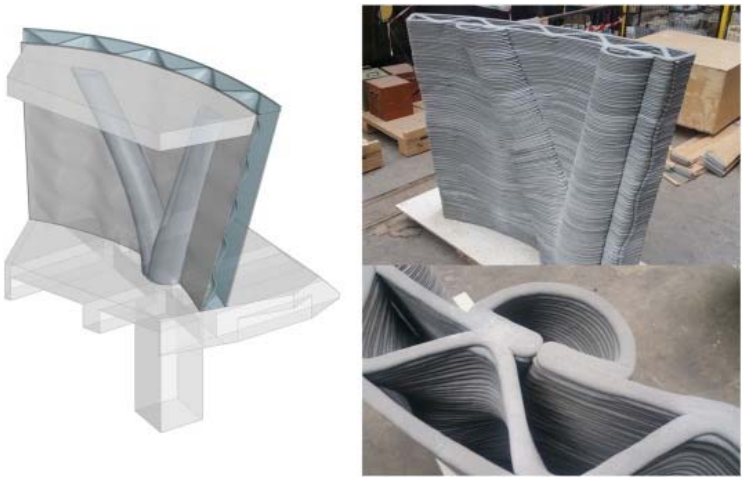


Figure 2.10 3D printed concrete (Gosselin et al, 2016)

While the visible layers in additive manufacturing can be considered as an unwanted effect, if the properties of the machine are known, it can be used to create different type of tectonics by using different layering alignments. In the above-mentioned research, layers are experimented with another form and enhanced the mechanical properties of the form through varying thicknesses of layers. (Gosselin et al, 2016)

Secondly, although it cannot be investigated in the context of precision, below example in Figure 2.11 is from Anish Kapoor's printed concrete sculptures. While every one of them is constructed with the same material and same manufacturing method, they are very different from the example above, considering architectural tectonics. Different from common layering, in this example, the randomness of the layers provides complexity.

Figure 2.11 Anish Kapoor – Greyman Cries, Shaman Dies, Billowing Smoke, Beauty Evoked, 2008–2009

Although computationally produced models can be very complicated and difficult to realize physically, it is possible to achieve precision in complexity. However, to fabricate such complexity in great precision, other constrains such as time, and material can be lacking in such process. Below example shows Michael Hansmeyer's Subdivided Columns (2010), which are designed algorithmically and fabricated with cutting and layering:

Figure 2.12 Michael Hansmeyer's Subdivided Columns (2010)

In the example above shown in Figure 2.12, algorithmic design complexity is shown at its best, while the process designing it is simpler than its complexity. It is constructed through layers of 1 mm sheets of paper, which enables to construct digital complexity, but it becomes a challenge to put the layers together, because of the high quantity of the parts, which is 2700 sheets in this situation. Therefore, it becomes difficult to save time or material in such approaches, similar to working with zero tolerance, or high precision 3D printers.

Another example might be given in paneling. Even though it is one of the most used fabrication methods, paneling might lead to inconsistencies. In constructing freeform surfaces; surface subdivisions, panel height, and curve network gain importance. Below example in Figure 2.13, as explained by Eigensatz et al., (2010) shows challenges in freeform surface fabrication.

Figure 2.13 Hungerburg funicular railway, Innsbruck, Zaha Hadid Architects

The example in Figure 2.13 includes double-curved panels with separate molds, which is a highly challenging approach, since each panel and their molds are manufactured separately. Yet, the surface is still not continuous, panels have gaps in between, and space between them is changing.

While machine and tolerances have an effect on the precision of the physical artifact, fabrication method itself also creates an influence on architectural tectonics, and which part of the building should be emphasized, such as its structure or its façade. (Kolarevic, 2001) Although it is not in building scale, below example in Figure2.14

shows the fabrication of a bunny through sectioning with mesh joinery (Cignoni et al., 2014) and two 3D printing methods, one as solid, one with tessellating/tiling:

Figure 2.14 Prototypes in different fabrication methods

While the sketch is perceived as solid, mesh joinery example emphasizes the structure of the 3D model. 3D printed solid one resembles more the sketch one as it presents its solid characteristics better, and tessellated one emphasizes the surface characteristics. In other words, tectonics of form perceived differently in different fabrication methods. Also, accuracy changes between each fabrication method.

With the light of the above example, it can be asserted that not all fabrication techniques are suitable for the designed building/product/building part's tectonics. It can be said that although we have examples that what is seen on the computer screen is what we get, but it does not mean that it is relevant in terms of tectonics, even with robotic fabrication approach. In the example given in Figure 2.15; an extreme case is modeled through a parametric design software. Even though it is possible to fabricate such a wall accurately with robotic fabrication, brick layout does not seem to continuously follow the surface geometry, which breaks the precision of the surface, and may cause structural defects, considering this is a wall structure. This might be due to brick sizes, or different type of stacking/or tiling should be used to construct such surface.

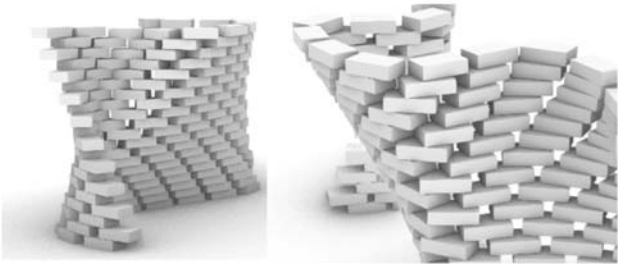


Figure 2.15 A parametric brick wall (produced by author)

Considering precision, accuracy and tectonic aspects of fabrication principles, for architecture, if fabrication is integrated in the design process, architect can design the architectonics of the building, which will enable the architect to be more aware of the digital design process. In this sense, 3D model should not be only a tool for fabrication representation or mass production, but a prototype of the physical, which should be designed in a way that contains the fabrication data, and technique. This approach might be called as a holistic design process.

2.5 Holistic Design Process

Design problems are usually multi-dimensional, and includes the design of the process in addition to the end product. Therefore, it can be claimed that it is not possible to design without thinking of material aspects. However, sometimes, the computational design freedom can mislead the designer that anything in the cyber space can be constructed physically, which is due to the separation of cyber and physical making.

Given a digital design problem in architecture, mostly fabrication and construction are considered as the last stage of design process. (Ozturk, 2018) The process mostly continues as follows: Firstly, a concept idea or inspiration of design is derived, then design parameters, objectives, or constrains are defined. After that, design alternatives might be explored through virtual or physical mockup models. Lastly, model is prepared for fabrication. However, in this approach, if the last step fails,

other design alternatives are searched, and iterations occur. (Hogrefe, 2010) Not entirely, but this approach can be defined as a top-down approach. The process can be demonstrated as below (Figure 2.16):

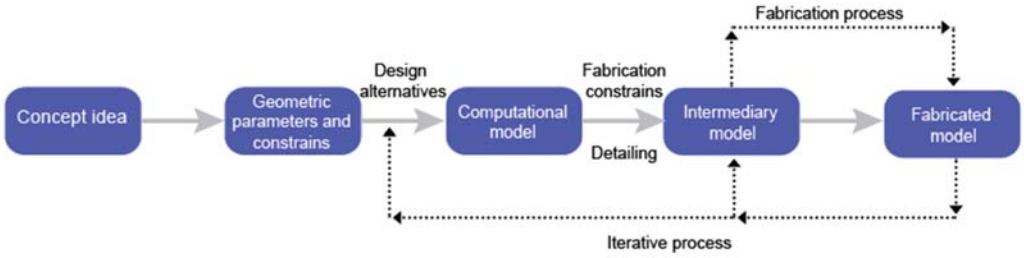


Figure 2.16 Top-down design process (Produced by author)

Rather than a top-down approach, architects can claim a bottom-up approach considering the tectonics in digital model, in the earlier stages of design process, which can enable architectural tectonics to inform initial design. (Larsen, 2012) In other words, it can be claimed that "Form follows tectonics." (Diamon, 2013) In this integrated approach, after the concept ideas, material and fabrication method are defined as inputs or constrains of design. So, the algorithm leads to more constructable design alternatives, which eliminates the iterative process of design alternative trials and detailing. With this approach, the process now looks like below (Figure 2.17):

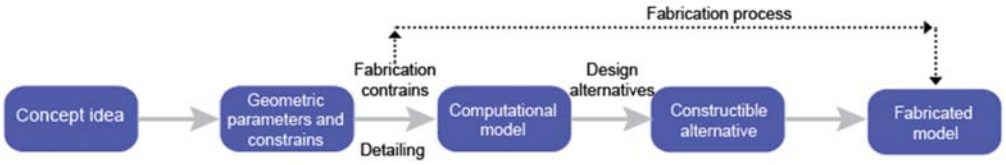


Figure 2.17 Bottom-up design approach (Produced by author)

Although concept ideas are rationalized through parametric design process, and variety of design alternatives are achieved, the first approach is linear without the fabrication limitations in digital model. This leads design alternatives to be explored intuitively, which increases the errors in fabrication process. In addition, fabrication process becomes iterative, which causes time and material loss. On the other hand, with a bottom-up approach, including physical parameters in digital model, provides opportunities to explore design alternatives in a more detailed manner. Thus, it enables designer to save time and material lost in fabrication trials.

In addition, with an integrated, bottom-up approach, fabrication process starts within the computational model, in which the fabrication constrains, and details are defined. Through this approach, differences between digital and physical models can be reduced. Moreover, since the rules of design are defined, rather than the final geometry, accuracy of the final product can be improved in a more controlled way.

This approach can be defined as a part of "Design for X", which has several examples like design for "manufacturing", "assembly", "sustainability", or "quality", that aims to develop a product according to a design goal. (Kuo et al., 2001) The "X" s in this approach can be increased, and with the advances in generative design as explained in 2.2.1, this approach can be used for a design space exploration process aiming to increase manufacturability of multiple design alternatives. Also, with such a generative design process, these alternatives can be obtained rapidly and compared by designer. As topology optimization process is included, designer can also evaluate the alternatives both in terms of manufacturability and aesthetics.

Moreover, the technological lead to the integration of digital communications between architects, engineers, and builders, which eventually changes the hierarchy of design process, that can be called as a digital workflow. (Marble, 2012) Since digital workflows ease the communication between different disciplines, it leads to an integrated design process. One example of this approach in architecture is the use of building information modeling (BIM) from early design stages to the end of the construction, by integrating all structural, architectural and MEP information without

any data conversions or loss. Additionally, in fabrication, choosing the material, manufacturing method, and defining assembly / joint details and combining all of this information in a single parametric 3D model speeds up the design process as it enables to see design alternatives, while minimizing the changes in design. In both BIM and fabrication cases, 3D model environment becomes very important, because it provides the integration of all design process by bringing different disciplines' together to work into realization. (Marble, 2012)

With Industry 4.0 developments like machine-to-machine interactions and cloud use in design processes, 2D and 3D model environments, also fabrication data such as G-codes can be considered as digital ecosystems. These have their own functional units, and different operations. While it can be in single ecosystem, like BIM environments, it can also be separated ecosystems with a broader one additionally includes all communication data, and interaction of different digital environments. In this sense, continuing the design process in a single digital ecosystem can provide more integrated results.

Firstly, when all the data interact in a single ecosystem, or 3D environment, data losses during conversions can be prevented. Secondly, since all of the data is stored in a single model, designer's interruptions to the digital process becomes easier, and iterative processes are eliminated. To elaborate, when working with BIM environment with different disciplines, the advantage of it is to store the information from different disciplines in a single computational model, which prevents data loss caused by conversion between different ecosystems. Furthermore, having a single ecosystem also shortens the time spent during the data conversion processes. Thus, to minimize iterations, and for a smooth "file-to-factory" process, a bottom-up design approach with a digital workflow interacts in a single digital ecosystem accelerates the process and provides integration.

2.6 Evaluation and Summary of the Literature

To sum up, with the 3rd industrial revolution, computers became a big part of the design process. Additionally, with the introduction of computer-aided design and parametric design software, architects have the ability of designing the process and complex forms through computer algorithms. Also, the introduction of mass customization, and developments in computer-aided fabrication enabled the accelerated realization of these complex forms, and provided freedom in design. It can be asserted that both digital design process and fabrication have effects on architectural tectonics. As digital processes create physical outputs, the notions of digital tectonics and digital materiality are emerged.

While digital design process can provide freedom in experimenting design alternatives, if fabrication and material are defined in the last stage of design process, since fabrication has an effect on architectural tectonics, it can change the initial design. This top-down design approach creates problems regarding precision and accuracy. Moreover, it creates a gap between design and fabrication processes, and makes the design process iterative.

With recent developments in technology, digital design and fabrication processes are merging, and the use of cyber-physical approaches is also started to be used in construction and architecture, with digital workflows such as BIM or generative design and optimization.

There are several applications such as cyber-physical making, and machine learning based robotic construction are studied in the field. However, the availability of such approaches in architecture remain in building component or pavilion scale. While feedback-based applications are discussed, more efficient design approaches can be achieved with a bottom-up design powered by machine learning and generative design. The implementation of machine learning in form-finding is studied in the field, however the integration with computer-aided fabrication is rather recent and can be studied further.

CHAPTER 3

RESEARCH DESIGN

This chapter describes the research design by defining material and method. The research is designed to be composed of two stages. The first stage includes an intuitive exploration of design alternatives, which is based on the fabrication of a wall system that is generated from a given parametric model (see Figure 3.2) with different fabrication techniques. These different techniques include tessellating, 3D printing, sectioning, CNC milling as explained in the previous section. The aim of the first part is to see how a top-down design approach effects final fabricated product, as well as design alternatives.

Moreover, the objective of the first phase of the experiment is to observe how different fabrication techniques change initial computational model and the resulting tectonic qualities. It is important to understand the role of initial design model, its adaptability to materiality and manufacturability even in the design process a prior to physical fabrication.

The second part of the research is a controlled experiment, which includes an integrated method for design and fabrication. The aim is to see how the final product and the design process are effected, when fabrication is an initial input for the design process. In this step, in contrast to the first experiment, AI-based tools are used for topology optimization to observe their effects on iterative actions of design process, also in addition to the process of exploration of different design alternatives.

Another objective of this study is to observe how fabrication changes the digital model. Moreover, in order to study the role of AI in decision making, the design alternatives are used as a database for a classification algorithm, which learns from

the parameters of design alternatives and make predictions regarding the manufacturing method for future data.

Diagram given below in Figure 3.1 summarizes and demonstrates the methodology adopted in this study:

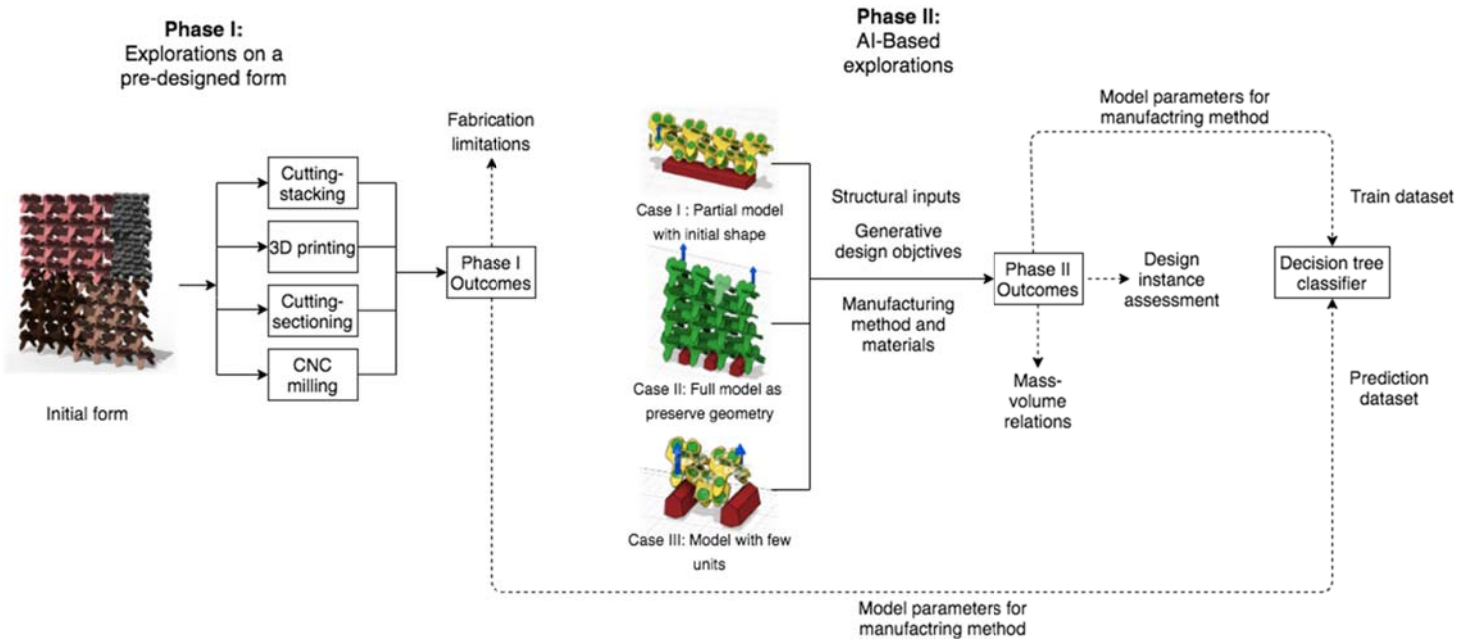


Figure 3.1 Methodology

3.1 Exploration on a Pre-designed Form

The first stage of this research includes an exploration by testing different manufacturing techniques. The aim of the first stage is to observe the necessities and the accuracy of different fabrication processes and to examine the time and precision loss during the optimization of the model. The optimization of the model and exploration of the design alternatives are based on intuitions, along with solving problems during the fabrication process. In other words, an iterative and top-down design process is applied. The design alternatives in this process are arbitrary and can be defined as experimental, since they are produced through error detection, and revision processes, in the last stage of design.

The first model (Figure 3.2) is designed as an 80 cm x 80 cm tessellated wall, comprising of four different fabrication techniques. The selected pattern is based on a stacking type of design, with a biomimetic approach derived from the tensile behavior of frozen water bubbles beneath lakes. Each unit of pattern is interlocking. The aim in this design is to see how it changes its tectonics in physical products when fabricated differently. For instance, it is observed if the pattern, complexity or double curvature of the surface remain the same when fabricated with different techniques.

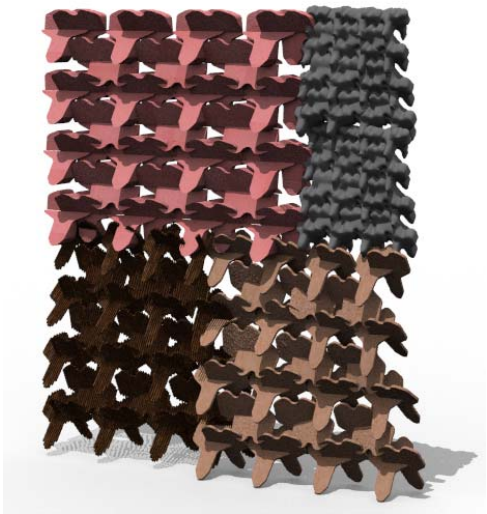


Figure 3.2 Assembled model with different fabrication techniques (Rendering)

The initial model is prepared for stacking type joint detailing, with thin 2D plates of craft paper formed with laser cutters. Then, the same model is used for different fabrication techniques. Note that on the one hand, while designing the digital model, fabrication is not considered in the first stage, which lead the pattern to an assembly type of construction in cutting and CNC milling. On the other hand, its intermediary model for 3D printing becomes a monolithic object.

For this experiment, four different fabrication techniques are used to fabricate pilot model as listed below:

- Stacking-Tessellating: Smaller units are fabricated with laser cutting machine and joinery details are designed computationally. Each piece is designed to snap each other.
- 3-D printing: Creating a digital file based solid object, through a 3D printer, which lays down layers of material on each other to create form.
- CNC Milling (2.5 axis): Subtraction of material to create form produced in digital file through a computer controlled milling machine, machine depth limit is 6 millimeters.
- Additive manufacturing with laser cutting / sectioning: Like 3D printing, however layers of materials are cut in 2 axis laser cutting machine and added on top of each other by hand.

In first stage, material of research is a parametric model generated on Grasshopper 1.0.0007 and its revised models on Rhinoceros 6 for different fabrication systems. The reason why it is generated on Grasshopper is the ease of designing parametrically. The algorithm producing the model does not change, even though the surface it depends on changes. Also, the surface complexity requires data precision, which Grasshopper can provide, while decreasing the time it was produced. For fabrication, process regarding the need to have different file formats and the ease of some operations such as splitting or trimming the surface, Rhinoceros 3D is chosen.

For each fabrication system, models have different properties and different materials are used. (Table 3.1) Being a common tool, and the advantages of thin material, laser cutter is used in two different techniques as stacking (joinery) and sectioning with two different materials (Cardboard and MDF board). Other than laser cutters, 2.5 axis CNC milling is used for a large portion of the model, since it is a convenient machining operation for the proposed details.

On the other hand, the use of CNC machine is limited by the available material at that time and thus the model is fabricated with expanded polystyrene foam. 3D printing is used on a small portion of model due to availability, the cost of material, and the manufacturing process. As fabrication method or material changes, their limitations are noted, and different design alternatives are experimented until finding the one that is physically producible. Table 3.1 given below summarizes the methods and properties of the intermediary models:

Table 3.1 Properties of models with different fabrication techniques

Tessellating (Stacking)	•Actuator: 2 axis Laser Cutter Machine • Model: Each piece is drawn as 2D polylines for laser cutting. Joint details are acquired computationally. • Format: .dxf (AutoCAD) • Material: Cardboard
Additive Manufacturing	• Actuator: 3-D printer (FDM) • Model: Whole model is drawn as solid mesh. • Format: .stl (Rhinoceros 3D) •Material: Plastic filament
Contouring/ Sectioning	• Actuator: Laser Cutter Machine • Model: Isocurves are extracted from whole model and sections/one way layers are created for laser cutter. • Format: .dxf (AutoCAD) • Material: MDF board
Subtractive Manufacturing	•Actuator: CNC Milling Machine (2 axis) •Model: 2 solid pieces to be assembled. Double curves are removed for 2 axis CNC milling. •Format: .stl (Rhinoceros 3D) • Material: Styrofoam sheet

3.2 AI-Based Explorations

Following the exploration on conventional optimization of the digital model, in the second stage of the research, the implementation of cloud computing-AI based generative design approach is applied to the same model. The aim of this experiment is to calculate iterative actions done in form-finding phase, including fabrication and generate different design alternatives while decreasing the material volume, mass, and scrap. In order to decrease fabrication time, assembly logic such as stacking, or sectioning are avoided, and the results are expected to be monolithic. Obtained design alternatives are used as a training-test dataset for classification.

This experiment is performed through Autodesk Fusion 360's Generative Design interface (version 2020). The reason of the selected software is its ease of use in modeling, and its inclusion of fabrication and material as design inputs. It enables to define a design problem with real life constraints, and provides manufacturing-ready models, with a variety of design alternatives. These design alternatives are the results of a generative design process, or topology optimization process, in which all iterative actions are solved via machine learning algorithms and cloud computing. With this approach, form-finding process, which includes fabrication constrains, is solved in a cloud network by machine learning algorithms. In this way, many design instances by learning from available data in the network are obtained. The advantage of this approach is to enable designer to explore design alternatives without any advanced programming skills or any need of high-tech computational power, with a simple graphic interface. Also, with this approach, all fabrication processes are observable and experimented in a single digital ecosystem, which prevents errors and undesired modifications in the model within the data conversion processes.

3.2.1 Design Space

In this exploration, the most important part is to define a design space to generate alternatives. Design space includes geometries in model such as preserve geometry, obstacle geometry, and starting shape for topology optimization. Following the definition of design space, structural constraints such as forces, supports and gravity are also determined. Lastly, the design objectives and the manufacturing assets are set on the digital model. Although, the current software chosen in this study is user-friendly and quite powerful in design space and alternative exploration, it is still encountered some failures in the search process in obtaining the initial shape, which lead to use partial models as explained in later cases.

Figure 3.3 shows the initial (intended) design space. Here, layout geometry is splitted to preserve geometry and obstacle geometry. Green circles show preserve geometry, since the actual unit geometry is derived from a surface combining three

circles. Preserve geometries are the ones that will be kept both in the outcome generation process and in the minimization of volume. Red shapes are the obstacle geometries defining the voids in the model. They are placed at the bottom of the model to prevent algorithm to create solids or surfaces on bottom part of the model. In addition to the preserve geometry, and obstacle geometry, an initial shape can be set, which is defined as starting shape in this software environment. The yellow one in the Figure 3.3 is the starting shape, which is optional for the generative design process, but its presence limits the surface area and turns the process into topology optimization. It is the exact model from the first exploration phase, except that it is split from the preserve geometry.

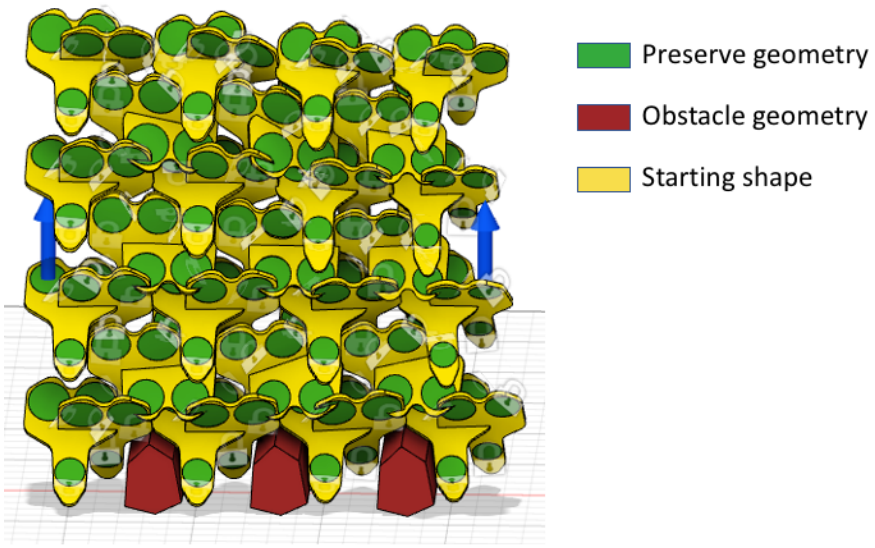


Figure 3.3 Intended Design Space (produced by author)

Due to failure in outcome generation for the intended design space, it is extended to further explorations to have more data on the process. Accordingly, three different study is designed, two of them includes partial models of the intended form, and the remaining one includes the whole model. In the partial studies, a starting shape is

defined, and for the one with the whole model, all of the geometry is preserved instead of setting an initial shape

3.2.1.1 Case I: With Initial Shape

In order to find out the cause of errors in the intended model, first case includes a small portion of initial model. (Figure 3.4) The aim is to find out if the algorithm works with a simpler geometry. Preserve geometry and starting shape are defined as the same, obstacle geometry is different due to bottom part being different than the whole model. Through this study, topology optimization algorithm is tested with a simpler geometry, and different design alternatives are experimented.

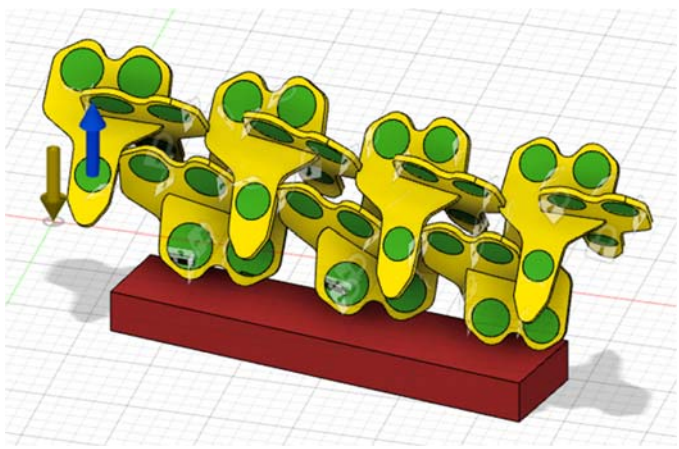


Figure 3.4 Case I Design Space (produced by author)

Since there is a pre-defined starting shape, the task in this case will be topology optimization rather than a full generative design process. In this case, it is observed how volume minimization influence the model and the adaptation of the model to the fabrication process. Since the model in first phase includes assembly logic, the

results of this case where only a part of the model is taken into consideration, gives way new design alternatives for the larger/whole model,

3.2.1.2 Case II: Preserve All of the Model

In second case, there is no predefined starting shape, instead the whole model is set as preserve geometry, and obstacles are kept as the same with the intended design space. (Figure 3.5) The aim of this case is to find out if the algorithm will work for complete model without any initial shape. In other words, the aim is to find out if the errors occur are dependent on the starting shape. Although it can be defined as a generative design task, it does not act as a complete generative process, since all of the model is expected to be preserved. Therefore, it is anticipated that this setup will not offer a variety in design alternatives, however, it is useful as a topology optimization task, and the objective is to observe the accuracy of the optimized design alternatives.

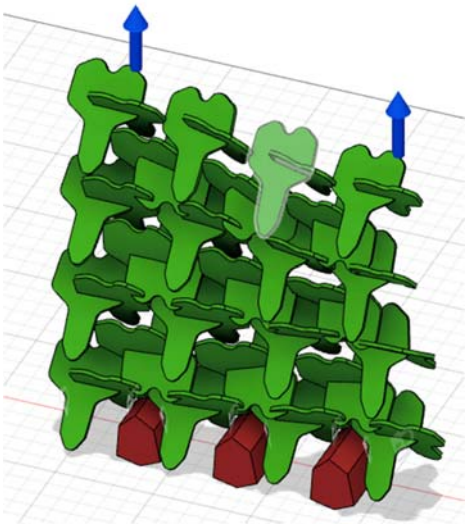


Figure 3.5 Case II Design Space (produced by author)

In concluding this case, it is seen that the outcomes of this case are similar to the first case, even though there isn't any starting shape. Since all of the model is preserved, it can be claimed that it acts like a predefined starting shape and produce similar outcomes.

3.2.1.3 Case III: Smaller Size - With Starting Shape

The aim for the last setup is to observe the level of detailing and change in initial design precision when the model size decreases. Additionally, objectives include to increase the data claimed, and the accuracy of classification algorithm. It is similar to the first design space, but the portion of the model is different and includes less units in quantity. Preserve geometry and obstacles are formed with the same logic explained in Case I. Instead of a horizontal alignment like Case I, this case is smaller and constructed more compact. (Figure 3.6)

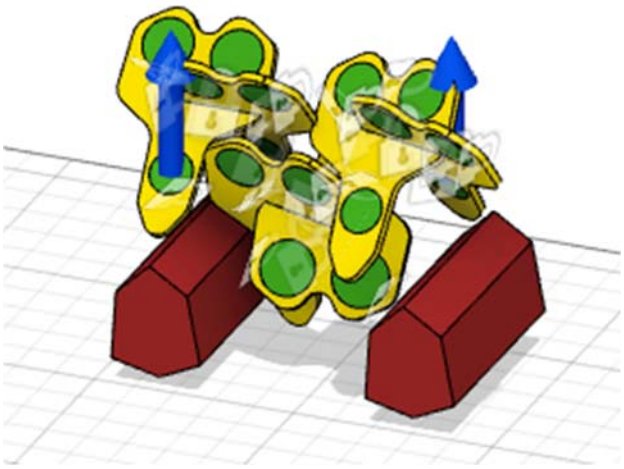


Figure 3.6 Case III Design Space (produced by author)

In this design space, outcomes are expected to be similar to Case I, since this case can be defined as a partial configuration of the actual model.

3.2.2 Structural Inputs

Constrains are defined within the model, and on the boundaries of the preserve geometry. The model is static, and each face is defined with a fixed constraint. Case I and Case III constraints are the same with the intended setup, whereas in Case II fixed constraints are placed at the bottom, where the model interacts with its boundary.

Since this study's concern is surface precision and exploring design alternatives, rather than structural stability, gravity is set as default, and structural loads are set in the opposite direction, and equal to gravity total. (Figure 3.7)

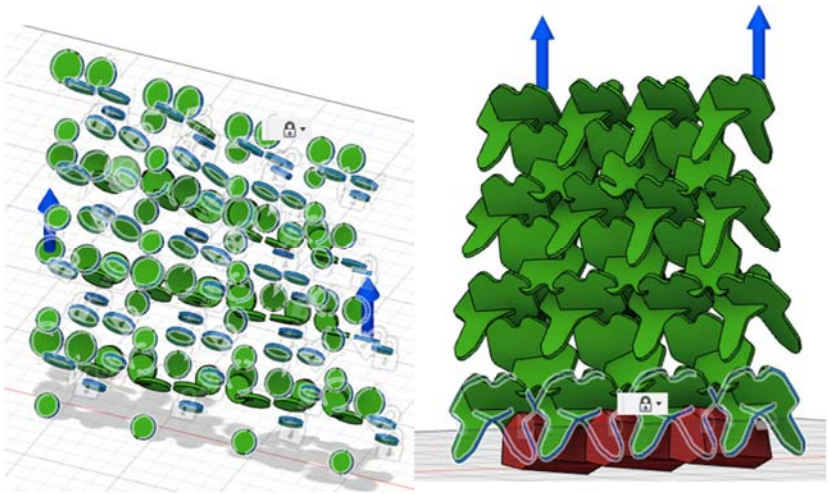


Figure 3.7 Structural inputs (Intended case & Case II) (produced by author)

3.2.3 Generative Design Objectives

It is defined two objectives for the generative process, which are minimizing the mass or maximizing stiffness with a minimum factor of safety limit, which is defined as 2 by default in the program used. In all cases, the same objective is defined, which is to minimize the mass of the object, with a factor of safety limit of 2.

3.2.4 Manufacturing and Materials

The program employed in this study provides simulations for four manufacturing methods namely, cutting, additive manufacturing, milling and die casting-forming. Forming requires different type of materials as well as high computation power, and it is not included in the manufacturing methods for the given studies. Additive manufacturing in this study refers to FDM 3D printing. Materials are chosen as the same materials in the first stage except cardboard, due to limitations of the program. Cardboard is replaced with MDF, also Aluminum is added as another material to explore design alternatives, as it is defined as one of the default materials in the program. Besides it has a higher Young's modulus which makes the modules more resistive to plastic deformation. Another material concerned in the cases is thermoplastic resin, since it has also elastic behavior. Manufacturing volume is set to 2500 pieces, as default.

For additive manufacturing (3D printing), overhead angle is set to 45 degrees and minimum thickness allowed is set to 2 millimeters. CNC milling is defined in three different cases, which are 2.5 axis, 3 axis and 5 axis milling. For all of the milling operations, tool diameter is set as 3 millimeters. For 3 axis and 5 axis milling, shoulder length (4 cm) and head diameter (6 cm) are set as software default. Since the model orientation is in the XZ plane, 2.5 axis milling tool direction is set as Y axis, and 3 axis milling tool directions are set as X+, Z+ and Y (+-) axes. Similar to 2.5 axis milling, cutting direction is also set as Y axis. (See Figure 3.8)

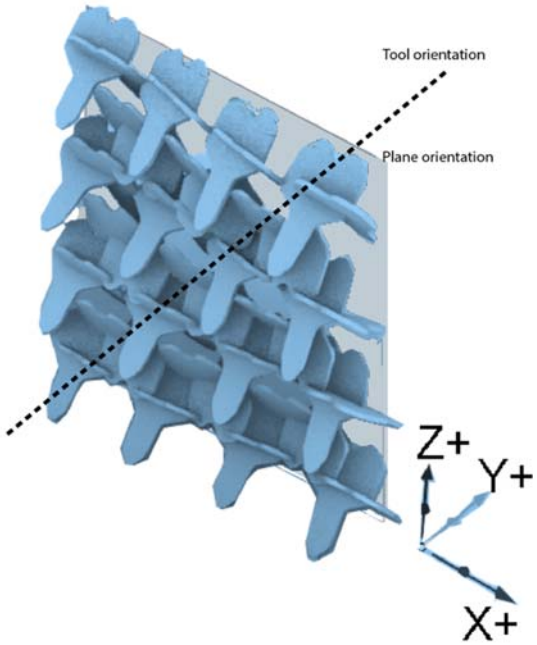


Figure 3.8 Tool orientation for CNC milling and 2 axis cutting (produced by author)

Although 2-axis cutting and 2.5 axis milling are set as manufacturing methods, it is seen that complexity of the intended model and its modular structure will be an obstacle for the milling operations in general, since milling treats the model as a monolithic object. Yet, since the aim is to see how model is affected by manufacturing constraints, and still to be able to get accurate design alternatives for the proposed/intended design for such manufacturing operations, cutting and milling are included.

Additionally, besides outcomes related with predefined fabrication methods, there are also suggestions like unrestricted which is not referring any specific fabrication method. The aim is to observe if there are any changes in design alternatives when the algorithm is freer in outcome generation.

Manufacturing methods and materials proposed for them are summarized in Table 3.2 below:

Table 3.2 Manufacturing and materials

Manufacturing

Tools	Setup
Unrestricted	Unrestricted
3D Printing	Overhead angle: 45 degrees Minimum mat. Thickness: 2 mm
2.5 axis milling	Tool diameter: 3 mm Tool direction: Y (Including reverse sides)
Cutting	Tool direction: Y
3 axis milling:	Tool diameter: 3 mm Shoulder length: 4 cm (default) Head diameter: 6 cm (default) Tool direction: X+ Y (+-) Z+ (Including reverse sides)
5 axis milling:	Tool diameter: 3 mm Shoulder length: 4 cm (default) Head diameter: 6 cm (default) Tool direction: Unrestricted

Materials

ABS Plastic
MDF
Expanded Polystyrene Foam
Aluminum (AlSi10Mg)
Thermoplastic Resin

3.3 Decision Tree Classifier

Selecting the manufacturing method is usually a decision made by the designer based on a design goal such as aesthetic aspects or economic constraints, in which the objectives can also be conflicting. With a data collected by manufacturing constraints, it can be open to AI interpretation through decision support algorithms.

Since manufacturing data is usually multifaceted, which includes both qualitative and quantitative data, decision tree classifiers are beneficial in such tasks (Priyanka & Kumar, 2020) Decision tree classifiers are used in manufacturing method selection including historical case-based approaches and rapid prototyping methods (Evans et al., 2013; Park & Tran, 2017) . They can be studied further in architectural fabrication for suggesting a manufacturing method for the designer to evaluate.

With the alternatives and parameters claimed from topology optimization based generative design, a dataset is constructed from different model qualities of design alternatives, such as complexity, planarity or material characteristics like density, mass and volume. The aim is to get an insight of the data collected and provide a machine learning based tool for decision making, in order to predict a more suitable manufacturing method, based on digital 3D model surface, and material data. This task can be defined under decision making, and since the data claimed is not that big, the dataset is fit into a decision tree classifier algorithm through Python, and scikit.learn. Here, the proposed machine learning model learns the decision rules that are present in the given dataset and makes its predictions accordingly.

The advantage of this approach is that it does not require advanced scripting, the algorithm does not have to be written from the scratch, as it is readily modeled with many Python libraries in scikit.learn from other open sources.

3.3.1 Parameters of Models in Classifier Algorithm

In order to construct the dataset to be fitted, 10 different parameters are noted for each obtained 3D model, along with their ID number, and processing status. Processing status is noted in order to observe if any of the other parameters affect the number of iterations. The parameters from Fusion 360 are stored in a table. Furthermore, additional parameters that may effect fabrication process are claimed through meshes that are exported. Parameters used are listed as below:

- **Manufacturing method:** Above listed manufacturing methods are noted for each 3D model. It is also defined as the label parameter for decision tree classifier, as it will predict the manufacturing method.
- **Material density (g/cm^3):** To translate the physical data of materials to a digital environment, material density is taken as one of the material parameters.
- **Material E value (Young's Modulus, GPa):** Another material parameter is elasticity. In order to measure the elastic or brittle behavior of materials, Young's modulus is included.
- **Volume (cm^3):** 3D model volume is one of the objective parameters. Outputs of different outcomes are noted in order to minimize the volume of future inputs.
- **Mass (kg):** 3D model mass is one of the objective parameters. Outputs of different outcomes are captured in order to minimize the volume of future inputs. Mass and volume information is provided directly from Fusion 360.
- **Planarity:** The model's curvature characteristics, whether it is composed of plane surfaces, or curvilinear surfaces, or whether it is planar solid, or prismatic solid. This parameter is taken as true (1) or false (0).
- **Model depth (as bounding box, cm):** The depth of the bounding box of the 3D model. For example, the stock material for CNC milling can be considered.

- **Edge quantity (joint curves):** To give an idea of the model complexity, edge quantity is measured through meshes. Curves are joint, since manufacturing models mostly consist of joint curves, or solids, naked curves are not accepted. Also, the aim of this to prevent misconceptions since many open curves can increase the model complexity.
- **Reverse sides:** Whether the base plane of the 3D model can be reversed according to the manufacturing method. This parameter is either true (1) or false (0).
- **Multi-axis:** This parameter is set as true if the model allows multi-axis machining.

The parameters given above show the complexity of the model, under the presence of material and the manufacturing methods as a part of the design process. Hence, using decision support algorithms in the design process and having feedback is crucial for designer. Fitting such data to a decision tree classifier model, it is aimed to predict the manufacturing method of future 3D model data. This extends the design process, and a more holistic process can be achieved.

The dataset obtained is edited before trained. Firstly, failed outcomes are removed before fitting the data, since there is no data can be implemented. Secondly, data with "unrestricted" manufacturing method is removed, since it is not preferred as an outcome label.

The table including raw data can be found in Appendix A.

3.3.2 Assessment of Accuracy

The decision tree classifier is trained under stratified 5-fold cross validation (Figure 3.9), in which, data is partitioned as one test and four training data in five iterations, in order to make sure that the proposed machine learning model is accurate, and to prevent overfitting. In each iteration, training and test datasets change, but their ratio

is the same. Since the data obtained from Fusion 360 is too repetitive, it is shuffled before partitioning, in order to have random samples in splits.

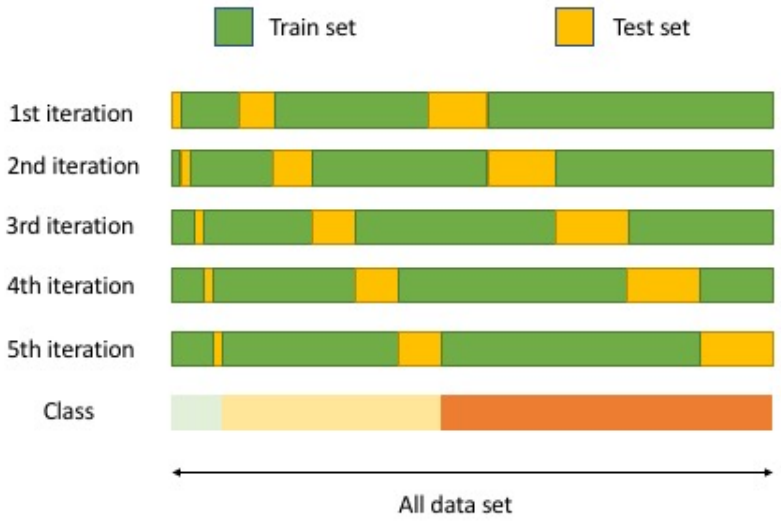


Figure 3.9 Stratified k fold cross-validation, 5 folds (produced by author)

In this method, all the partitions include different labels, which are manufacturing methods, distributed in a similar way to all data, in order to make sure that provided clusters represent all data. With this approach, we obtained 5 different accuracy from different train and test sets and calculated balanced accuracy by taking the average of the five different values.

Additionally, a small dataset is obtained from the outcome models in the first phase of this research by randomly choosing different modules from the assemblies. 1 module is selected from each assembly and the data obtained from these are noted with the parameters mentioned in 3.3.1. Then the label data (manufacturing method) is removed, and it is expected to ML algorithm to predict the manufacturing methods. Findings are compared with the real-life cases.

CHAPTER 4

RESULTS AND ANALYSIS

This chapter presents the results and an analysis of the two stages of the explorations. Results are composed of two sections. Firstly, results of the observational methods are presented side by side in order to provide a comparison between digital and fabricated models. Secondly, the results of the generative study is presented for three cases as matrices to see differences of design alternatives within materials and manufacturing methods.

4.1 First Phase

The outcomes of the first phase are physically fabricated models. (Figure 4.1) Problems during design process, and changes on accuracy, and design tectonics are observed.

With four fabrication methods, four different digital and physical models are obtained at the final stage, also there are intermediary stages that are observed in the fabrication process, which lead to iterations, and necessity of new altered/modified digital models. Limitations of fabrication methods are observed.

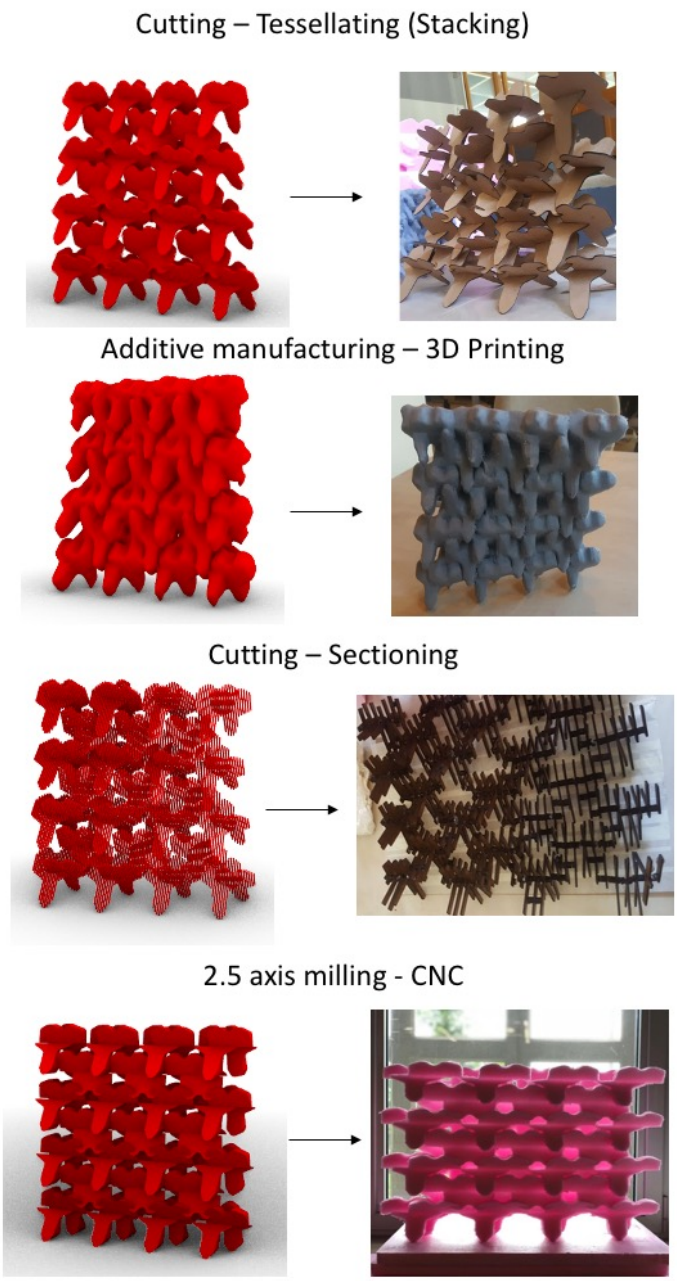


Figure 4.1 Outcomes of the first stage (Fabricated models)

The first stage of design shows that each fabrication method has its own tectonics and can change the initial design due to limitations of material and fabrication method, resulting in time loss, and problems in detailing or even forcing the design to be changed considerably. The main reason of such problems is the elusiveness of freedom in initial computational model itself where author explored any relation and intricate forms in cyberspace without any constraint.

For example, in 3D printing, the problem was that this method is not allowing large voids in the design and the outcome model at the end became very bulky and solid. In CNC milling, it is observed that the double curved form of the wall cannot be implemented with 2.5 axes, and it is needed to be eliminated. For sectioning, the problem became the structural stability of the system since it was failing in bending due to intuitive process in detailing and failure of bonding material, which can be concluded as assembly problems.

The example below in Figure 4.2 shows the optimization process of same digital model for 3D printing. Form is experimented with voids and more complex solids to see potentials of 3D printing. However, since FDM 3D printing does not allow slender elements or surfaces, the optimal shape came out very bulky and solid. Modifications were done in the model when 3D printer failed to produce the input model. Final model is reached after three design alternatives.

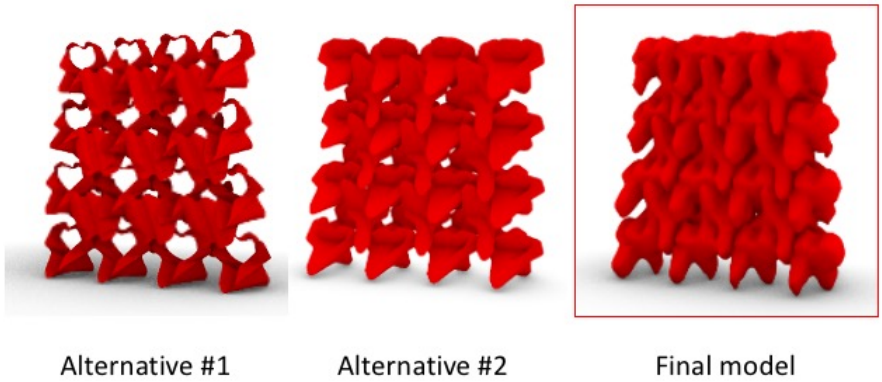


Figure 4.2 Design alternatives for 3D printing (intuitively modeled)

Another point with this exploration that can be derived comes from layering-sectioning. The model consisted of 929 pieces (including supporting elements), and small elements are produced multiply in order to keep substitutes. Total of 8 MDF boards are used as stock material. Figure 4.3 shows the nesting process of this method. As it is seen that this method does not only change the initial tectonic, but since the nesting process is done by hand, also labor cost increases considerably.

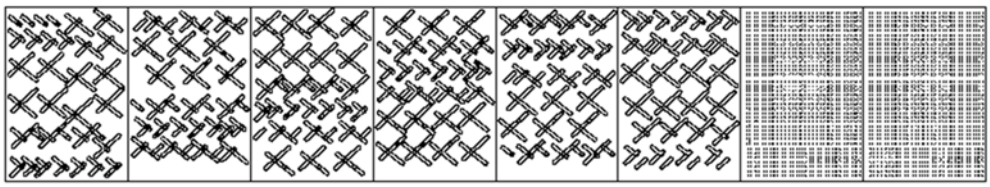


Figure 4.3 Nesting of 3D model (sectioning)

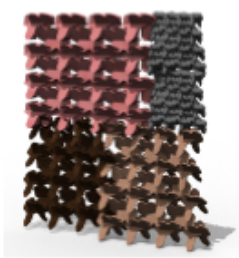
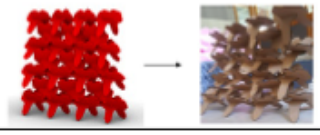
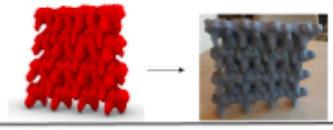
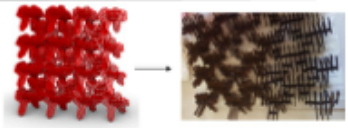
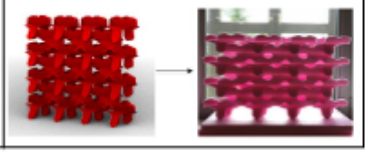
This experimentation shows that fabrication methods and thus material to be used have very strong impact on the tectonics of the design. If computational models are mostly focused on form finding, the idea of "file to factory" can fail easily resulting in loss of precision, accuracy, high material consumption and even a complete change in the design. To conclude, results obtained from each fabrication method can be summarized as below:

- Stacking-laser cutting: The outcome is the closest one to the initial model which is due to modular-assembly logic, however the model fails in stability and detailing. Nesting and scrap material issues occurred.
- 3D printing: Manufacturing method is not suitable for models with voids. Eventually, the 3D model becomes more thick and solid. Although it is relatively accurate compared with the computational model that is developed, initial design is still changed during intermediary process. Iterations between fabrication and 3D modeling occurred.

- Sectioning: Although this design alternative is very experimental, problems in stability and material are occurred due to not suitable detailing and material for this type of fabrication. While the design alternative achieved is more lightweight, it has a high cost due to material loss.
- CNC milling: Initial model precision is lost due to machine limitations. However, it is noted as the most practical manufacturing technique in terms of assembly. A CNC machine with more axes can increase model precision and eliminate assembly process.

Table 4.1 given below summarizes the objectives, methods and outcomes of the first study.

Table 4.1 Summary matrix of Phase I

 • Limitations of fabrication methods are observed • Tectonic changes in models are observed • Dataset for ML model is obtained for prediction	Tessellating • 2D laser cutting • Cardboard	
	Additive Manufacturing • FDM 3D Printing • ABS plastic filament	
	Sectioning • 2D laser cutting • MDF	
	Subtractive Manufacturing • 2.5 axis CNC milling • Styrofoam	

A dataset is constructed from the outcomes of this phase for decision tree classifier algorithm to predict the manufacturing method. The data obtained from this experiment for prediction is presented as below, four computational models are evaluated.

Table 4.2 Data obtained from first phase

Material E value (Gpa)	Material density (g/cm3)	Volume (cm3)	Mass (kg)	Non-Planar	Model Depth (cm) (BBOX)	Edge QTY (joined)	Revers e Sides	Multi Axis	MFR
2.240	1.060	801.65	0.20600	1	7.24	3337	1	1	Additive
0.028	0.050	1963.70	0.57000	1	4.57	160	0	0	2.5 axis milling
0	0.93	8.64	0.00592	0	0.2	29	0	0	Cutting
2.400	0.800	1.43	0.00700	0	0.3	12	0	0	Cutting

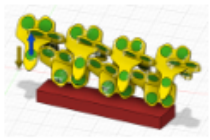
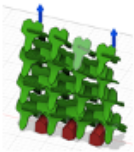
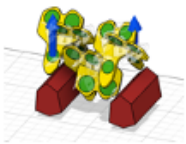
The data shown in Table 4.2 is formatted in a similar way to the parameters explained in 3.3.1 to give an idea of complexity and materials of the manufactured model. Although the dataset is not big enough for generalization, it can exemplify a comparison between ML predicted manufacturing methods and real-life cases.

4.2 Second Phase

In the second phase of the research, different optimal design alternatives of the same model are obtained to form a dataset to train decision tree classifier. To achieve more constructable design alternatives, topology optimization process is conducted by Fusion 360's generative design algorithm, results are presented for three different cases. Fusion 360 fails in generating outcomes for total of 15 of the outcomes. For the generated ones, while 45 outcomes are converged achieving the factor of safety limit, 90 outcomes are completed allowing further optimization. Converged outcomes include complete, as well as incomplete alternatives, in which generative design objectives are achieved with low iterations, and the algorithm stopped further iterations for form-finding. The situation here can be defined as overfitting, in which the algorithm only aims to reach the numbers given in generative design objective, and it neglects other aspects such as model detail generation.

For creating these outcomes, the generative design process is ended with total of 3217 iterations. While lowest iteration count to generate one outcome is 2, it can go up to 99 iterations to complete the process. Some outcomes are seen to be converging with low iterations, without completing model details. For the classification algorithm, incomplete outcomes are also included as design alternatives, since it is possible to obtain 3D model aspects. Table 4.3 summarizes the studies and present generative design results in general.

Table 4.3 Summary of generative design cases

	Case I	Case II	Case III
			
Attributes			
Scale	◔	●	◔
Starting shape	✓	✗	✓
MFR & Materials	Refer to Table 3.2	Refer to Table 3.2	Refer to Table 3.2
Objectives			
Obtain design alternatives	✓	✓	✓
Topology optimization	◔	✓	◔
Observe detail precision			✓
Obtain dataset	✓	✓	✓
Observe mass And volume	✓	✓	✓
Results			
# of design alternatives	35	50	50
Time past to generate	appx. 1 hr	appx. 1 day	appx. 1 to 2 hrs
Similarity to initial model by MFR method			
Unrestricted	Similar	Similar	Similar
Additive	Similar	Mostly similar	Similar
5 axis milling	No outcomes	Similar	Similar
3 axis milling	No outcomes	Not similar	Similar
2.5 axis milling	Not similar	Not similar	Not similar
2 axis cutting	Not similar	Not similar	Not similar

Results listed above are investigated in depth with case specific design alternatives, and mass-volume graphs presented in further sections.

4.2.1 Case I

Since the software is not able to develop outcomes for the intended design space, partial model is studied in Case I. The aim of this case is to provide generative design alternatives for a given initial shape and see how the design changes.

The research objectives of Case I are as follows:

- To compare the mass and volume relations with the manufacturing method and materials when generative design includes an initial shape
- To see how manufacturing method changes the initial design
- To observe the material's effect on design alternatives
- To obtain a dataset for decision tree classifier

4.2.1.1 Outcomes

Results of the first case of the controlled experiment are presented in the matrix below. (Figure 4.4) Total of 50 outcomes are listed, 15 of them are failed to be generated due to software limitations, or model complexity. 10 of them are converged with satisfying the objectives. 25 of them are completed without reaching the objectives due to material and manufacturing constraints, and allowing further optimization. The ones with the blue frames in the matrix show converged outcomes.

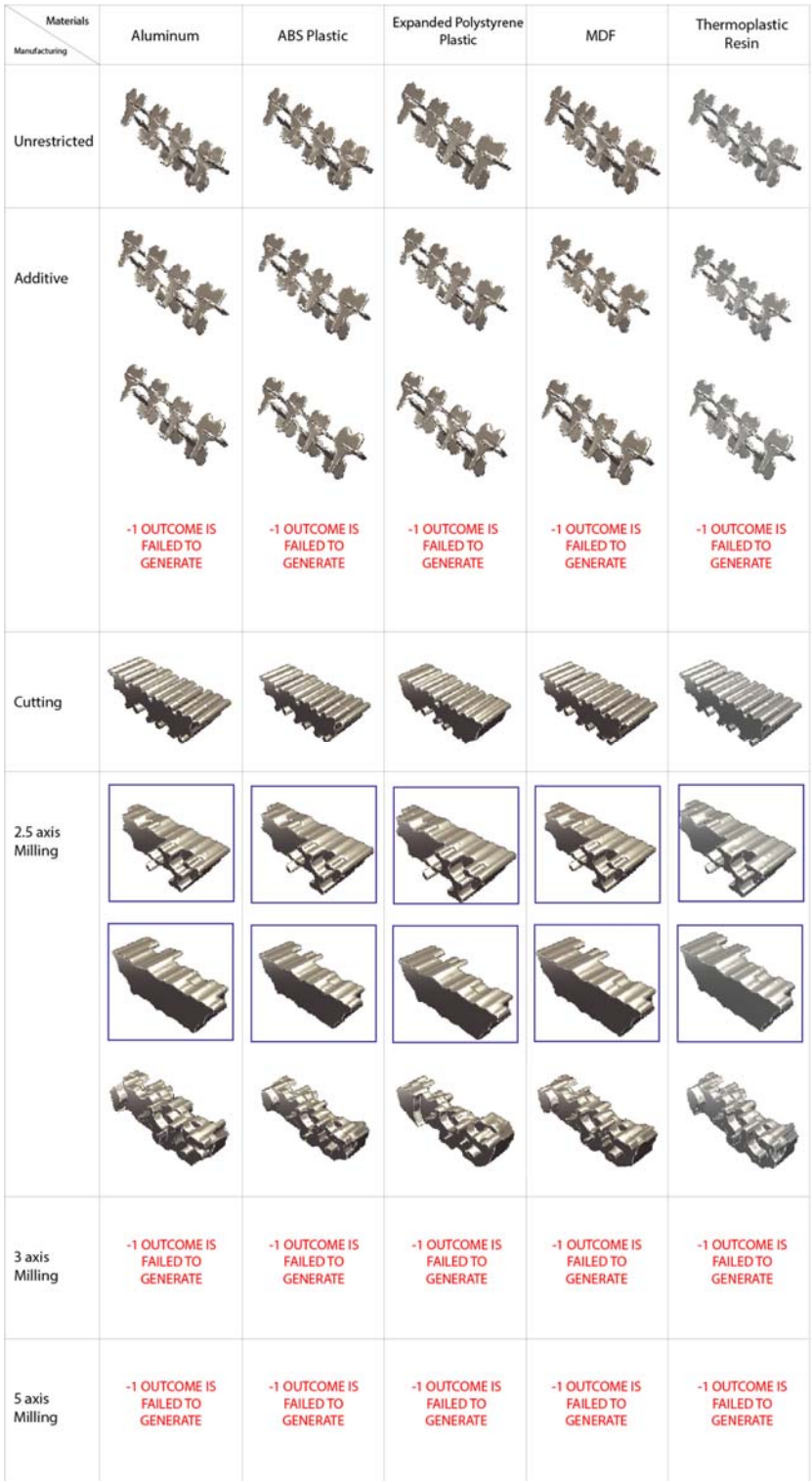


Figure 4.4 Outcomes of Case I

The graphs below show Fusion 360's comparison graphs for first setup. (Figure 4.5 and 4.6) Figure 4.5 shows volume and mass relations for different materials, while Figure 4.6 shows the same for different manufacturing methods. When sorted through material, the results seem to be aligned in horizontal axis, and it is vertical in the second graph. This shows that material has an impact on decreasing the mass, while manufacturing method effects the volume more.

Figure 4.5 Case I-Mass and volume graph in relation with materials (produced by author)

According to material graph in general, material seems to be effecting the mass directly, while volume changes through design alternatives dependent to manufacturing methods. While the lowest mass is observed with XPS, the change in mass seems also to be minimum. On the other hand, as the material density increases, the mass seems to be dramatically increasing with the volume as expected.

Figure 4.6 Case I-Mass and volume graph in relation with manufacturing methods (produced by author)

Volume seems to be in its lowest when there is not any manufacturing method is defined, or it is defined as additive manufacturing. On the other hand, in cutting and 2.5 axis milling, volume seems to be increased.

Also, by examining mass-volume graph together with the design alternatives, which are given in Figure 4.4, it can be seen that the initial design changes drastically through 2.5 axis milling and cutting, with losing its void properties. As the model gets far from the initial design, mass and volume seem to be increasing.

In order to combine both graphs with design alternatives, two extreme cases of materials, which are XPS and Aluminum, are presented below:

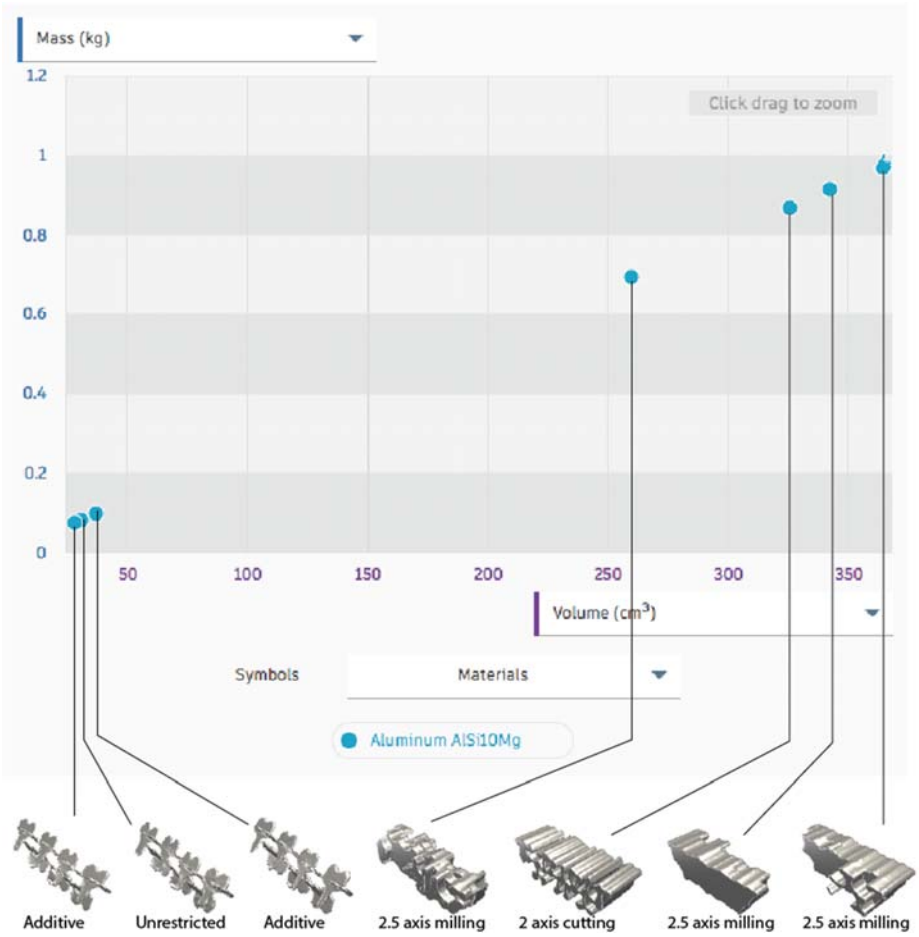


Figure 4.7 Case I Mass-Volume Graph – Manufacturing methods with design alternatives with one material (Aluminum)

Through analyzing the mass volume graph, together with the design instances with material and manufacturing properties, it can be asserted that, if manufacturing method becomes more restrictive, the initial design changes more. Also, material mass and volume seem to be increasing with the decreased void properties of the design.

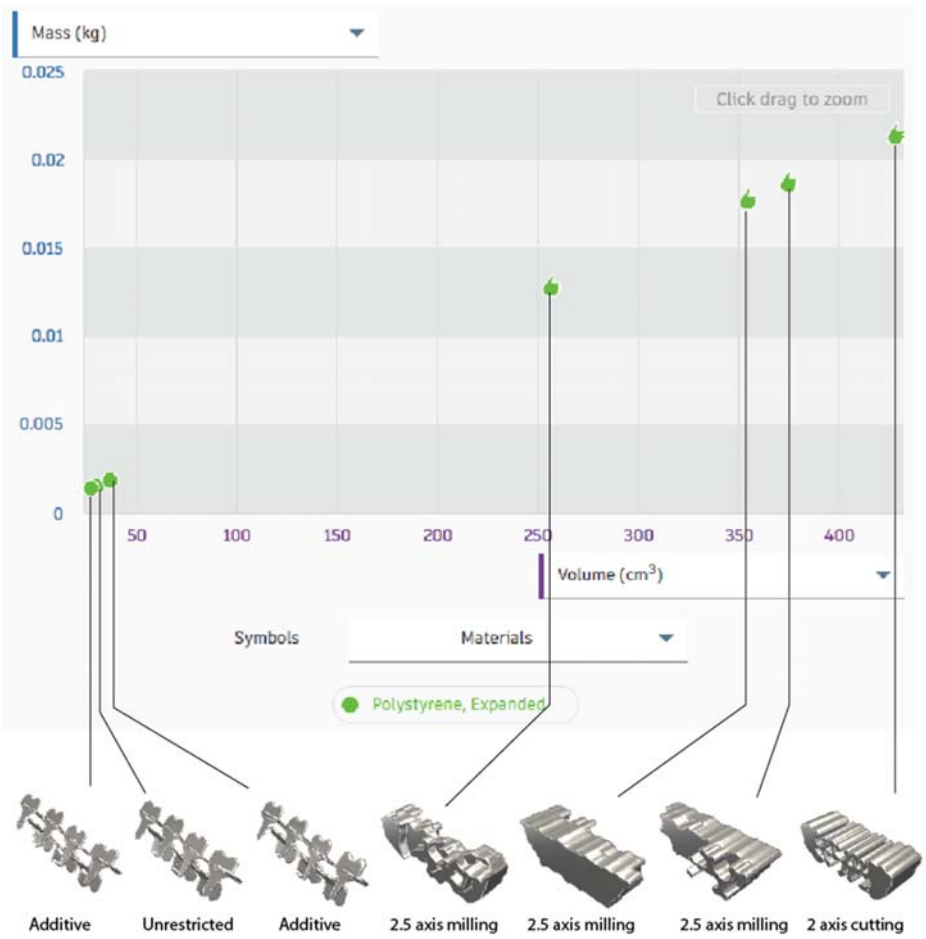


Figure 4.8 Case I Mass-Volume Graph – Manufacturing methods with design alternatives with one material (XPS)

On a closer look to Figure 4.8, the increase in mass in XPS seems similar to the increase in aluminum. However, due to material properties, the densities of them and thus mass values are far less than the design alternatives with aluminum. The significant change in this graph seems to be the maximum mass and volume, which are observed through cutting. The aluminum design alternative with cutting has more voids, and more elaborated, compared to the one with XPS. Thus, it is closer to the initial design.

The summary of Case I is presented in the matrix given below in Figure 4.9:

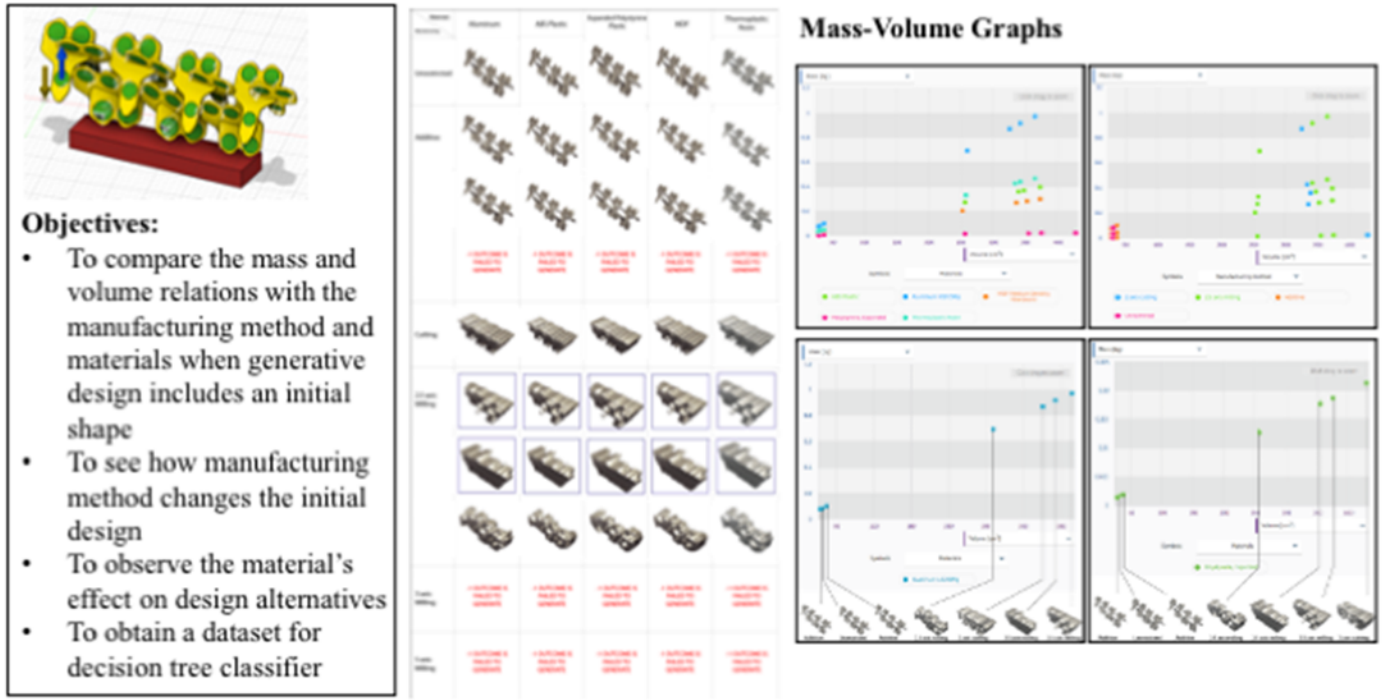


Figure 4.9 Outcome matrix of Case I

4.2.2 Case II

Case II design space includes the complete initial design model as preserve geometry. The aim of this case is to see if the initial design changes when algorithm tries to keep the form of the initial model.

The research objectives of the Case II are presented below:

- To compare the mass and volume relations with the manufacturing method and materials when generative design algorithm preserves all of the model.
- To see how manufacturing method changes the initial design
- To observe the material's effect on design alternatives
- To obtain a dataset for decision tree classifier

4.2.2.1 Outcomes

Results of the second case of the controlled experiment are presented in the matrix below (Figure 4.10). Similar to first case, software tried to generate 50 outcomes, as the combination of different materials and manufacturing methods is the same with the first case. None of the outcomes are failed to be generated, 24 of them reached generative design objectives and converged, 26 of them are completed without reaching the objectives, and allowing further optimization. In Figure 4.10, Design alternatives with blue frames show converged outcomes. Unlike Case I, here it is seen that some of the converged outcomes are incomplete and lacking model details, which means the algorithm is overfitting.

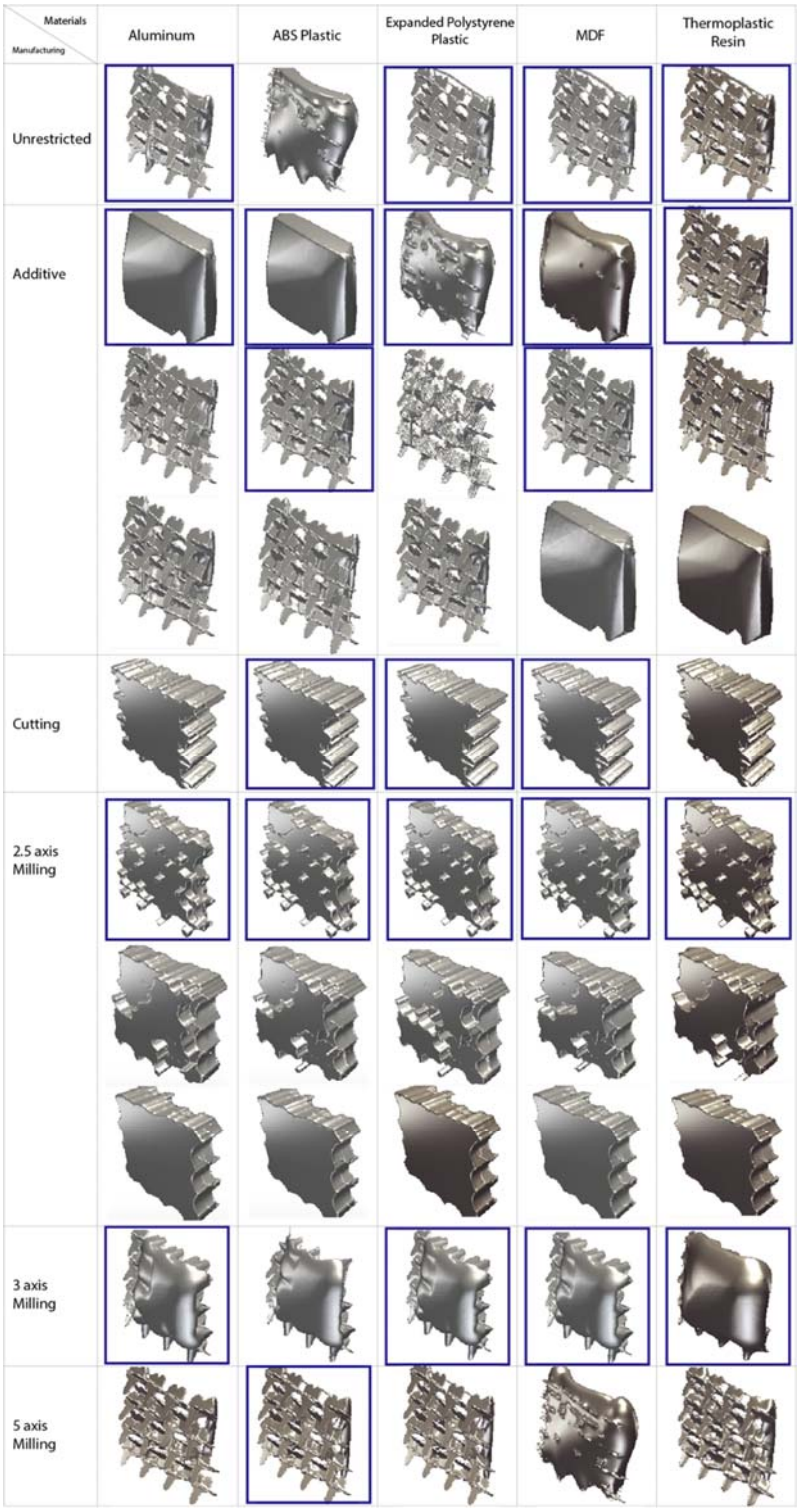


Figure 4.10 Outcomes of Case II

Comparing the above alternatives to the Case I, it can be said that generative design works similar when a starting shape is defined, or all model is preserved. Although all the model is selected as preserve geometry, there are significant differences between initial design and some of the design alternatives due to manufacturing constrains, which is similar to the outcomes with a predefined starting shape.

For second setup, graphs in Figures 4.11 and 4.12 below show the volume-mass relations compared to different materials and manufacturing methods like in the first setup. While the data alignments are similar to the first setup given in the material graph, manufacturing graph shows differences. Firstly, since the first setup failed to generate outcomes for 3 and 5 axis milling, here as these graphs show there are more alternatives.

Figure 4.11 Case II- Mass and volume graph in relation with materials (produced by author)

Similar to Case I, the lowest mass is observed in XPS, and the maximum is observed in Aluminum. As the material elasticity and density increases, the change in mass seems to be more. Like Case I, the maximum volume value is observed in XPS.

Figure 4.12 Case II- Mass and volume graph in relation with manufacturing methods (produced by author)

The lowest mass and volume are observed when the algorithm is not dependent on a manufacturing method, and maximum volume is shown in cutting, which is expected due to loss of voids in the initial design.

However, the significant change in this case is while the size of the mass increases, mass and volume obtained through additive manufacturing seems to be increasing. Some design alternatives with additive manufacturing are close to the maximum mass and volume presented. Additionally, although it is expected that 5 axis milling

and 3D printing produce similar design alternatives to the initial design, their mass and volume show significant differences

Similar to Case I, materials show maximum and minimum mass are presented below with the design alternatives:

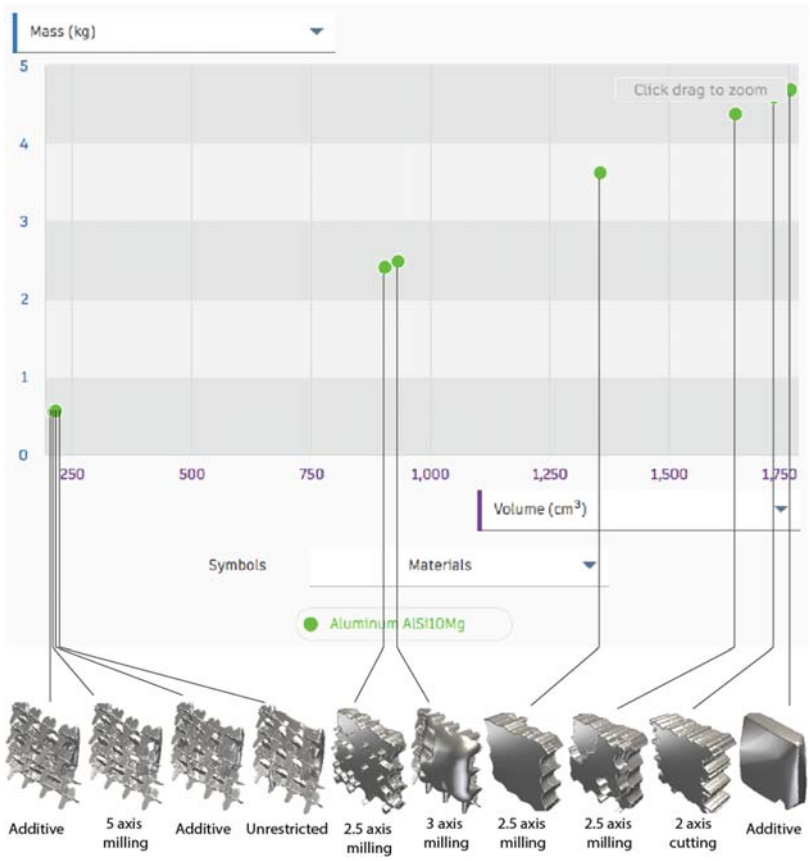


Figure 4.13 Case II Mass-Volume Graph – Manufacturing methods with design alternatives with one material (Aluminum)

When the combined graph is observed closely with the design alternatives, it is seen that unrestrictive methods of manufacturing such as 3D printing or 5 axis milling, are lower in mass and volume, and more similar to the initial design. The significant example in this graph is that the maximum volume that is also seen in an additive

example. However, observing the design alternative, it is in block form, and not elaborated like other additive examples. The one shown with the maximum volume on the in Figure 4.13 is one of the alternatives that is converged by achieving generative design objectives with less iterations and stopped making further iterations to elaborate details.

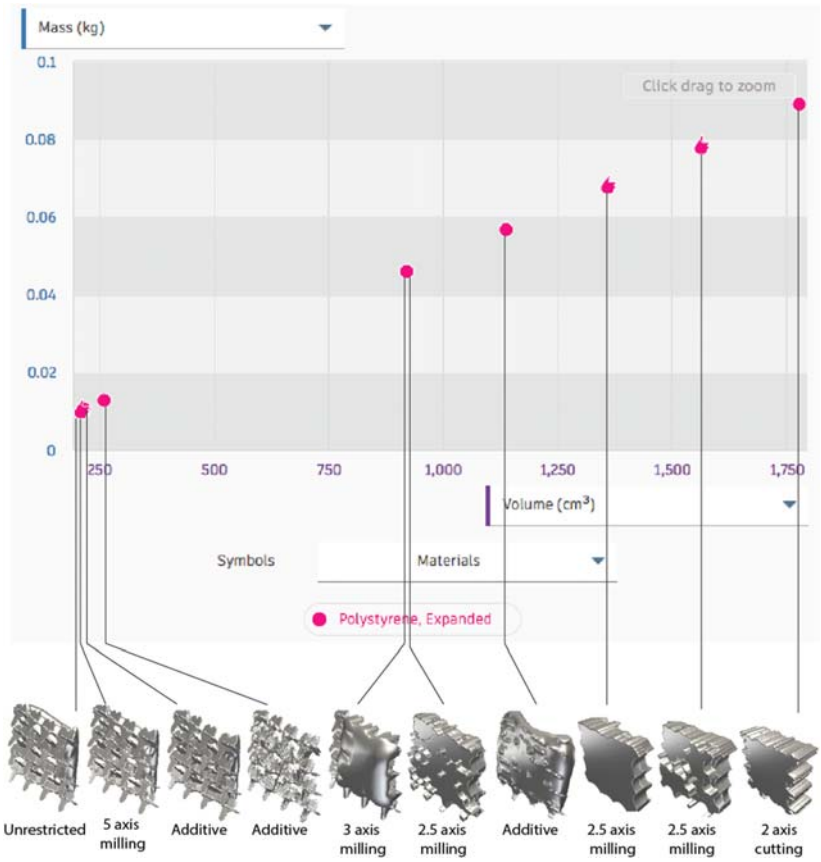


Figure 4.14 Case II Mass-Volume Graph – Manufacturing methods with design alternatives with one material (XPS)

As expected, the mass values in XPS are lower than aluminum like in the first case due to material density. However, the maximum volume is observed in cutting. In this study, like aluminum, 3D printing and 5 axis milling examples are closest to the

initial design, however there is one additive example that seems to be incomplete. Again, this is one of the converged examples with overfitting.

The summary of Case II is given in the matrix in Figure 4.15 below:

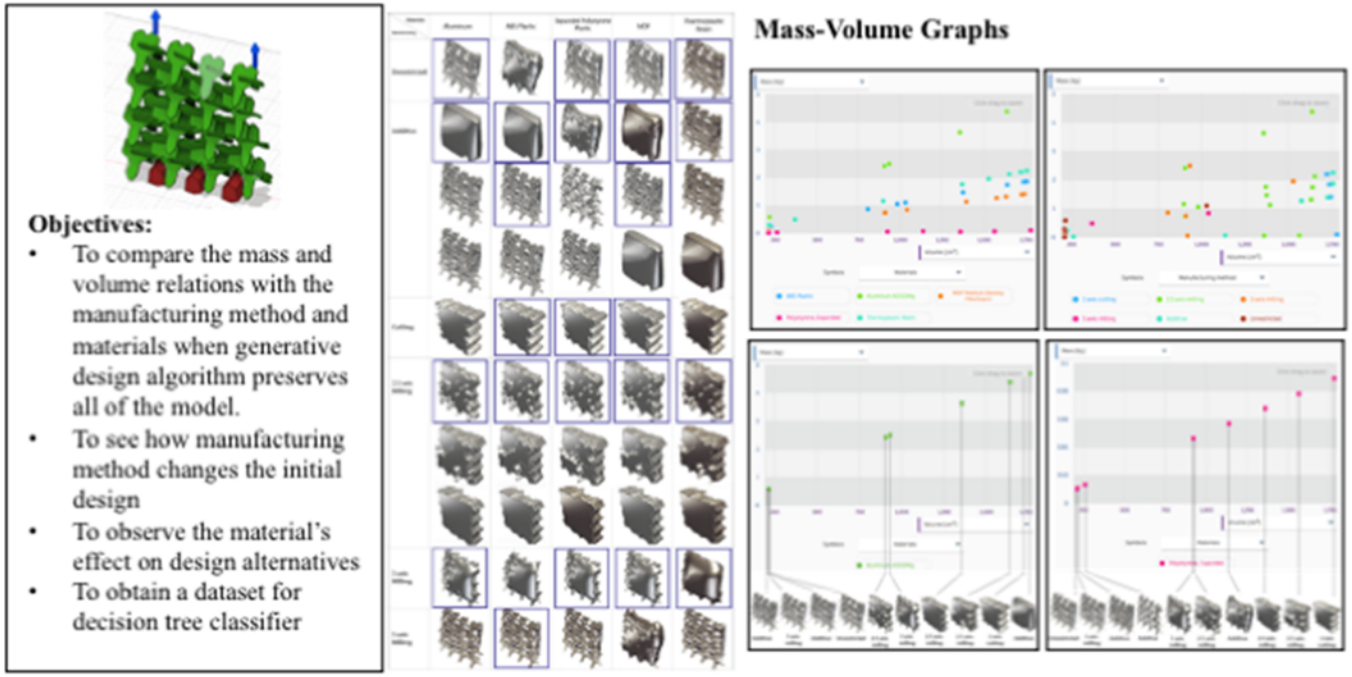


Figure 4.15 Outcome matrix of Case II

4.2.3 Case III

Finally, Case III design space is similar to Case I, and includes a starting shape. However, it contains just a few units of the intended design space. The aim of this case is to see if the level of detail changes when the overall size is smaller having very few modules.

The research objectives of the Case III are presented below:

- To compare the mass and volume relations with the manufacturing method and materials when the model is smaller
- To see how manufacturing method changes the initial design
- To observe the material's effect on design alternatives
- To obtain a dataset for decision tree classifier

4.2.3.1 Outcomes

The data obtained from the third design space setup is presented below. (Figure 4.16) The software created 50 outcomes, similar to the other two cases. 11 of the obtained outcomes are converged, and 39 of them are completed allowing further optimization. Compared to Case II, here, the converged ones seem to be successful examples with completed models, rather than overfitted outcomes.

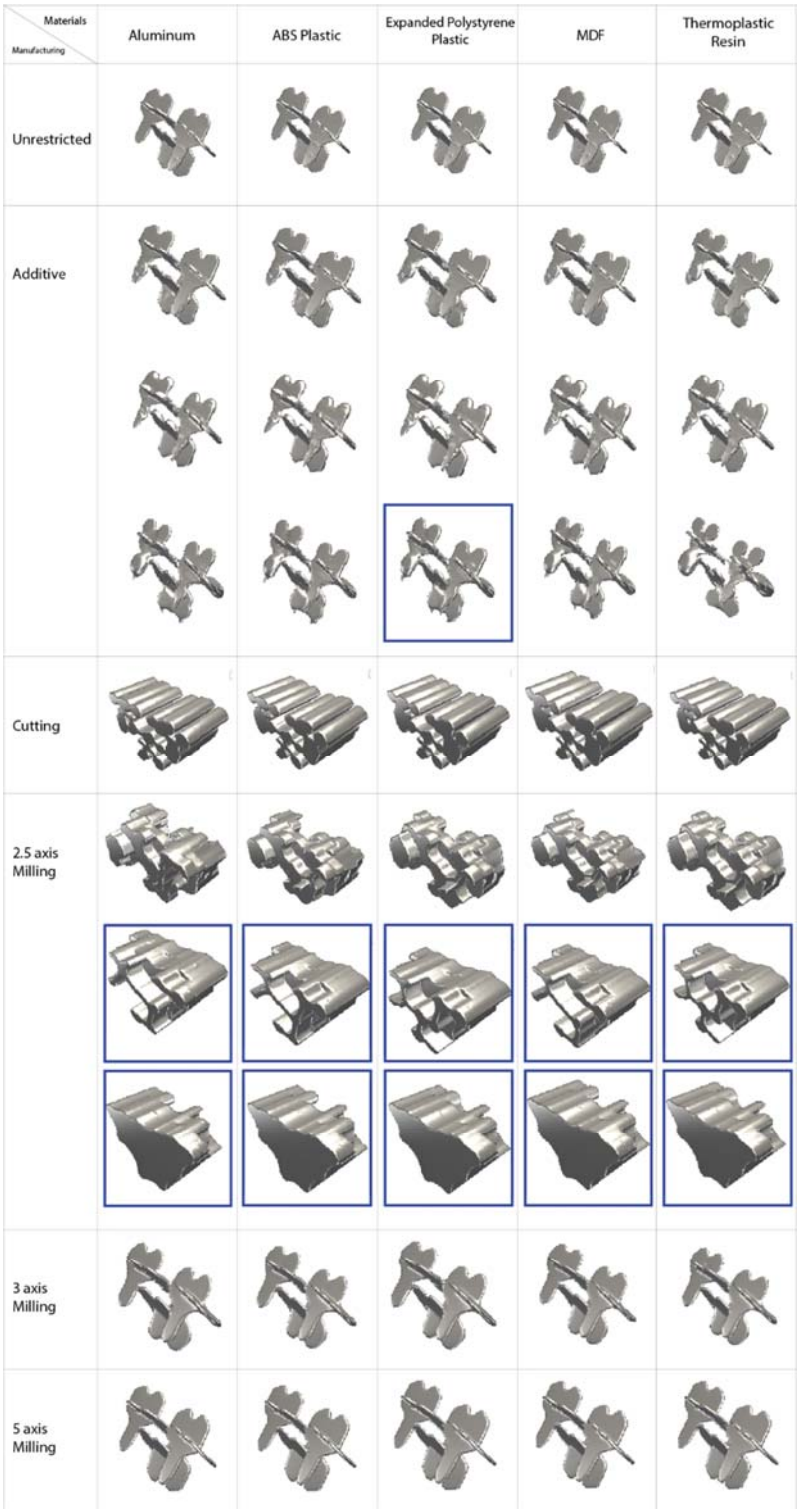


Figure 4.16 Outcomes of Case III

The matrix above shows that as the number of components reduces, the level of detail, thus the precision of the design alternatives seems to be increasing. Regarding accuracy of initial design, it is similar to the other cases as the initial design transforms itself in accordance with manufacturing methods.

Mass-volume graphs of the third case is illustrated as below. (Figure 4.17 and 4.18)

Figure 4.17 Case III- Mass and volume graph in relation with materials (produced by author)

Similar to the first two cases, lowest mass is observed in XPS and the highest mass is with aluminum. Although the distribution looks similar to the second case, the change in mass and volume is minimum due to small size.

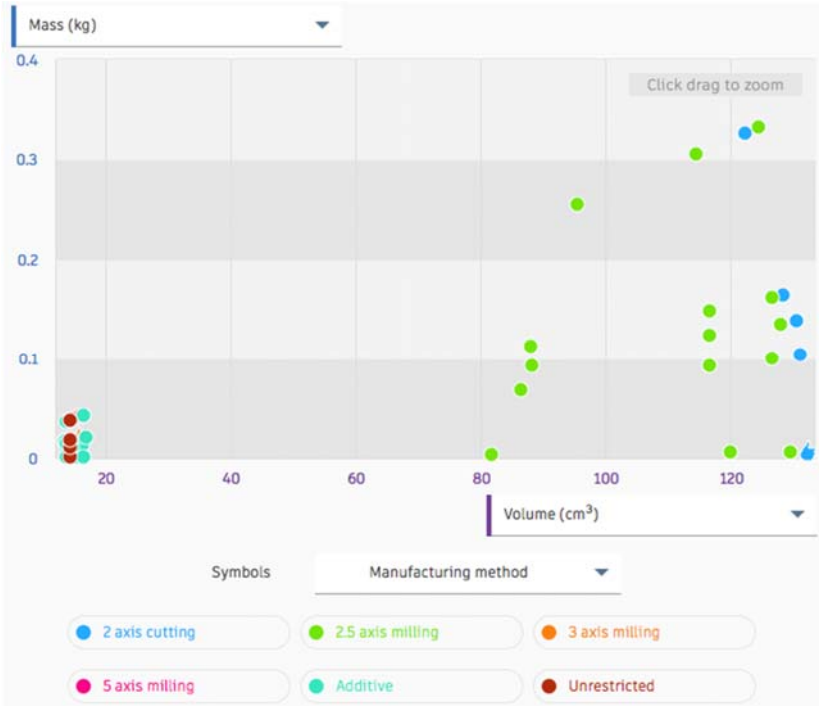


Figure 4.18 Case III - Mass and volume graph in relation with manufacturing methods (produced by author)

When aligned according to the manufacturing method, similar to the earlier cases, the data seems to be aligned vertically. The lowest mass and volume is observed in when the algorithm is not dependent on any manufacturing method. If a manufacturing method is defined, 5-axis milling and additive manufacturing, additionally in this case, 3 axis milling seem to produce similar results to these.

The combined graphs of XPS and aluminum are presented below, in order to make a comparison for the design alternatives:

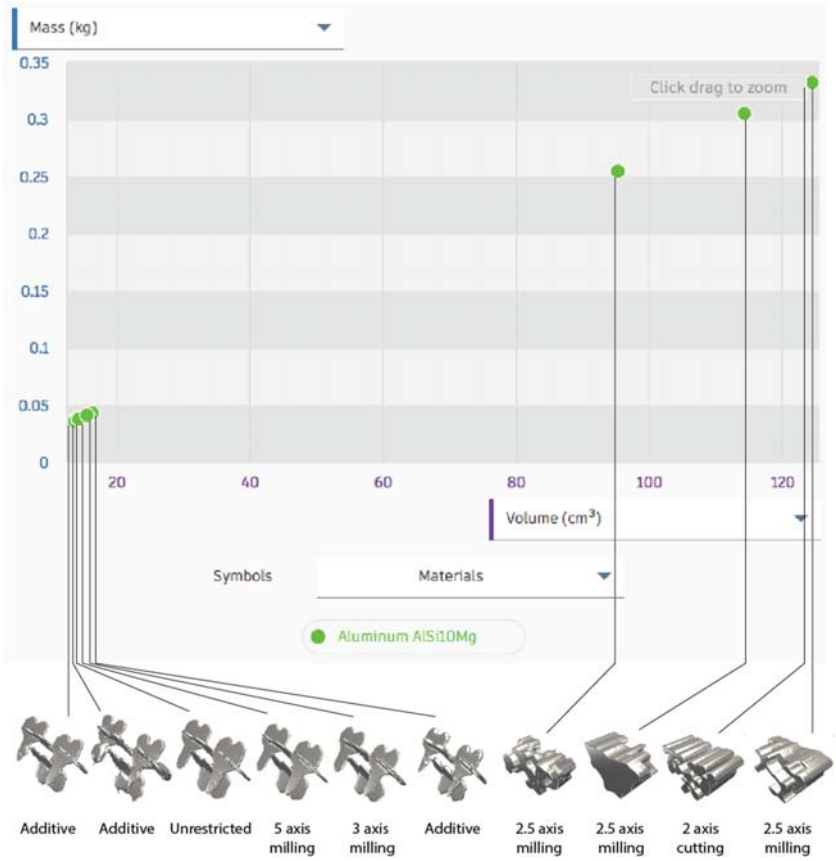


Figure 4.19 Case III Mass-Volume Graph – Manufacturing methods with design alternatives with one material (Aluminum)

According to the graph above, it can be claimed that as the scale goes smaller, 3 axis milling and 5 axis milling produce closer outcomes to the initial design. If the manufacturing method is more restrictive, mass and volume seem to be increasing, and design alternatives are more and more differing from the initial design. In this example, the maximum volume observed is in 2.5 axis milling, but the difference with cutting is very small. The design alternative with cutting seems to be more elaborated when the size is smaller.

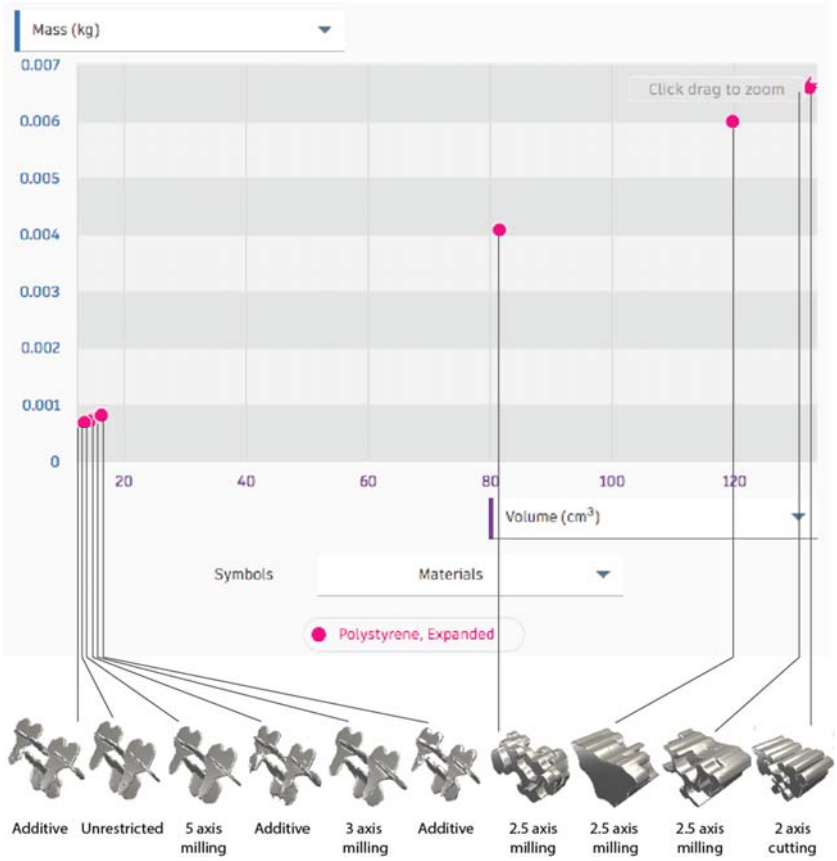


Figure 4.20 Case III Mass-Volume Graph – Manufacturing methods with design alternatives with one material (XPS)

The graph showing XPS is similar to the aluminum graph. The only difference is, similar to the other cases, cutting requires more volume. This might be due to material characteristics of XPS, as it is brittle, and cannot handle many voids. More outcomes are becoming similar to the initial design, like presented in the aluminum graph.

The summary of the Case III is presented below in the matrix given in Figure 4.21:

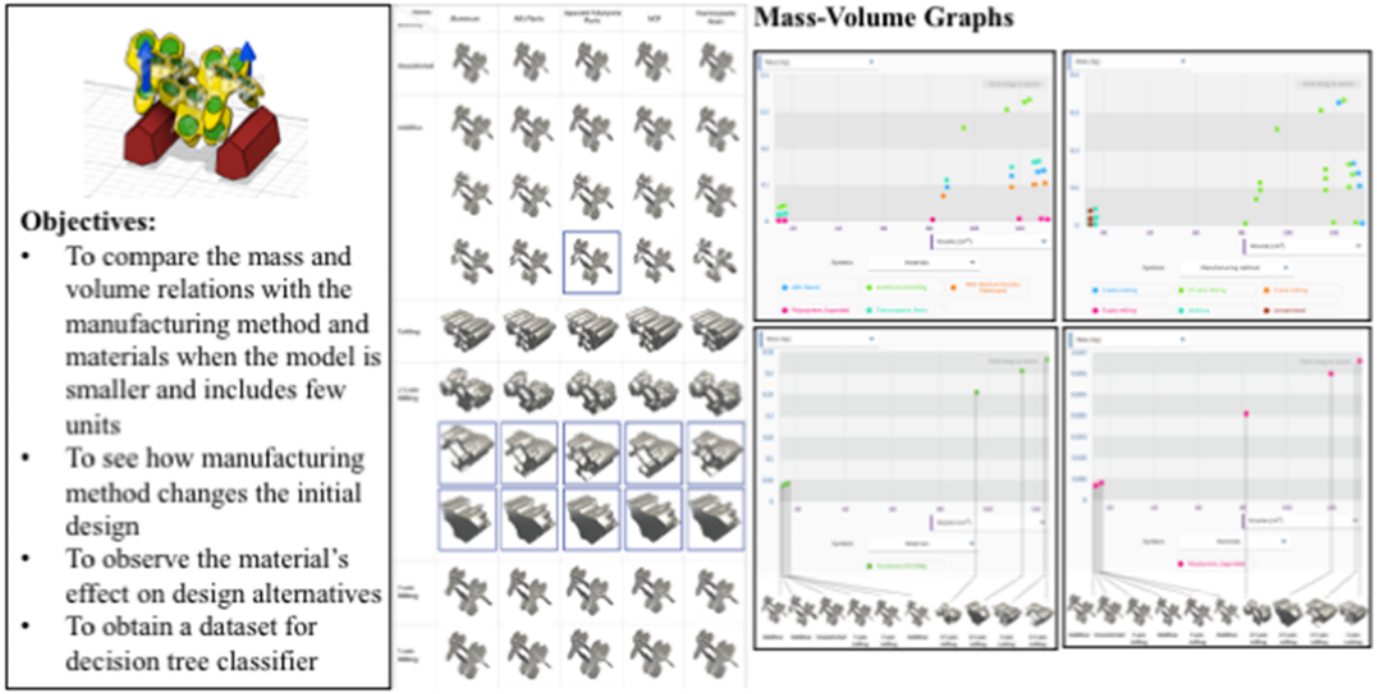


Figure 4.21 Outcome matrix of Case III

4.3 Decision Tree Classifier

After the train-test process is finished, the balanced accuracy of the proposed ML model is measured around 88 percent through stratified k-fold cross validation. Additionally, comparison of predicted data and real-life cases are presented below in Table 4.4, the ML model predicted 3 out of 4 outcomes correct.

Table 4.4 Comparison: Prediction and real-life cases

Status	**Outcome 1**	**Outcome 2**	**Outcome 3**	**Outcome 4**
Actual	Additive	2.5 axis milling	Cutting	Cutting
Prediction	**5 axis milling**	**2.5 axis milling**	**Cutting**	**Cutting**

Although dataset from real-life case is very small and cannot be generalized, above table exemplifies the ML model predictions. While it predicts the manufacturing methods of less complex examples successfully, it predicted 5 axis milling instead of additive manufacturing. While it is possible to manufacture complex outcomes through both manufacturing methods, and the outcomes of these are very similar, the dataset might be improved to be more elaborated to differentiate these two methods. Yet, since we cannot generalize the above table, it can be said that the intermediary model prepared for 3D printing is more suitable for 5 axis milling.

CHAPTER 5

DISCUSSION

This chapter presents an evaluation of the experimental results, and their discussion in the context of research aim and objectives. Firstly, the problems and limitations are presented for the first experiment. Secondly, the design alternatives are evaluated within the context of manufacturing and materials. Also, the accuracy of the ML model is evaluated within general discussion, and the comparison between real life cases and predicted ones are discussed.

Additionally, to give an insight, all design alternatives are discussed through architectural tectonics, compared with initial design. Also, differences between top-down and generative design approaches are evaluated, advantages and problems are noted.

Lastly, the design process in the first phase is considered to be re-designed within the conclusions derived from the experiments, and steps of the design process before fabrication are discussed.

5.1 Top-Down Design Approach

The first experiment demonstrates a top-down design process as explained in Chapter 2.5. Although computational models are rule-based and derived from parametric design principles, the initial design fails in the fabrication process. This failure occurs due to considering fabrication and physical properties of design at the last stage of the design process. Such problems can occur not only in small detail scale, but also they can force designer to quit some of design alternatives even they are favored by the designer, due to fabrication problems.

Each of the fabrication techniques, their limitations and effects on architectural tectonics are discussed below. Additionally, problems within each process are evaluated:

- Tessellating-laser cutting: While tessellating is a very common technique, errors in detailing can occur as mentioned in Chapter 2.4 with paneling. The double curvature of the surface is preserved since it is constructed as assembly, through surface subdivisions or tessellations. However, assembly brings the problems of detailing and nesting, as when the fabrication details are not modeled before the fabrication process, the outcome tends to have structural stability issues. On the other hand, the tectonics of this design alternative is very similar to the initial one since it is designed as modules, yet, it has minor differences due to structural constraints and improper detailing.
- 3D Printing: The problem with 3D printing in these design alternatives are not experienced unless the model is sent to manufacturing, and fails during the manufacturing process. Figure 4.2 shows the process of reaching the final design alternative. As the initial model was composed of thin elements, it is seen that, additive manufaturing changed considerably the porosity of the model. It is changed to more bulky and solid due to supports in 3D printing. Moreover, 3D printing can be very costly depending on the material and time consuming in relation with scale. Hence, the iterative process of failing and re-manufacturing it causes losses in material, time and cost.
- Sectioning-cutting: The main issue with sectioning is that since it is fabricated by hand, and consisted of many pieces, it makes very hard to try other design alternatives in case of failure. The design alternative in this case could not be fabricated due to structural stability. As for the tectonics, this outcome was more experimental, and the design goal was mainly to reduce the volume of the initial design. Another problem with this technique is nesting and scrap material as shown in Figure 4.3. This method of fabrication is similar to Hansmeyer's Subdivided Columns (2010) shown in Chapter 2.4.

As explained previously in that chapter, this design outcome requires great deal of time and material, although in the presented case in the experiment, the manufacturing tolerance is not set as zero.

- CNC Milling (2.5 Axis): While the initial design might be constructed as a single object with multi-axis CNC machines, with 2.5 axis it needs to be constructed as assemblies in order to keep some of its qualities. However, even with the assembly, initial design lost its double curved surface characteristics, and thin modules due to machining tolerances and material.

To conclude, with a top-down design approach, it can be seen that when fabrication is the last stage of design process, it has the capacity to change the initial design. In other words, what is initially designed might not be the final product. Changes mainly occur at the stage of preparing the design for fabrication at the last stage or during fabrication. Additionally, since time is a concern in design process, not so many design alternatives can be derived from initial design, and not all the alternatives are constructable.

5.2 AI-Based Approach

The second experiment, on the other hand, is a bottom-up approach powered by generative design and artificial intelligence. This approach is studied in three cases, and a detailed analysis of results is presented in Chapter 4. If the generative design outcomes are grouped according to their visual similarity, eight groups are claimed and presented as below:

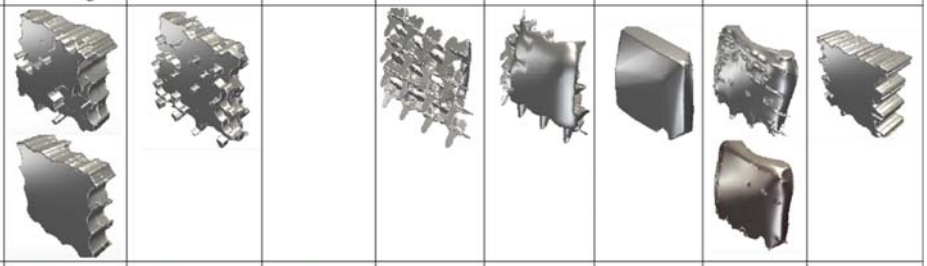
Cases	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8
Case 1								
Case 2								
Case 3								
Similarity	Model details are extrusions One sided	Model details are extrusions Reverse sides	Planar, yet there is an attempt to generate details	Detail accuracy to the initial model	Incomplete One side of the model remains undetailed	Incomplete Form stays as block	Incomplete Form stays as block Attempt to generate details	Planar, Details are lost
MFR Method	2.5 axis milling	2.5 axis milling (with reverse sides)	2 axis cutting	3D Printing 3 axis milling 5 axis miling	3 axis milling	3D Printing	3D Printing	2 axis cutting

Figure 5.1 Design alternatives grouped according to visual similarity

In the Figure 5.1 above, alternatives representing visual similarity groups from each case are presented with their manufacturing methods and formal aspects. The groups show that visual similarity is dependent to their manufacturing method. Also, for each manufacturing method, if the size of the model decreases, the level of detail increases. Although it is possible to construct complex forms with 3D printing, due to the material limitations, or support structures in 3D printing, or overfitting, some of the outcomes are incomplete in Case II. On the other hand, it provides very detailed and accurate design alternatives when the model size is decreased. Same can

also be observed for cutting, as the size of the model decreases, they can be generated with more details.

If the initial design would be fabricated through this process, each group has different criteria in deciding which alternative should be fabricated. While incomplete outcomes can be eliminated, other groups can show how manufacturing methods transform the initial design. To exemplify, Group 4 seems to include most preferred outcomes regarding precision and accuracy to the initial design, the manufacturing methods listed are 3D printing, 3 axis and 5 axis milling. Considering the size of the initial design, with the economic aspects and availability, these methods can be eliminated. Still, it might be preferred to manufacture its units through these methods in order to keep the level of detail since the model size seems to be affecting it. Secondly, if volume and mass of the model are concerned within the design process, approaches such as cutting, or 2.5 axis milling can be avoided, because especially in large models with volumes, the voids are observed to be disappeared and double curved units creating voids are replaced by extrusions.

In order to elaborate the criteria given above, and to show an example to the way of thinking as a designer, the initial design computational model, its fabricated outcomes in the initial experiments, and generative design instances per several criteria are shown side by side in Figure 5.2.

Intended design instance	Initial experiments	Instance per design and fabrication constrains							
		Accuracy	Manufacturing Availability	Material Availability	Ease of Fabrication	Cost	Manufacturing Time	Detail Precision	Material Waste
		ABS Plastic 3D Printing (as assembly unit)	MDF 2.5 axis milling (as assembly unit)	ABS Plastic 3D Printing (as assembly unit)	ABS Plastic 3D Printing	MDF 2 axis cutting (as assembly unit)	MDF 2 axis cutting	Aluminum 5 axis milling (as assembly unit)	ABS Plastic 3D Printing
		Aluminum 3D Printing	ABS Plastic 3D Printing (as assembly unit)	MDF 3 axis milling (as assembly unit)	XPS 2.5 axis milling	XPS 2 axis cutting (as assembly unit)	XPS 2.5 axis milling	ABS Plastic 3D Printing (as assembly unit)	Aluminum 3D Printing (as assembly unit)
		MDF 5 axis milling (as assembly unit)	MDF 2 axis cutting (as assembly unit)	XPS 2.5 axis milling (as assembly unit)	XPS 5 axis milling	MDF 2 axis cutting	XPS 2 axis cutting	Thermoplastic Resin 3D Printing (as assembly unit)	Aluminum 3D Printing (as assembly unit)

Figure 5.2 Instances per design and fabrication criteria

Figure 5.2 exemplifies the design instance variations for the case studied in this thesis. Eight criteria are considered for the fabrication process, which are accuracy, manufacturing availability, material availability, ease of fabrication, manufacturing cost and time, detail precision and material waste/sustainability. All of the manufacturing methods are represented. The cases that include the model partially are considered as assembly units.

- Accuracy: If accuracy to the initial design is the main concern, and there are not any problems with the availability of the manufacturing machines, materials, or economic constrains; non-restrictive manufacturing methods such as any type of 3D printing, or 5 axis milling can be preferred, and for surface precision, materials such as aluminum, plastic or MDF can be used. The model can be produced both as a monolithic object or assembly as long as it keeps the computational model accuracy.

- Manufacturing availability: For non-industrial environments, high technology 3D printers or multi axis CNC machines are not always accessible to use. Considering availability, 2 axis laser cutters, 2.5 axis CNC machines, and smaller 3D printers are more common tools, and can be preferred by the designer. It is seen that initial model changes according to the manufacturing method availability. For example, if 2-axis cutting or 2.5 axis milling is used it can be seen that details are lost. Therefore, the models manufactured through these methods can be used as assembly units in order to preserve details. Additionally, for smaller printers, initial model can be fabricated as assembly units.

- Material availability: Regardless of manufacturing availability, if material availability is considered, it is more reasonable to prefer common materials such as MDF or expanded polystyrene foam. If 3D printing is used, ABS or PLA filaments are more accessible compared to aluminum 3D printing. Additionally, it becomes more logical to manufacture the initial design as assembly units, considering stock material sizes for cutting or milling.

- Ease of fabrication: If ease of fabrication is the main concern, assembly logic can be eliminated to avoid manpower used in fabrication and model can be produced in full scale to eliminate multiple manufacturing processes and detailing in joining assembly units.
- Cost: Similar to manufacturing and material availability, if the cost of the process is considered, it is more reasonable to use common tools and materials such as laser cutting with MDF or XPS. However, it can be seen that the initial design changes and loses its details, or double curved geometry.
- Manufacturing time: Similar to cost, if manufacturing time is the main concern, some of the design details can be eliminated. For example, as the details are lost, contours in CNC machining are decreasing and it becomes faster to obtain manufactured models. Similarly, 2-axis cutting produces faster results than 3D printing, however it can be seen that model complexity is lost since the initial design becomes planar.
- Detail precision: If detail precision is important, the model can be manufactured as assembly units, with 3D printing or 5 axis milling. Although these manufacturing methods provide the most accurate design alternatives, as the size and the complexity of the manufacturing model increases, the precision of it becomes distorted as presented in Chapter 4.
- Material waste: Since CNC milling or 2 axis cutting leave scrap materials, they can be avoided if material waste and sustainability are considered. Additionally, more recyclable materials can be used such as aluminum or ABS plastic, instead of non-recyclable resins or MDF.

While the criteria presented above can be increased, considering multiple constrains of fabrication process, in Figure 5.2, it can be seen that the intended design instance starts to compromise. Knowing material and fabrication constrains enables the designer to compare different design variations and to choose what to avoid. AI and

simulations are powerful in this process since they can produce a large number of design variations and visualize them, which gives an idea about the alternatives to the designer in this evaluation process. This can be considered as a holistic design approach and can overcome the gap between digital design and fabrication processes since fabrication becomes a part of the design constraints and there are no separate "design" and "fabrication" processes. Since design alternatives are dependent to fabrication constraints, the end product can be less surprising, and be produced in a more controlled process. Instead of experiencing fabrication errors, and its effects on the initial design during fabrication process, the designer has options to evaluate and choose the alternative that fits the design and fabrication objectives. In other words, initial design leaves its place to a variety of design instances and fabrication constrains become a part of the form-finding process. In this sense, simulation of computer-aided fabrication through design space explorations, can act as a bridge between design and fabrication processes.

Additionally, this AI-based approach can provide several other advantages regarding the design process. The first advantage of such method is the time efficiency, as it can provide a broad variety of design alternatives within a short time. The use of cloud computing provides over 3000 iterations to achieve best option for each design alternative, which shortens the time experimenting with alternatives. Considering technologies in this method, and the integration of physical data in a digital workflow, this approach can connect those processes and can be claimed to be efficient in distributed manufacturing which conforms the expectation of Industry 4.0.

Regarding architectural tectonics, since the alternatives are not fabricated, but include fabrication data, we can speak of an in-between state like digital tectonics and materiality as claimed in Chapter 1. The first point regarding tectonics is that, regardless of the size of the case and the material, the generative design algorithm generates similar design alternatives for same manufacturing method. Examining matrices in Figure 4.4, 4.10 and 4.16, while manufacturing method changes the design alternative, material seems to effect mass directly, as expected. (Figure 5.3)

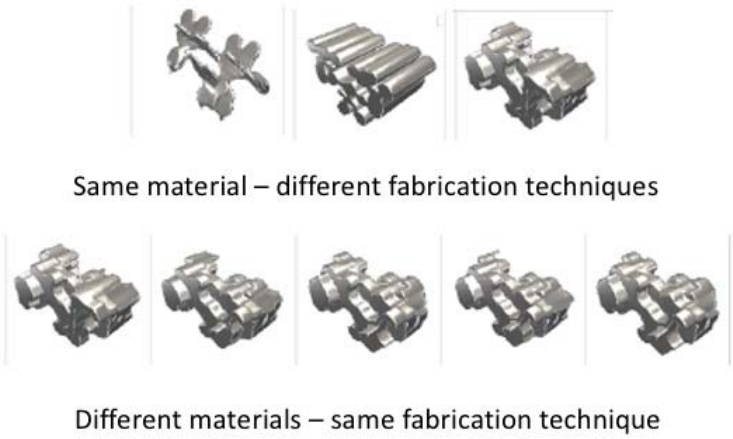


Figure 5.3 Effects of manufacturing methods and materials on design alternatives, claimed from Case III

Secondly, since this approach provides 3D models for design alternatives, if used for monolithic objects, file-to-factory process is achieved in a single digital ecosystem, which prevents data loss among different digital processes. Thus, it may reduce problems related with precision and accuracy between digital model and fabricated outcome.

One issue with the generative approach is that when fabricated, design alternatives shown in Figure 5.2 can exhibit tectonic differences due to material characteristics, or manufacturing tolerances. However, by knowing the material and manufacturing constrains, these differences can be simulated and minimized, which eventually makes design process less intuitive and iterative.

The mass and volume graphs in Chapter 4 show that the mass is effected directly from the material properties, manufacturing methods directly effect design alternatives such as their voids, or curvature, thus their volume. For the investigated cases, since the initial designs are non-planar, unrestrictive methods such as additive manufacturing, or 3D printing presents more accurate results with minimum mass and volume. However, if the initial design was planar, 2-axis cutting, or 2.5 axis

milling might become more practical solutions. Additionally, it is observed that as the scale of the initial model decreases, accuracy of the generative design alternatives increases. Therefore, it is logical to run generative design studies for assembly units for complex forms.

With the data collected from two experiments, it can be said that ML algorithms can be used for both form-finding as in generative design process and classifying the manufacturing method. Within the discussion in the second chapter, form-finding task can be defined as ML for fabrication data, and the decision tree classifier part can be defined as ML for fabrication process. (Ramsgaard Thomsen et al., 2020) The classification accuracy of the case presented in this research shows that it predicts true outcomes in 88% of the cases, which can be considered as satisfactory.

The accuracy of the model can be increased with the addition of more data to the training set. The comparison presented in Table 4.4 shows the ML model predicted labels 75% correct. Yet, the inaccurate prediction that is made is placing 5-axis milling instead of 3D printing. These two methods can both be used for complex 3D model fabrication.

The challenge in this process is noted as to find structured and related data for 3D models to be fitted into the algorithm. This challenge led dataset to be limited, and it is not possible to make generalization from the comparison given in Table 4.4, but it can exemplify the idea of how the ML model can select the manufacturing method, and it can give an idea to the designer about the manufacturing method of a 3D model.

Rather than feedback based, or robotic fabrication-based approaches in digital fabrication, a generative design and machine learning-based approach might be more available in connecting digital and physical processes of design. Additionally, the cases show that this type of approach does not require advanced scripting, or high costs, which can ease the adaptation of these processes to architectural practices.

5.3 Re-designing the Process

With the light of the discussion above, if the wall in the case would be designed from the start, the design process would progress different from the first experiment. Before fabricating the model, design process would include below main steps:

- Form-finding
- Instance assessment
- Checking the Model

5.3.1 Form-finding

Although the first experiment gone through a form finding process through a set of rules, material and manufacturing method were not considered as design inputs.

Below screenshot (Figure 5.4) shows the intuitive form-finding process through Rhinoceros, without considering fabrication. It can be seen that although parametric design software provide freedom in complexity of forms, the manufacturability constrains this freedom and convert the initial design to a manufacturable outcome. This intuitive exploration shows that, in most cases, the final model of the design process is mostly a compromise between designer's intention and fabrication.

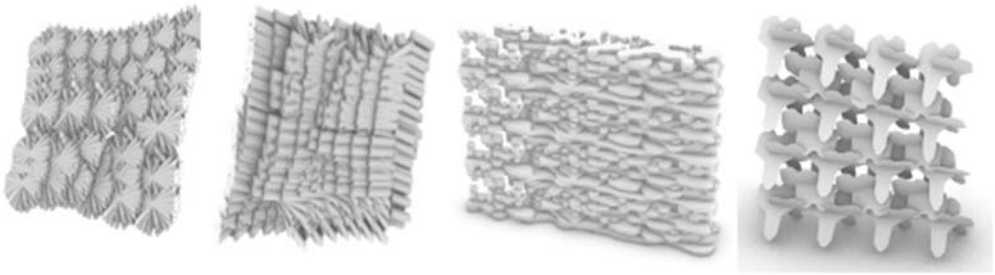


Figure 5.4 Intuitive form-finding without fabrication

If fabrication is considered in the last stage of the design, it creates a second form-finding stage in the process, in which the selected computational model is adapted to the manufacturing inputs, which transforms the initial design.

In the AI-based phase of the experiment, it can be seen that, if the design rules and manufacturing inputs are considered together, the difference between design alternatives are minimized as presented in the results in Chapter 4. It can be concluded that considering aesthetics aspect of design, when fabrication changes the initial design, the final outcome may not always what designer intended. If the difference between, initial design and outcomes are minimal, it provides more control to the designer.

If the wall in the case were to be designed again, instead of eliminating fabrication in the first steps, it would be considered as an initial design input. In other words, instead of finding the form initially, setting the rules and manufacturing inputs would be a more preferred method in form-finding. While this method limits in a way the computational design freedom, it also helps to find feasible solutions for the design alternatives in terms of manufacturing and eliminates further form-finding phases. Additionally, form-finding process would have been done with the help of AI to decrease the time spent and increase the number of design outcomes. In this case, units forming the assembly can be designed through several optimization methods, and how they assemble in real life will be simulated without need of reviewing other design alternatives.

5.3.2 Instance Assessment

Instead of simultaneously finding and assessing the form, the step after form-finding would be the assessment. Since the form finding process includes the fabrication data, and generative design software can provide great number of design instances, alternatives can be evaluated before the fabrication process. Since the instances would include material thicknesses, and certain tectonic properties dependent to

manufacturing restrictions, this approach can give an insight to the designer that what the form might look like after manufacturing and enable the designer to choose the most aesthetically, or tectonically preferable one. Additionally, through this method, in this stage, deciding on the design alternative, also provides the decision that how the model is going to be fabricated.

In the re-designed process, rather than attempting to fabricate one design alternative, a method would be followed with assessing several design alternatives including their fabrication data. A process of this stage can progress as presented in Figure 5.5 given below:

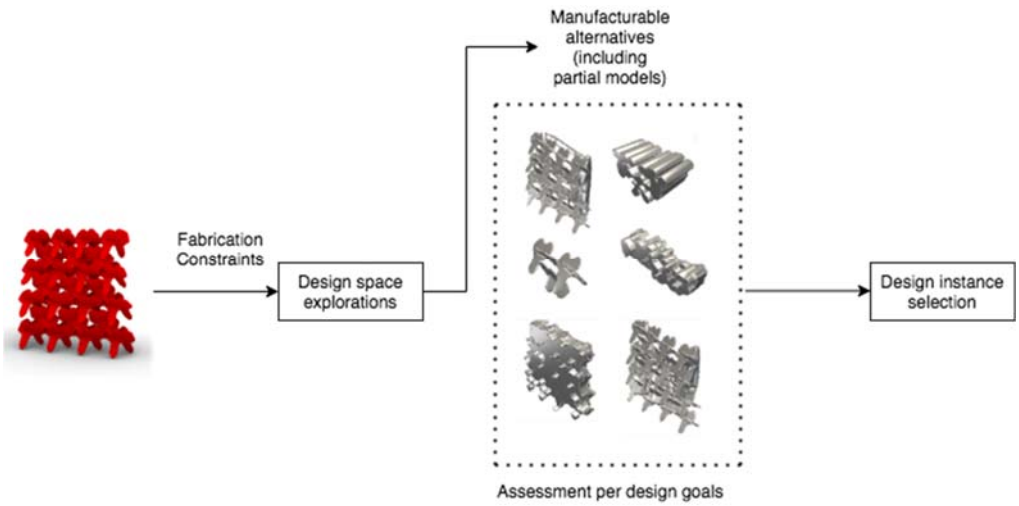


Figure 5.5 Instance assessment process

5.3.3 Checking the Model

The next stage after instance assessment would be preparing the selected instance for fabrication. Although the intended process progresses with single computational model, which is fabrication-aware, and intermediary model is eliminated in this process, the model preparation in this process becomes rather "model-checking", which aims to see if the selected instance meets the requirements such as file format,

or fabrication specific requirements. This stage can be run through computer simulations. For example, while it can be possible to create anything with 3D printing, in FDM type of printing, it is useful to check the support locations, and sizes in order to see if there is an impact on design.

Through this stage, fabrication errors can be detected, and solutions can be provided, which can prevent time and material loss occurring from these errors. Figure 5.6 given below exemplifies the model checking process.

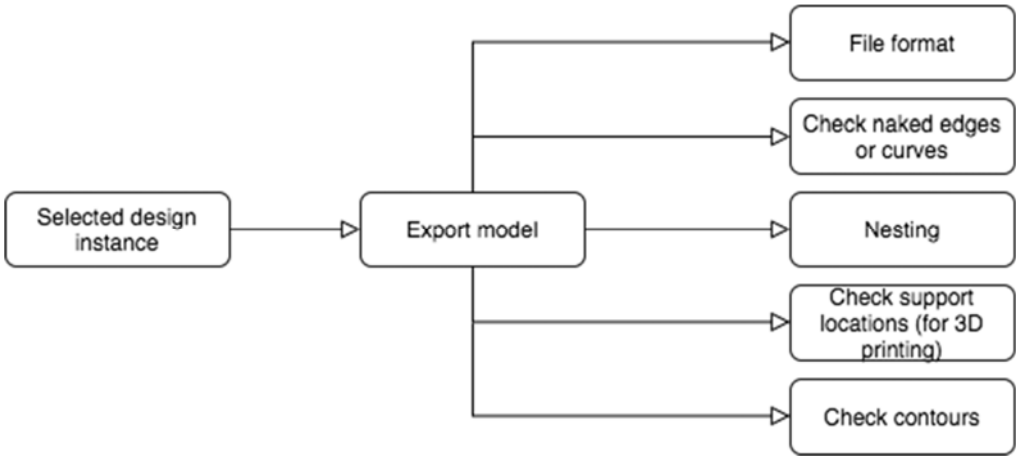


Figure 5.6 Process of checking the model for fabrication

The last step of design process can be considered as fabrication; however, its inputs would be present from the start of the design process as explained above. It can be concluded that fabrication inputs transform the initial design in every step of design process. Therefore, it should be included in the preliminary stages of design.

CHAPTER 6

CONCLUSION

Starting with the 3rd industrial revolution, concepts of paramtetric design, mass customization and file-to-factory are introduced in architecture. Architects embrace and started to implement them in their design practice which immediately shows its impact on contemporary buildings and other artefacts. Although "file-to-factory" paradigm is well accepted, there is still need for further efforts to extend computational design process to incoporate fabrication phase to avoid discrepancy between what is designed and what is built as discussed in this thesis. Especially today, with the advents brought by Industry 4.0, the problem of adapting file to factory becomes more significant.

While computational design provides freedom in form-finding and thorough design process, considering fabrication as the last step of design creates a significant gap between design and fabrication, which causes loss of accuracy, precision, alteration/modification of materials and/or detailings even complete change of the design, resulting in inefficient design and construction processes as well as high computational and labor cost.

Moreover, in the new-cyber physical era, although technologies such as robotic fabrication, or 3D printing can be applied to construction practices, their use is still in the scale of pavilion or building components. One of the major reasons of this limited use of such technologies can also be related with late inclusion of fabrication and construction. Architects should recognize fabrication related constraints and potentials in the very initial phases of design proceses and in form finding explorations.

In this thesis, a novel approach aiming to overcome the gap between computation and fabrication is provided on a model in two stages. In the first stage an intuitive

and top-down design process is adopted, and in the second stage an AI-based design space exploration is conducted with three cases derived from the same 3D model. The main headings, summary and outcomes of this thesis are presented in Table 6.1 given below:

Table 6.1 Summary and conclusion of each chapter

	Chapter 1 - Background	Chapter 2 - Research Design	Chapter 3 - Research Results	Chapter 4 - Discussion	Chapter 5 - Conclusion
Headings	Architecture 4.0 Recent Technologies Generative Design CPSs Machine Learning Cloud Computing Effects on Architectural Tectonics Impact of CAF Impact of Algorithm Accuracy and Precision Examples in art, architecture and prototyping Design approaches Linear and bottom-up Digital workflows and ecosystems	Linear design approach AI-based method Design space configuration Case I: Partial model with initial shape Case II: Full scale model as preserve geometry Case III: Model with less unit qty Decision tree classification learning for manufacturing method Model parameters Description of evaluation metrics	Intuitive modeling Fabricated models Fabrication limitations AI-based method Generated outcomes Mass-volume graphs Prediction results of the ML model	Top-down approach Limitations and problems Discussion of each manufacturing method AI-based method Visual similarity of generated outcomes Discussion of design instance change per fabrication criteria Advantages of AI-based method Redesigning the Process Form finding Design instance assessment Model-checking	General discussion and summary of the research Limitations Future work
Summary	Architecture's development through industrial revolutions are summarized. Architecture's role in Industry 4.0 is surveyed. Recent technologies and their implementation on design and manufacturing are studied. Effects of computational processes on architectonics are studied. Accuracy and precision in fabrication are discussed, examples from literature are presented. Different design approaches in computational design are presented.	Material and method of this thesis are described. Manufacturing methods are introduced for intuitive experiment. Design space configuration including preserve geometry, obstacle geometry, and initial shape is introduced. Generative design objectives, constraints and manufacturing methods for AI-based method are determined. Classification parameters and accuracy are described.	Results of two stages are presented. Problems occuring in first phase are noted for each fabrication technique. Generative design outcomes are presented with matrices. Mass and volume graphs are examined for extreme cases of materials (XPS and Aluminum in this experiment) A dataset is obtained through generative design outcomes. ML algorithm predicted manufacturing methods for outcomes of the first phase for comparison.	Results of the top down appoach are discussed in the context of architectural tectonics. Design instances in AI-based method are grouped according to their similarity. Several instances are presented along with eight design and fabrication criteria, changes are discussed within each. Advantages of AI-based method are presented. The design process is redefined within the conclusions of the research.	A summary of the thesis is presented along with its context in the main problem statement. Limitations of the research are presented. Recommendations for future research are noted.
Outcomes	Artificial intelligence plays a great role in recent technologies, which provides several opportunities in manufacturing. The implementation of the recent technologies in architecture is mainly on interactive or smart buildings, and feedback based fabrication systems. Algorithms and CAF have a great impact on architectural tectonics. Material and fabrication have several limitations and can change the design in terms of accuracy and precision. This change can occur due to intermediary steps in file-to-factory process, which causes data loss. Adopting a bottom-up design approach within a single digital ecosystem can prevent time, data and precision loss	Each fabrication technique used in the first stage require different model properties, such as assembly details, voids, file formats, materials, etc. The second stage shows that design space explorations do not require advanced programming skills with the use of cloud computing. Parameters in the training dataset can give an idea of model complexity, and considerations in selection of manufacturing method.	Designing without considering fabrication eventually changes the final product. Each fabrication technique has its own limitations. Design process in the first phase caused problems regarding time, cost and labour. Generative design process shortens the time spent in form-finding and iterating design instances. Material mass is directly effected from material as expected, while volume is more dependent to mfr. method. As the model gets closer to initial design, its volume and mass is decreased. When the size of the model decreases or it includes small qty of units, generative design algorithm provides more precise alternatives	Fabrication problems can force designer to quit some design alternatives. Therefore, knowing fabrication constrains become important. AI-based simulations can give the designer an idea about the fabricated outcomes for different manufacturing methods. Per different design and fabrication criteria, different manufacturing methods can be selected, which makes the initial design to compromise. Decision support algorithms are useful in selection of manufacturing method, in instance assessment process. If the process is redesigned, a bottom-up approach would be adopted to eliminate additional form-finding processes.	General conclusions: Adopting an AI-based and bottom up approach in computational design process shortens the time spent in form-finding and provides a controlled design process Knowing fabrication constraints enables the designer to select among different design alternatives without actually fabricating them, which can minimize accuracy changes. AI can make accurate predictions for manufacturing methods, but the presented case needs more data for generalization.

In the first chapter, technologies related with what this research aims are presented. Their use in architecture and manufacturing are investigated. Additionally, since file-to-factory problems lead to tectonic changes, the impact of algorithm and CAF is studied, and each are found to have crucial impacts on architectonics. Since architectural tectonics are the main concern, the concepts of accuracy and precision are discussed with the cases from different disciplines.

The change in accuracy is dependent on the translation of digital to physical in design process, top-down and bottom-up design approaches are introduced along with the concepts of digital workflows in digital ecosystems. Both design approaches are experimented within a single computational model.

The first set of study which is referred as intuitive shows the problems when fabrication and related materiality and technologies are not included in the design phase. This case clearly shows how fabrication techniques and principles in terms of 3D model parameters effecting the proper choice of fabrication process and thus, how intended model is evolving under the control of fabrication rather than the designer. AI-based process included topology optimization based generative design approach to claim design alternatives, and it is observed a decrease in time that is spent in iterative cycles in design process through cloud computing. Moreover, a decision tree classifier ML model is employed in order to make predictions for manufacturing method for future 3D models based on generative design outputs.

To conclude, compared to the top-down approach, AI-powered bottom-up approach showed that when manufacturing is taken as an initial design input for design space explorations, a large number of manufacturable design alternatives can be assessed before fabrication, which minimizes the difference between initial design and its instances. With this approach, the time spent in form-finding, and fabrication is reduced considerably. Also, the method used in this thesis shows that with cloud computing, a digital workflow can be achieved without the use of advanced scripting or computer power. Additionally, although the cases given in this study are not including all possible fabrication methods and/or possible materials, it is seen that in

learning from design alternatives, artificial intelligence can serve designers to provide accurate predictions for manufacturing method.

This study also demonstrates that, from a designer point of view, if the wall in the case study is designed again, the design process would be included below points:

- The selection of materials and manufacturing method would be integrated in the first steps of the design process.
- The computational model would be formed in a more controlled aspect, including material thicknesses, and joint details.
- Rather than constructing one design instance, the design alternatives per fabrication and design constraints would be considered before proceeding with fabrication process.
- The process of form-finding would be done with the help of artificial intelligence to obtain possible and feasible outcomes under given constraints of material, time, fabrication and etc.
- Intermediary model would be eliminated, the only intermediary step before fabrication would be controlling the model format and its precision in the digital ecosystem of manufacturing system.

To conclude, considering points listed above, a more fabrication-aware and AI integrated process would be followed, to decrease the time spent, and increase the manufacturability of design alternatives.

6.1 Limitations

The major limitation of this thesis can be concluded as, since the research is case specific, the data obtained from design alternatives is limited. It can be increased with inclusion of different cases of 3D models in both phases. Additionally, dataset for prediction can be increased in order to provide generalization. Secondly, forming is excluded from the scope of this thesis, because of the time concerns.

6.2 Future Work

The future research can focus on three main aspects that are left outside of the scope of this thesis. Firstly, the generative examples in this thesis are not studied for assemblies, and the partial models do not include joint details. Future research can study assembly unit generation including joint details in order to move the research to the building scale. Secondly, since the program used can offer alternatives for forming, it can be studied in future research within a broader time frame, and a suitable environment. Lastly, unsupervised learning models can be studied for manufacturing and fabrication with a larger dataset in order to see how this approach works without human supervision.

Additionally, since the research in design space exploration for form finding in pre-fabrication stage is rather a recent approach, the program used is still under development and updated, and it might provide more accurate design alternatives if the generative studies are repeated for future work. Combinations of different real-life structural constrains and loading scenarios can also be added to the study to provide stress-strain analyses of design alternatives.

REFERENCES

Afify, H. M. N., & Elmoghazy, Z. (2007, October). *Advanced Digital Manufacturing Techniques (CAM) in Architecture*.

Ahlquist, S. (2015). Social Sensory Architectures: Articulating Textile Hybrid Structures for Multi-Sensory Responsiveness and Collaborative Play. *Association for Computer-Aided Design in Architecture (ACADIA)*, 262–273.

Akella, R. (2018, March 16). What Generative Design Is and Why It's the Future of Manufacturing. *New Equipment Digest (Web)*.

Alpaydin, E. (2010). *Introduction to Machine Learning*. MIT press.

Aranda, B., & Lasch, C. (2006). *Pamphlet Architecture 27: Tooling* (Issue 27). Princeton Architectural Press.

Beesley, P., & Seebohm, T. (2000). Digital Tectonic Design. *Promise and Reality: State of the Art versus State of Practice in Computing for the Design and Planning Process,18th ECAADe Conference Proceedings*, 287–290.

Beghini, L. L., Beghini, A., Katz, N., Baker, W. F., & Paulino, G. H. (2014). Connecting Architecture and Engineering through Structural Topology Optimization. *Engineering Structures*, *59*, 716–726.

Bier, H., & Knight, T. (2014). Data-Driven Design to Production and Operation. *Footprint*, 1–8.

Brettel, M., Friederichsen, N., Keller, M., & Rosenberg, M. (2014). How Virtualization, Decentralization and Network Building Change The Manufacturing Landscape: An Industry 4.0 Perspective. *International Journal of Mechanical, Industrial Science and Engineering*, *8*(1), 37–44.

Buonamici, F., Carfagni, M., Furferi, R., Volpe, Y., & Governi, L. (n.d.). *Generative Design: An Explorative Study*.

Cardoso, J. M. P., Coutinho, J. G. F., & Diniz, P. C. (2017). Chapter 8 - Additional Topics. In J. M. P. Cardoso, J. G. F. Coutinho, & P. C. Diniz (Eds.), *Embedded Computing for High Performance* (pp. 255–280). Morgan Kaufmann. https://doi.org/https://doi.org/10.1016/B978-0-12-804189-5.00008-9

Carpo, M. (2017). *The Second Digital Turn: Design beyond Intelligence*. MIT Press.

Carrillo, E., Benitez, V., Mendoza, C., & Pacheco, J. (2015). IoT Framework for Smart buildings with Cloud Computing. *2015 IEEE First International Smart Cities Conference (ISC2)*, 1–6. https://doi.org/10.1109/ISC2.2015.7366197

Chandler, D. L. (2013, August 15). *How to Make Big Things out of Small Pieces*. MIT News (Web).

Chen, Y. (2015). *Swarm Intelligence in Architectural Design* [University of California, Berkeley]. https://doi.org/10.1007/978-3-319-41000-5_1

Cignoni, P., Pietroni, N., Malomo, L., & Scopigno, R. (2014). Field-Aligned Mesh Joinery. *ACM Transactions on Graphics (TOG)*, *33*(1).

Denari, N. (2012). Precise Form For an Imprecise World. In S. Marble (Ed.), *Digital Workflows in Architecture: Design–Assembly–Industry*. Walter de Gruyter.

Development of Architecture During the Industrial Revolution. (2018). Ukessays.Com. https://www.ukessays.com/essays/architecture/development-of-architecture-during-industrial-revolution.php?vref=1

Diamon, F. (2013). *Form Follows Tectonics: Architectural Theory in a Digital World*.

Dunn, N. (2012). *Digital Fabrication in Architecture*. Laurence King Publishing.

Eigensatz, M., Kilian, M., Schiftner, A., Mitra, N. J., Pottmann, H., & Pauly, M. (2010). Paneling Architectural Freeform Surfaces. In *ACM SIGGRAPH 2010 papers* (pp. 1–10).

Evans, L., Lohse, N., & Summers, M. (2013). A Fuzzy-Decision-Tree Approach for Manufacturing Technology Selection Exploiting Experience-Based Information. *Expert Systems with Applications*, *40*(16), 6412–6426. https://doi.org/https://doi.org/10.1016/j.eswa.2013.05.047

Fisher, T. (2014, January 24). Architecture and the Third Industrial Revolution. *Architect Magazine (Web)*.

Fisher, T. (2015). Welcome to the Third Industrial Revolution: The Mass-Customisation of Architecture, Practice and Education. *Architectural Design*, *85*, 40–45.

Fox, M. (2010). Catching Up with The Past: A Small Contribution to a Long History of Interactive Environments. *Footprint*, 5–18.

Fox, M. (2016). *Interactive Architecture: Adaptive World*. Chronicle Books.

Fuchkina, E., Schneider, S., Bertel, S., & Osintseva, I. (2018). *Design Space Exploration Framework-A Modular Approach to Flexibly Explore Large Sets of Design Variants of Parametric Models within a Single Environment*.

Gebhardt, A. (2011). Basics, Definitions, and Application Levels. In A. Gebhardt (Ed.), *Understanding Additive Manufacturing* (pp. 1–29). Hanser. https://doi.org/https://doi.org/10.3139/9783446431621.001

Gibson, I., Rosen, D., & Stucker, B. (2014). *Additive Manufacturing Technologies (Vol. 17)*. Springer.

Giuseppe, S., Lanza, G., & Peters, S. (2014). Optimization in Manufacturing. In Laperrière Luc & G. and Reinhart (Eds.), *CIRP Encyclopedia of Production Engineering* (pp. 929–932). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-20617-7_6565

Gosselin, C., Duballet, R., Roux, P., Gaudillière, N., Dirrenberger, J., & Morel, P. (2016). Large-Scale 3D Printing of Ultra-High Performance Concrete – a New Processing Route for Architects and Builders. *Materials & Design*, *100*, 102–109. https://doi.org/https://doi.org/10.1016/j.matdes.2016.03.097

Hager, I., Golonka, A., & Putanowicz, R. (2016). 3D Printing of Buildings and Building Components as the Future of Sustainable Construction? *Procedia Engineering*, *151*, 292–299.

Hogrefe, A. (2010). *Evaluating the Digital Design Process: Bottom-up vs. Top-down*.

Iwamoto, L. (2013). *Digital Fabrications: Architectural and Material Techniques*. Princeton Architectural Press.

Jabi, W. (2004). Digital Tectonics: The Intersection of the Physical and the Virtual. *Fabrication: Examining the Digital Practice of Architecture, Proceedings of the 23rd Annual Conference of the Association for Computer Aided Design in Architecture and the 2004 Conference of the AIA Technology in Architectural Practice Knowledge Community*, 256–269.

Kang, E., Jackson, E., & Schulte, W. (2011). An Approach for Effective Design Space Exploration. In R. Calinescu & E. Jackson (Eds.), *Foundations of Computer Software. Modeling, Development, and Verification of Adaptive Systems* (pp. 33–54). Springer Berlin Heidelberg.

Kaur, J., Sehrawat, M. A., & Bishnoi, M. N. (2014). Survey Paper on Basics of Cloud Computing and Data Security. *International Journal of Computer Science Trends and Technology (IJCST)–Volume*, *2*.

Kolarevic, B. (2001). Designing and Manufacturing Architecture in The Digital Age. *Architectural Information Management*, 2001117–2001123.

Kolarevic, B. (2000). Digital Architectures. *ACADIA 2000: Eternity, Infinity and Virtuality in Architecture*, 251–256.

Ku, K., & Chung, D. (2015). *Digital Fabrication Methods of Composite Architectural Panels for Complex Shaped Buildings*.

Kuo, T.-C., Huang, S. H., & Zhang, H.-C. (2001). Design for Manufacture and Design for 'X': Concepts, Applications, and Perspectives. *Computers & Industrial Engineering*, *41*(3), 241–260. https://doi.org/https://doi.org/10.1016/S0360-8352(01)00045-6

Kusiak, A. (2019). Editorial: Intelligent Manufacturing: Bridging Two Centuries. *Journal of Intelligent Manufacturing*, *30*(1), 1–2. https://doi.org/10.1007/s10845-018-1455-2

Larsen, N. M. (2012). *Generative Algorithmic Techniques for Architectural Design*.

Leach, N. (2009). Digital Morphogenesis. *Architectural Design*, *79*(1), 32–37.

Leal, B. M. F., Salgado, M. S., & Silvoso, M. M. (2018). Impact of Fourth Industrial Revolution in Architecture Undergraduate Course. *Zero Energy Mass Custom Home, Zemch*, 403–415.

Lee, J., Bagheri, B., & Kao, H.-A. (2015). A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems. *Manufacturing Letters*, *3*, 18–23.

Leonardi, P. M. (2010). Digital Materiality? How Artifacts Without Matter, Matter. *First Monday*, *15*(6).

Loh, P. (2015, October). Articulated Timber Ground, Making Pavilion As Pedagogy. *Conference of the Association for Computer Aided Architectural Design Research in Asia*.

Lojanica, V., Colic-Damjanovic, V.-M., & Jankovic, N. (2018). Housing of the Future: Housing Design of the Fourth Industrial Revolution. *2018 5th International Symposium on Environment-Friendly Energies and Applications (EFEA)*, 1–4.

Mahamood, R. M., Akinlabi, E. T., Shukla, M., & Pityana, S. (2014). *Revolutionary Additive Manufacturing: An Overview*.

Marble, S. (2012). *Digital Workflows in Architecture: Design–Assembly–Industry*. Walter de Gruyter.

Martins, P. F., de Campos, P. F., Nunes, S., & Sousa, J. P. (2018). The Tectonics of Digitally Fabricated Concrete. A Case for Robotic Hot Wire Cutting. *RILEM International Conference on Concrete and Digital Fabrication*, 311–322.

Mathur, R. (2016). 3D Printing in Architecture. *International Journal of Innovative Science, Engineering & Technology*, *3*(7), 583–591.

Menges, A. (2015). The New Cyber-Physical Making in Architecture: Computational Construction. *Architectural Design*, *85*(5), 28–33.

Microsoft, & RIBA. (2018). *Digital Transformation in Architecture*.

Monostori, L, Markus, A., Brussel, H. Van, & Westkämpfer, E. (1996). Machine Learning Approaches to Manufacturing. *CIRP Annals*, *45*(2), 675–712. https://doi.org/https://doi.org/10.1016/S0007-8506(18)30216-6

Monostori, László, Kádár, B., Bauernhansl, T., Kondoh, S., Kumara, S., Reinhart, G., Sauer, O., Schuh, G., Sihn, W., & Ueda, K. (2016). Cyber-Physical Systems in Manufacturing. *CIRP Annals*, *65*(2), 621–641.

Nilsson, F. (2007). New Technology, New Tectonics?-On Architectural and Structural Expressions with Digital Tools. *Tectonics - Making Meaning. Conference Proceedings*. https://www.researchgate.net/publication/255992716

Oh, S., Jung, Y., Kim, S., Lee, I., & Kang, N. (2019). Deep Generative Design: Integration of Topology Optimization and Generative Models. *Journal of Mechanical Design*, *141*(11).

Oosterhuis, K. (2004). *File to Factory and Real Time Behavior in Architecture*.

Ozturk, S. (2018). *A Classification Matrix Proposal For Digital Fabrication Techniques In Architecture*. Bilkent University.

Paoletti, I. (2018). Mass Customization in the Era of Industry 4.0: Towards Immaterial Building Technology. In *Informed Architecture* (pp. 77–87). Springer.

Park, H.-S., & Tran, N.-H. (2017). A Decision Support System for Selecting Additive Manufacturing Technologies. *Proceedings of the 2017 International Conference on Information System and Data Mining*, 151–155.

Priyanka, & Kumar, D. (2020). Decision Tree Classifier: A Detailed Survey. *International Journal of Information and Decision Sciences*, *12*(3), 246–269.

Ramsgaard Thomsen, M., Nicholas, P., Tamke, M., Gatz, S., Sinke, Y., & Rossi, G. (2020). Towards Machine Learning for Architectural Fabrication in the Age of Industry 4.0. *International Journal of Architectural Computing*, 1478077120948000.

Schwartz, C. J. (2017). A Taxonomy of Architectural Tectonics. *Building Technology Educators' Society 2017 Conference: Poetics and Pragmatism*. https://www.researchgate.net/publication/322253624

Seely, J. C. (2000). *Digital Fabrication in the Architectural Design Process*. Massachusetts Institute of Technology.

Shaffer, M. (2017). Developing Robotic Formwork: Enhancing Formwork Mobility and Variability through Mechanization. *Construction Robotics*, *1*(1), 77–83. https://doi.org/10.1007/s41693-017-0004-4

Sigmund, O., & Maute, K. (2013). Topology Optimization Approaches. *Structural and Multidisciplinary Optimization*, *48*(6), 1031–1055.

Sorguç, A. G., Özgenel, Ç. F., & Yemişcioğlu, M. K. (n.d.). *Architecture 4.0: A New Manifestation of Contemporary Technology*.

Taghavi, T., & Pimentel, A. D. (2010). Visualization of Multi-Objective Design Space Exploration for Embedded Systems. *2010 13th Euromicro Conference on Digital System Design: Architectures, Methods and Tools*, 11–20.

Tamke, M., Nicholas, P., & Zwierzycki, M. (2018). Machine Learning for Architectural Design: Practices and Infrastructure. *International Journal of Architectural Computing*, *16*(2), 123–143.

Toenshoff, H. K. (2014). Cutting, Fundamentals. In L. Laperrière & G. Reinhart (Eds.), *CIRP Encyclopedia of Production Engineering* (pp. 345–357). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-20617-7_6633

van Berkel, B. (2020). Architecture and the Impact of the Fourth Industrial Revolution. *Architectural Design*, *90*(5), 126–133.

Wiertelarz, K. M. (2016). *Processes of Making: Algorithmic Methods in Architectural Practise.* Kassel University Press GmbH.

Wu, J., Qian, X., & Wang, M. Y. (2019). *Advances in Generative Design*. Elsevier.

Wuest, T., Weimer, D., Irgens, C., & Thoben, K.-D. (2016). Machine Learning in Manufacturing: Advantages, Challenges, and Applications. *Production & Manufacturing Research*, *4*, 23–45. https://doi.org/10.1080/21693277.2016.1192517

Zavoleas, Y., & Taylor, M. (2019). From Cartesian to Topological Geometry: Challenging Flatness in Architecture. *Nexus Network Journal*, *21*(1), 5–18. https://doi.org/10.1007/s00004-018-0414-8

APPENDICES

A. Raw Data Derived From Generative Design Outcomes

Name	Status	Material	MFR Method	Material E value (Gpa)	Material density (g/cm3)	Volume (cm3)	Mass (kg)	Non-Planar	Model Depth (cm) (BBOX)	Edge QTY (joined)	Reverse Sides	Multi Axis	Iteration
Study 1 - Outcome 1	Complete	Thermoplastic Resin	Unrestricted	3.30	1.28	30.81	0.039	1	5.88	1629	1	1	2
Study 1 - Outcome 2	Complete	Thermoplastic Resin	Additive	3.30	1.28	27.13	0.035	1	5.76	1774	1	1	4
Study 1 - Outcome 3	Complete	Thermoplastic Resin	Additive	3.30	1.28	36.82	0.047	1	6.08	1213	1	1	4
Study 1 - Outcome 4	Failed	Thermoplastic Resin	Additive	3.30	1.28	-	-	-	-	-	-	-	0
Study 1 - Outcome 5	Complete	Thermoplastic Resin	Cutting	3.30	1.28	418.07	0.535	0	6.32	497	0	0	66
Study 1 - Outcome 6	Failed	Thermoplastic Resin	3 axis milling	3.30	1.28	-	-	-	-	-	-	-	0
Study 1 - Outcome 7	Complete	Thermoplastic Resin	2.5 axis milling	3.30	1.28	257.60	0.330	1	6.32	775	1	0	21
Study 1 - Outcome 8	Converged	Thermoplastic Resin	2.5 axis milling	3.30	1.28	365.02	0.467	1	6.32	532	0	0	29
Study 1 - Outcome 9	Converged	Thermoplastic Resin	2.5 axis milling	3.30	1.28	342.05	0.438	1	6.32	545	0	0	30
Study 1 - Outcome 10	Failed	Thermoplastic Resin	5 axis milling	3.30	1.28	-	-	-	-	-	-	-	0
Study 1 - Outcome 11	Complete	Polystyrene, Expanded	Unrestricted	0.03	0.05	30.19	0.002	1	6.30	3079	1	1	2
Study 1 - Outcome 12	Complete	Polystyrene, Expanded	Additive	0.03	0.05	27.74	0.001	1	5.86	1735	1	1	3
Study 1 - Outcome 13	Complete	Polystyrene, Expanded	Additive	0.03	0.05	36.79	0.002	1	6.07	1202	1	1	4
Study 1 - Outcome 14	Failed	Polystyrene, Expanded	Additive	0.03	0.05	-	-	-	-	-	-	-	0
Study 1 - Outcome 15	Complete	Polystyrene, Expanded	Cutting	0.03	0.05	466.78	0.023	0	6.32	457	0	0	75
Study 1 - Outcome 16	Failed	Polystyrene, Expanded	3 axis milling	0.03	0.05	-	-	-	-	-	-	-	0
Study 1 - Outcome 17	Complete	Polystyrene, Expanded	2.5 axis milling	0.03	0.05	256.40	0.013	1	6.32	785	1	0	33
Study 1 - Outcome 18	Converged	Polystyrene, Expanded	2.5 axis milling	0.03	0.05	374.50	0.019	1	6.32	468	0	0	58
Study 1 - Outcome 19	Converged	Polystyrene, Expanded	2.5 axis milling	0.03	0.05	354.75	0.018	1	6.32	476	0	0	62
Study 1 - Outcome 20	Failed	Polystyrene, Expanded	5 axis milling	0.03	0.05	-	-	-	-	-	-	-	0
Study 1 - Outcome 21	Complete	ABS Plastic	Unrestricted	2.24	1.06	30.87	0.033	1	5.87	1694	1	1	2
Study 1 - Outcome 22	Complete	ABS Plastic	Additive	2.24	1.06	27.73	0.029	1	5.85	1691	1	1	3

Name	Status	Material	MFR Method	Material E value (Gpa)	Material density (g/cm3)	Volume (cm3)	Mass (kg)	Non-Planar	Model Depth (cm) (BBOX)	Edge QTY (joined)	Reverse Sides	Multi Axis	Iteration
Study 1 - Outcome 23	Complete	ABS Plastic	Additive	2.24	1.06	36.80	0.039	1	6.08	1137	1	1	4
Study 1 - Outcome 24	Failed	ABS Plastic	Additive	2.24	1.06	-	-	-	-	-	-	-	0
Study 1 - Outcome 25	Complete	ABS Plastic	Cutting	2.24	1.06	419.20	0.444	0	6.32	507	0	0	65
Study 1 - Outcome 26	Failed	ABS Plastic	3 axis milling	2.24	1.06	-	-	-	-	-	-	-	0
Study 1 - Outcome 27	Complete	ABS Plastic	2.5 axis milling	2.24	1.06	255.91	0.271	1	6.32	793	1	0	21
Study 1 - Outcome 28	Converged	ABS Plastic	2.5 axis milling	2.24	1.06	372.66	0.395	1	6.32	462	0	0	34
Study 1 - Outcome 29	Converged	ABS Plastic	2.5 axis milling	2.24	1.06	347.51	0.368	1	6.32	463	0	0	35
Study 1 - Outcome 30	Failed	ABS Plastic	5 axis milling	2.24	1.06	-	-	-	-	-	-	-	0
Study 1 - Outcome 31	Complete	MDF Medium Density Fiberboard	Unrestricted	2.40	0.80	30.45	0.024	1	5.87	1633	1	1	2
Study 1 - Outcome 32	Complete	MDF Medium Density Fiberboard	Additive	2.40	0.80	27.11	0.022	1	5.79	1768	1	1	4
Study 1 - Outcome 33	Complete	MDF Medium Density Fiberboard	Additive	2.40	0.80	36.81	0.029	1	6.07	1208	1	1	4
Study 1 - Outcome 34	Failed	MDF Medium Density Fiberboard	Additive	2.40	0.80	-	-	-	-	-	-	-	0
Study 1 - Outcome 35	Complete	MDF Medium Density Fiberboard	Cutting	2.40	0.80	419.54	0.336	0	6.32	505	0	0	69
Study 1 - Outcome 36	Failed	MDF Medium Density Fiberboard	3 axis milling	2.40	0.80	-	-	-	-	-	-	-	0
Study 1 - Outcome 37	Complete	MDF Medium Density Fiberboard	2.5 axis milling	2.40	0.80	252.23	0.202	1	6.32	723	1	0	19
Study 1 - Outcome 38	Converged	MDF Medium Density Fiberboard	2.5 axis milling	2.40	0.80	372.67	0.298	1	6.32	470	0	0	35
Study 1 - Outcome 39	Converged	MDF Medium Density Fiberboard	2.5 axis milling	2.40	0.80	352.53	0.282	1	6.32	420	0	0	37
Study 1 - Outcome 40	Failed	MDF Medium Density Fiberboard	5 axis milling	2.40	0.80	-	-	-	-	-	-	-	0
Study 1 - Outcome 41	Complete	Aluminum AlSi10Mg	Unrestricted	71.00	2.67	30.50	0.081	1	5.88	1623	1	1	2

Name	Status	Material	MFR Method	Material E value (Gpa)	Material density (g/cm3)	Volume (cm3)	Mass (kg)	Non-Planar	Model Depth (cm) (BBOX)	Edge QTY (joined)	Reverse Sides	Multi Axis	Iteration
Study 1 - Outcome 42	Complete	Aluminum AlSi10Mg	Additive	71.00	2.67	27.75	0.074	1	5.85	1721	1	1	3
Study 1 - Outcome 43	Complete	Aluminum AlSi10Mg	Additive	71.00	2.67	36.79	0.098	1	6.07	1173	1	1	4
Study 1 - Outcome 44	Failed	Aluminum AlSi10Mg	Additive	71.00	2.67	-	-	-	-	-	-	-	0
Study 1 - Outcome 45	Complete	Aluminum AlSi10Mg	Cutting	71.00	2.67	414.79	1.107	0	6.32	493	0	0	67
Study 1 - Outcome 46	Failed	Aluminum AlSi10Mg	3 axis milling	71.00	2.67	-	-	-	-	-	-	-	0
Study 1 - Outcome 47	Complete	Aluminum AlSi10Mg	2.5 axis milling	71.00	2.67	259.66	0.693	1	6.32	778	1	0	23
Study 1 - Outcome 48	Converged	Aluminum AlSi10Mg	2.5 axis milling	71.00	2.67	364.79	0.974	1	6.32	541	0	0	27
Study 1 - Outcome 49	Converged	Aluminum AlSi10Mg	2.5 axis milling	71.00	2.67	342.10	0.913	1	6.32	554	0	0	27
Study 1 - Outcome 50	Failed	Aluminum AlSi10Mg	5 axis milling	71.00	2.67	-	-	-	-	-	-	-	0
Study 2 - Outcome 1	Converged	Thermoplastic Resin	Unrestricted	3.30	1.28	210.43	0.269	1	6.78	12658	1	1	47
Study 2 - Outcome 2	Complete	Thermoplastic Resin	Additive	3.30	1.28	210.49	0.269	1	6.59	12915	1	1	51
Study 2 - Outcome 3	Complete	Thermoplastic Resin	Additive	3.30	1.28	1754.73	2.246	1	7.00	271	1	0	3
Study 2 - Outcome 4	Converged	Thermoplastic Resin	Additive	3.30	1.28	213.95	0.274	1	6.60	14147	1	1	55
Study 2 - Outcome 5	Complete	Thermoplastic Resin	Cutting	3.30	1.28	1719.42	2.201	0	6.62	2122	0	0	10
Study 2 - Outcome 6	Converged	Thermoplastic Resin	2.5 axis milling	3.30	1.28	895.56	1.146	1	6.62	1934	1	0	15
Study 2 - Outcome 7	Complete	Thermoplastic Resin	2.5 axis milling	3.30	1.28	1652.03	2.115	1	6.62	1604	0	0	8
Study 2 - Outcome 8	Complete	Thermoplastic Resin	2.5 axis milling	3.30	1.28	1369.27	1.753	1	6.62	1703	0	0	8
Study 2 - Outcome 9	Converged	Thermoplastic Resin	3 axis milling	3.30	1.28	1527.16	1.955	1	8.52	421	1	1	22
Study 2 - Outcome 10	Complete	Thermoplastic Resin	5 axis milling	3.30	1.28	367.88	0.471	1	6.82	4610	1	1	54
Study 2 - Outcome 11	Converged	Polystyrene, Expanded	Unrestricted	0.03	0.05	208.51	0.010	1	7.01	12947	1	1	47
Study 2 - Outcome 12	Converged	Polystyrene, Expanded	Additive	0.03	0.05	1136.79	0.057	1	6.58	1337	1	1	12
Study 2 - Outcome 13	Complete	Polystyrene, Expanded	Additive	0.03	0.05	260.27	0.013	1	7.03	15350	1	1	43

Name	Status	Material	MFR Method	Material E value (Gpa)	Material density (g/cm3)	Volume (cm3)	Mass (kg)	Non-Planar	Model Depth (cm) (BBOX)	Edge QTY (joined)	Reverse Sides	Multi Axis	Iteration
Study 2 - Outcome 14	Complete	Polystyrene, Expanded	Additive	0.03	0.05	215.44	0.011	1	6.73	16229	1	1	48
Study 2 - Outcome 15	Converged	Polystyrene, Expanded	Cutting	0.03	0.05	1778.23	0.089	0	6.62	1961	0	0	10
Study 2 - Outcome 16	Converged	Polystyrene, Expanded	2.5 axis milling	0.03	0.05	921.49	0.046	1	6.62	1872	1	0	14
Study 2 - Outcome 17	Complete	Polystyrene, Expanded	2.5 axis milling	0.03	0.05	1562.51	0.078	1	6.62	1769	0	0	9
Study 2 - Outcome 18	Complete	Polystyrene, Expanded	2.5 axis milling	0.03	0.05	1358.96	0.068	1	6.62	1763	0	0	11
Study 2 - Outcome 19	Converged	Polystyrene, Expanded	3 axis milling	0.03	0.05	920.70	0.046	1	8.17	3047	1	1	18
Study 2 - Outcome 20	Complete	Polystyrene, Expanded	5 axis milling	0.03	0.05	210.63	0.011	1	6.86	11338	1	1	46
Study 2 - Outcome 21	Complete	ABS Plastic	Unrestricted	2.24	1.06	1028.32	1.090	1	7.14	1784	1	1	14
Study 2 - Outcome 22	Complete	ABS Plastic	Additive	2.24	1.06	212.15	0.225	1	6.59	13066	1	1	50
Study 2 - Outcome 23	Converged	ABS Plastic	Additive	2.24	1.06	1754.84	1.860	1	7.03	281	1	0	3
Study 2 - Outcome 24	Converged	ABS Plastic	Additive	2.24	1.06	223.90	0.237	1	6.63	13515	1	1	53
Study 2 - Outcome 25	Converged	ABS Plastic	Cutting	2.24	1.06	1733.65	1.838	0	6.62	2032	0	0	11
Study 2 - Outcome 26	Converged	ABS Plastic	2.5 axis milling	2.24	1.06	980.96	1.040	1	7.23	1983	1	0	14
Study 2 - Outcome 27	Complete	ABS Plastic	2.5 axis milling	2.24	1.06	1638.97	1.737	1	6.62	1613	0	0	8
Study 2 - Outcome 28	Complete	ABS Plastic	2.5 axis milling	2.24	1.06	1374.80	1.457	1	6.62	1677	0	0	8
Study 2 - Outcome 29	Complete	ABS Plastic	3 axis milling	2.24	1.06	804.09	0.852	1	7.33	2955	1	1	19
Study 2 - Outcome 30	Converged	ABS Plastic	5 axis milling	2.24	1.06	215.15	0.228	1	6.63	10901	1	1	46
Study 2 - Outcome 31	Converged	MDF Medium Density Fiberboard	Unrestricted	2.40	0.80	211.24	0.169	1	6.78	12689	1	1	46
Study 2 - Outcome 32	Converged	MDF Medium Density Fiberboard	Additive	2.40	0.80	1577.26	1.262	1	7.00	593	1	0	5

Name	Status	Material	MFR Method	Material E value (Gpa)	Material density (g/cm3)	Volume (cm3)	Mass (kg)	Non-Planar	Model Depth (cm) (BBOX)	Edge QTY (joined)	Reverse Sides	Multi Axis	Iteration
Study 2 - Outcome 33	Complete	MDF Medium Density Fiberboard	Additive	2.40	0.80	1723.87	1.379	1	6.99	371	1	0	3
Study 2 - Outcome 34	Converged	MDF Medium Density Fiberboard	Additive	2.40	0.80	211.15	0.169	1	6.66	14388	1	1	53
Study 2 - Outcome 35	Converged	MDF Medium Density Fiberboard	Cutting	2.40	0.80	1742.36	1.394	0	6.62	2078	0	0	11
Study 2 - Outcome 36	Converged	MDF Medium Density Fiberboard	2.5 axis milling	2.40	0.80	901.85	0.721	1	6.62	2227	1	0	14
Study 2 - Outcome 37	Complete	MDF Medium Density Fiberboard	2.5 axis milling	2.40	0.80	1631.85	1.305	1	6.62	1711	0	0	8
Study 2 - Outcome 38	Complete	MDF Medium Density Fiberboard	2.5 axis milling	2.40	0.80	1394.92	1.116	1	6.62	1786	0	0	10
Study 2 - Outcome 39	Converged	MDF Medium Density Fiberboard	3 axis milling	2.40	0.80	910.09	0.728	1	8.16	3140	1	1	18
Study 2 - Outcome 40	Complete	MDF Medium Density Fiberboard	5 axis milling	2.40	0.80	1039.86	0.832	1	7.81	1705	1	1	14
Study 2 - Outcome 41	Converged	Aluminum AlSi10Mg	Unrestricted	71.00	2.67	214.84	0.574	1	6.87	11259	1	1	47
Study 2 - Outcome 42	Complete	Aluminum AlSi10Mg	Additive	71.00	2.67	211.52	0.565	1	6.60	12635	1	1	48
Study 2 - Outcome 43	Converged	Aluminum AlSi10Mg	Additive	71.00	2.67	1754.72	4.685	1	7.00	270	1	0	3
Study 2 - Outcome 44	Complete	Aluminum AlSi10Mg	Additive	71.00	2.67	209.64	0.560	1	6.73	15673	1	1	48
Study 2 - Outcome 45	Complete	Aluminum AlSi10Mg	Cutting	71.00	2.67	1717.63	4.586	0	6.62	2097	0	0	10
Study 2 - Outcome 46	Converged	Aluminum AlSi10Mg	2.5 axis milling	71.00	2.67	904.01	2.414	1	6.62	1818	1	0	15
Study 2 - Outcome 47	Complete	Aluminum AlSi10Mg	2.5 axis milling	71.00	2.67	1637.78	4.373	1	6.62	1622	0	0	8
Study 2 - Outcome 48	Complete	Aluminum AlSi10Mg	2.5 axis milling	71.00	2.67	1356.42	3.622	1	6.62	1857	0	0	8
Study 2 - Outcome 49	Converged	Aluminum AlSi10Mg	3 axis milling	71.00	2.67	931.32	2.487	1	8.40	3206	1	1	17
Study 2 - Outcome 50	Complete	Aluminum AlSi10Mg	5 axis milling	71.00	2.67	211.06	0.564	1	6.60	11311	1	1	49
Study 3 - Outcome 1	Complete	ABS Plastic	Unrestricted	2.24	1.06	14.28	0.015	1	4.89	1896	1	1	2
Study 3 - Outcome 2	Complete	ABS Plastic	Additive	2.24	1.06	13.59	0.014	1	4.41	760	1	1	3

Name	Status	Material	MFR Method	Material E value (Gpa)	Material density (g/cm3)	Volume (cm3)	Mass (kg)	Non-Planar	Model Depth (cm) (BBOX)	Edge QTY (joined)	Reverse Sides	Multi Axis	Iteration
Study 3 - Outcome 3	Complete	ABS Plastic	Additive	2.24	1.06	16.27	0.017	1	4.52	932	1	1	4
Study 3 - Outcome 4	Complete	ABS Plastic	Additive	2.24	1.06	13.55	0.014	1	4.36	944	1	1	5
Study 3 - Outcome 5	Complete	ABS Plastic	Cutting	2.24	1.06	130.37	0.138	0	4.91	404	0	0	65
Study 3 - Outcome 6	Complete	ABS Plastic	3 axis milling	2.24	1.06	15.45	0.016	1	4.35	566	1	1	3
Study 3 - Outcome 7	Complete	ABS Plastic	2.5 axis milling	2.24	1.06	88.04	0.093	1	4.91	710	1	0	21
Study 3 - Outcome 8	Converged	ABS Plastic	2.5 axis milling	2.24	1.06	127.88	0.136	1	4.91	467	0	0	45
Study 3 - Outcome 9	Converged	ABS Plastic	2.5 axis milling	2.24	1.06	116.45	0.123	1	4.91	427	0	0	47
Study 3 - Outcome 10	Complete	ABS Plastic	5 axis milling	2.24	1.06	14.53	0.015	1	4.82	548	1	1	2
Study 3 - Outcome 11	Complete	Polystyrene, Expanded	Unrestricted	0.03	0.05	14.28	0.001	1	4.89	1896	1	1	2
Study 3 - Outcome 12	Complete	Polystyrene, Expanded	Additive	0.03	0.05	13.59	0.001	1	4.33	809	1	1	3
Study 3 - Outcome 13	Complete	Polystyrene, Expanded	Additive	0.03	0.05	16.29	0.001	1	4.55	923	1	1	4
Study 3 - Outcome 14	Converged	Polystyrene, Expanded	Additive	0.03	0.05	14.97	0.001	1	4.56	765	1	1	4
Study 3 - Outcome 15	Complete	Polystyrene, Expanded	Cutting	0.03	0.05	132.26	0.007	0	4.91	384	0	0	99
Study 3 - Outcome 16	Complete	Polystyrene, Expanded	3 axis milling	0.03	0.05	16.12	0.001	1	4.30	595	1	1	4
Study 3 - Outcome 17	Complete	Polystyrene, Expanded	2.5 axis milling	0.03	0.05	81.61	0.004	1	4.91	674	1	0	67
Study 3 - Outcome 18	Converged	Polystyrene, Expanded	2.5 axis milling	0.03	0.05	129.34	0.006	1	4.91	432	0	0	92
Study 3 - Outcome 19	Converged	Polystyrene, Expanded	2.5 axis milling	0.03	0.05	119.81	0.006	1	4.91	457	0	0	74
Study 3 - Outcome 20	Complete	Polystyrene, Expanded	5 axis milling	0.03	0.05	14.53	0.001	1	4.82	548	1	1	2
Study 3 - Outcome 21	Complete	MDF Medium Density Fiberboard	Unrestricted	2.40	0.80	14.28	0.011	1	4.89	1896	1	1	2
Study 3 - Outcome 22	Complete	MDF Medium Density Fiberboard	Additive	2.40	0.80	13.59	0.011	1	4.42	744	1	1	3
Study 3 - Outcome 23	Complete	MDF Medium Density Fiberboard	Additive	2.40	0.80	16.26	0.013	1	4.55	938	1	1	4

Name	Status	Material	MFR Method	Material E value (Gpa)	Material density (g/cm3)	Volume (cm3)	Mass (kg)	Non-Planar	Model Depth (cm) (BBOX)	Edge QTY (joined)	Reverse Sides	Multi Axis	Iteration
Study 3 - Outcome 24	Complete	MDF Medium Density Fiberboard	Additive	2.40	0.80	14.53	0.012	1	4.39	807	1	1	5
Study 3 - Outcome 25	Complete	MDF Medium Density Fiberboard	Cutting	2.40	0.80	131.01	0.105	0	4.91	398	0	0	68
Study 3 - Outcome 26	Complete	MDF Medium Density Fiberboard	3 axis milling	2.40	0.80	15.56	0.012	1	4.47	574	1	1	3
Study 3 - Outcome 27	Complete	MDF Medium Density Fiberboard	2.5 axis milling	2.40	0.80	86.37	0.069	1	4.91	729	1	0	22
Study 3 - Outcome 28	Converged	MDF Medium Density Fiberboard	2.5 axis milling	2.40	0.80	126.52	0.101	1	4.91	434	0	0	47
Study 3 - Outcome 29	Converged	MDF Medium Density Fiberboard	2.5 axis milling	2.40	0.80	116.47	0.093	1	4.91	435	0	0	48
Study 3 - Outcome 30	Complete	MDF Medium Density Fiberboard	5 axis milling	2.40	0.80	14.54	0.012	1	4.82	548	1	1	2
Study 3 - Outcome 31	Complete	Thermoplastic Resin	Unrestricted	3.30	1.28	14.28	0.018	1	4.89	1896	1	1	2
Study 3 - Outcome 32	Complete	Thermoplastic Resin	Additive	3.30	1.28	13.14	0.017	1	4.26	825	1	1	3
Study 3 - Outcome 33	Complete	Thermoplastic Resin	Additive	3.30	1.28	16.67	0.021	1	4.61	770	1	1	4
Study 3 - Outcome 34	Complete	Thermoplastic Resin	Additive	3.30	1.28	13.50	0.017	1	3.96	2689	1	1	7
Study 3 - Outcome 35	Complete	Thermoplastic Resin	Cutting	3.30	1.28	128.34	0.164	0	4.91	445	0	0	64
Study 3 - Outcome 36	Complete	Thermoplastic Resin	3 axis milling	3.30	1.28	15.55	0.020	1	4.35	593	1	1	3
Study 3 - Outcome 37	Complete	Thermoplastic Resin	2.5 axis milling	3.30	1.28	87.91	0.113	1	4.91	726	1	0	20
Study 3 - Outcome 38	Converged	Thermoplastic Resin	2.5 axis milling	3.30	1.28	126.48	0.162	1	4.91	446	0	0	51
Study 3 - Outcome 39	Converged	Thermoplastic Resin	2.5 axis milling	3.30	1.28	116.47	0.149	1	4.91	447	0	0	46
Study 3 - Outcome 40	Complete	Thermoplastic Resin	5 axis milling	3.30	1.28	14.53	0.019	1	4.82	548	1	1	2
Study 3 - Outcome 41	Complete	Aluminum AlSi10Mg	Unrestricted	71.00	2.67	14.28	0.038	1	4.89	1896	1	1	2
Study 3 - Outcome 42	Complete	Aluminum AlSi10Mg	Additive	71.00	2.67	13.58	0.036	1	4.43	783	1	1	3

Name	Status	Material	MFR Method	Material E value (Gpa)	Material density (g/cm3)	Volume (cm3)	Mass (kg)	Non-Planar	Model Depth (cm) (BBOX)	Edge QTY (joined)	Reverse Sides	Multi Axis	Iteration
Study 3 - Outcome 43	Complete	Aluminum AlSi10Mg	Additive	71.00	2.67	16.27	0.043	1	4.53	939	1	1	4
Study 3 - Outcome 44	Complete	Aluminum AlSi10Mg	Additive	71.00	2.67	14.20	0.038	1	4.36	940	1	1	6
Study 3 - Outcome 45	Complete	Aluminum AlSi10Mg	Cutting	71.00	2.67	122.16	0.326	0	4.91	465	0	0	62
Study 3 - Outcome 46	Complete	Aluminum AlSi10Mg	3 axis milling	71.00	2.67	15.53	0.041	1	4.37	562	1	1	3
Study 3 - Outcome 47	Complete	Aluminum AlSi10Mg	2.5 axis milling	71.00	2.67	95.38	0.255	1	4.91	749	1	0	25
Study 3 - Outcome 48	Converged	Aluminum AlSi10Mg	2.5 axis milling	71.00	2.67	124.37	0.332	1	4.91	505	0	0	43
Study 3 - Outcome 49	Converged	Aluminum AlSi10Mg	2.5 axis milling	71.00	2.67	114.26	0.305	1	4.91	501	0	0	41
Study 3 - Outcome 50	Complete	Aluminum AlSi10Mg	5 axis milling	71.00	2.67	14.53	0.039	1	4.82	548	1	1	2