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Robotic Training for the Integration of Material Performances in Timber Manufacturing

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I, Giulio Brugnaro, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Signature

Abstract

The research focuses on testing a series of material-sensitive robotic training methods that flexibly extend the range of subtractive manufacturing processes available to designers based on the integration of manufacturing knowledge at an early design stage. In current design practices, the lack of feedback information between the different steps of linear design workflows forces designers to engage with only a limited range of standard materials and manufacturing techniques, leading to wasteful and inefficient solutions. With a specific focus on timber subtractive manufacturing, the work presented in this thesis addresses the main issue hindering the utilisation of non-standard tools and heterogeneous materials in design processes which is the significant deviation between what is prescribed in the digital design environment and the respective fabrication outcome.

To begin, it has been demonstrated the extent to which the heterogeneous properties of timber affect the outcome of the robotic carving process beyond the acceptable tolerance thresholds for design purposes. Resting on this premise, the devised strategy to address such a material variance involved capturing, transferring, augmenting and integrating manufacturing knowledge through the collection of real-world fabrication data, both by human experts and robotic sessions, and training of machine learning models (*i.e.* Artificial Neural Networks) to achieve an accurate simulation of the robotic manufacturing task informed by specific sets of tools affordances and material behaviours. The results of the training process have demonstrated that it is possible to accurately simulate the carving process to a degree sufficient for design applications, anticipating the influence of material and tool properties on the carved geometry.

The collaborations with the industry partners of the project, ROK Architects (Zürich) and BIG (Copenhagen), provided the opportunity to assess the different practical uses and related implications of the tools in a real-world scenario following an open-ended and explorative approach based on several iterations of the full design-to-production cycle. The findings have shown that the devised strategy supports decision-making procedures at an early stage of the design process and enables the exploration of novel, previously unavailable, solutions informed by material and tool affordances.

Impact Statement

The work presented in this thesis is part of a broader research field investigating the role of digital fabrication technologies in challenging how things are designed and suggesting novel strategies to engage with materials, tools and manufacturing techniques. The relevance of this has been recognised by the European Union's Horizon 2020 Research and Innovation Program which funded this research as part of the Innochain Training Network (Marie Skłodowska-Curie Actions) to foster a new generation of interdisciplinary researchers across Europe examining the impact of these technologies on our building and design culture. The network provided a stimulating framework for discussion, dissemination of the findings and public engagement through the organisation of several activities such as conferences, talks and exhibitions. Part of this research has been presented at some of the most relevant conferences in the field, such as ACADIA and ROB|ARCH, and collected in two peer-reviewed published paper (see Publications section). Furthermore, the work has been widely discussed in a series of lectures, presentations and workshops at renown institutions such as the Massachusetts Institute of Technology, ETH Zürich, University of Toronto, University of Michigan, University of Florence, Institute for Advanced Architecture of Catalonia and the Academy of Arts, Architecture and Design of Prague.

Innochain focused on bringing together academic researchers with leading practitioners across the design and manufacturing industry, ensuring the relevance of the range of issues addressed and fostering the development of integrated solutions. The industry collaborations with ROK Architects and BIG represented an invaluable opportunity for this research as they made possible testing in practice the validity of a series of fundamental claims and findings while providing a context for speculating about the impact these novel design-to-fabrication strategies could have over the future of the profession. From the perspective of designers, the access to packages of instrumental knowledge extends the range of materials and manufacturing techniques available as the trained models bring a significant increase in the simulation accuracy of non-standard fabrication processes. Designers willing to engage with the curation of the training process have the opportunity of creating customised design-to-manufacturing workflows validated by feedback data and statistical models. At the same time, the trained system does not require the designer to be a manufacturing expert, computer scientist or a skilled craftsman to engage with the production process as feedback information is provided through a familiar 3D interface. In this case, the access to material and manufacturing knowledge could be compared to the specialised knowledge made available within other simulation frameworks (*e.g.* Finite Elements Analysis, Computational Fluid Dynamics) to a larger group of design professionals, enabling the evaluation of complex structural or environmental analysis. Finally, for manufacturing companies, the research shows how to establish a possible strategy for encapsulating manufacturing knowledge and making it available to all the stakeholders involved in the design workflow, ensuring from the beginning a fruitful communication between the different parts and avoiding inefficient decisions which could be very expensive and challenging to adjust at a later stage of the process.

Acknowledgements

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The Innochain network has provided an invaluable framework for learning, discussing and working together with some of the brightest people in the field. It has certainly been an enriching experience from which this research, along with my personal and professional development, has greatly benefited. I am particularly grateful for the time, dedication and expertise provided by the industry partners of the project, ROK Architects and BIG. A special thank goes to Silvan Oesterle who extensively dedicated his time to engage in stimulating discussions and provided precious insights on the impact that these technologies could have in the industry.

I want to thank Peter Scully and the BMADE Staff for their continuous advice and availability to help me both inside and outside the workshop. This research would have been impossible without the guidance, support and encouragement of my supervisors Sean Hanna and Bob Sheil to whom goes my greatest thanks.

Finally, I am most grateful to my family and closest friends who supported me throughout these years.

London, September 2019

Giulio Brugnaro

List of Figures

List of Tables

Publications

The following published papers are related to the research presented in this thesis:

- Brugnaro, G., Hanna, S. 2017. Adaptive Robotic Training Methods for Subtractive Manufacturing. In: T. Nagakura, S. Tibbits, C. Mueller, eds. ACADIA 2017: Disciplines and Disruption, Proceedings of the 37th Annual Conference of the Association for Computer Aided Design in Architecture (ACADIA), Cambridge, MA: Acadia Publishing Company, pp. 164–169.
- Brugnaro, G., Hanna, S. 2018. Adaptive Robotic Carving: Training Methods for the Integration of Material Performances in Timber Manufacturing. In: J. Willmann, P. Block, M. Hutter, K. Byrne, T. Schork, eds. Robotic Fabrication in Architecture, Art and Design 2018. Zürich, CH: Springer, pp. 336-348.
- Brugnaro, G., Figliola, A. and Dubor, A., 2019. Negotiated Materialization: Design Approaches Integrating Wood Heterogeneity Through Advanced Robotic Fabrication. In: Bianconi, F. and Filippucci, M. eds. Digital wood design: innovative techniques of representation in architectural design (24). Springer, pp. 135-158.
- Brugnaro, G., Hanna, S., Scully, P., Sheil, B. and Oesterle, S. 2020. Integration of Material and Fabrication Affordances within the Design Workflow. In: B. Sheil, M.R. Thomsen, M. Tamke and S. Hanna, eds. Design Transactions: Rethinking Information Modelling for a New Material Age. UCL Press.

Table of Contents

1 Introduction

1.1 Problem Definition

Despite the increasing accessibility of digital fabrication technologies (Kolarevic, 2004), manufacturing and material knowledge are only rarely integrated within the established workflows of design practices whose main task is the production of instructions sets, such as drawings, digital models or technical reports (Hauck, Bergin and Bernstein, 2017). As a result, whereas skilled human craftsmen are able to cope with the uncertainty of the making process thanks to their skills and knowledge, continually adjusting their action in a dialogue with the materials and tools (Ingold, 2013), standard digital fabrication processes are currently unable to deal with such variance. While the term "*digital craftsmanship*" has become popular in the literature (Scheurer, 2012; Stary, 2015; Jacobs *et al.*, 2016), the cognitive abilities of human craftsmen remain a critical aspect unmatched by the digital counterpart, enabling learning and knowledge creation through experience.

Within a conventional design process driven by drawings and notations, "*materialisation*" processes are still regarded as the last stage of linear design-to-manufacturing workflows, in which materials are considered as passive receivers of a previously generated ideal form stored in a CAD model (De Landa, 2002). This linear progression from the design intention to its materialisation entails a lack of feedback between the different stages of the process and forces design practices to engage only with a limited range of standard manufacturing methods. The main criterion for any manufacturing task is the resemblance of the fabricated outcome to its digital or analogue specification. Nevertheless, only highly constrained and standardised fabrication processes can successfully achieve this without collecting actual fabrication feedback for adjustments at the production stage. As a consequence, standard design-to-fabrication strategies require the use of a narrow range of industrially-graded materials whose composition is homogeneous and behaviour is characterised in specification reports.

This approach is particularly detrimental for a natural, heterogeneous, material such as timber as it needs to be homogenised before becoming suitable for a conventional manufacturing environment, requiring heavy industrial processing and material waste. As the material is set to play a crucial role in the future of the design and construction industry due to its excellent technical performance and sustainable qualities (Sathre, 2007), it seems critical devising strategies to take advantage of its natural properties. The transformation from sawn log into an "engineered timber" product (*e.g.* a plywood panel) begins with chopping down the material into smaller elements (*e.g.* thin layers) to a size at which they could be considered homogeneous, discarding a significant amount of material in the process of removing all its natural "defects" (*e.g.* knots, coloured stains). Subsequently, these elements are reassembled into a specific arrangement (*e.g.* for plywood each layer is orthogonal to the next) using strong adhesives and industrial jigs or presses, obtaining a final product in which the heterogeneous properties of the natural material have been mostly eliminated. As part of such standardisation process, only a limited range of tools are utilised in CNC manufacturing systems for timber, excluding a variety of techniques which have been widely used before industrialisation to take advantage of its heterogeneous qualities (Schindler, 2007).

Focusing on natural solid timber, the thesis addresses the main issue hindering the utilisation of heterogeneous materials in current design-to-manufacturing workflows which is the difficulty of specifying their properties and behaviour in response to the fabrication tools, necessary to deliver consistent information along the design process and comply to the established quality standards. The bottleneck of digital fabrication processes then becomes the significant deviation between what is prescribed in the digital design environment and the respective operation outcome, precluding the utilisation of heterogeneous materials and non-standard manufacturing methods from most of the design applications. For instance, fabrication tools such as carving gouges and chisels are not able to eliminate the variance determined by the material behaviour and the final geometry results from a complex negotiation between design intentions and fabrication affordances. For manufacturers, the lack of full control over the process outcome at the agreed level of precision, to which they are contractually bound through its notational form, is not a viable business model beyond the prototyping stage. For designers, the lack of access to manufacturing and material knowledge leads at an early stage to blindly guess about the manufacturability of a project which is both challenging and economically risky.

1.2 Research Proposition

The approach proposed in the research seeks to encapsulate manufacturing knowledge specific to the material properties of timber into a transmissible form and make it available to designers at an early stage of the design process. In this way, design-to-manufacture workflows can advance through a series of decisions directly informed by manufacturing and material feedback across the full range of solutions available within a given process. The precise definition of parameter boundaries and constraints from the beginning is intended to prevent inefficient and costly operations.

Operating in the field of robotic subtractive manufacturing, the novelty of the approach is in capturing, transferring, augmenting and integrating manufacturing knowledge through the collection of real-world fabrication data, both by human experts and robotic sessions, and training of machine learning models (*i.e.* Artificial Neural Networks) to achieve an accurate simulation of the manufacturing task informed by specific sets of tools affordances and material behaviours. Such a knowledge base can be used to inform any fabrication task without the need for the designer to explicitly define each fabrication parameter necessary to achieve an intended design outcome. Furthermore, the integration of instrumental knowledge within a design interface represents an opportunity to extend the range of manufacturing processes and materials available to designers as the system can be iteratively tuned to a particular set of fabrication conditions. The processing and reconstruction of such specific features move beyond the industrial concept of "*standard*" and material "*defects*", integrating into the design tools a granular level of material understanding, unthinkable only a few decades ago (Sabin and Carpo, 2017).

Manufacturing processes could be then devised as moments of design exploration, where the digital model is directly informed by fabrication affordances and designers are able to curate their custom design-to-manufacturing workflow, integrating real-world material behaviours to make better-informed design decisions, rather than working within a standard CAM framework, in which geometry only is represented, and material ignored. With the integration of manufacturing knowledge at an early design stage, the potential impact of the research lies in devising a series of training methods that flexibly extend the range of subtractive manufacturing processes available to designers and provide an accurate prediction of non-standard operations on timber. Access to the same knowledge resources can be used to establish a fruitful dialogue between designers and manufacturers and develop a custom design-to-manufacturing workflow informed by feedback information along each stage of the process, avoiding inefficient solutions and material waste.

1.3 Research Design & Methodology

The research design and methodological frameworks have been strongly influenced by the Innochain Research Network context, within which this research has taken place, based on a fruitful collaboration between leading academic institutions and industry partners across Europe.

The dual nature of the project is reflected in the structure of this research which is based on two complementary components focused, on one hand, on the technological development of the design simulation and fabrication framework, and the other, on their testing within the workflows of design practices.

The first two research hypotheses belong to the technology-led component and concern the relationship between material and end product, testing the degree to which the fabrication system can successfully encapsulate manufacturing and material knowledge into a transmissible form that can be accessed during the design process.

While conventional CAM (Computer-Aided Manufacturing) simulation frameworks do not consider timber material behaviour, **Hypothesis A** claims that:

T*he heterogeneous qualities of natural materials such as timber substantially affect the outcome of operations performed with different carving tools, hindering their utilisation within current design workflows*.

To address this, it means establishing a series of methods to record, measure, process and compare the variance of robotic carving operations performed under different material and fabrication conditions. The acquisition of data will need to be structured within rigorous and statistically valid recording sessions using a combination of sensor devices that will accurately reconstruct the fabrication task and store its key features into a dataset. This first hypothesis seeks to find which are the relevant parameters affecting the operation outcome and demonstrate that such a variance is above the acceptable threshold of production tolerances for design purposes.

Based on these premises, **Hypothesis B** states the following:

Given input parameters of (a) measurable properties of the given material, such as wood grain structure and density, and (b) tool affordances, a prediction can be made of (c) the geometrical outcome of the fabrication procedure to a level of accuracy sufficient for design purposes.

The integration of material and fabrication knowledge implies the possibility of modelling it in a form that can be accessed and queried during the design process. The strategy adopted in this research will focus on a series of predictive methods based on sensor data and machine learning models which will be used to investigate to what extent it is possible to encapsulate such knowledge as part of a simulation environment. The aim is to prove that the devised strategy can anticipate the variance occurring in the fabrication outcome to a degree of accuracy within the acceptable threshold of tolerance, therefore demonstrating that is possible to use the fabrication system for design applications.

The design-led component of the research, driven by **Research Question C,** rests on the validity of **Hypothesis A** and **B** to test the integration of the devised strategy within the established workflow of real-world design firms:

How does the integration of manufacturing and material knowledge at an early stage of the design process affect the exploration and evaluation of design solutions for robotic carving operations?

While the first two hypotheses face a technical challenge addressed through the collection of quantitative experimental data, **Research Question C** investigates the broader implications that the integration of manufacturing and material knowledge could have over the design process and the role of designers.

Overall, the research adopted the methodological framework of the living laboratory as a strategy for refining complex solutions based on an early engagement with the potential users driven by experiments, as tangible artefacts, taking place within a real-world setting (Almirall and Wareham, 2011; Guzmán et *al.*, 2013).

The investigation of such a research question was structured using a case study methodology based on the opportunity of engaging in a series of industry collaborations established within the context of the Innochain project.

The critical aspect behind such a methodological choice lies in the necessity of covering the contextual conditions within which the tools would find applications (Yin, 2017), moving beyond a purely academic context and adopting an exploratory approach based on a series of open-ended experiments in the shape of full design-to-production cycles.

As discussed by Baxter and Jack (2008), it is critical to ensure the convergence of the different type of collected data in an attempt to understand, and later discuss, the overall case rather than treat it in its separate components. Direct observation, voiced opinions and annotated accounts abouth the use of the devised system by the different teams of designers involved in the case studies represent the qualitative component of the research. This is further combined with the collection of quantitative data related to the training sessions and choices that informed the series of design explorations.

1.4 Thesis Outline

The central part of the work is presented in **Chapter 3, 4** and **5** along two main strands which entail the technological developments and design applications of the research. In **Chapter 6**, the findings from these two components are woven together to discuss how they relate to the body of work presented in the Literature Review (**Chapter 2**) and their further outlook. Finally, **Chapter 7** directly addresses the research hypotheses put forward in this chapter and summarises the key contributions of the research.

02. Literature Review: The perspectives of design practices, traditional crafts and industrial manufacturing are tied together around the central role of knowledge across different domains, evaluating the established methods for capturing, manipulating, extending and integrating it as part of design-to-manufacturing workflows. The review is structured in three main parts: **i)** Material Agency, **ii)** Making Knowledge and **iii)** Learning Systems. In the first section, the role of material agency and feedback information within design practices, traditional crafts, and industrial production is assessed together with its potential of linking digital practices to physical fabrication processes to radically reconfiguring the exploration of design solutions. The body of work discussed in the second section deals with the study of cognitive processes and methodological strategies linking design and making in traditional craftsmanship and compare them to the acquisition of knowledge in industrial manufacturing and its formalisation within simulation frameworks. In the third section are presented a series of strategies aiming to synthesise instrumental and material knowledge using machine learning models to inform the action of automated means of production, supporting decision-making procedures based on the affordances provided by specific sets of fabrication and material affordances.

03. Knowledge Acquisition: Hypothesis A is addressed through the discussion of a series of relevant findings demonstrating that the material variance of timber substantially affects the outcome of carving operations, supporting the need of a strategy to control such uncertainty for design applications. The focus of the chapter is on the first stage of the training workflow which concerns the acquisition of real-world fabrication and material data collected through different sensor devices, its subsequent processing and storing into a library of fabrication datasets. Two different data acquisition methods, based on human demonstration and robotic sessions, are presented and compared to identify how these affect the overall training process. Finally, the extent to which the material variance of timber influences the carving operations is assessed through a series of recording sessions based on a Design of Experiment (DOE) strategy which is a statistically valid method to efficiently investigate which combinations of factors and their respective values (or levels) generate variations in the collected information.

04. Knowledge Synthesis: The validity of **Hypothesis B** has been demonstrated utilising a combination of machine learning strategies to identify relevant correlations in the collected fabrication data and establish a simulation model for robotic carving operations, supporting key design decisions before moving to the production stage. Besides the validation process after the training of each model, the discussed methods are assessed in the simulation of a series of carving operations produced with different fabrication parameters, measuring the deviation of the prediction from the actual fabricated outcomes. Following this, a comparative analysis of multiple simulation models trained with different sets of fabrication affordances is presented to demonstrate the versatility of the system and its ability to model the variance determined by various combinations of material properties, wood species and carving tools.

05. Knowledge Integration: The findings from the industry collaborations with ROK Architects (Zürich) and BIG (Copenhagen) are presented and discussed to address **Research Question C**, demonstrating how the devised strategy has been applied to explore a range of design solutions previously unavailable to the designers. The extended catalogue of digital design iterations and several robotically fabricated pieces is organised as a series of case studies presented and discussed in three main sections: **i)** Separation Between Design and Making, **ii)** Fabrication as Design Curation Practice and **iii)** Design Negotiation Platform: Top-Down Decisions vs Bottom-Up Affordances.

06. Discussion: The findings from the previous chapters are woven together and their relevance is discussed in relation to the current literature along three main sections. **i)** Embracing Material Variance: discusses the modelling and integration of the agency of materials as a key component to enable holistic design feedback and support decision-making processes. **ii)** Learning Tools: presents the vision of designer curating her/his custom design-to-production process in dialogue with a tool which can be iteratively trained and optimised to accomplish tasks. **iii)** Knowledge Exchange: discusses the generation, transfer and augmentation of manufacturing knowledge between machines and human experts in the context of automation.

07. Conclusions: The contribution of the research lies in testing a series of material-sensitive robotic training methods that flexibly extend the range of subtractive manufacturing processes available to designers based on the integration of manufacturing knowledge at an early design stage. It has been demonstrated that the heterogeneous properties of timber significantly affect the outcome of the robotic carving process, hindering the adoption of the manufacturing method into design workflows. As a strategy to address such a material variance, the training of the fabrication system, based on collected sensor data and machine learning models, demonstrated that is possible to accurately simulate the carving process to a degree sufficient for design application. Following the training validation, the tool has been tested in a series of industry collaborations to assess its practical use and implications in a real-world scenario. The results have shown that the devised strategy supports decision-making procedures at an early stage of design-to-production workflows and enables the exploration of novel, previously unavailable, design solutions informed by material and tool affordances.

2 Literature Review

This chapter provides an overview of the critical terms, relevant methods and case studies around the synthesis and integration of material knowledge in design-to-manufacturing workflows. The literature review ties together the perspectives of design practices, traditional crafts and industrial manufacturing around the central role of knowledge as a strategy to identify opportunities across a wide breadth of disciplinary fields revolving around the design and making of physical artefacts. The analysis is structured in three main parts: **i)** Material Agency, **ii)** Making Knowledge and **iii)** Learning Systems.

The first section presents the separation between the stages of design and fabrication in current design practices based on the lack of feedback information and discusses its consequences on design workflows. The role of the material agency is assessed together with its potential of linking digital practices to physical fabrication processes to radically reconfigure the exploration of design solutions. The body of work discussed in the second section deals with the study of cognitive processes linking design and making in traditional craftsmanship and compare them to the acquisition of knowledge in industrial manufacturing and its formalisation within simulation frameworks. In the third section are presented a series of strategies aiming to synthesise instrumental and material knowledge using machine learning models to inform the action of automated means of production, supporting decisions making based on the affordances provided by specific sets of fabrication tools and materials. Finally, a summary of the trends and opportunities identified by the review is provided at the end of the chapter.

2.1 Material Agency

2.1.1 Timber as a Heterogeneous Material

Timber has been one of the first materials adopted for the production of artefacts in human history and it has been widely used for centuries across different civilisations, leading to rich building cultures and technological developments, evolving from hand-driven tools to information-driven ones (Schindler, 2007). The demand for timber as a construction material has been growing over the last years due to recent advancements in the timber processing industry and, perhaps more importantly, sustainability concerns regarding non-renewable resources consumption and CO2 production throughout the AEC industry (Alcorn, 1996; Sathre, 2007; Kolb, 2008).

Timber is a natural, grown, composite material made of strands of tightly-packed cellulose fibres embedded in a lignin matrix whose parallel arrangement determines its anisotropic behaviour, meaning that it responds differently to mechanical stresses applied along different directions. In the specific, its structural stiffness is higher along the grain direction which is usually described as "*the direction of the dominant longitudinal cells in a tree*" (Hoadley, 2000) while is much weaker along the transversal plane of the grain (Dinwoodie, 2000) (***Fig. 2.1***).

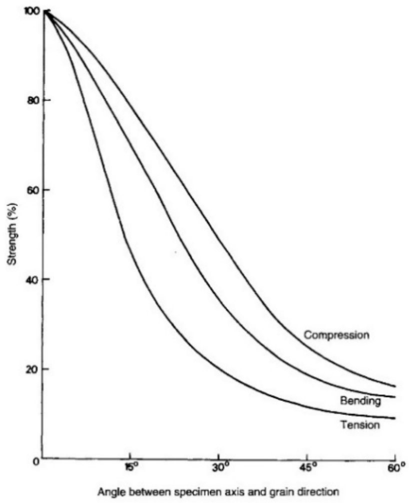


Figure 2.1 "Effect of grain angle on the tensile, bending and compression strength of timber. (After R. Baumann, 1922)" - Source: Dinwoodie, 2000.

Besides its structural behaviour, the grain direction plays a crucial role also in the processing and machining of timber. There are two fundamental types of cutting actions: **i)** orthogonal cutting, where "*the cutting edge of the tool is more or less perpendicular to its direction of motion*" and **ii)** peripheral milling where a rotary cutter is intermittently put in contact with the material and removes a certain amount of it at each rotation (Dinwoodie, 2000).

While the methods developed in this research are potentially valuable for both techniques, the focus of this thesis is on **i)** orthogonal cutting (***Fig. 2.2***) performed with tools such as chisels, gouges, knives, planers and axes. The main reason for this choice is that this family of techniques receive a more significant impact from the material than **ii**) peripheral milling, showing a higher variance in the fabrication outcome and yielding to clearest results in the experiments.

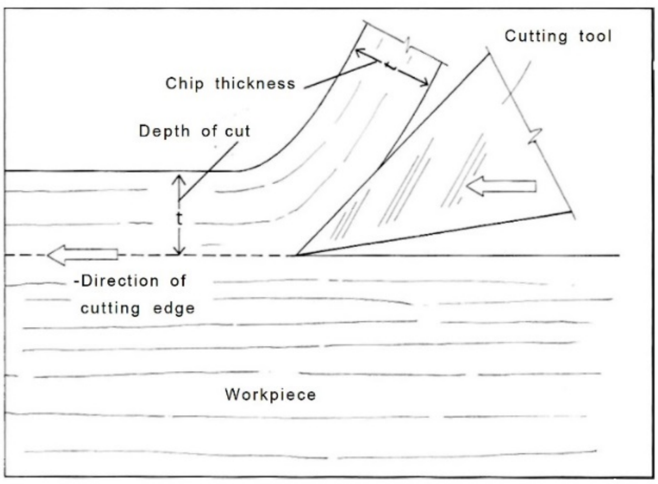


Figure 2.2 "Idealized cutting action. Energy is consumed in severing the wood to form the chip, in deforming or rotating the chip, and in friction of the tool face against both the chip and the workpiece" - Source: Hoadley, 2000.

McKenzie (1961) identified two main parameters for this technique which are the angles between the grain direction and **i)** the cutting edge and **ii)** the carving direction. The interaction between the tool and material with respect to those parameters significantly affects the outcome of the operation. For instance, carving along the main grain direction will produce cuts with a smoother surface, while moving against the grain will tear the workpiece. Similarly, a small cutting angle will transmit a compression force mostly along the parallel direction of the grain while it would be desirable to have a diagonal transmission depending on the geometry of the tool itself (***Fig. 2.3***).

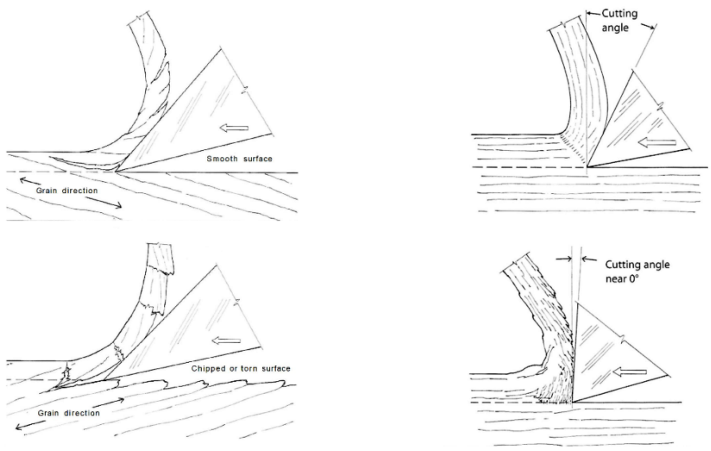


Figure 2.3 Cases of Interaction of orthogonal cutting tools and different grain directions - Source: Adapted from Hoadley, 2000.

Despite several studies in this field (Kivimaa, 1950; McKenzie, 1961; Koch, 1964, Axelsson *et al.*, 1993; Scholz *et al.*, 2009; Eyma *et al.* 2004; Chuchala *et al.*, 2013) aiming to identify the correct selection of tools and related parameters to improve the efficiency and accuracy of the process, the analysis and modelling of wood cutting behaviour still represent a challenging task due to its heterogeneous structure (Cristóvão, 2013). As a natural material, the makeup of its internal arrangement can vary significantly according to intrinsic (*e.g.* tree species) and external *(e.g.* environment) conditions (***Fig. 2.4***).

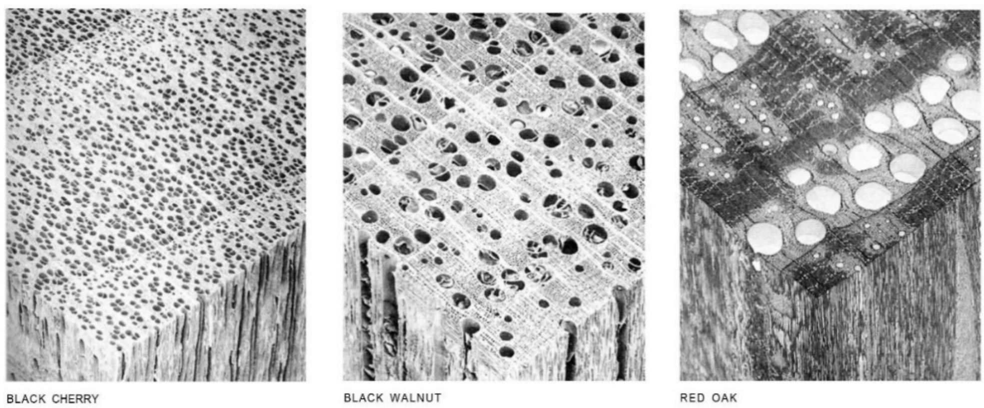


Figure 2.4 Wood cells structure in different tree species - Source: Hoadley, 2000 (Photos by W. Cote).

Besides technical considerations, the heterogeneity of timber has wider economic and environmental implications. Tree logs, or parts of them, could be considered flawed and discarded if they do not respond to the requirement defined by the commercial grading specifications (Hensel, 2009). Weston (2012) argues that the whole history of architectural materials has been guided by a "*hostility toward the natural tendencies of materials as found in nature*". This is particularly valid for timber as heavy industrial processing is utilised to transform the material as found in nature into a broader range of engineered and standardised products such as plywood (***Fig. 2.5***).

Figure 2.5 Comparison between plywood and natural timber - Sources: plywoodmaster.com (left), Lee Rentz (right).

Over the last century, there have been significant efforts in the timber industry to correct the so-called defects of the material determined by its anisotropic characteristics. This is still reflected in the range of commercially available software for subtractive manufacturing tasks, completely neglecting the complex role played by the grain arrangement and replacing it with a homogeneous block of generic matter (DeLanda, 2002; Fure, 2011). Nevertheless, the recent developments in computational design strategies, sensor data acquisition and robotic manufacturing which will be discussed in the next sections have the potential to radically reconsider the role of timber as part of design processes to take advantage of the heterogeneous nature of the material (Menges, 2009; Menges, Schwinn and Krieg, 2016).

2.1.2 Properties, Qualities, Capacities and Affordances

The distinction between the terms "*property*", "*quality*", "*capacity*" and "*affordance*" is particularly relevant for this research as it directly depends on the role played by different types of knowledge in relation to the material medium.

For the design theorist and craftsman David Pye (1968), properties are objective and measurable, while qualities are subjective and depending on the individual's knowledge and sensibility. Because scientifically measurable, properties can be used to compile characterisation of industrial materials. Steel is an example of an industrial material which comes in a series of standardised shapes and whose properties are specified into a series of readily available tables. Interestingly, the current approach in the engineering of complex materials, such as fibre composites, is not based on the definition of "*typical*" properties but rather on the fine-tuning of their behaviour using a performance-driven approach (Gordon, 1988; DeLanda 2002). Similarly, in the field of additive manufacturing, there have been several attempts to develop highly-detailed digital representation models of functionally graded materials exhibiting complex, heterogeneous, properties achieved through multi-material 3d-printing (Jackson, 2000; Bader *et al.*, 2016).

Menges and Reichert (2012) describe the hygroscopic-driven actuation of engineered wood veneers as an intrinsic capacity immanent in the material itself which is expressed through the interaction of the component with the surrounding environment and its humidity level. According to De Landa (2005), while properties imply possession, capacities are always relational: "*a knife may possess the property of being sharp and this may give it the capacity to cut, but the latter can only be exercised with respect to another object that has the capacity of being cut*". The relational aspect plays a crucial role also in the definition of the term "*affordance*" given by the by the perceptual psychologist James Gibson in his seminal book *The Ecological Approach to Visual Perception* (1979) which he describes as the set of actions that a system or environment allows being performed by an actor (*e.g.* an animal). As this always entails a mutual interaction, the existing affordances and their qualities are dependent on the respective structures of the two systems (Maier and Fadel, 2007).

The shift from isolated attributes to system thinking introduced with the term "*affordance*" provides a useful framework for the modelling of manufacturing processes as it could be argued that the outcome geometry generated by a subtractive operation does not depend exclusively from a specific individual property (*e.g.* wood grain density) of one of the two systems but rather from the reciprocal interaction of the cutting tools with the wooden workpiece. While for Gibson the affordances provided by a system are independent of perception, *i.e.* they are present regardless of the ability of an animal to perceive them, Norman (1990), introducing the concept in the field of Human-Machine Interaction (HMI), suggests that these are contingent and "*dependent on the experiences of the perceiver within some cultural framework*" (Mateas, 2003). This latter position implies that the knowledge and experience of a designer, programmer or craftsman play a key role within such relational capacities. According to McCollough (1996), our perception of the world is defined by *"what we can do with it*", namely what sorts of affordances we are able to identify based on our senses, experience and knowledge. The medium is defined as the substance that receives the work of the tools and provides a *locus* for skills. A medium is a range of possibilities which once identified by the craftsman turn to affordances. He further argues that the affordances of a medium, such as timber, need to be discovered as they are not obvious as, for instance, the affordances of an industrial design product whose shape suggests possible uses. As affordances are necessarily limited, they are strictly related to the concept of constraint which defines the range of formal possibilities. Craftsmen seeking to explore the landscape of affordances offered by a medium asks themselves "*What can this medium do?"* as much as "*What do I wish to do with this medium*?". Therefore, an artefact is not a representation of an abstract model, but rather its final appearance is defined by the properties of the medium itself (McCollough, 1996).

What follows is that the identification and formalisation of instrumental and material affordances represents a critical aspect for manufacturing processes and human making in general, as only those affordances which have been identified become accessible and usable. One of the key propositions of this research is to establish a series of methods to make explicit the range of affordances available to support designers navigating through multiple design iterations. In the field of product engineering, the identification and design of the affordances that an object would create in relation to its user have been widely addressed in the literature (Galvao and Sato, 2006; Maier, Sandel and Fadel, 2008; Cormier and Lewis, 2015). While most of these relate to functional aspects of objects (*e.g.* a handle provides the affordance of being held to a cup), these methods could potentially be extended as well for the identification and specification of material and fabrication affordances. Among the strategies proposed by Maier and Fadel (2007), the *Direct Experimentation* and *Automated Identification* strategies seem to be the most promising for this research. One of the advantages of manufacturing processes is that the artefact necessary to experiment upon already exist, for instance, an aluminium block to be machined, therefore is possible to apply the *Direct Experimentation* method to determine via heuristics the affordances of the system. Moving one step further, the *Automated Identification* method implies the creation of a database where the affordances knowledge, or expert knowledge, identified through *Direct Experimentation* could be stored and integrated into a CAD environment to automatically assist future design endeavours (***Fig. 2.6***).

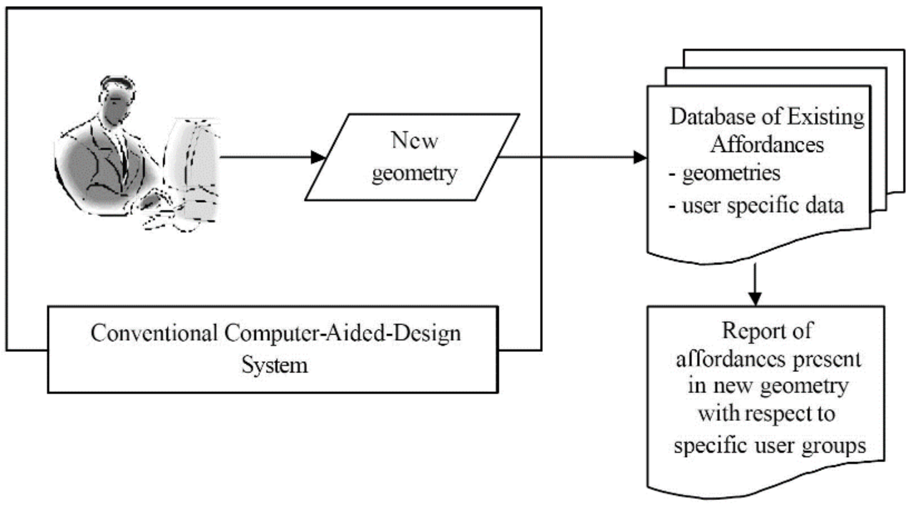


Figure 2.6 "Schematic of affordance identifying database system" - Source: Maier and Fadel, 2007.

The advantage of this method is the opportunity of exploring the potential provided by different affordances without relying exclusively on limited personal knowledge, fostering the exploration of a broader range of solutions. As the main limitation of such automated system is the impossibility of registering all the possible affordances into a database, designers are then asked to play an active in the identification and curation of their own specific set of affordances according to the assigned task. Using a similar approach, Kim (2015) suggests the creation of curated features repositories that could be retrieved based on the specific problem assigned and used to design new affordances through analogical reasoning (***Fig. 2.7***). As the collection of features defines the boundaries of the solution search, it seems evident that in these design frameworks based on affordances, the moment of design starts already from the creation or adoption of a specific feature database or repository.

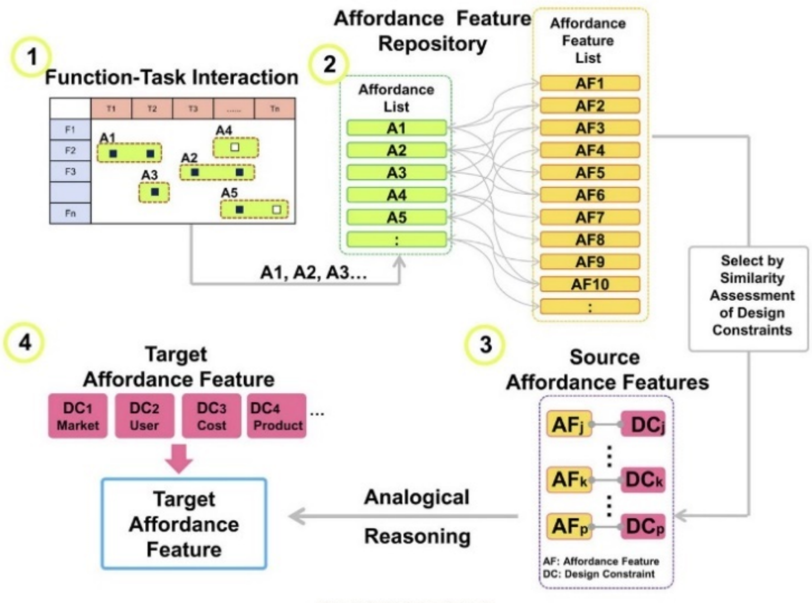


Figure 2.7 "Design for affordance framework" – Source: Kim, 2015.

2.1.3 Material Agency and Craftsmanship

Current design-to-manufacturing workflows are structured around a series of linear steps, from the definition of objects within a digital modelling environment to their faithful transposition into physical entities through a variety of *materialisation* technologies which are becoming increasingly available to designers (Kolarevic, 2004; Brandt, 2012). The process of imposing an ideal form onto a material *substratum*, intended as a passive receptacle, is defined in literature with the term *hylomorphism*, a compound of the Greek words *hyle* (matter) and *morphe* (form). Since its first philosophical formulation by Aristotle (Witt, 1987), the hylomorphic approach on design and making has profoundly permeated the Western culture and have emerged as the dominant paradigm for current design practices.

This view has been strongly opposed in more recent times by scholars advocating for the agency of materials and its crucial role in design and making processes. In his criticism of the hylomorphic model, Bryant (2012) argues that the creation of physical artefacts is much closer to a negotiation process and, since it is not possible to know in advance the outcome of any negotiation, its final outcome could not be considered exclusively as the result of previously defined form. Putting forward the example of a sculptor working with marble, he describes as the initial idea that starts the carving process is constantly redefined by the encounter of unique material features in the grain and veins structure as if the marble "*wants to become something else*" (Bryant, 2012).

The body of work of contemporary philosopher Manuel De Landa focuses on the emerging of a new materiality in which materials are active participants in the genesis of form and designers must consider their agency as an integral part of their design process (De Landa 1997; 2002; 2005). Such position not only implies that materials have something to say within the design process, but they also have the potential of bringing value to it through their variable properties, heterogeneity and complexity. To the hylomorphic approach of current design practices, he opposes craftsmen's approach to materiality, who "*did not impose a shape but rather teased out a form from the material, acting more as triggers for spontaneous behaviours and as facilitators of spontaneous processes than as commanders imposing their desires from above*" (De Landa, 2002).

Along the same line of thought, Ingold (2013) proposes to envision the process of making as a process of growth, where the maker joins as a participant in a process driven by active materials which are already ongoing and determine the forms of the world as we know it. The critical point is that even if the maker joins such process with a form in mind, this is not what creates the work but rather the engagement with materials. Artists like Constantin Brancusi expressed similar attention to the agency of materials, arguing that not only materials have their own life but that we need to reach a point where we can speak their unique language rather than impose ours (Dudley, 1927).

The work of Gilles Deleuze and Felix Guattari presented in their book *A Thousand Plateaus: Capitalism and Schizophrenia* (1980), of seminal importance for De Landa and what he defines as the "*inherent shape-generating capabilities of matter" (*De Landa, *2002)*, put forward the ability of active materials to lead human's action:

> *"It is a question of surrendering to the wood, then following where it leads by connecting operations to a materiality, such as the variable undulations and torsions of the fibres guiding the operation of splitting wood, instead of imposing a form upon a matter"* (Deleuze and Guattari, 1980)

The ability of establishing a dialogue with the material through an exchange of feedback information to adjust her or his actions is what distinguishes a craftsman, who "*can compensate for differences in the qualities of his materials, for he can adjust the precise strength and pattern of application of this to the material's local vagaries*" in contrast the standardisation enforced by industrial machines (Stanley Smith, 1992). Within this dialogue, Pallasmaa (2009) argues that tools gradually evolve through the affordances they need to address until becoming completely embodied in the cognitive process of craftsmen who look at them as new external organs able to dissolve the boundary between their working hands and the material.

Interestingly, while craft practices might have been seen as nostalgic or antiquate concepts, novel technological developments are leading toward a radical revaluation of the concept of "*craftsmanship*" described by Sennett (2008) as a methodological approach between "*concrete practice and making*", which played a key role in our modern history and is becoming more and more prominent in our contemporary society.

2.1.4 Digital Materiality and Robotics

Current notational systems available to designers, such as drawings or digital models, mostly encode and transmit only geometrical information, causing what the historian

Mario Carpo (2011) defines as a notational bottleneck: "*what can be built, it is determined by what can be drawn*".

These strategies for encapsulating design information seem incompatible with the experiential nature of material agency, which could only be discovered, as seen in the previous section, through direct engagement with the process and based on subjective knowledge and intuition. For this reason, the difficulty of transmitting non-geometrical information could be seen as the main factor determining its exclusion from the design process, pushing designers further away from the realm of production to focus on the creation of instructions sets in the form of drawings. At the same time, designers relying exclusively on drawings are necessarily removed from directly experiencing the properties of materials and unable to construct a personal, intuitive, knowledge of these. While craftsmen establish a dialogue with the process and material through the concurrent exchange of feedback information, designers, who do not have access to such type of knowledge, are forced to operate within a hylomorphic model, where the matter is considered as inert receptacles of the shapes defined in their digital models.

Despite such dominant paradigm, Koralevic (2008) argues that the increasing adoption of digital manufacturing technologies is leading towards a radical transformation of the design industry, where the design intention is closely coupled with its production. Drawing a parallel with crafts practices, he argues for the figure of architects as craftsmen and the adoption of such technologies as enablers of the cyclical exploration, rather than linear, of novel design solutions driven by material properties and manufacturing affordances, such as precision, speed and scalability. In the light of what described in the previous section, such claim sounds, perhaps, overly optimistic on the current state of technologies available to the vast majority of designers, and while they exert a positive force in bringing the stage of design and making closer together, the results are still far away from the concurrent exchange of feedback information and "*design through making*" paradigm at the foundation of crafts practices.

In this regard, Fure (2011) argues that digital fabrication technologies operate within the same notational bottleneck of previous production methods, having as a goal the production of an artefact which resembles as close as possible the original digital model, measured against tolerances leaving no room for any fabrication and material agency. While recognising the current limits of technologies, Menges (2015) advocates not only for the integration of material information within CAD models but as active drivers for the whole process through the integration of computational models able to tap latent design potential of material systems, moving beyond the idea of standardised building elements. The aim of the design process is shifted towards the creation of the computational interfaces that enable to link the stages of design and making rather than the individual formal outcome. Along the same line of thought, Gramazio and Kohler (2008) have previously indicated with the term *digital materiality* the interplay between digital and material processes enabled by controlling manufacturing processes through design data. Designers are not asked to devise static forms but material processes, giving up geometric notations and focusing on a performative-driven approach. The focus is shifted from blueprints to dynamic sets of rules which determines material behaviours with the advantage of creating an open-ended framework allowing interventions throughout the different stages of the process.

The enabling technology that connects the digital realm of computers with the physical world of production is represented by robotic manufacturing. While industrial robots have been already around for a few decades, more recently there has been a renovated interested in their application in the design and construction industry. Bechtold (2010) discusses how a first attempt to integrate such technologies in highly automated on-site factories for the construction of buildings has already taken place in the 1980s in Japan. The main issue back then was that the robots were highly-specialised and expensive machines performing standardised tasks without adding value to the overall process, whereas today's robots can perform a wide range of diverse tasks which would be challenging for a human to perform with similar speed and precision.

The industrial robotic arms are generic manipulator which can be programmed to a large variety of skills based on the application of task-specific end-effectors and sensors. Maxwell and Pigram (2012) compare the flexibility of industrial robotic arms to the generalist abilities of preindustrial craftsmen, in contrast with specialised industrial machines, which can perform only a very limited range of tasks. This is made possible through the combination of the robotic actuation with the collection of sensor data, effectively creating an interface between the digital and physical realms and enabling different modes of interaction between the human designer and the fabrication machine (Dörfler, Rist and Rust, 2012)(**Fig. 2.8**). The inherent adaptability of robots allows counteracting conservative tendencies such as the commitment to inert and industrially-homogenised materials to make sure the manufacturability of a large batch of products. Coupling industrial robotic arms with algorithmic design methodologies enable "*an explicit and bidirectional traversing of the modern division between design and making, establishing novel pathways and feedback between mind, hand, and machine"* (Maxwell and Pigram, 2012).

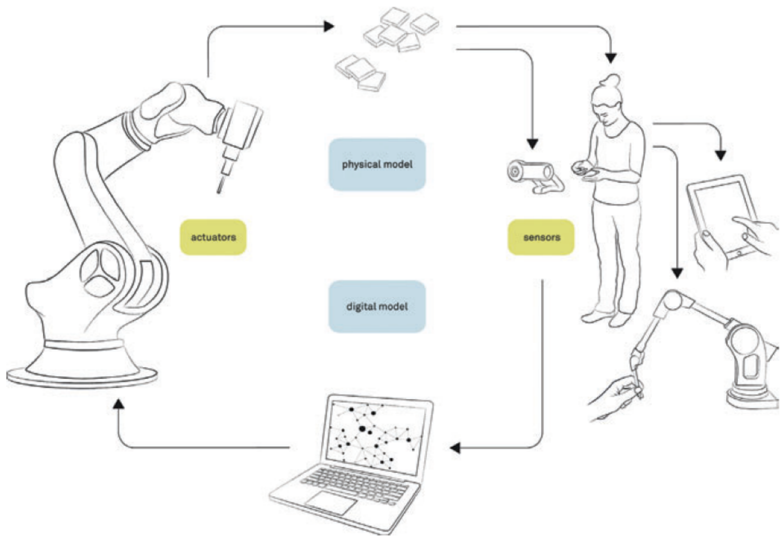


Figure 2.8 "Actuators and sensors as intermediaries between the digital and physical model" – Source: Dörfler, Rist and Rust, 2012.

2.1.5 Simulation Feedback

While craftsmen directly interact with materials, designers, detached from the process of making, need to find alternative ways of accessing knowledge and query the materials to receive feedback information and make informed design decisions. Design-to-manufacturing interfaces focused around process-driven models, rather than only geometrical notation, need to provide explicit feedback on material and fabrication constraints throughout the whole process, from the conceptual stage to the machine instruction code (Maxwell and Pigram, 2012).

A possible strategy to access such knowledge is through the creation of design hypotheses in the form of digital models which are tested within a simulation environment providing an understanding of performances before moving to the physical realm. While a static model, such as geometrical blueprints, can only represent a system at rest, simulation is necessary to investigate dynamic models concerned with processes, such as robotic fabrication, considered as "*a time-ordered sequence of states a system takes in a given time period* " (Guala, 2002).

As digital simulations are necessarily simplified and abstract models of reality, the aim is not to recreate a perfect reconstruction of materials but rather to provide a framework where designers could interact with their behaviours to explore design solutions that evolve accordingly to the affordances provided by the medium (Nicholas, 2012). While design problems are intrinsically ill-defined, simulation models are not used to predict future events but rather to identify a meaningful structure in the system explored (*e.g.* the robotic carving tool and the timber workpiece) that allow the investigation of a stable region of the system itself as part of the design process (Hanna, 2010). In the context of simulation as an abstract and partial proxy for reality (Turkle *et al.,* 2009), Brandt (2005; 2012) proposes to iteratively validate the model, which he defines as "*isomodel*", based on real-time feedback collected by sensors that can continuously provide information about the uncertainties occurring during the construction stage, closing the gap between the digital and physical realm. The main disadvantage of this simulation approach is that validation arrives only after the design stage and, therefore, adjustments are limited and expensive.

Conventional CAD environments embedding solid modelling procedures present to the user a simulation of operations performed on matter in its crystallised state. Subtractive operations based on Boolean operations are informed by a hylomorphic logic where the material volumes used are completely inert (DeLanda, 2002). As the characterisation of homogeneous materials, such as steel, is industrially defined, the integration of their mechanical behaviour within a simulation framework is relatively straightforward at the resolution needed for design purposes. Material standardisation means assuming that all the industrially-graded steel beams of the same type behave in the same way. In more complex materials such as synthetic fibre composites (*e.g.* carbon fibre), the layup is specified based on the performance requirements and, therefore, their behaviour is known from the design stage. In "found", heterogeneous, materials such as timber, however, this information is not readily available and generalisations are only partially possible due to the material variance occurring even in trees from the same species because of a combination of both internal and external factors. While there is variability across specific grades of steel as reported in their specification tables, the characterisation of timber components shows a much greater variance partly because these are treated like homogeneous elements. Reducing such a variance implies considering the material in its heterogeneous nature and including relevant additional parameters that can be used to construct a more accurate simulation of its behaviour.

For this reason, establishing and evaluating a simulation model for timber manufacturing operations requires gathering as much information as possible regarding the specific piece of timber which is going to be utilised at the fabrication stage. A first approach consists in collecting this information before production and compile it into a simulation framework that allows exploration without the need of physically engaging with the material. In the timber processing industry, Computed Tomography (CT) is used for the commercial grading of raw material and identification of "defects" such as knots which are detrimental for the homogeneity of the material, decreasing its value (Wei, Leblon and La Rocque, 2011; Fredriksson, 2014). The level of information about the tree's internal structure obtained with this method is highly detailed (***Fig. 2.9***), however, because of its high operational costs and complexity, this is rarely used in the timber manufacturing industry after the log leaves the sawmill (Menges, Schwinn and Krieg, 2016). A second approach, closer to how craftsmen operate, is to gradually develop an understanding of materials through direct engagement, where each operation performed brings further knowledge that can be used to adjust the overall process.

(a)
(b)

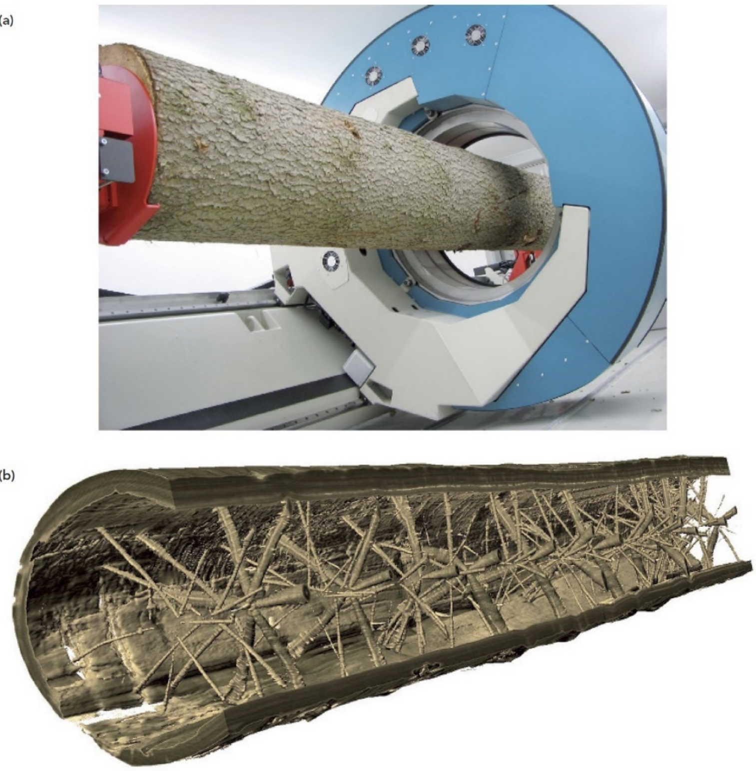


Figure 2.9 "Log computer tomography: advanced wood scanning techniques include (a) computer tomography, (b) which results in comprehensive, three-dimensional anatomic datasets of the log - Udo Sauter, FVA Freiburg" – Source: Menges, Schwinn and Krieg, 2016.

An example of this is found in the work of the artist Giuseppe Penone who created several art pieces starting from a solid trunk and carving out material following the tree's internal structure (***Fig. 2.10***) to reveal how the tree looked like at an early stage of its growth (Basualdo, 2019).

Carpo (2015) draws a parallel between the search of design solutions of pre-industrial craftsmen to iterative digital simulations as both based on heuristics and trial-and-error procedures. The advantage of simulation over physical making is that designers can make and break in few hours way more full-size trials of a design than a craftsman would be able to physically test in her or his entire life. Bringing these considerations a step further in the field of big data and learning systems, he argues that digitally-simulated models can be used to create a database of precedents if the experiments or design task has no previous comparable body of work from which gathering information, such as the robotically-wounded fibre Research Pavilion 2012 by the ICD and ITKE Institute at the University of Stuttgart (Waimer et *al.*, 2013).

Figure 2.10 Artist Giuseppe Penone carves a tree to reveal its inner structure – Source: Celant et al., 2013.

Nevertheless, if there are no comparable precedents in literature and there is no access to physical tests of the system explored, the main issue is to retrieve the knowledge necessary to validate the results of the digital simulation (*e.g.* Finite Element Analysis). This issue is addressed by Turkle *et al.* (2013) using a peculiar case study which is the simulation strategies adopted by the US in the field of nuclear weapons. The ban of nuclear testing in 1992 created a generational divide between those scientists who had experienced first-hand the explosion tests and a younger generation who could engage with such events only through a simulation based on the knowledge formalised by the first group. Given the complexity of the event, the veracity of the simulation is nearly impossible to be tested and, even in that case, there is no way of validating it with actual proofs. As simulations grew increasingly opaque, undermining trust in scientific findings, it has been necessary to avoid losing the personal knowledge of older scientists about to retire through the creation of a videotaped interview collection, organising an oral history of nuclear testing that could support the creation of simulation models.

The problem of acquiring knowledge, whether direct or indirect, to validate a simulation model is also central in the field of manufacturing where, in comparison to nuclear testing, data is abundant and readily available. Taking advantage of this, the approach explored in this thesis is to gradually build a knowledge base from the acquisition of sensor data with the aim of validating the simulation model through an inductive method.

2.2 Making Knowledge

2.2.1 Knowledge in Craftsmanship

The integration of materiality in design and manufacturing processes is strongly dependent on knowledge and its different formalisations which make it accessible to the participating stakeholders.

The process of *deskilling* refers to the progressive elimination of skilled labour determined by the increasing adoption of automated production systems within the manufacturing industry (Braverman, 1974). For Gordon (1988), the widespread use of steel as material is only partially due to technical reasons while is mostly dependent on its applicability within routinised design processes which relies on its standardisation to require the minimum amount of skills and knowledge. On the other hand, heterogeneous materials cannot be reduced to routines and require the integration of high-level knowledge which is difficult to formalise (De Landa 2002).

One of the main concerns in the process of knowledge transfer from human workers to automated means of production regards the loss of know-how determined by the impossibility of fully transferring human personal knowledge to a machine. The concept of tacit knowledge has been introduced by the philosopher Michael Polanyi (1966) to refer to that portion of subjective and non-codified knowledge which we cannot fully articulate, opposing the generally accepted notion that knowledge must be necessarily explicit (Sorri, 1994). While explicit knowledge can be codified and transferred, tacit knowledge cannot be communicated as *"we always know more that we can tell*" (Polanyi, 1966) and its acquisition requires practical experience through observation and direct participation (Eraut, 2000).

For Nonaka (1998), there are two dimensions to tacit knowledge: the first relates to the knowledge of skills, for instance riding a bike, and constitutes the personal "*know-how*", the second is the cognitive dimension composed of beliefs and mental models which shapes our perception of the world. Humans acquire new skills through experiential learning whereby "*personally experienced events are stored in episodic memory and, over time, used to construct generalised knowledge structures in semantic memory*" (Kolb, 1984). Such knowledge, posing the foundation of the personal know-how of every skilled craftsman, does not become formalised despite being used in everyday practice. Rather than having a codified constitution, the understanding of materials and processes is achieved through "*workability and practice*" (McCollough, 1996).

For each task approached by a craftsman, there are different evaluation criteria, for instance, aesthetic qualities, costs efficiency, technical procedures and material consideration involved that "*operate as positive forces for action not determinants of outcome*" (Keller and Keller, 1993). The experience knowledge of a craftsman, accumulated through years of practice, enable addressing these *dimensions* to create an original plan of action. However, as discussed by Sharif and Gentry (2015), this preconception only initiates the task, while the "*the design concept evolves concurrent with the craftsman's act of production and the received feedback from the evaluation of material and objective conditions of the work*".

Pye (1968) distinguishes between workmanship of *risk* and *certainty* to oppose traditional craftsmanship to industrial manufacturing. During the making process in crafts practice, the quality of the artefact is continuously at risk as it is based on the "*judgement, dexterity and care*" of the craftsman and the outcome is not predetermined. The uncertainty of the process, unfolding as the artefact is being made, determine its inherent fluidity and enable the exploration of solutions not available from the beginning. While designers utilise all their knowledge to codify information into a set of instruction drawings before the production stage, craftsmen are required to continuously utilise their knowledge at each step. Such distributed exertion of knowledge not only allows a constant adjustment of her or his action based on the contingencies of the process, but every bit of feedback information leads to reformulating the initial knowledge that initiated the task as assumptions are constantly questioned and evaluated.

2.2.2 Capturing Tacit Knowledge in Manufacturing

According to the *SECI Model* for knowledge transfer and conversion introduced by Nonaka and Takeuchi (1995), there are four main modes how tacit and explicit knowledge is created and shared within an organisation (***Fig. 2.11***).

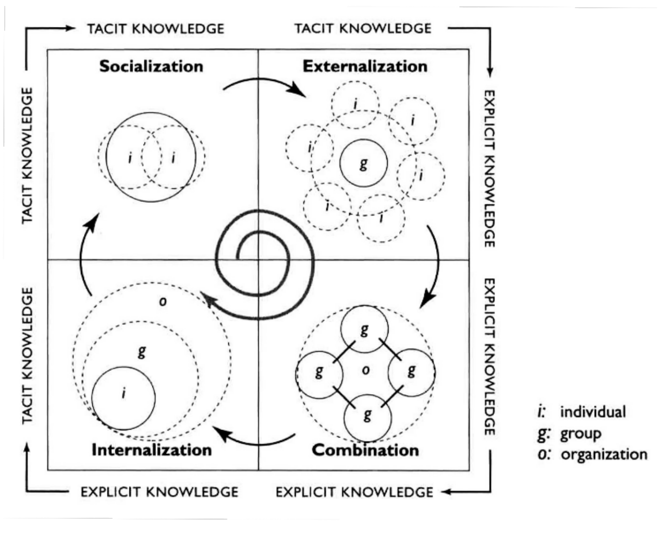


Figure 2.11 "Spiral Evolution of Knowledge Conversion and Self-transcending Process" – Source: Nonaka and Konno, 1998.

The first two deal with the transmission of tacit knowledge between individuals through imitation and observation (*Socialization*) and the attempt of its codification to turn it to explicit knowledge (*Externalization*). The second two are focused around explicit knowledge, which can be easily codified and combined to create new knowledge (*Combination*) and the assimilation of explicit knowledge and procedures into individual tacit resources (*Internalization*). One of the pioneering studies on recording human bodily motion within manufacturing environment conducted by Frank and Lillian Gilbreth led to the development of a recording and analysis technique named micromotion study (Gilbreth and Gilbreth, 1917). Recording with a camera the motion of humans performing the task with the help of light sources to track long sequences of operations (***Fig. 2.12***) enabled the creation of a scientific understanding of the task based on the approach chosen by the worker, introducing improvements based on scientifically-measured performances (Baumgart and Neuhauser, 2009). Furthermore, it could be used to expose other workers to such an improved understanding of the task (*Socialization*, SECI model) for training purposes.

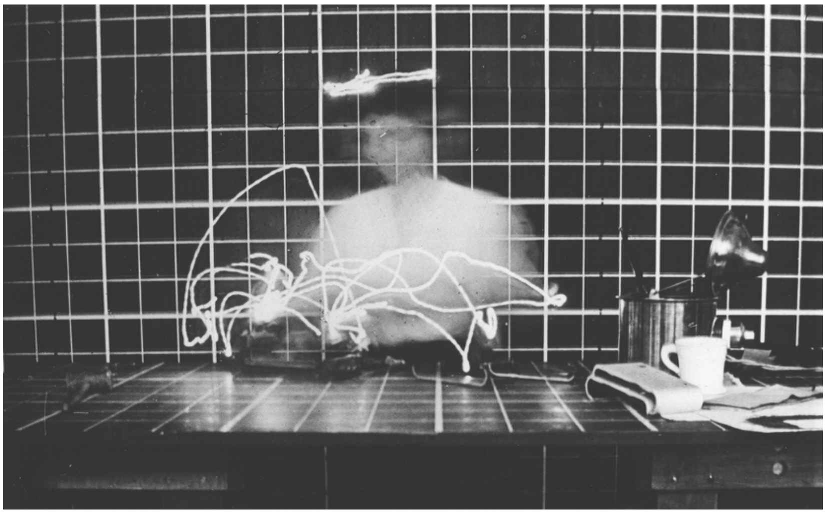


Figure 2.12 "Cyclegraphic Image of a Woman Working at a Gridded Table" - Source: Gainty, 2016.

While a master craftsman transmits knowledge mostly through *Socialization*, the transmission of human know-how to a machine within a manufacturing context requires an *Externalisation* process to turn it, at least partially, explicit into a transmissible form that could be used to program a machine. According to the American historian David Noble (1984), the development of the Numerically Controlled (NC) system for the manufacturing of mechanical parts, developed in the US immediately after the WWII, required to develop i*)* a mechanism to translate electric power to controlled motion and *ii)* a medium on which information can be stored and read later by a machine. As further discussed by Callicott (2003), the earliest attempt to develop automated machine tools sought to codify into a numerical transcription the "*dexterity, experience and intuition embodied in the skilled act*" of experienced human machinists. The first solution proposed to address such challenge is represented by the *Record/Playback* system developed in 1946-47 by General Electric. The solution focused on recording on magnetic tape the totality of operations and motions performed by a skilled machinist operating a modified lathe with the aim of using the numerical transcript to manufacture further identical parts (Noble, 1984). According to Callicott, this solution represents the attempt of distributing individual tacit knowledge to an automated system through its replacement with explicit rules, maintaining at the same time its link to the tacit identity of the maker. The NC system, developed in parallel at MIT and presented in 1952, was specifically aimed to separate completely such reliance on the tacit dimension of individual skills of the workforce, circumventing "*the role of the machinist as the source of the intelligence in the production*" with the intent of shifting the control over the manufacturing process from the shop-floor to the managerial level (Noble, 1984). With the definition of fabrication parameters into a software interface, the machinist is asked to externalize his tacit understanding of the task into an explicit form (Callicott, 2003).

In the recent years, several studies in the field of manufacturing have argued for the transfer of human tacit knowledge as a necessary step to automate tasks which still requires a high level of dexterity and constant parameters adjustment based on feedback information. The following analysis of relevant precedent aimed to address a series of methodological questions faced by this research in the process of defining a strategy to capture and formalise the knowledge of skilled human experts performing carving operations on timber.

- *How is it possible to break down a manufacturing task and extract relevant knowledge at each stage?*

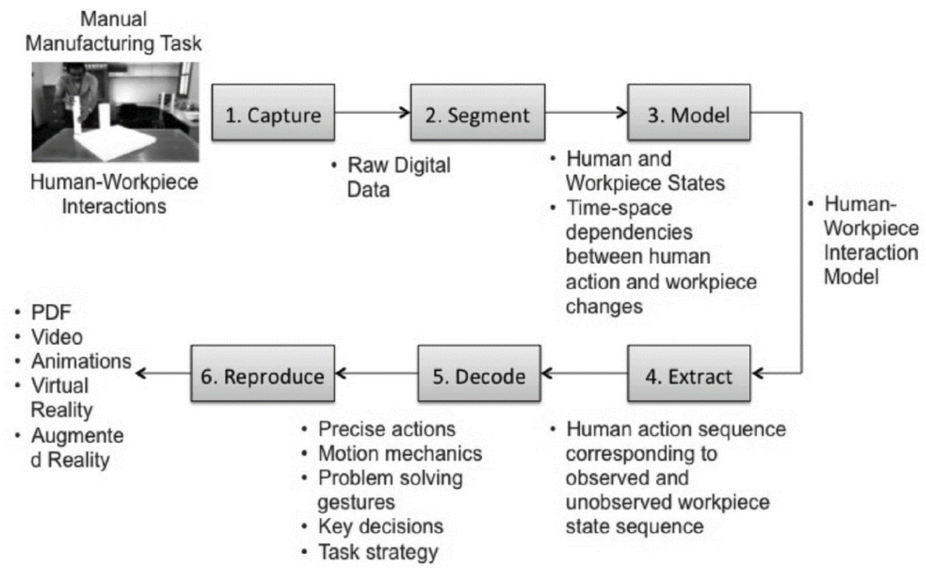


Figure 2.13 "6-step Digitisation Process" – Source: Prahbu et al. (2017)

Prahbu *et al.* (2017) presented a method to acquire skills for fibre composites layup from human experts and transfer them to novices or automated manufacturing systems. The study started identifying the key components of the task, for instance, the ply manipulation technique and utilised 3D scanning technology (*i.e.* Microsoft Kinect) to digitise the interaction between the expert's bodily motion and the workpiece. Such information is formalised in a series of discrete states and used in a Hidden Markov Model, a stochastic machine learning model to predict time series phenomena, with the aim of extracting manufacturing knowledge for each component of the overall manual layup task (***Fig. 2.13***).

- *What is the influence of expertise and subjective knowledge in the recording of human-based tasks?*

  Another study in the field of fibre-reinforced composites by Kikuchi *et al.* (2014) compared two human workers with significantly different levels of expertise performing the task of spraying up a mould. Tool and human's body motion were recorded using an optical motion capture camera system, while the tracking of the eye movement was capture with a goggle-like apparatus worn by the participants. The comparison between the data collected by recording the two workers made possible to identify key aspects of tacit knowledge developed by the more skilled craftsman in years of experience which allowed him to complete the task more efficiently and with better quality in the final product than the novice. Data generated by the skilled human demonstration could be then processed and translated to robotic movements, avoiding programming the task entirely from scratch.

- *Is it possible to inform a robotic fabrication task based on captured human knowledge and what are the main advantages?*

  In-contact subtractive manufacturing tasks are complex and diverse processes which require several years of experience by a human operator to maintain control over a series of key parameters which defines the surface quality of the product. For manual grinding tasks, Ng *et al.* (2014) identify a series of Key Process Variables (KPVs) such as contact force, toolpath and feed rate, which are recorded and used to generate an analytical material removal model which encapsulate the surface finishing skills of the operators. The key advantage of the methods is to reduce the need for costly robotic Design of Experiment (DoE) trials to develop an empirical model of the task. Polishing operations are particularly relevant for some industries, such as aeronautics, as it significantly affects the performance of the final manufactured part. Kalt, Monfared and Jackson (2016) developed a device that facilitates the capturing of data during manual polishing operations. The tool consists of a combination of different sensors such as multi-axial force-torque sensor, an inertial measurement unit monitoring the orientation of the piece together with a measure of vibrations and a combination of reflective markers used within a motion capture cameras system to record the part movements and polishing patterns (***Fig. 2.14***). The recording of skilled operators in a series of experiments led to the identification of recurring patterns (*e.g.* constant pressure, linear translation and surface profiling) utilised to complete the task. The identification of the patterns, described by a combination of different sensor data, together with an understand of the type of required feedback, mostly visual and tactile, represents the foundations to develop a robotic polishing system.

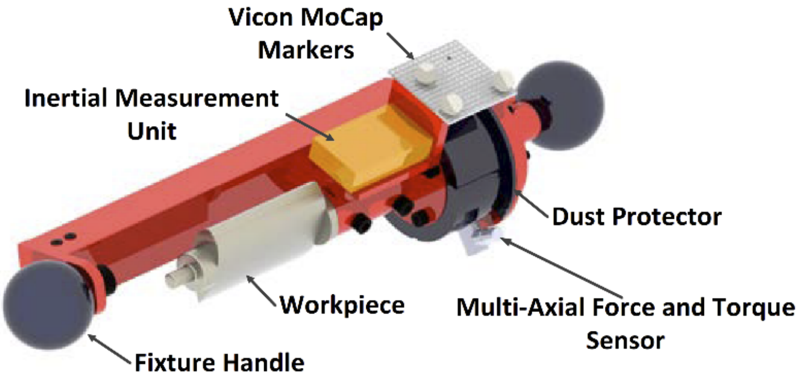


Figure 2.14 "Design of the fixture to capture manual polishing" – Source: Kalt, Monfared and Jackson (2016)

- *What are the main parameters to consider in carving operations performed with chisels or gouges and how these can be recorded?*

  Steinhagen *et al.* (2016) presented a series of methods for the recording of manual stone surface chiselling with the aim of informing a robotic fabrication system. Their analysis compares several manual traditional techniques measured with a high-speed camera system (*i.e.* GOM Pontos HS). The recording of the hammer's movement and speed made possible to extract the kinetic energy utilised by the craftsman for each operation, while the same camera setup has been used to calibrate the robotic chiselling end-effector, ensuring the correct translation of the kinetic energy values across the two different domains (***Fig. 2.15***). The comparison of chiselling operations for different types of stones allowed the identification of the correlation between kinetic energy and material removal volume for each configuration, generating an understanding of how material properties influences the outcome of manual and automated subtractive techniques (Steinhagen and Kuhlenkötter, 2015).

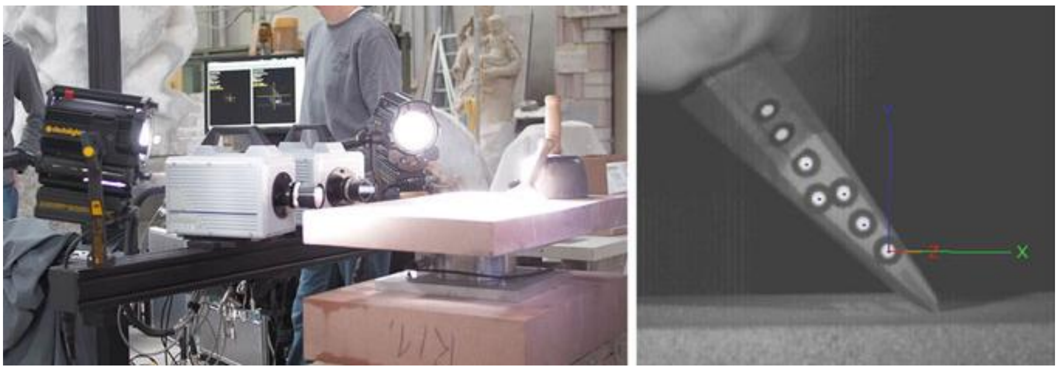


Figure 2.15 "Setup of the camera system with camera and stone specimen for chiselling (left), Picture of a filmed chisel with the measured coordinates (right)" – Source: Steinhagen et al. (2016).

2.2.3 Computer-Aided Process Planning

The integration of expert knowledge through the *Combination (SECI Model)* of rules, procedures and specifications for subtractive operations into software have been gradually implemented into design-to-manufacturing software under the term *Computer-Aided Process Planning* (CAPP).

CAPP methods supported by a knowledge base seek to determine the sequence and parameters of manufacturing processes to efficiently produce a part (Ham and Lu, 1988; Alting and Zhang, 1989) based on the domain expertise available to the planning system. Some of the typical aspects of CAPP are described by Park (2003) as "*manufacturing features recognition, assigning machining operations to each machining feature, sequencing machining operations, set up and fixture, planning, and NC generation"*.

Automatic features recognition methods aim to break down a solid geometry into individual features and match each of them to a previously defined catalogue of geometries supported by the software (Verma and Rajotia, 2010). The concept of *machining feature* is particularly relevant in knowledge-driven processes as it represents a strategy to map a set of geometrical features to a set of manufacturing operations (Mawussi and Tapie, 2011), directly linking the stages of design and fabrication.

The most pressing issue around such activities is the creation of a knowledge base that would reflect the experience of a domain expert. Imitating such intelligence is necessary to support the sequence of the decisions of the automated system:

> *"…the solution space of process planning is too extensive for searching in an exhaustive manner, which is why the imitation of intelligence is necessary. No matter how extensive the solution space, a human expert can find a reasonably good solution in a feasible time by quickly decreasing the solution space. The logical procedure for decreasing the solution space without losing reasonably good solutions involves the intelligence of domain experts."* - Park (2003)

Referring to the *SECI Model*, the integration of domain expert knowledge within CAPP software could be structured in two main strategies:

- *Combination*: The software provides access to an extensive database compiled by expert and collecting cutting data such as machining features strategies, tools and machine specifications or fabrication parameters.
- *Externalization*: Integrating personal knowledge with the addition to the databases of the specificities of the shop floor. Preserving the machinist know-how and expedite the programming of known machining procedures. Each machinist can create personalised templates for collection of operations to achieve predefined geometrical features.

These methods could potentially provide the opportunity to constantly expand the capabilities of the system and refine the initial knowledge base. Nevertheless, despite their several advantages, the requirement of strictly organising knowledge by predefined categories, its description by a limited range of parameters and the compulsory use of standard machining techniques significantly reduce the applicability of these tools. On the one hand, the link between geometric features and machining operations expedite the toolpath planning process and programming of operation but, on the other, it strictly determines the range of shapes available and their modelling requirements. As it is not possible to define all the possible geometric features and their possible combinations, these methods are often incomplete and require substantial adjustments by a skilled human operator (Kiritsis,1995; Marri, Gunasekaran and Grieve, 1998; Xu, Wang and Newman, 2011).

2.2.4 Design for Manufacturability Feedback

A critical aspect of Knowledge-based CAPP systems is the formulation and communication of design feedback determined by manufacturability considerations. Design for Manufacturability (DFM) is defined as the process of designing products focusing on the optimisation of manufacturing functions, such as fabrication, assembly or testing, to ensure the lowest cost of production and highest quality of the final product (Anderson, 2014).

As discussed by a number of scholars in the field of manufacturing (Gupta *et al.*,1997; Barnawal *et al*., 2015), the increasing specialisation and distribution of knowledge over large teams of professional hinder the communication between different functional teams involved in the design-to-manufacturing workflow. As design engineers do not necessarily possess manufacturing knowledge, the designed product might satisfy functional requirements while resulting not suitable for the production stage. For this reason, the design team relies on the manufacturability feedback given by the manufacturing engineers and the design evolves through multiple iterations of such a process which end up in a lengthy development stage and delays in the production. Furthermore, as decisions taken at an early design stage are critical as any change made at a later manufacturing stage results increasingly more and more expensive (Verhagen *et al.*, 2012), it is necessary to provide designers with a DFM automated tool which enable them to receive feedback on a given manufacturing technique from the beginning of the design process and swiftly evaluate multiple solutions without delaying the development of the product (***Fig. 2.16***).

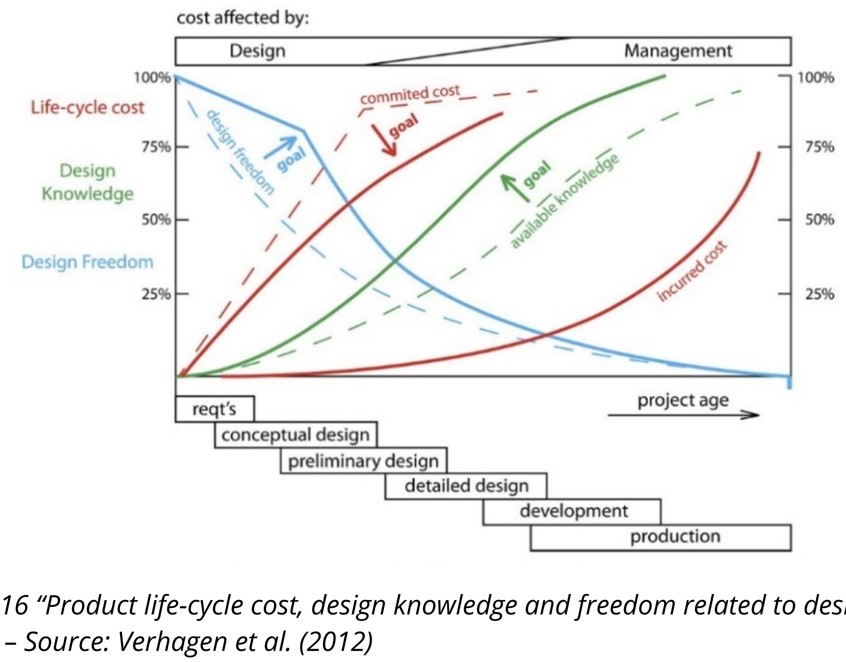


Figure 2.16 "Product life-cycle cost, design knowledge and freedom related to design process" – Source: Verhagen et al. (2012)

In a "*What-If*" design development approach (Vaneker and van Houten, 2006), designers are supplied with continuous, automated, DFM feedback at every alteration of the design, making possible to evaluate the quality of the design instance provided and compare the effects of the applied changes further down the process. Feedback information can be formulated in many different forms such as text, 2D drawings or 3D visualisations and could prompt the designer to check, for instance, the match between product's shape and chosen material, geometrical adjustments based on process constraints or availability of the necessary production tools within the company's supply chain.

According to Gupta *et al.* who put together a comprehensive survey of the available DFM feedback systems (1997), the automated manufacturability problem is generally divided into three steps: i) Determine if the design is manufacturable; ii) If manufacturable, define its manufacturability rating which represents an evaluation of the difficulties of manufacturing the product; iii) If not manufacturable, identify what design attributes determine the issue and propose solution. Performing automated manufacturability analysis integrated into intelligent CAD systems allows designers to focus on the creative aspect of the process without having to memorise manufacturability checklist or material specifications (Ferrer, 2010; Verhagen *et al.*, 2012).

In concurrent engineering, the design of a mechanical part in aluminium for the automotive industry, for instance, is fully integrated with DFM feedback, making possible to significantly increase the efficiency of the overall workflow. If a simplified version of the process is to be considered, in the first stage, manufacturability is defined according to a series of evaluations focused around parameters such as shape, bounding box dimensions, tools accessibility, tolerances and finishing requirements. Some of these parameters determine in a binary way whether the product is machinable or not. For instance, if its size exceeds the workable volume of the machine available, the design is not manufacturable. If the design passes the first stage, the design is deconstructed in the individual machining operations necessary to obtain the final geometry and an analysis of their complexity determine the difficulty of fabrication and costs approximation. If a design does not pass the first stage, the design attributes responsible for the failure are highlighted. For machined parts, typical issues are using right-angle corners for internal pockets, not considering the minimum tool radius diameter, or placing geometric features in areas not accessible by the tools due to specific machine limitations, for instance, a limited number of mechanical axes. The individual analysis of features of the second stage allows comparing individual production time and costs, prompting valid alternative and costs/benefits charts to the designer to support the decision-making process.

The formulation of DFM feedback for specific manufacturing process with standard materials, such as metal machining, has been developed throughout decades of applied research with an increasing crystallisation of the range of analytical procedures available. While these could undoubtedly have a significant impact in reducing production time and costs, the rigidity of the protocols necessary to establish for benefitting from this approach (*e.g.* definition of a codified range of design features) hinders the adoption of similar methods within design practices dealing with more open-ended and explorative design strategies using non-standard materials and tool affordances.

2.2.5 Instrumental Knowledge in Design Practices

From the perspective of design practices, the early access to *instrumental knowledge*, defined by Witt (2010) as an understanding of the set of procedures necessary to operate a technological mean toward an intended outcome, through DFM feedback represents the opportunity of linking the design and manufacturing stage within an integrated production process. This type of knowledge enables the creation of "*systems of interrelated technologies intended to facilitate the aims of design*" and its encapsulation into a design/fabrication/construction system allows making it "*easily accessible, communicable, repeatable, hackable and transformable*" (Witt 2010). One of the examples he proposes, referencing Lynn (1999), is the encapsulation of calculus-based mathematics which makes possible for designers to operate with NURBS curves in a 3D modelling software without really having to explicitly acquire that type of mathematical understanding.

The integration of knowledge within an interface allows the designer/user to continuously query it and have in return a validated design simulation directly informed by operative constraints encapsulated in the tool itself. Access to knowledge does not necessarily imply an understanding of it by the final user: the knowledge could only be possessed by the tool-maker, *e.g.* the software developer, yet support any design endeavour if appropriately integrated into the tools available to the designer. Eventually, as discussed in **Chapter 6**, neither the tool-maker and designer-user might have a full understanding of the instrumental knowledge made available as this can be captured, transferred, augmented and integrated without necessarily becoming fully explicit during any step of the process.

2.3 Learning Systems

2.3.1 Machine Learning in Manufacturing

One of the key challenges in manufacturing today is the management of risks due to the increasing complexity of technical aspects of production, processes organisation and business logistics (Wiendahl and Scholtissek, 1994). The acquisition of a large amount of data for monitoring, diagnostic, scheduling and optimisation of the production process has been increasingly adopted as one of the most compelling strategies to mitigate such risks (Monostori, 2002; Harding, Shahbaz and Kusiak, 2006; Larose and Larose, 2014).

As manufacturing environments produces data in large amounts and different varieties, one of the inherent challenges of such a strategy is the ability and capacity of collecting, storing, parsing and ultimately making sense of such high load of information (Monostori, Márkus, Van Brussel, and Westkämpfer, 1996; Wuest *et al.*, 2016).

The development of automation at an information level, such as Computer Numerically Controlled (CNC) systems, made possible to increase the efficiency of manufacturing processes, however, as discussed by Lu (1990), the necessary next step of automation development should concern the knowledge level, where computational processes, supported by a large amount of data collected, will be used to "*improve productivity of critical decision-making tasks in design and manufacturing*". The transition from information-intensive to knowledge-intensive systems implies the development of technologies which not only generate and retrieve information but also synthesise knowledge and its integration to support decision-making procedures.

One of the key requirements for the synthesis of knowledge is the ability to continually adapt and reconfigure based on collected data to face the constantly evolving and rapidly changing condition of contemporary manufacturing environments. The definition of learning systems given by Simon (1983) addresses this specific requirement: "*Learning denotes changes in the system that is adaptive in the sense that they enable the system to do the same task or tasks drawn from the same population more effectively the next time"*. As argued by Winston (1980), the adaptability of learning systems is achieved through the creation of mental models which are gradually improved through observation and experience to generate an understanding of the environment which directly determines individual performances.

Machine Learning (ML) models have emerged as promising candidates to achieve the transition from information-intense to knowledge-intense systems in manufacturing (Whitehall and Lu, 1991; Monostori, 2002; Hansson et al., 2016). ML consists in programming computational models to achieve an assigned task based on the collection of data and past experiences (Alpaydin, 2014). The advantage of using such an approach in manufacturing is the ability of such systems to find "*highly complex and non-linear patterns in data of different types and sources and transform raw data to features spaces, so-called models, which are then applied for prediction, detection, classification, regression, or forecasting*" (Lu, 1990). In this way, it is possible to identify implicit relationships within the dataset and access previously unavailable sources of knowledge.

Inductive learning, based on the generation of generalised statements out of many examples provided to the system (Duffy, 1997), is particularly suited for all those tasks which are data-rich but knowledge-sparse, as usually it is the case for problems in engineering and manufacturing. Such an approach seeks to fill in the gaps of a specific knowledge domain and is compared by Lu (1990) to the synthesis task that engineers perform within decision-making processes. Michalski (1983) argues that a promising application of inductive learning is for the refinement of knowledge bases initially developed by human experts, where it could be used to *"detect and rectify inconsistencies, to remove redundancies, to cover gaps, and to simplify expert-derived decision rules*" (Michalski, 1983).

One of the advantage of synthesising knowledge from manufacturing applications is that most of the collected data in production environment is already structured and labelled, which makes it suitable for a type of inductive learning defined as "supervised", where the model learns "*from examples provided by a knowledgeable supervisor*" (Sutton and Barto, 2014) who provides, during the training, the pairing between input and output data. One of the most popular categories of models for supervised learning in manufacturing is called Artificial Neural Network (ANN) (Zhang and Huang, 1995; Monostori, 2002).

In the next section is presented a review of the advantages and disadvantages of ANNs in manufacturing applications through a series of case studies while a technical description of the algorithm is presented later in **Chapter 4** to provide the reader with a more in-depth understanding of the learning mechanisms applied during the training workflow for robotic carving operations.

2.3.2 Applications in Subtractive Fabrication Strategies

One of the main challenges presented by subtractive processes, especially in metals machining, is the difficulty of creating a simulation framework that would make possible to increase the amount of control over a broad and diverse range of production techniques. In these regards, the main risk of using an analytical approach is using sets of simplified assumptions which are not able to fully describe the interplay of different factors involved in the production, rendering it unusable for real-world applications. Luttervelt *et al.* (1998) argue that the only viable method to modelling is to adopt an empirical approach based on the collection of qualitative (*e.g.* machinist domain knowledge) and quantitative information (*e.g.* fabrication parameters data) during the performing of the machining process.

While statistical regression techniques are widely used in the field of manufacturing, the key advantage of ANNs for subtractive applications is their ability of identifying complex non-linear relationship and patterns among large quantities of collected data, resulting in a significant improvement in the prediction accuracy rate of production parameters and qualities (Tsai, Chen and Lou, 1999). Another advantage of using ANNs is that the training does not require any preliminary assumption about the process or mechanism sought to be modelled and it is possible to expand the model, for instance with additional input parameters or collecting larger experimental datasets, without altering the structure of the model itself (Zain, Haron and Sharif, 2009).

Several studies have collated and compared ANNs applications for metal machining tasks, providing an understanding of the modelling strategies adopted across the industry (Pontes *et al.* 2010; Razak *et al.*, 2010; Al-Zubaidi, Ghani and Haron, 2011). The main variables sought to be predicted are **i)** surface roughness, **ii)** tool wear, **iii)** cutting force and **iv)** material removal rate. The main features used in literature to predict those variables are **a)** cutting speed, **b)** feed, **c)** depth of cut (***Fig. 2.17***).

These factors affect significantly the efficiency of the production process as they concern either the quality of the final product or the monitoring of the machine and tools used. The predictors, namely the fabrication parameters used for the prediction, are strictly dependent on the task, as their relevance might vary according to different techniques. Nevertheless, parameters such as cutting speed, feedrate, depth of cut are taken into consideration in most of the applications.

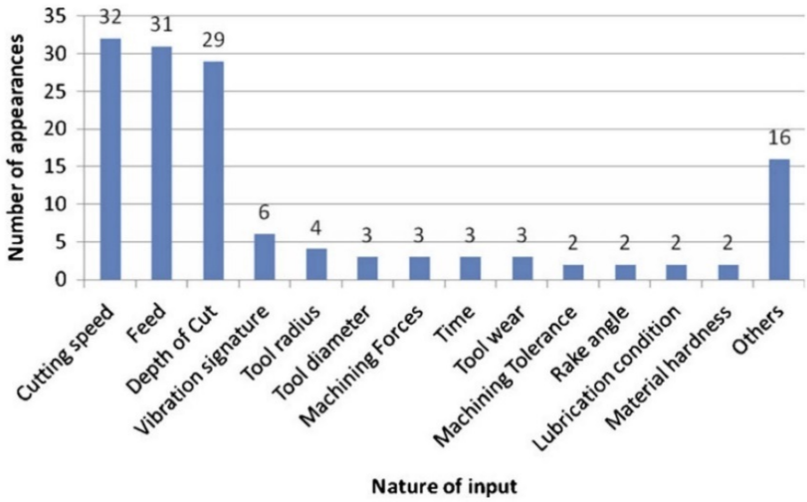


Figure 2.17 "Nature of predictors employed in model building" – Source: Pontes et al., 2010.

Other relevant parameters are related to specific sensor devices, such as vibration signature or cutting force components, or physical components and properties, such as material and size of the cutting tool, workpiece hardness and lubrication condition. While in the considered machining tasks the workpiece is devised as a homogenous block of matter, also reflected in the parameters chosen to describe each individual task (**Fig. 2.17**), this research proposes to include material-specific parameters that could describe the heterogeneous nature of the material and its impact on the fabrication process. According to the survey conducted by Pontes *et al.* (2010) on ANN-based strategy for machining applications, the development of the model is generally structured in 5 stages (***Fig. 2.18***):

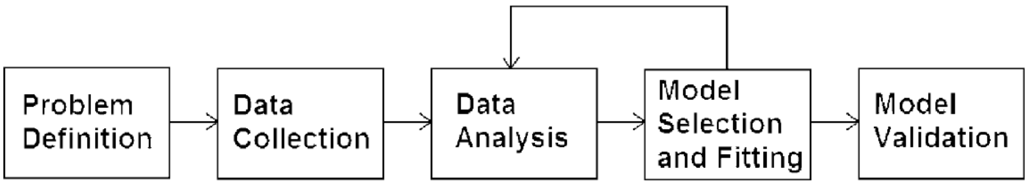


Figure 2.18 "Forecasting process" - Source: Pontes et al., 2010 (adapted from Montgomery et al.2008)

1) **Problem Definition**: Specification of the variable to predict, the predictors, namely the independent variable used for the prediction, and definition of the intended use of the trained model in the production environment.

2) **Data Collection**: Definition of the techniques and devices (*e.g.* force-torque sensors, laser scanner) used to collect meaningful data for the description of the subtractive operation.

3) **Data Analysis**: Series of processing steps to transform the collected data into useable information for the training process.

4) **Model Selection and Training**: Definition of the model topology (*e.g.* the number of layers and neurons), parameters and training process.
5) **Model Validation**: Application of the trained model to predict a series of new cases, excluded from the training, to provide a performance measure and assess its quality.

For instance, surface roughness is one of the parameters affecting the most manufacturing costs as it directly determines not only the aesthetic quality but also several mechanical properties such as friction ratio or resistance to corrosion (Stark and Moon, 1999). Bernardos and Vosniakos (2002) have identified the series of parameters which affects the surface quality (***Fig. 2.19***) and used them for its prediction for face milling operations on aluminium.

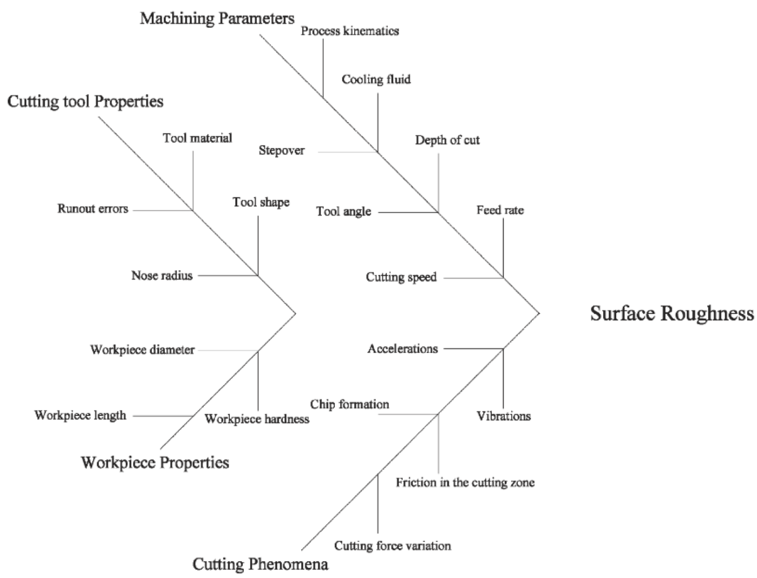


Figure 2.19 "Fishbone diagram with the parameters that affect surface roughness" – Source: Bernardos and Vosniakos, 2012.

A further set of applications of ANNs in subtractive strategies is focused on the prediction of manufacturing conditions for diagnostic and maintenance purposes. The prediction is structured as a binary classification task which aims to predict whether a specific event would occur given an input set of conditions such as fabrication parameters and relevant status descriptors. ANNs models have been applied in several studies (Li and Elbestawi, 1996; Chen and Jen, 2000; Dimla Sr. and Lister, 2000; Balazinski *et al.,* 2002) to predict with high accuracy the status of the tool (i.e. wear level measure) and whether it would break during the machining operation.

Together with the several advantages of ANNs described above, Zain, Haron and Sharif (2009) argues that the main limitation of such modelling approach for machining applications consist in the necessary collection of empirical data which could be costly and time-consuming as the amount of data provided to the system directly affect the prediction performances. Furthermore, as ANNs are based on stochastic procedures, the repeatability of the training parameters across different version of the model is not assured.

2.3.3 Machine Learning as Design Tool

In machining applications, machine learning models are used for the optimisation of task to reduce costs and time, and it involves the fine-tuning of production parameters or physical configurations of the machine, the cutting tool or blank of material. As such process takes place only at the fabrication stage, the solution proposed by the trained system never involves alterations of the design of the object to be manufactured, significantly limiting the range of solutions available. Nevertheless, since the synthesis of design solutions directly depends on the knowledge of the designer, it would be beneficial to support crucial early-stage design decisions with an automated system that can provide knowledge acquired through induction from previous examples relevant for the specific task (Potter *et al.*, 2011).

As already argued by Negroponte (1975), learning systems could have a significant impact if integrated within the design process as designers, especially architects, cannot handle large-scale problems because too complex or small-scale ones as they are too individual and specific. As such systems could gain experience over time, the aspiration is to establish a dialogue and partnership between two intelligent systems, the learning machine and the human designer:

> "*Imagine a machine that can follow your design methodology and at the same time discern and assimilate your conversational idiosyncrasy. The same machine, after observing your behavior, could build a predictive model of your conversational performance. Such a machine could then reinforce the dialogue by using a predictive model to respond to you in a manner that is in rhythm with your personal behavior and conversational idiosyncrasies*."
>
> — Nicholas Negroponte, 1970.

With the greater availability of data and computational power, machine learning models are becoming increasingly integrated within design-to-manufacturing workflow as they can provide precious insight on the overall process and guide the exploration of solutions, otherwise unavailable, through the simulation of scenarios based on different type of analysis such as structural, environmental, functional or material-based considerations.

According to Duffy (1997), a design system not able to learn provide a static source of knowledge to the designer which is destined to become obsolete if not continuously updated by further knowledge and identifies machine learning as an effective strategy to aid the synthesis of design solutions and provide guidance supported by relevant domain expertise.

Hanna (2007) utilises inductive machine learning (*i.e.* Support Vector Machine) to optimise the design of modular lattice structures to evaluate decisions based on a structural performance analysis of previously generated structural examples, deriving a function that directly maps between an assigned load condition and an optimal lattice configuration. Using a similar approach, Wilkinson, Bradbury and Hanna (2014) presented a method to approximate wind pressure on tall buildings based on local geometric features for generative design explorations and optimisation (***Fig. 2.20***). The machine learning model (*i.e*. ANN) has been trained using a large dataset of computational fluid dynamics data generated with the analysis of 600 procedurally generated tall buildings.

For both studies, the key advantage of such an approach is the significantly increase in computational speed in comparison to time-consuming physics-based simulation models. This allows the integration of the trained system within a design workflow for the rapid evaluation of multiple solutions supported by structural or environmental considerations. The drawback of spending time in generating the initial training dataset is justified for those cases where similar optimisation tasks are required for several design instances and the trained system could be utilised multiple times, guiding each design iteration.

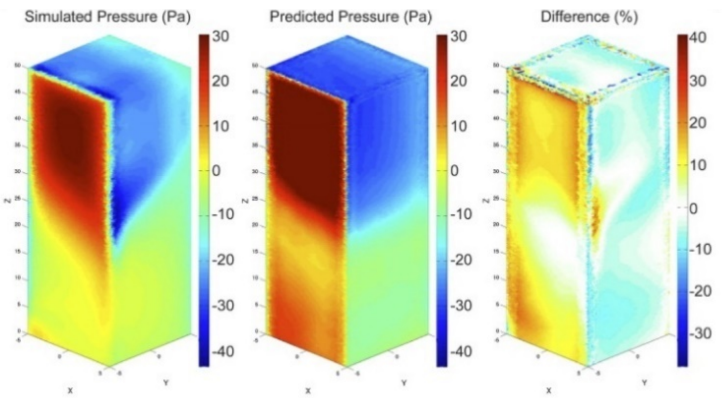


Figure 2.20 "Case 1 – (left) simulation; (centre) prediction; (right) error" – Source: Wilkinson, Bradbury and Hanna, 2014.

ML models, such as Self-Organising Maps (SOM), have also been integrated within design-to-manufacturing workflow for their ability to convert high-dimensional data to a lower-dimensional space. In this way, designers can systematically explore solutions entailing a combination of several parameters conveniently arranged in a 2-dimensional space (Harding, 2016).

Simulation of material behaviour based on heuristics is one key advantage for designer dealing with techniques and materials which have not been formalised at an industrial level or whose behaviour is too complex to be modelled with an analytical, rule-based, approach. Zwierzycki, Nicholas and Ramsgaard Thomsen (2018) proposes the use of a supervised machine learning model (*i.e.* ANN) to predict the spring-back of thin metal sheets in robotic incremental forming processes. The learning process maps between local geometric features of size 5x5 cm encoded as 2-dimensional image-based heightfield (10x10 pixels), together with distance value from the supporting frame, and the depth value of each incrementally-formed point of the panel, acquired via 3d scanning. Such mapping aims to provide a simulation tool evaluating how the material behaviour is influenced by shape-based features and compensating the fabrication process to obtain a product closer to the original design intention described in the digital model (***Fig. 2.21***).

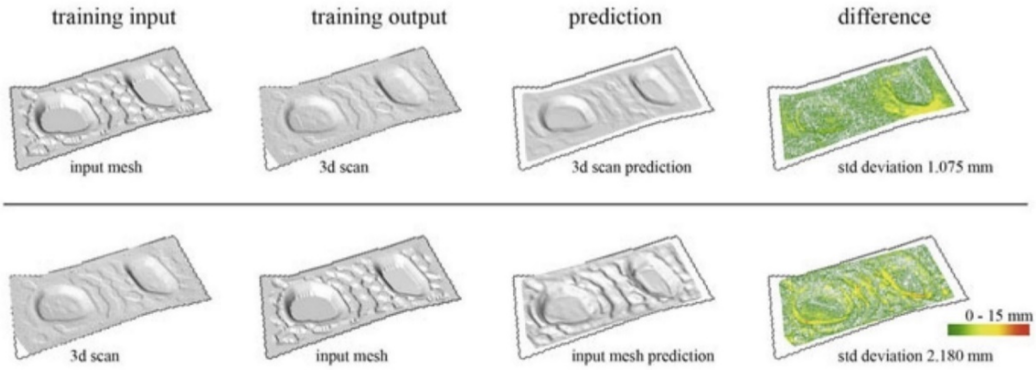


Figure 2.21 "The comparison of different input-output training sets and the achieved accuracy. Top row "forward" prediction, bottom row "reversed" prediction" – Source: Zwierzycki, Nicholas and Ramsgaard Thomsen, 2018.

2.4 Summary

The increasing integration of digital fabrication technologies within design practices is challenging the separation between design and making in current production workflows. A new sensibility toward materials and tool technologies have become a central part of the architectural discourse where designers are asked to envision performance-driven processes bridging between the digital and physical realms rather than focusing on the creation of static forms. Simulation tools and robotic fabrication technologies are regarded as enabling frameworks to establish information feedback loops driving the design and making of artefacts. Moving beyond the *hylomorphic* models requires the development of interfaces which enable designers to seamlessly engage with production processes, providing instrumental knowledge at an early design stage to explore novel solutions based on tools and material affordances.

The degree to which such a knowledge integration is possible, specifically for carving operations on timber, is central to **Hypothesis A** and **B** and it has been addressed in the literature review analysing and comparing different strategies from the manufacturing industry, traditional crafts and design practices.

In human making, the design of an artefact evolves through direct engagement with the process and is driven by individual sensibility, experience and knowledge. The "*design through making*" (Ingold, 2013) approach at the foundation of traditional crafts practices based on what Sennett (2008) describes as "*a dialogue between concrete practices and thinking*", provides a compelling alternative to the notation-based paradigm defining the current separation between design and making in design practices. In the field of manufacturing, the automation of fabrication processes based on the integration of human knowledge, both tacit and explicit, has proved to be an efficient method for its applicability to a large variety of non-trivial tasks which requires a combination of dexterity, high-level understanding of the process and constant adjustments based on sensor feedback.

The development of sensor devices to record and reconstruct manufacturing tasks has led to the adoption of machine learning models able to synthesise and integrate knowledge to support decision-making procedures based on the processing of large datasets. Artificial Neural Networks (ANN) have been identified as particularly suited to address this task because of their ability to identify complex non-linear patterns among large quantities of data, enabling the optimisation of individual fabrication parameters in relation to the physical output of the task, increasing the overall efficiency of the production process. While most of machine learning applications in the field of subtractive manufacturing processing are related to metal machining tasks, in which the material is considered as homogeneous, there is a lack of precedence concerning natural materials such as timber. The inclusion of material-specific parameters that could describe the heterogeneous nature of the material and anticipate its impact on the fabrication process appears as a valuable approach to reduce the variance of the fabrication outcomes and develop a design-to-production system whose training and performance are tested in the following chapters.

From the designer's point of view, which is the perspective adopted for **Hypothesis C**, the encapsulation of manufacturing knowledge within a design engineering interface enables better-informed decision making and provides direct feedback at an early stage about the manufacturability of a part based on time, costs and functional parameters. The creation of knowledge bases from human expertise and manufacturing data accumulated over decades of developments made possible defining precise, rule-based, analytical models for a range of subtractive manufacturing techniques. However, currently available CAPP interfaces present two main disadvantages: **i)** The manufacturability evaluation of components forces industrial designers to work within a highly-constrained environment based on the identification and creation of a limited set of geometric features which could be then easily translated for the generation of machine's instruction. **ii)** The design and making processes are still considered within a linear workflow, restricting the availability of knowledge to a limited range of highly codified techniques and industrially-graded homogenous materials which directly hinders the exploration of novel design solutions. While the knowledge integrated in these tools is limited and destined to become obsolete if not continuously updated, the integration of machine learning models as part of design processes represents a promising strategy increasingly adopted in the design industry to flexibly extend the range of design solutions available and support their synthesis supported by relevant domain expertise, potentially based on fabrication and material considerations.

3 Knowledge Acquisition

The core of the research, structured around the three hypotheses presented in **Chapter 1**, is concerned with the acquisition of data (**Chapter 3**) for the synthesis of material and instrumental knowledge (**Chapter 4**) to be integrated at an early stage of design-to-manufacturing workflows (**Chapter 5**). Such knowledge base directly supports decision-making procedures which could have a significant impact if considered from the beginning of the design process. These evaluations concern the affordances provided by specific sets of fabrication tools and material systems and their influence on the original design intention expressed through a digital notation before the fabrication stage.

This chapter addresses **Hypothesis A,** claiming that *the heterogeneous qualities of materials such as timber substantially affect the outcome of operations performed with different carving tools, hindering their utilisation within current design workflows*. The focus of the chapter is on the first stage of the training workflow which concerns the acquisition of real-world fabrication and material data collected through different sensor devices, its subsequent processing and storing into a library of fabrication datasets. Two different data acquisition methods, based on human demonstration and robotic recording, are presented and compared to identify how these differently affect the overall training process. Finally, the extent to which the material variance of timber affects the carving operations is assessed through a series of recording sessions based on a Design of Experiment (DOE) strategy which is a statistically valid method to efficiently investigate which combinations of factors and their respective values (or levels) generate variations in the collected information.

3.1 Training Workflow and Instrumentation

The design-to-manufacturing workflow developed in the research specifically addressed subtractive fabrication tasks performed on timber, a highly heterogeneous composite material, with different sets of carving tools such as chisels and gouges. Such operations require a high-level understanding of the complex interaction between the fabrication tool and the local properties of the material being cut. Given the high variance in the outcomes determined by the combination of multiple timber properties, species and carving techniques, there is not a comprehensive analytical model able to provide an accurate simulation of such family of subtractive operations.

Rather than proposing a universal simulation model, this thesis sought to establish a flexible workflow to train a design system towards a specific set of fabrication affordances through the collection of real-world sensor data based on the constraints and resources available. The developed strategy aims to capture, transfer, augment and integrate the instrumental knowledge necessary to perform those tasks into a design-to-manufacturing interface, enabling its access to designers without prior understanding of manufacturing processes or material behaviours.

The access to such knowledge extends the range of tools and manufacturing methods available to designers for the exploration of previously unavailable design solutions.

Furthermore, the lack of precedence in robotic manufacturing for the examined carving techniques made possible to radically reconsider from first principles how fabrication systems could be trained to perform operations which are not part of standard manufacturing environments.

The training process is based on a sequence of three main stages (***Fig. 3.1***):

- **Recording:** The acquisition of fabrication data is structured through a series of carving sessions aimed to collect into a dataset the combination of fabrication parameters driving the carving operation (*i.e.* Tool/Surface Angle, Tool/Grain Direction Angle, Force Feedback, Input Cut Length, Input Cut Depth) and pair them with their respective outcomes measured as the Actual Length, Width, Depth of the cut and Total Removal Volume. Such information is captured, both in real-time and at a later stage, using an array of motion capture cameras (MOCAP) to track the position and orientation of the carving tools, a force feedback sensor to measure the intensity of the force applied by the craftsman and 3D photogrammetric techniques to reconstruct in a highly detailed mesh geometry the result obtained by the carving operations.
- **Learning**: The collected datasets are used to train a supervised machine learning model, *i.e.* Artificial Neural Network (ANN), whose main learning objective is to predict the geometric outcome of a subtractive operation from a user-defined toolpath and the series of fabrication parameters described above, or conversely, generate a robotic toolpath out of a digitally carved geometry. Each robotic toolpath is a sequence of target frames which defines the position and orientation of the carving gouge along the cut. Given a sequence of target frames, the trained ANN predicts at each frame the geometric output parameters of the cut (*i.e*. Length, Width, Depth) considering the influence of material properties determined by differences in wood species (*i.e.* grain arrangement and density) and resulting angle of the carving operation with the principal grain direction.
- **Fabrication**: The trained ANN represents a package of instrumental knowledge that can be transferred, re-used, extended and, most importantly, integrated within an interface to digitally evaluate multiple design solutions informed by tools and material properties before moving to the production stage. The chosen design solution, once robotically fabricated, is assessed through a deviation analysis which compares it to the predicted simulation.

The training workflow should not be considered as a linear progression from the recording to the fabrication stage but rather as a knowledge platform that can continuously be remodelled through several cycles with new fabrication data, further trained to improve its prediction performance and applied to different sets of design tasks.

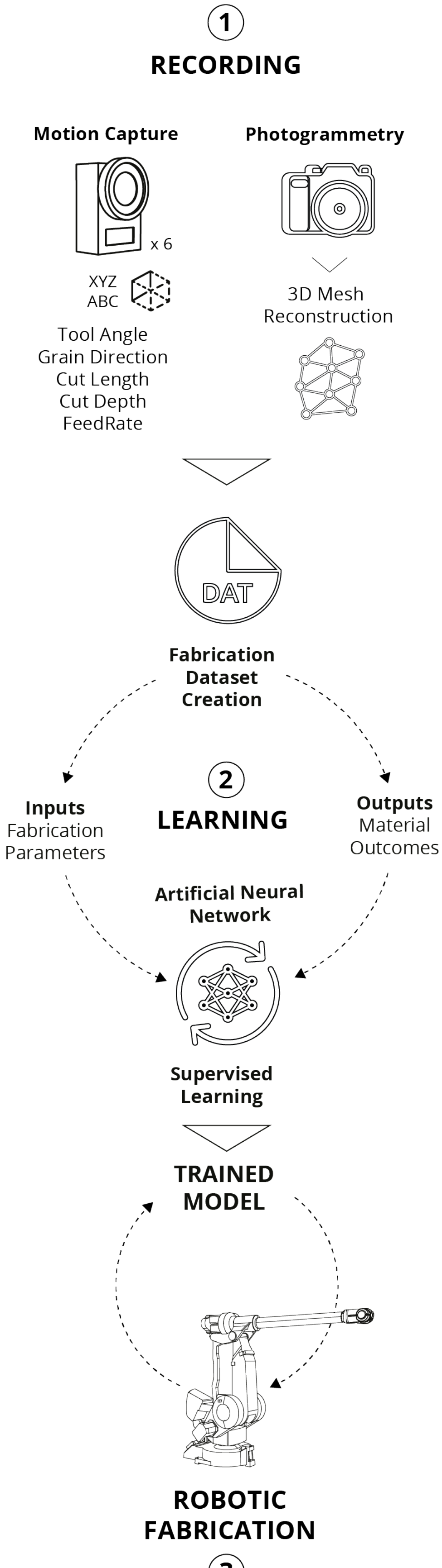
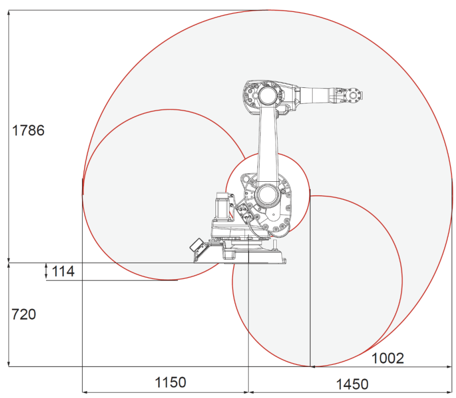


Figure 3.1 Robotic Training Workflow - Diagram.

3.1.1 Industrial Robotic Arm and Carving End Effector

The main element of the manufacturing system is a 6-axis industrial robotic arm, an ABB IRB1600/1.45 model which has been used both for the several training sessions and following industry secondments projects.

The robotic arm is considered as part of the medium-small category for industrial actuators with a working range, described as a spherical envelope, of radius 1450 mm (***Fig. 3.2***) and payload, *i.e.* how much the robot can carry without losing in accuracy or speed, of 10 kg. The system is composed of three main components: the industrial robotic arm, the teaching pendant, through which the user can interact with the system, and the controller itself, which is the computer that runs the system. The robotic arms run programs written in RAPID, ABB proprietary language. The ABB controller version is 5.0.



IRB 1600-6/1.45

Axis movement	Working range	Axis max speed
Axis 1	+180° to -180°	180°/s
Axis 2	+150° to -90°	180°/s
Axis 3	+65° to -245°	185°/s
Axis 4	+200° to -200° def. +/-190° revolution	385°/s
Axis 5	+400° to -400° def.	400°/s
Axis 6	+/-288 revolution	460°/s

Figure 3.2 ABB IRB 1600 Working Range – Source: ABB, Product Specification – IRB 1600/1660 Manual, 2019.

An end effector, or End-of-Arm Tooling (EOAT), is the device attached at the end of the industrial robotic arm used to perform actions and interact with the fabrication environment. Since traditional carving tools have been excluded from standard industrial fabrication environments, it has been necessary to develop a custom end-effector to use such a toolset within a robotic manufacturing process. The main component of the end effector is an electric reciprocating carving tool developed by a third-party company and mostly used by human craftsman to perform more efficiently carving operations, reducing the daily work fatigue and obtaining more consistent results. The motor powering the tool is a single-phase electric motor which generates a power of 0.25 kW. The main advantages of including such mechanism are: **i)** Increase of speed and consistency of the cut, **ii)** Possibility of easily swapping different chisels and gouges with their standard fit, **iii)** The reciprocating mechanism works in relation to the material resistance, providing higher frequency vibration with harder type of wood, and lower frequency with softer ones.

The main body of the reciprocating tool is inserted into a mounting fixture which does not allow any translation. The carving gouge is mounted on a cart that can slide linearly on a rail to maintain intact the reciprocating function (***Fig. 3.3***). As more resistance is found during the cut, the more the carving gouge slide back into the electric tool and more current is drawn to generate higher frequency vibrations, allowing the cutting operation to be performed more smoothly.

The gouges and chisels utilised in the experiments are standard traditional carving tools made by Stubai, an Austrian tooling company, used by human craftsman and fitted with a custom handle adaptor to insert them in the electric tool (***Fig. 3.4***).

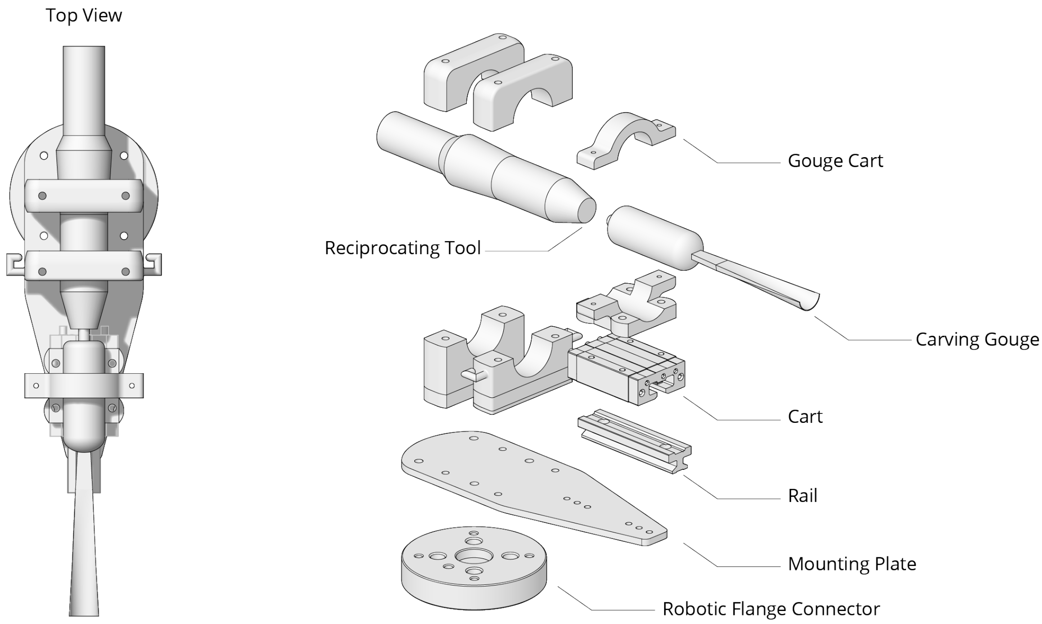


Figure 3.3 Robotic Carving Effector - Diagram.

Figure 3.4 Robotic Carving Effector.

3.1.2 Sensing Systems

Testing **Hypothesis A** implies identifying those parameters (*e.g.* the angle between the grain direction and the tool's cutting edge) which affect the operation outcome and measuring whether such a variance is so significant to hinder the design process. To achieve this, in the recording stage a series of methods have been tested with the aim of collecting a sufficiently large and comprehensive amount of data which is necessary to describe the observed fabrication task and its respective outcome.

Such a task presents a series of methodological challenges that need to be addressed in the definition of the sensing strategy as they might prevent the collection of statistically valid information necessary to support or refute what is claimed in the first hypothesis of this research:

- **Noise**: Data collected from physical environments, such as manufacturing settings, are extremely noisy, namely, they carry a large amount of meaningless information. If the noise is higher than the signal generated by the sensors, the collected data are unusable.
- **Relevance**: Identification of the relevant parameters necessary to reconstruct the fabrication process. While collecting the largest as possible amount of data is theoretically advisable, as even secondary conditions could play a role in the system being recorded, limited time and resources required to estimate the "*vital-few*" parameters which most significantly affect the outcome of the task and discard the "*trivial-many*" (*i.e.* Pareto Principle). In this regard, previous knowledge of the fabrication task might lead to a biased selection and this could be mitigated through careful planning the design of the experiment, ensuring its statistical validity.
- **Scale**: A manufacturing task can be analysed at different resolutions, leading to a different description of the same process. It is necessary to define what is the relevant scale to consider during the recording based on the type of knowledge integration which should be made later available during the design stage. For instance, the same carving operations could be defined as part of a carved texture, as an individual cut or as a collection of multiple timeframes, each with specific local parameters values.
- **Time**: Evaluation of the timing of the data acquisition in relation to the performing of the operation. For instance, it might be necessary to record tools position and trajectories in real-time simultaneously with the carving process or limit the recording to the reconstruction of the carved outcome on the wooden board after the task has been completed.

Based on these considerations, the devised sensing strategy for the recording of carving operations makes use of two main scanning techniques: **1)** Motion Capture Cameras (***Fig. 3.5***) and **2)** Photogrammetric Reconstruction (***Fig. 3.6***).

Motion Capture Cameras (MOCAP) is a sensor technology based on the recording of the movement of objects in space. It has a wide variety of application in different fields such as the movie industry, sports or computer vision for robotics. An array of cameras arranged around a recording area are used to track with a high degree of precision (≅ 0.1 to 0.2 mm) the position of spherical reflective markers. The calibration of the system is performed with a calibration wand which presents a cluster of markers in a known position which is measured by the cameras while the user moves the wand in different orientations through the recording space.

The MOCAP system used for the recording stage is composed of 6 x Flex 13 cameras by Optitrack and their proprietary recording software Motive (*v. 1.9*). Each camera has a resolution of 1.3 Megapixels, a Field-Of-View (FOV) of 56° and a record at a Frame Rate per Second (FPS) of 120. The data is streamed in real-time from the Motive interface to the 3D modelling design environment (Rhino3D/Grasshopper) through a custom script component. This utilises the NatNet client/server architecture to share motion tracking data, both as single markers and clusters (*i.e.* rigid bodies), to third-party applications through a standard local network interface.

Photogrammetry reconstruction technique consists in reconstructing 3D objects based on a collection of photographs of the same object taken from different points of view. The reconstruction accuracy depends on the circumstances of the captured images and the object itself. The collection of pictures was taken with a Sony Alpha 6000 camera and was processed for compensating any lens distortion. For each board, a collection of about 100 pictures was generated with each picture shoot from 30 to 50 cm in a controlled light environment. The reconstruction was performed with the software Recap Photo by Autodesk which has the advantage of running the computation on its cloud-based service rather than relying on the local hardware specifications. This reduced the processing time to a range between 30 to 60 min with the final output consisting of highly detailed textured meshes. The reconstruction process does not provide an indication of the actual dimensions, therefore, it has been necessary to scale the resulting mesh according to manual measurements of the physical board to obtain a reconstruction with the correct size.

Figure 3.5 Motion capture cameras used in the Recording stage to track the tools and reconstruct the carving operation.

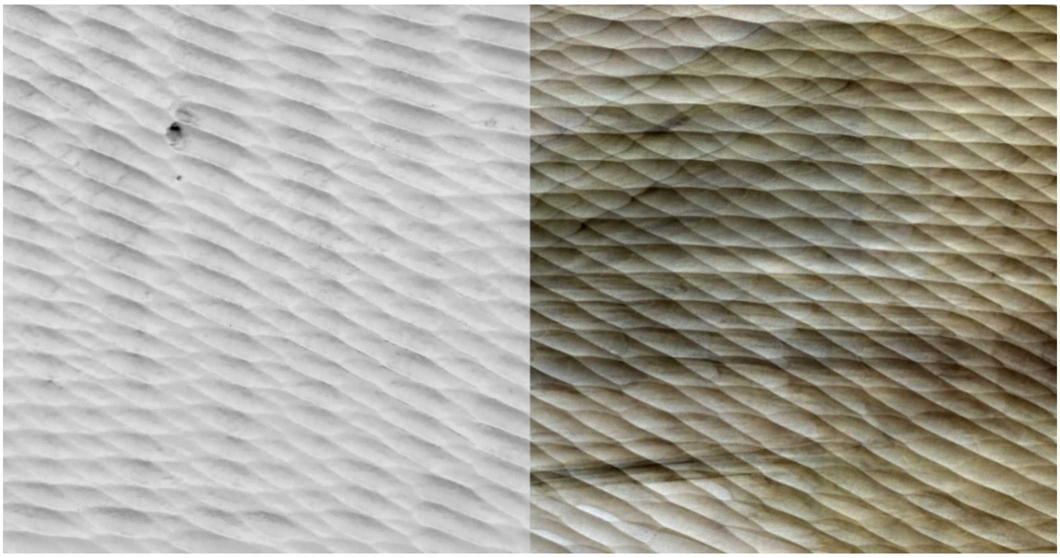


Figure 3.6 Photogrammetric reconstruction of a robotically-carved wooden board.

3.2 Recording Stage

Knowledge acquisition is described by Lucas (1991) as the "*process of collecting and structuring knowledge in a problem domain*". The creation of a knowledge base begins with consulting multiple *knowledge sources* such as human experts, textbooks, and databases with the aim of gathering relevant information which can be encoded into a valid knowledge representation.

The Recording stage is the first part of the workflow addressed in the thesis as it focuses on the collection of real-world fabrication data which will be used to synthesise and integrate the instrumental and material knowledge necessary to perform carving operations on timber.

To achieve this, two different knowledge sources are considered for the data collection: **i)** Carving demonstrations performed by human experts, **ii)** Structured robotic carving session.

At this stage, the selection of materials and carving tools has significant implications over the use of the trained simulation interface in terms of solution space available to the designer. These will be discussed in detail in **Chapter 5** through a series of design case studies.

The chosen medium to collect fabrication data has been a series of wooden boards carved with a set of carving gouges. In each dataset are stored the cuts obtained with one carving tool on the same wood species and fabricated during the same session. The boards have a uniform size of 300x250 mm and both sides have been used. Each side counts between 20 to 35 operations, depending on the different configurations of fabrication parameters. Several training boards are used in one recording session, generating a collection of cuts between 180 and 300 samples.

One of the key steps in the data acquisition is the abstraction of the carving outcomes into a series of quantifiable measures which could be used to describe the selected family of subtractive fabrication operations. The photogrammetric reconstruction of the training boards makes it possible to store and analyse the outcome of each operation which is decomposed in its main geometrical components and subsequently processed into a series of features information to be used in the Learning stage. The selected measures are the depth, width, length of the cut and the estimation of the total removal volume.

The operations have been analysed at two different scales, each providing a different description of the process and respective different type of datasets. In the first recording strategy, individual operations have been decomposed in a sequence of keyframes of fixed number with each attached a set of fabrication information for that specific local instance, generating a refined description of the operation and variation of key parameters along the cut. The focus of the analysis is then shifted from the results of the overall cut to the changes between each keyframe. At the same time, global measures could be derived from local information considering the whole sequence, for instance, the sum of length measurements for each frame could be used to obtain the total length of the cut. The second approach focuses specifically at this global scale with every single cut considered as the result of a single operation and described with global descriptors such as maximum depth or width of the cut, total length or feed rate. Different dataset resolutions of the same operations allow setting up a combination of predictive processes, presented in the next chapter, to significantly increase the efficiency of the overall fabrication task.

For the robot-based dataset, it is always possible to compare between digital input and physical output and the learning objective is to define a function able to map between the two with a reasonable degree of error. For the human-based dataset, however, it is not possible to compare between the two, as the cognitive functions that drive the action of the human reside inside the brain. What it is possible to capture then, it is not the design intention itself but rather what are the effect of such on the fabrication parameters, or features, devised to describe the carving process. For this reason, the recording of skilled human demonstration requires a different approach which aims to devise, from the accurate photogrammetric description of the cuts, how the skilled craftsman physically steered the tools to obtain that specific result.

To achieve this, human-based recording requires a more complex sensing strategy in which data are collected both simultaneously to the carving operation with MOCAP and at a later stage through photogrammetric reconstruction. At the same time, robot-based recording sessions, which are technically more straightforward to implement, are presented with the challenge of capturing instrumental knowledge without a previously formalised understanding of the task available. The definition of fabrication parameters is then based on the indirect intuition of the programmer who does not engage directly with the fabrication process and materials. As a result, this approach requires a series of expensive, both in terms of resources and time, trial-and-error sessions for parameters tuning which lead to the following considerations:

i) The parameter space necessary to consider is usually significantly large and the relationship between fabrication parameters is not necessarily linear. Therefore, generating a mapping of such space is either highly inefficient as it requires time and material waste, or not comprehensive, as the data points are too sparse to synthesise usable knowledge.

ii) More efficient methods for parameters space explorations, such as Reinforcement Learning (RL) strategies, are still based on physical tests with an error-reward system which, in a manufacturing context, could lead to dangerous situation determining the damaging of the industrial arm, the effector or the material. The strength of the RL approach based on millions of attempts performed in a digital environment is not applicable in this case, as producing an accurate simulation of the carving task is the end goal of the training process and, as such, it is not available ahead.

As time and resources for the training session are limited, it is necessary to put in place a strategy to define a subset of the fabrication parameters space that is worth exploring in relation to the assigned design brief. However, without an understanding of the task based on a direct experience of the manufacturing process, the relationship between parameters is unknown. For instance, what values should be assigned to the Tool/Surface Angle parameters given a user-defined set of cut lengths? How do these change from the beginning to the end of the cut? How the depth profile of the cut should be matched accordingly?

The proposed approach is to collect this information from an initial human demonstration of the task and combine it with a further extended robotic search of the refined parameter space.

3.2.1 Human Expert Demonstration

The issue of exploring a large fabrication parameters space is addressed through the discussion of the methods that enable the recording of human experts demonstrating the fabrication task and the analysis of an example dataset.

The goal is to provide guidance for efficiently setting up the series of robotic training sessions, narrowing down the search space through the definition of domain boundaries for the selected features rather than arbitrarily assigning them.

Each robot operation has been defined following these steps:

i. Definition of the position and orientation of the cut in respect to the wood grain direction and its length. This implies arranging in the digital design environment a series of straight lines on the reconstructed model of the board.

ii. From the straight line, generation of the arc describing the operation, defining its depth.

iii. Definition of the orientation of the tool and its variation along the cut, focusing specifically on the angle between the cutting profile of the gouge and workpiece surface.

While the parameters of the first point are directly defined by the user based on geometrical considerations, *e.g.* number of operations that can fit on a board, the second and third point require an operational understanding of the interaction of the tool with the material.

The human demonstration is not intended as a definitive and extensive formalisation of the task but rather as a safe starting point which could be used to orient the subsequent robotic exploration towards a more specific direction. On the other hand, the modelling of the task based on skilled craftsmen presents two main limitations: **i)** Human tacit knowledge is subjective and based on individual experience. **ii)** Its record is always partial and biased by the point of view of the observer and chosen measuring devices. Therefore, the main difference with recording a human expert in comparison to a machine is that the cognitive intention driving the action is not measurable and remains as part of craftsman tacit knowledge. The lack of access to such requires measuring, instead, the action of the craftsman as she or he performs the operation and use this as an expression of the intended action although mediated by the physical world. For this reason, the aim of the sensing strategy is to capture in real-time, as the craftsman carves the wooden board, all the relevant fabrication parameters which makes it possible to create a specific carved geometry. This information is processed and compiled simultaneously into a dataset.

The real-time updating reconstruction of the tool in the digital interface is performed with the MOCAP through the application of 3d-printed custom markers to the carving tool (***Fig. 3.7***). Through this method, it has been possible to record the cartesian coordinates (XYZ) of the tool and its orientation along the three principal axes (ABC). From such information is then possible to extract a series of relevant fabrication parameters such as the angle between the tool and the carving surface or its angle in relation to the main grain direction. As the data collected through the human demonstration are further extended and used to guide the robotic recording sessions, it is important that the two sets of operations are performed with the same tools and wood species. The sensor data collected by the human are processed through a series of steps to extract useful information that can be used to inform the subsequent robotic training session. A demonstration of such process is presented below through the analysis of an example dataset generated by a novice craftsman using a traditional carving gouge on a series of lime wood boards, counting 155 operations in total.

Figure 3.7 Custom tracking markers are applied to the carving tools to reconstruct in real-time their position and orientation in the digital recording environment.

Besides the collection of sensor data concurrently with the actual carving session, the training boards have also been recorded through photogrammetric reconstruction to keep a precise measure of the outcomes of carving operations (***Fig. 3.8***).

Figure 3.8 Photogrammetric reconstruction of a series of training boards carved by a human expert.

A first step in the extraction of instrumental knowledge from the human demonstration is the definition of the domain boundaries of the recorded fabrication parameters values and their related distribution. This significantly narrows down the following robotic training session to a range of parameters that are known to be generating a successful carving operation. For instance, the values of Tool/Surface angle at the beginning and end of the cut are contained within relatively small domains, between 48° to 37° and 30° to 20° respectively (***Fig. 3.9***).

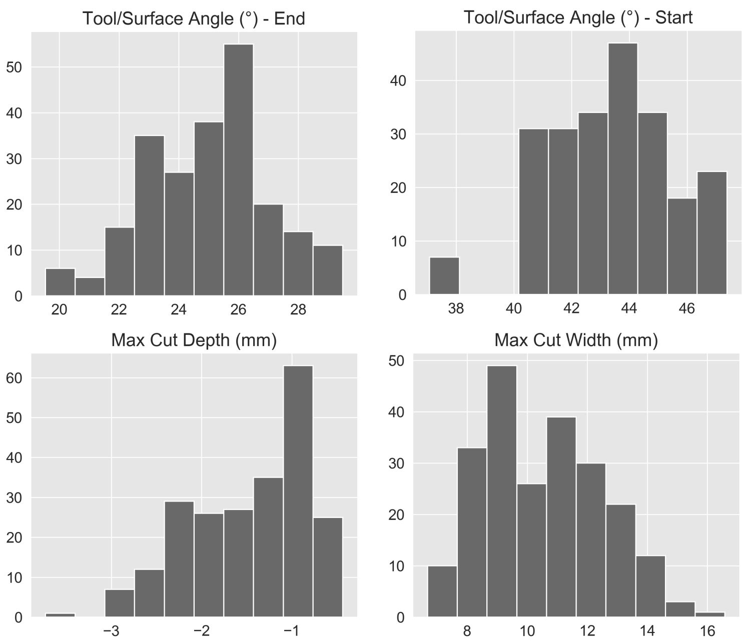


Figure 3.9 Recorded features from the human-based carving session – Histograms.

In the bar plots below (***Fig. 3.10***), the recorded operations are arranged in groups according to the length value within intervals of 5 mm each and analysed in relation to the respective width and depth of the cut. The analysis shows how the geometrical features of the cuts performed by the human are positively correlated with each other, *i.e.* an increase in the length corresponds to a deeper and wider carved geometry. For instance, longer cuts allow the tool to cut through the wooden fibres more in-depth rather than shorter ones where the tool does not have enough space to perform the action.

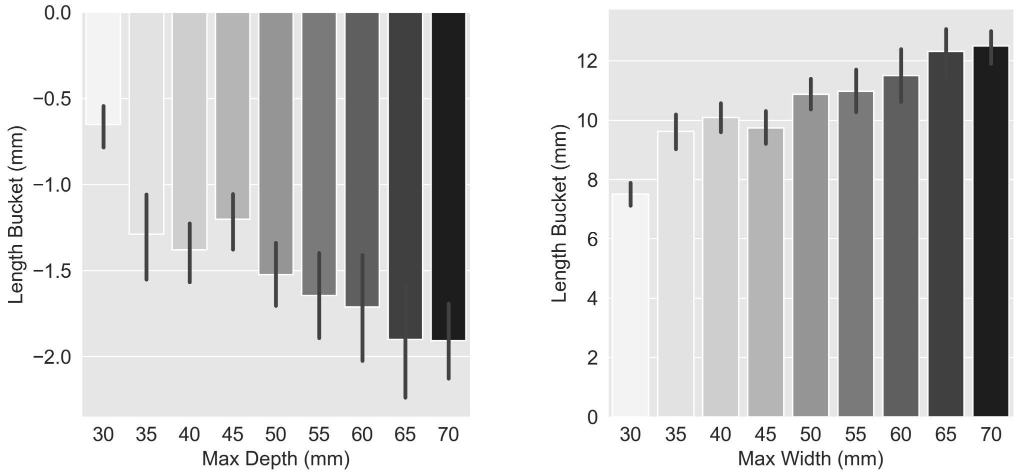


Figure 3.10 Plots showing the correlation between the geometric features (i.e. Length, Depth, Width) of the cuts created by the human expert.

It is important to quantify such trends in a way that, for instance, during the robotic task, the depth of the cut that is achievable in a 8 cm long cut is not applied to one half of the length, leading to a potentially dangerous manufacturing condition. Based on such requirements, an arc profile was defined based on the human demonstration data for each group length. This profile not only is important to define the advisable maximum depth of the operation but also to define the geometric shape of the arc itself. The final curve is based on the average of all the operations within the same, relatively small, group, sharing similar values of length, depth and width (***Fig. 3.11***).

In ***Fig. 3.12***, the entire collection of 155 operations is plotted to show the overall trend followed by the Tool/Surface Angle parameter along the length of the cut. The dark grey points represent the individual target frames composing an operation, a collection of 20 units for each cut, while the red line is the 2nd order polynomial regression curve that describes the overall trend. The initial Tool/Surface Angle values range between 48° to 37° while at the end of the cuts the values decrease between 30° to 20°. As shown in ***Fig. 3.13*** using the same length intervals previously utilised, shorter cuts necessarily have less space to perform such variation between the beginning and the end of the operation, therefore, the change of the Tool/Surface Angle parameter from one robotic target frames to another is significantly larger.

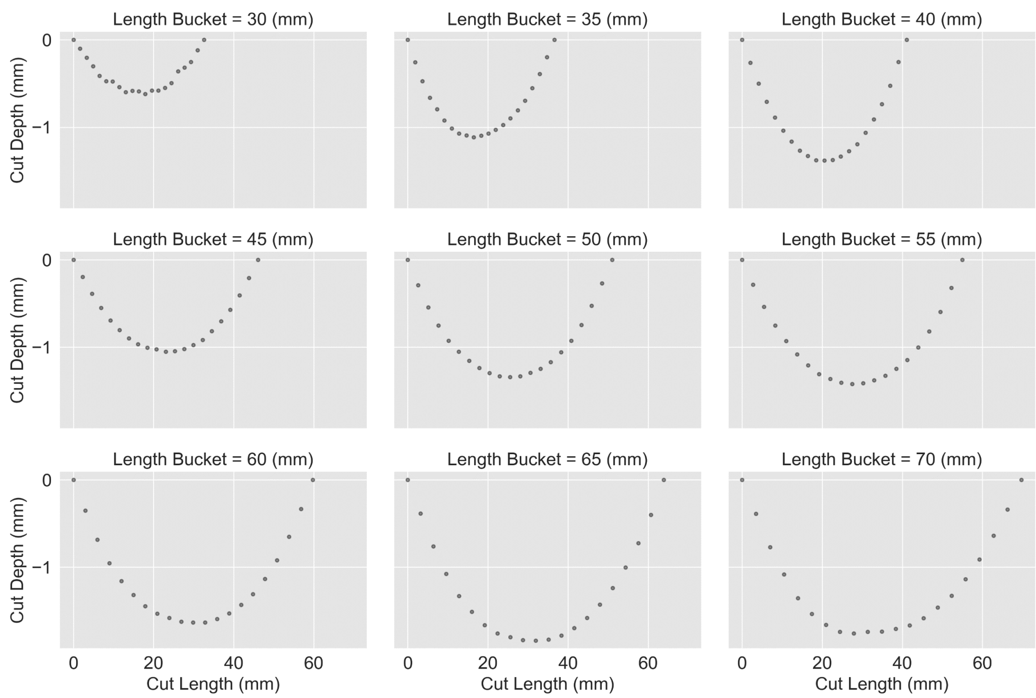


Figure 3.11 Analysis of the depth “profile” of cuts across groups of different lengths.

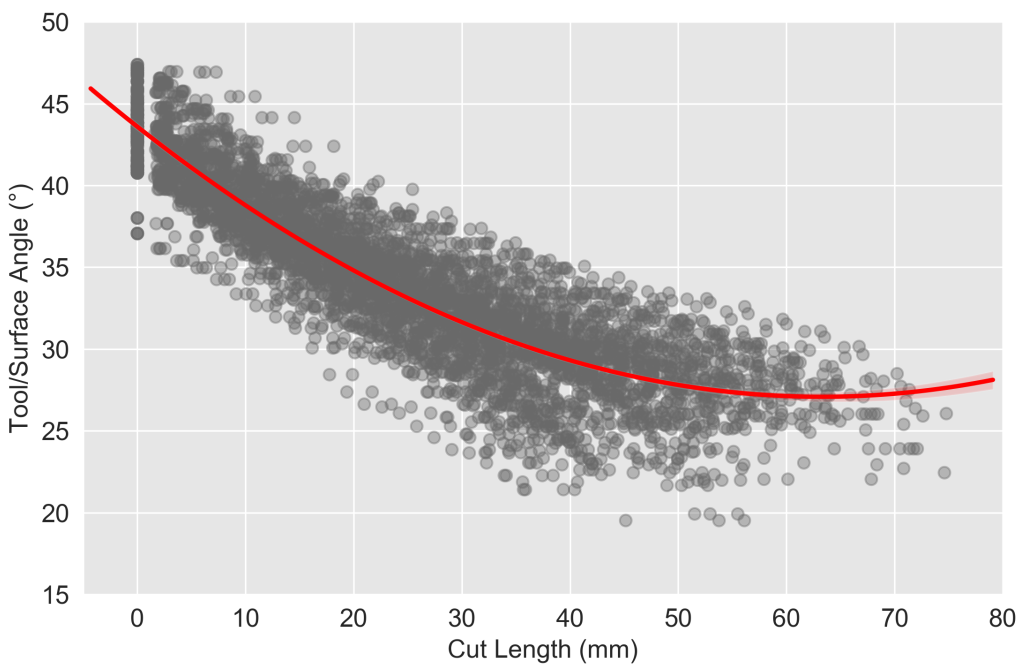


Figure 3.12 Tool/Surface Angle variation between the beginning and end of the cuts in the human-generated dataset.

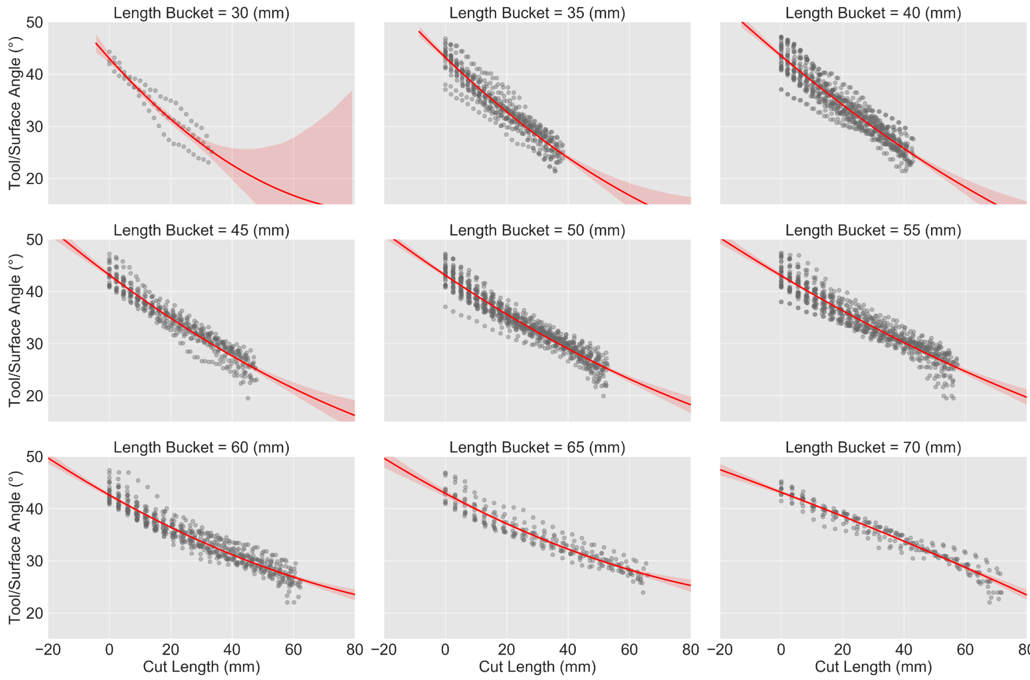


Figure 3.13 Tool/Surface Angle variation between the beginning and end of the cuts across groups of cuts of different lengths.

Finally, the dataset indicates that the structure of the wood grain affects the action of the human craftsman, steering the tool differently according to the carving direction. Cutting the wood fibres across the grain seems to afford the creation of wider and deeper cuts in comparison to operations performed along the main grain direction (**Fig. 3.14**). This is likely due to the counteracting action applied by the craftsman to avoid the tool cutting increasingly deeper and creating long splinters when carving along the main grain direction.

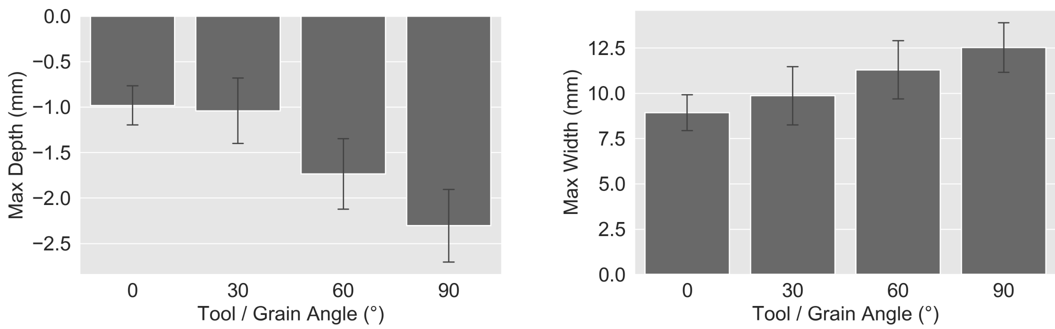


Figure 3.14 Plots showing the correlation between the angle of the carving direction in relation to the wood grain and the geometric features of the resulting cuts.

3.2.2 Robotic Data Collection

The robot-based dataset stores two main categories of information: **i)** Digitally-defined fabrication parameters, **ii)** Measures of the physical outcomes of the operation on the material. The first is defined in the digital design environment and recorded before the actual fabrication stage, while the second is recorded immediately after the completion of the fabrication task. As the final goal is to map between the original desired outcome and the actual fabricated one, there is no need to record sensor data simultaneously with the carving operation itself.

In the digital environment, each operation is initially described as a straight line of the desired length arranged, together with many others, on the training board. Once the position and orientation in respect of the main grain direction, the next step consists of assigning the desired overall length and the arc profile that will determine the depth of the cut. Length and depth of the cut are the primary descriptors for the intended outcome, as the width of the cut will be a function of the type of carving tool used in relation to the previous two parameters.

The curve defining the operation is then broken down into multiple points and, for each of those, the position and orientation that the end effector will have to follow along the cut are defined through the generation of a plane. The main parameter is represented by the definition of the angle between the tool and the material surface and how this changes along the cut. Each plane is transformed into a robotic target frame defined by the 6-dimensional vector {X, Y, Z, A, B, C} defining position and orientation of the end effector based on the assigned robotic coordinates system. An ordered collection of robotic target frames fully describes the robotic task for each carving operation (***Fig. 3.15***).

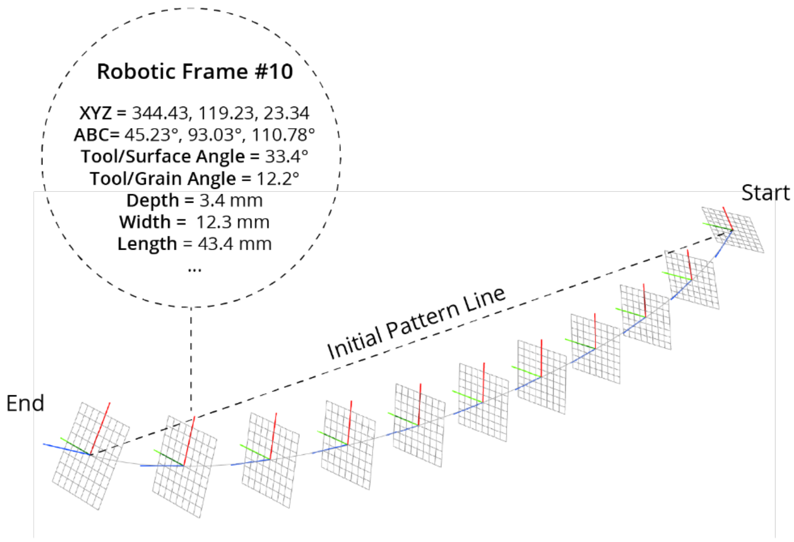


Figure 3.15 Robotic operations are defined digitally through a sequence of target frames storing local fabrication parameters and geometric features of the resulting cut.

After the fabrication stage, the outcome generated by the robotic carving operation is measured digitally through the photogrammetric reconstruction of the training board. Each mesh is segmented down into the single operation and the curve defining the cut is reconstructed. As for the digital input, the output curve is subdivided into a collection of equally spaced planes to extract local information about the length, depth and width of the cut for each frame. As the number of frames is the same between the input and output curves, it is then possible to compare the two sets and understand the influence of the fabrication process on the original digital design and, ideally, adjust the process accordingly to the correct combination of fabrication parameters.

3.2.3 Tolerance Threshold

In CNC metal machining, geometric tolerances are essential information necessary for the manufacturing of any mechanical part as they determine the time and resource necessary to complete the production cycle. Different levels of precision are required according to the industry, application, material and manufacturing technique as specified through internationally-accepted tolerance grades (*i.e.* ISO 2768).

The definition of tolerance in timber manufacturing is more challenging, at least at the level of precision of metal machining, and there is no universally accepted specification of tolerance grades across the industry. The main difficulty is due to its inherent variance as a natural material across different species, geographical areas, environmental conditions and unique individual features. Furthermore, the material shows a complex behaviour of shrinkage and expansion based on its moisture content, increasing the difficulty of measuring the precision of individual features as they go through constant geometrical deformation.

Nevertheless, for specific categories of engineered timber products, it has been possible in some countries to adopt a standard code defining a precision threshold necessary to maintain for a given use. For timber elements used for structural applications in the UK, for instance, there are permissible cross-sectional deviations (detailed in BS EN 336:2013) that need to be respected in construction projects (*e.g.* for sections of machined timber with side length < 100 mm, the accepted tolerance is ± 1mm, while for side length > 100 mm, the tolerance is ± 1.5 mm).

While the use of engineered timber partially mitigates the issue of dimensional consistency, the definition of tolerances level for solid timber in its natural state is more challenging due to its variability. Craftsmen know how to deal with its heterogeneous properties and complex behaviour through years of experience and learn how to steer their action in relation to the affordances provided by the material to achieve the desired level of precision.

For this reason, it is important to define from the beginning the threshold within which this variance due to timber heterogeneous properties is acceptable in respect of the chosen resolution for the design process, mostly depending on the function and field of application of the artefact being produced. For instance, timber joinery in a furniture piece would require a higher level of precision (with tolerance around ± 1 mm), while particular surface textures might require lower tolerances (± 2-5 mm). Besides its function, there is another critical aspect to consider in the definition of the desired tolerance threshold: the deviation error between the prescribed digital model (or as if it were manufactured on a completely homogeneous, dull, material) as prescribed by the designer and the fabricated outcome on that specific piece of timber.

In the context of this chapter, in which are considered only individual carving operations producing a linear cut, a deviation of 5 mm on a 20 mm length cut is more significant than the same deviation on a cut with length 50 mm, as it would represent a deviation of 25% against 10% between the digital notation and physical outcome. For this reason, the analysis of the fabricated cuts is measured against a threshold based on a percentage measure between deviation and total size of the feature (*e.g.* Length, Depth, Width of the cut). The variance measure in the next section has been conducted against different tolerance thresholds of 2%, 5% and 10%. Such a measure, together with the functional requirements determined by the specific application of the produced artefacts, should provide designers with a valuable indication, only partially subject to personal judgement, on what is the precision level required to engage with the design process.

3.3 Design of Experiments

The central assumption, claimed in **Hypothesis A**, at the base of this research is that properties of timber, such as grain density and direction, substantially affect the interaction of the carving tool with the material and produce a variance in the fabrication outcome.

For this reason, it is necessary to identify **a)** whether such variance occurs across different material conditions and to what extent, **b)** what are the relevant parameters that determine such variations, **c)** how the recording sessions should be structured to efficiently acquire data with the recording methods previously described, **d)** whether the variance level is suitable for design purposes based on an accepted tolerance threshold.

To achieve this, it has been necessary to establish an initial set of experiments aimed to collect robotic fabrication data performing a range of carving operations with different configurations of fabrication parameters and material conditions. The methodology used to perform these is described as *Design-Of-Experiments* (DOE) which *is* "*the name given to the techniques used for guiding the choice of the experiments to be performed in an efficient way*" to test the hypothesis and explain the sources of variation in the collected information (Cavazzuti, 2013). According to the survey on the application of ANNs in subtractive fabrication process by Pontes *et al.* (2010), over one-third of the examined studies made use of DOE methods to build the Training dataset.

One common approach in the manufacturing industry is to perform a set of experiments where only one factor is changed at a time (OFAT) with all the other variables fixed. While such method is relatively easy to perform, it presents the main disadvantage of failing to consider the interaction between factors, namely "*the failure of one factor to produce the same effect on the response at different levels of another factor*" (Montgomery 2017). As the thesis revolves around the interaction of the tool with different material properties, such a strategy is inadequate to understand the variability involved across different fabrication tasks.

An alternative DOE technique able to deal with multiple factors varied at the same time is known as factorial experiments. As demonstrated by Czitrom (1999), such a method not only makes possible to estimate the interactions between factors but it also **a)** requires fewer resources (*i.e.* time, material, experiments), **b)** it is more precise than OFAT, **c)** the collected experimental information concerns a larger region of the factor space.

Full-factorial experiments consist of all the possible combinations of factors and respective levels considered to test the hypothesis (Antony 2014). One the main risks for these experiments is known as "*combinatorial explosion"* (Schuster, 2000), where the number of combinations of parameters considered determines a level of complexity which rapidly exceeds the resources available to address the hypothesis. Such issue is particularly valid in the field of manufacturing, where performing multiple production tests come with a high cost in terms of time and waste of material.

As the collection of a larger, rather than sparse, amount of fabrication data would be beneficial for the subsequent stages of the training workflow, the strategy adopted has been to perform a full factorial experiment set yet mitigating the risk of combinatorial explosion through the information acquired by the human demonstration. The advantage of using the recording of skilled human experts performing a series of carving operation is to start the robotic experiments with an initial understanding of the task grounded on real-world fabrication data acquired efficiently in terms time and material resources.

For setting up such experiments, it is necessary to define which are the factors that hypothetically determine the variations in the outcome of the fabrication task and their respective levels, or values, which determine both the resolution and extension of the experiments search space. The Factors-Levels combinations have been defined based **a)** on the human data analysis presented in **Section 3.2.1**, **b)** the domain of design applications of the tool once successfully trained, **c)** the resources available and related costs, **d)** the physical constraints of the fabrication setup. This information allowed a significant reduction of the search space considered and focus on a targeted range of parameters and material conditions.

The selected factors and respective levels are presented below in ***Table 3.1***. As the chosen methodology is a Full Factorial DOE, this implies a total of 144 (*i.e.* 3x4x3x4) operations to be performed by the robot, combining the variation of all level values.

Factor	Levels	Values
Wood Species	3	Tulip, Lime, Oak
Grain Direction	4	0°, 30°, 60°, 90°
Input Cut Length	3	35, 45, 55 [mm]
Tool Angle (Start)	4	25°, 30°, 35°, 40°

Table 3.1 Factors and levels examined in the Full Factorial DOE.

The key response value measured in the experiment has been the deviation between the Input Cut Length and the Actual Cut Length of the carved operation throughout the different Factors-Levels. Since the experiment considers three levels for the Input Cut Length factors, the percentage of every single deviation in relation to the respective nominal length has been considered rather than using its absolute measure. The deviation value = 0.0 indicates no deviation between Input and Actual, while deviation value = 1.0 indicates a deviation corresponding to the full Input Length of the cut. As we consider cuts with length between 35 and 55 mm, with a deviation threshold of 10% the accepted tolerances for the cut length are between ±3.5 and ±5.5 mm, which it is quite high and suited to a limited number of applications, while, with a higher threshold of 2%, the accepted tolerances range from ±0.7 to ±1.1 mm.

An analysis of the cut length deviation across the different combinations of factors considered is presented below in ***Fig. 3.16***.

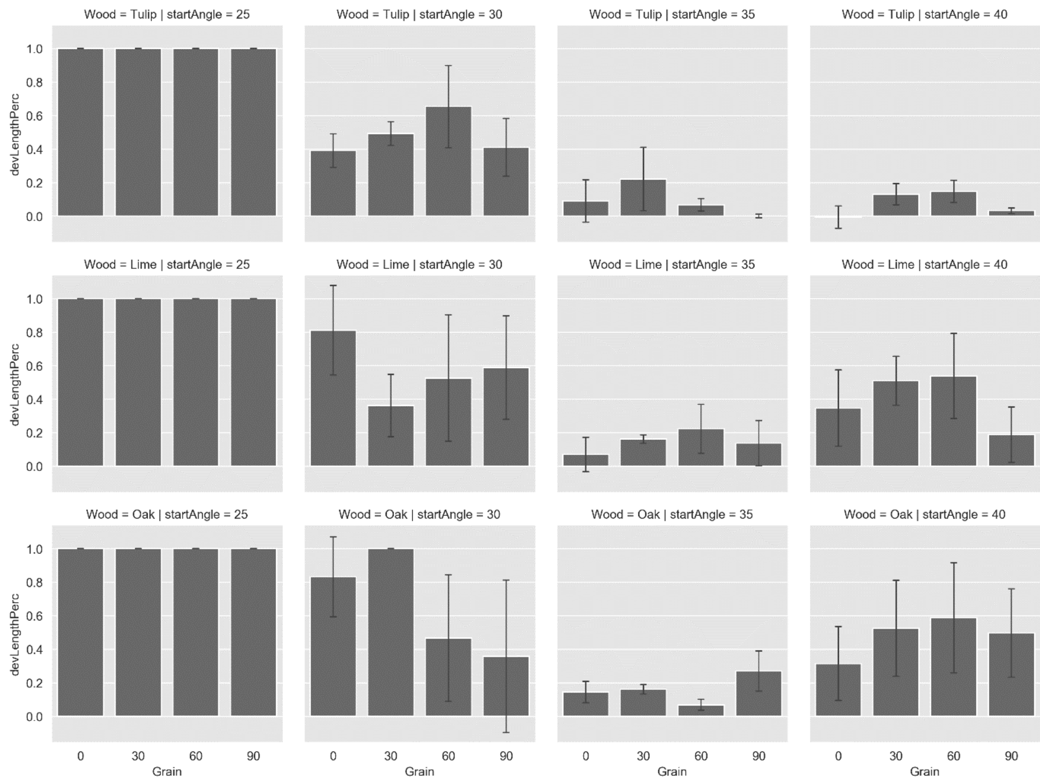


Figure 3.16 Analysis of the deviation error (%) in the length parameter of carving operations performed with different fabrication and material configurations.

The results of the analysis indicate the following:

- Material properties such as grain arrangement and density (*i.e.* Wood Species) and grain direction (*i.e.* Tool/Grain Angle) substantially affect the outcome of the carving operations and determine a deviation between the intended length of the cut and the actual physical result of the operation. In most of the cases, the percentage deviation error goes way above even the highest acceptable deviation threshold of 10%, with some combinations of factors (*e.g.* the leftmost column in plots collection with Tool/Surface Angle = 25°) with a deviation error of 100% due to the failing of the operation in removing any material.

- The influence of different material properties has different effects on the fabrication results. For instance, the same operations (*i.e*. Tool Angle Start = 40°) performed in Tulip and Oak present deviation values significantly different.
- There are sets of factors levels which determine a significantly lower cut length deviation. For this reason, these could be considered optimal, however, in relation to the next stages of the training workflow, this is not particularly significant as the trained system needs to be able to predict any operation regardless of its deviation value from its input condition.
- The Tool/Surface Angle factor has been confirmed as a key input fabrication parameter which substantially affects the result of carving operations.

The Full-Factorial DOE supported **Hypothesis A** as the measured variance in robotic carving operations with timber is above the acceptable threshold for design purposes, even in respect to the conservative one of 10% deviation error, confirming the necessity of developing a strategy to accurately map between the digital input and fabrication outcome of carving operations. For each recording session, the acquisition of fabrication data has been structured, based on the results stated above, through sets of robotic operations.

Before the recording session, it is necessary to establish the two key meta-parameters of the selected wood species and carving tools. Following this, the three key parameters variated for each cut of the sessions are the Tool/Surface Angle, Tool/Grain Angle, and the Input Cut Length. Given the importance of the first parameters as shown by the Full Factorial experiment, this has been studied at a greater resolution which would also be beneficial for the following learning stage of the workflow. A typical recording session is then composed of a minimum of 180 robotic operations performed on a series of wooden boards with 4 Tool/Grain Angle, 3 Input Cut Length and 15 Tool/Surface Angle variations (*i.e*. 4x3x15). The operations outcome generated by a robotic recording session performed with the described structure is compared to the human demonstration data with the same meta-properties in terms of wood species and tool presented in **Section 3.2.1**.

In **Fig. 3.17** the features of length, depth and width of the carved geometries are presented in a 3D scatter plot, where the light blue dots represent the human-based dataset while the red dots the robotically generated cuts. The robotic search space has been limited to the cuts between 35 to 55 mm long, so only a portion of the human dataset presented in this section has been utilised. However, considering such a narrow-down range made possible, in the subsequent robotic recording session, to have a "safe" starting point from which to further explore the boundaries of the initially defined parameters space, robotically obtaining cuts with both lower and higher values in terms of depth and width of the cut.

The human-based demonstration provides a subset of the parameters space determined by the understanding of both of carving tools and timber properties, and past experience. The subset represents an advantageous position from which starting the robotic training process, as all the recorded parameters set describe successful operations, which effectively remove material without creating dangerous conditions, potentially damaging tools and the workpiece.

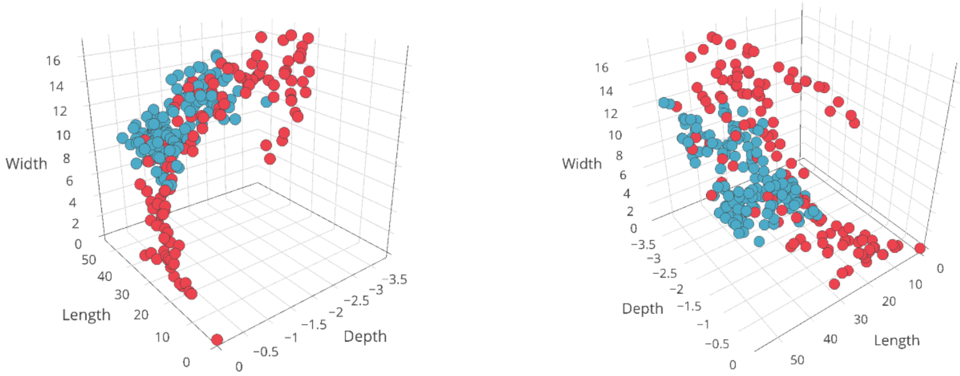


Figure 3.17 Comparison of the geometric features of the cuts and respective distribution between the human (blue) and robotic (red) datasets.

The robotic training sessions can then be configured towards two main directions, one not necessarily excluding the other. On the one hand, the robot could perform an in-depth exploration within the domain boundaries defined by the human demonstration, changing with incremental steps individual parameters, on the other hand, it could be directed toward extending the range of recorded operations with a gradual exploration outside the "safe" boundaries previously defined. In the second case, the robotically generated dataset will consist of both successful and unsuccessful operations. The prediction of which sets of fabrication parameters will generate a successful operation represents one of the aims of the learning methods described in the next chapter.

3.4 Results: Summary

The results presented in this chapter demonstrate that the material variance of timber substantially affects the outcome of carving operations above the established threshold of acceptable tolerances, supporting the necessity of developing a strategy to control such variance for design applications. To this purpose, the devised sensing methods can successfully reconstruct carving operations to a degree of accuracy to which becomes possible to record and analyse the variance occurring in their respective outcome. The integration of an initial human demonstration of the task with the data acquisition sessions performed with the industrial robotic arm is particularly beneficial as it provides guidance, narrowing down the mapping of the parameter space and avoiding dangerous or inefficient solutions. The DOE approach made it possible to efficiently structure the data acquisition process to support **Hypothesis A** and quantify the variance levels generated by different combinations of factors. Furthermore, such understanding of the task has been applied to organise the following robotic recording sessions through the identification of relevant fabrication parameters (*e.g.* Tool/Surface Angle) and material conditions (*e.g.* Grain Direction Intervals).

4 Knowledge Synthesis

The chapter rests on the premise that the heterogeneous qualities of timber substantially affect the outcome of carving operations, as demonstrated in the previous chapter, and directly addresses **Hypothesis B** which claims that is possible to accurately predict and control such material variance for design purposes.

The central proposition is to utilise a combination of machine learning strategies to identify relevant correlations in the collected fabrication data and establish a simulation model for robotic carving operations that could support early design decisions, before the production stage. This is based on the encapsulation of instrumental knowledge into a portable, re-usable and extendable package that can be integrated within a design interface. Besides the validation process after the training of each model, the discussed methods are assessed in the simulation of a series of carving operations produced with different fabrication parameters, measuring the deviation of the prediction from the fabricated outcomes. Following this, a comparative analysis of multiple simulation models trained with different sets of fabrication affordances is presented to demonstrate the versatility of the system and its ability to model the variance determined by numerous combinations of material properties, wood species and carving tools.

4.1 Learning Stage

The computational methods necessary for the Learning stage should not only "*generate, record and retrieve information*", as accomplished with the techniques presented in **Chapter 3**, "*but also digest and synthesise information into knowledge and represent this knowledge properly to support decision making*" (Lu 1990). As previously discussed (**Section 2.3**), machine learning models, in the specific ANNs, showed great potential to achieve similar tasks in the manufacturing field.

The training workflow is organised and presented in two main sections (**Fig 4.1**): **i)** Binary classification for prediction of manufacturing conditions or "events" occurring during the robotic carving process (**Section 4.2**), **ii)** Regression-based prediction of geometrical features of the carving operation based on a set of input fabrication parameters (**Section 4.3**).

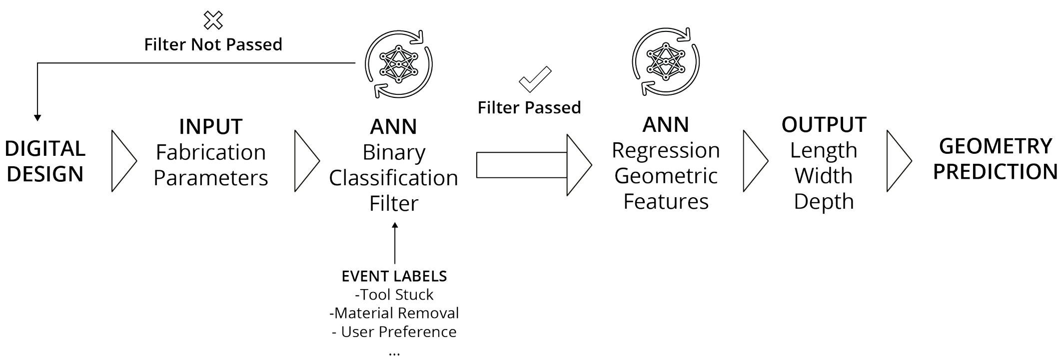


Figure 4.1 Integration of the trained system as part of a design workflow – Diagram.

4.1.1 Features

The term "feature" represents "*an individual measurable property or characteristic of a phenomenon being observed*" (Bishop 2006). A set of features is described as a "*feature vector*". For each recorded subtractive operation, a features vector is extracted from the collected sensor data and stored into a dataset for that recording session. The same carving operation is analysed at two different scales, generating two main categories of feature vectors stored in separate datasets:

1) **Global Dataset**: The carving operation is considered as one single event defined by a set of fabrication parameters and respective outcome that these have generated. This level of analysis is used in **Section 4.2** for the binary prediction of specific manufacturing conditions. The feature vector for the global analysis is summarised below in **Table 4.1**:

Feature	Unit	Type
Tool Angle - Start	Degrees	Fabrication Parameter
Tool Angle - End	Degrees	Fabrication Parameter
Grain Direction	Degrees	Fabrication Parameter
Input Length	mm	Fabrication Parameter
Input Max Depth	mm	Fabrication Parameter
Actual Length	mm	Material Outcome
Actual Max Depth	mm	Material Outcome
Actual End Depth	mm	Material Outcome
Actual Max Width	mm	Material Outcome
Actual Width	mm	Material Outcome

Table 4.1 Global Dataset – Recorded Features.

2) **Local Dataset**: The carving operation is subdivided into a series of perpendicular robotic target frames arranged sequentially along the curve defining the cut. Each frame stores local information about the fabrication parameters and material outcomes in that instant and constitutes one entry in the dataset. For comparability reasons, all the analysed cuts are composed of the same number of target frames. This level of analysis is used in **Section 4.3** for the prediction of the geometric features of carving operations. The feature vector for the local analysis is summarised below in **Table 4.2**:

Feature	Unit	Type
Tool/Surface Angle	Degrees	Fabrication Parameter
Tool/Grain Direction Angle	Degrees	Fabrication Parameter
Input Depth	Degrees	Fabrication Parameter
Input Unit Length	mm	Fabrication Parameter
Input Length	mm	Fabrication Parameter
Actual Depth	mm	Material Outcome
Actual Unit Length	mm	Material Outcome
Actual Length	mm	Material Outcome
Actual Width	mm	Material Outcome

Table 4.2 Local Dataset – Recorded Features.

Each recorded item, compiled in the described features vectors, constitutes a sample, or entry, of the dataset. For the local level, each target frame is a sample, while for the global level, it is the entire cut.

4.1.2 Supervised Learning Models

The collected sensor data, processed in features vectors, are used within a Supervised Learning (SL) process, a type of machine learning task which aims to infer a function that maps an input to an output (*i.e.* $Y = f(X)$) based on a collection of input-output pairs data, representing the Training Data. Once the function has been learned, the system could be used for mapping unseen new data, also called Testing Data (Russel and Norvig, 2010).

For the predictive task examined in this chapter, the recorded features are divided into two main groups and the final learning objective is to define a function mapping between them: **X)** the digital fabrication parameters defining the robotic carving operation and **Y)** the material outcomes that such parameters have generated at the fabrication stage.

4.1.3 SL: Artificial Neural Networks

The primary SL model used for the task is a nonlinear statistical data modelling tool called Artificial Neural Network (ANN), which, loosely inspired by its biological equivalent, could be described as a layered and interconnected network of "*neurons*" able to "*process information by their dynamic state response to external inputs*" (Hecht-Nielsen, 1990).

While there are many types of ANN (*e.g.* Convolutional Neural Networks, Generative Adversarial Networks, Kohonen's Self-Organizing Maps…), this research utilised feed-forward Multi-Layer Perceptron (MLP) models with three different types of fully interconnected layers (**Fig. 4.2**): an input layer, a number of hidden layers and an output layer. Each layer is composed of nodes, or neurons, which accept a weighted sum of inputs, process it through a non-linear function, *e.g.* sigmoid function, and pass the result to all the nodes in the next layer. For the MLP to learn the weights necessary for each node to compute, the training process is based on a *backpropagation* learning technique. With this strategy, after randomly initialising the weights for all the nodes, the error between the final network output to the actual target value in the training data is calculated using a loss function after each pass. Starting from the final layer and moving backwards, each weight's contribution to the error is calculated and adjusted using a gradient descent algorithm.

The implementation of the MLP architecture has been performed using *Keras*, a high-level neural networks API (Application Programming Interface) that works in combination with *Tensorflow*, an open-source software library for high-performance numerical computation. Additionally, several evaluation methods and data processing strategies have been deployed from the *scikit-learn,* a popular machine learning library for the Python programming language.

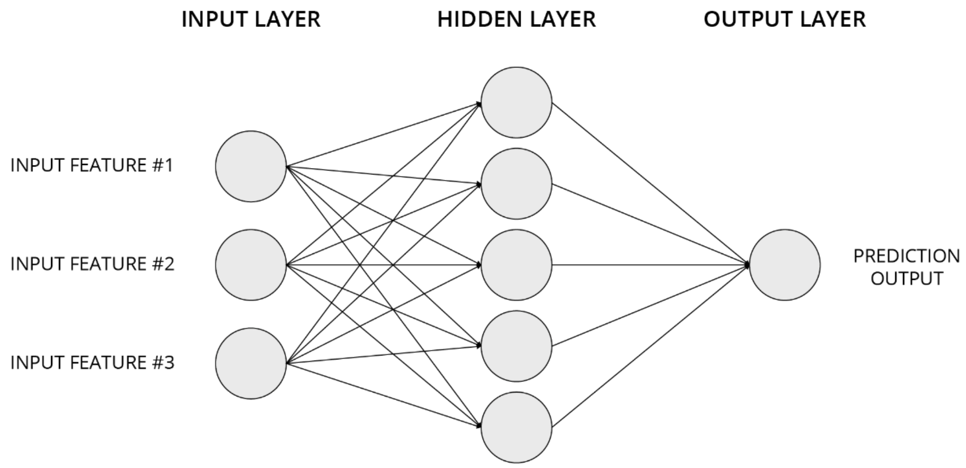


Figure 4.2 Artificial Neural Network Topology – Diagram.

The term *hyperparameter* indicates all those parameters which are defined before the actual learning process and which defines the behaviour of the model itself. The primary hyperparameters which are going to be considered in the next sections are the following:

- **Loss Function**: The function responsible for computing the error between the ANN output and the actual target stored in the Training Data (*e.g.* Mean Squared Error).
- **Activation Function**: The non-linear function responsible for computing each node's output based on the received weighted sums of inputs (*e.g.* Sigmoid function)
- **Epochs**: Defines the number of times that the learning process will pass through the entire training dataset.
- **Batch Size:** Defines the number of training samples shown to the network during one pass.

4.1.4 Validation Method

The main strategy adopted for testing the performance of the trained model is the Train/Test Split Validation, or Hold-out (Reich and Barai, 1999), method in which the dataset is split into two subsets, defined as *training* and *testing* dataset according to a ratio where usually the former is significantly larger (generally more than 2/3 of the total dataset). The training dataset is used to train the model, while the testing dataset is used to evaluate its performance. To obtain a visual understanding of the predictive abilities of the model, the predicted values are plotted against the real ones. With a perfect predictor, all the points would be arranged along the 45 ° inclined bisecting line of the plot. Plotting the training history of the model with its performance score after each epoch makes it possible to understand how well the model can generalise and whether over/under-fitting is occurring at a specific stage of the training.

4.2 Manufacturing Events Prediction

Predicting the occurrence of a specific manufacturing event (*e.g.* whether a cut is successful or not) given a set of fabrication parameters is a critical step in the training of the robotic fabrication system, avoiding potentially dangerous or inefficient operations and allowing the optimisation of individual parameters.

The presented methods are based on the creation of event labels as Boolean values, to be assigned to each operation for a series of observed manufacturing condition. If the operation has been successfully completed the Boolean label will be 1, otherwise, it will be 0. For instance, the removal of material is awarded a value = 1, while the tool getting stuck into the material is assigned a value = 0. The learning objective for the ANN is to predict such events through the assignment of a Boolean value given a set of fabrication conditions. Such a decision-making task, where "*categories*" are predefined, is described as a classification problem. The dual nature of the occurrence or not of the event makes it a binary classification problem for which the trained model is used to categorise new probabilistic observations in either successful or unsuccessful cuts.

4.2.1 Robotic Dataset Analysis

The analysis of the robotic dataset aims to identify the distribution of recorded features values in relation to the observed event labels, existing positive or negative correlations between these and whether it seems possible to divide the data collection into two distinct groups of fabrication parameters and material conditions based on the occurrence of a specific event. The dataset used in this section for the modelling of event thresholds considers each carving operation at a global scale as one entry of the dataset and consists of a collection of 181 robotically-carved cuts obtained with a carving gouge on a series of lime wood boards (**Table 4.3**).

Dataset	Samples	Features	Wood	Robot	Tool
Cuts	181	12	Lime	ABB IRB1600	Stubai 9/20

Table 4.3 Robotic Dataset Info – Global Scale.

After the robotic carving session, the boards have been reconstructed digitally through photogrammetric reconstruction (***Fig. 4.3***). The physical outcome of each operation, broken down into individual features, as described in **Section 4.1.1,** has been recorded and paired into a dataset with the related fabrication parameters that generated it.

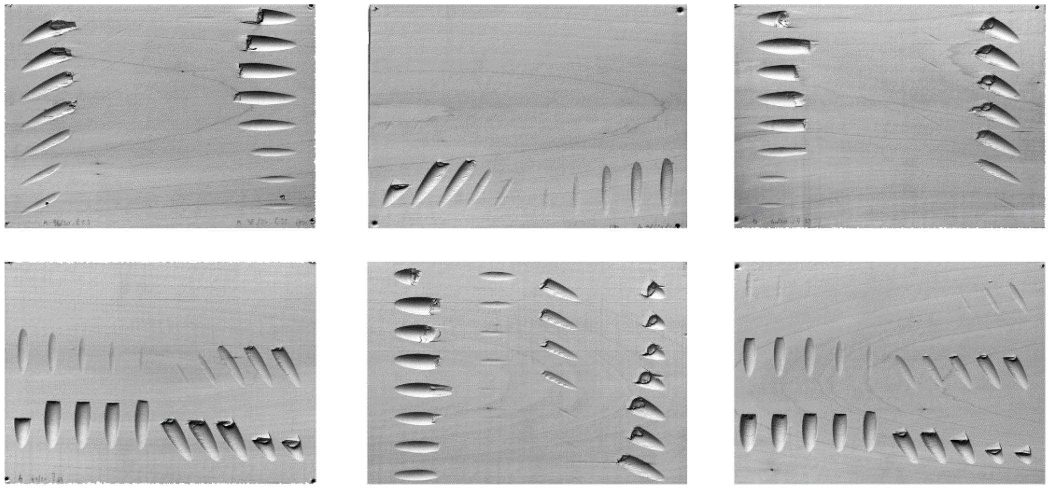


Figure 4.3 Photogrammetric reconstruction of the robotically carved boards used for creating the dataset.

A statistical description of the features of the dataset is reported in **Table 4.4**. In addition to these, the two events which will be considered for the presentation of the binary classification methods are **i**) the tool getting stuck into the material and **ii**) the actual removal of material volume, respectively described by the categorical labels “Stuck” and “Cut”.

Measure	Stuck	Cut	AngleStart	AngleEnd	Grain	Input Len.	Actual Len.	Max Depth	End Depth	Max Width	End Width
Count	180.0	180.0	180.0	180	180.0	180.0	180.0	180.0	180.0	180.0	180.0
Mean	0.63	0.68	32.5	20	44.5	45.03	21.26	-1.01	-0.79	6.52	4.92
Std	0.48	0.47	4.74	0	34.08	8.18	17.11	1.18	1.12	5.86	6.5
Min	0.0	0.0	25.0	20	0.0	35.04	0.0	-3.83	-3.83	0.0	0.0
25%	0.0	0.0	28.47	20	0.0	35.04	0.0	-2.01	-1.56	0.0	0.0
50%	1.0	1.0	32.43	20	45.0	45.03	25.36	-0.36	-0.04	5.51	0.0
75%	1.0	1.0	36.28	20	67.5	55.03	34.5	0.0	0.0	12.55	12.51
Max	1.0	1.0	42.0	20	90.0	55.03	55.07	0.0	0.0	16.87	16.87

Table 4.4 Statistical analysis of the dataset – Global Scale.

The statistical analysis is an important step to decide whether the selected features, in this case, all of them, need to be normalised. This step is crucial to increase the performance of the ANN: as data flows from layer to layer through additions and multiplication, the resulting values could get large quickly, affecting negatively the ability of the network to deal with non-linear relationships (Dertat, 2017).

The following plots (***Fig. 4.4***) describe the distribution of the two categorical features, “Stuck” and “Cut”, in relation to the three main input fabrication parameters, namely the Tool/Surface Angle, the Tool/Grain Direction Angle and Input Length for the cut.

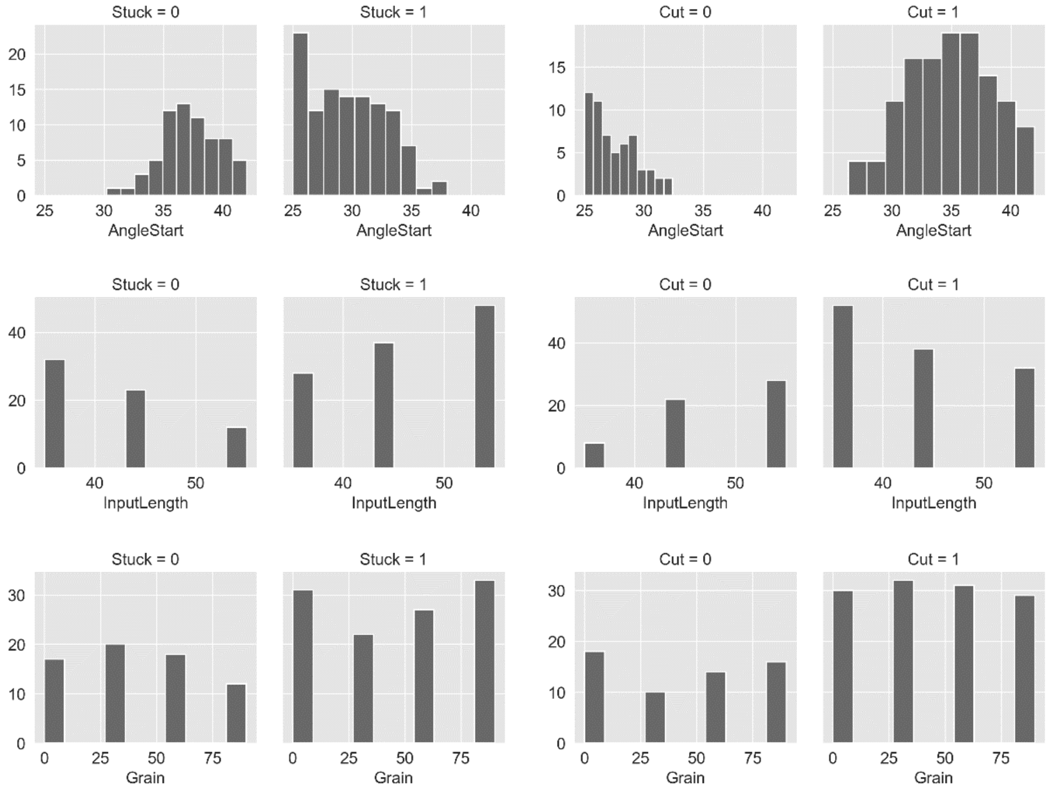


Figure 4.4 Histograms showing the distribution of the two event labels ("Stuck" and "Cut") in respect to the input fabrication parameters.

Overall, the three considered features seem to be significantly correlated to the occurrence or not of the analysed manufacturing conditions. The Tool/Surface Angle plots describe a neat distinction between samples, with a threshold around 32° to 35° for the "Stuck" event and around 30° to 27° for the "Cut" event. Moreover, the two events appear to be correlated, as the occurrence distribution is inverted in the respective plots. For instance, cutting along or across the grain present a higher number of cuts where the tool has managed to exit successfully from the material rather than intermediate Tool/Grain direction angles. Conversely, for the "Cut" label, there is a lower number of cuts along 0° and 90° of the wood grain direction able to successfully remove material.

To investigate the potential linear relationship between the considered features and event labels, the Pearson Correlation Coefficient has been calculated and plotted into a heatmap (***Fig. 4.5***). Such coefficient requires data to be normalised and consist of values ranging from +1 to -1, in the case of positive or negative correlation respectively. Among the fabrication inputs, the Tool/Surface Angle parameter is the one with the highest correlation, with a negative coefficient of -0.78 for the "Stuck" label, meaning, as expected, that shallower angles have fewer chances of getting the tool stuck into the material. On the opposite, a positive coefficient of 0.73 for the "Cut" label, shows that steeper angles have more chances of actually removing material. On the other hand, the Tool/Grain Direction Angle parameter does not present a linear relationship with the two labels as the recording session has been structured to look for the occurring of the two manufacturing conditions in all the different analysed grain directions.

Furthermore, the study of output features makes possible to better understand how these relate to the two event labels: for instance, the Stuck label=1 is inversely correlated to the Max Width and End Width features, *i.e.* smaller values for the End Width features are more likely to be related to successful cuts, as the cut is not interrupted in the middle of the operation where the Width is larger.

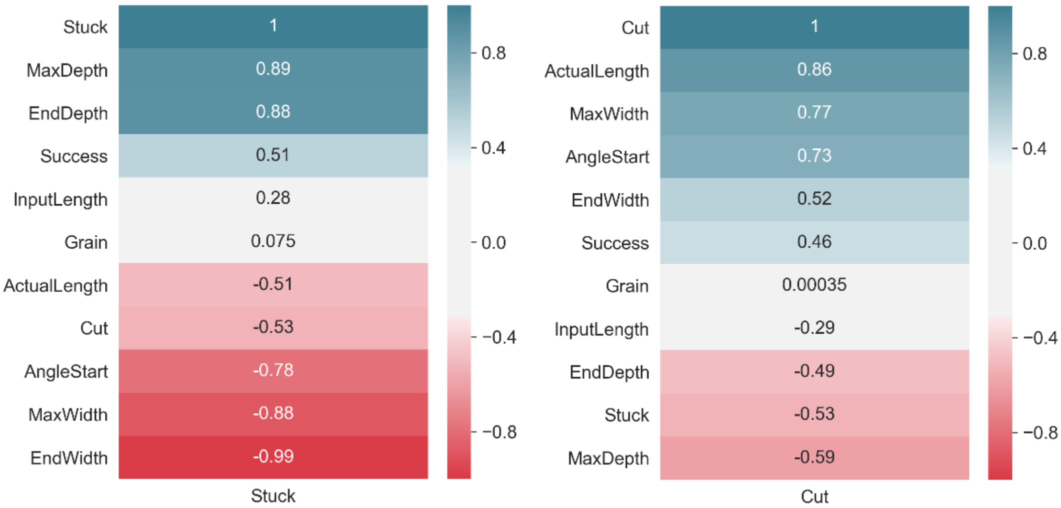


Figure 4.5 Pearson Correlation Coefficient analysis between the event labels and the other recorded features (global scale).

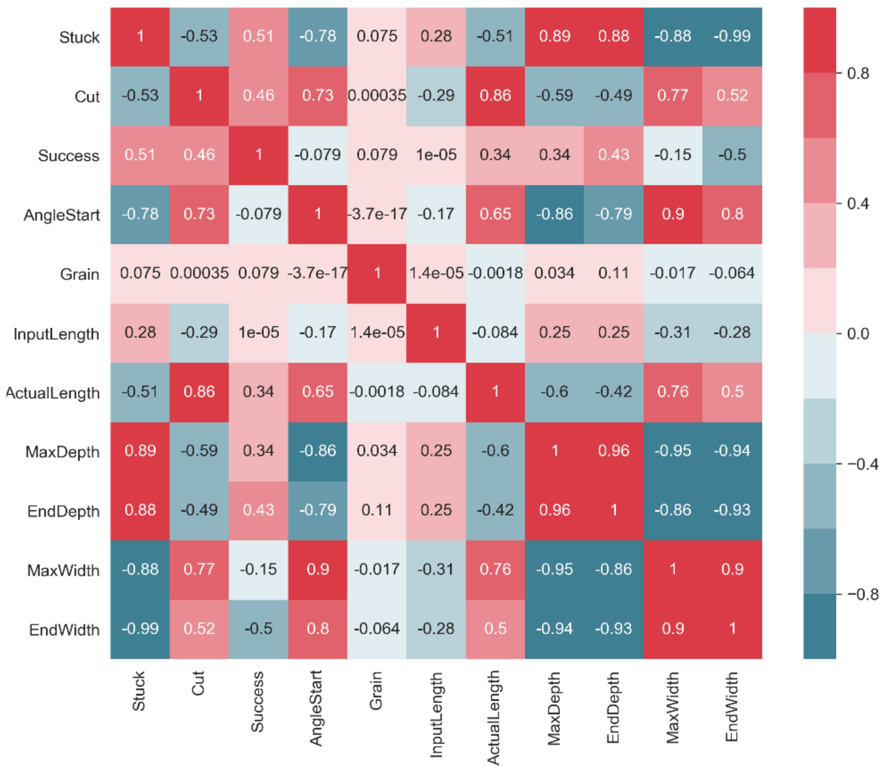
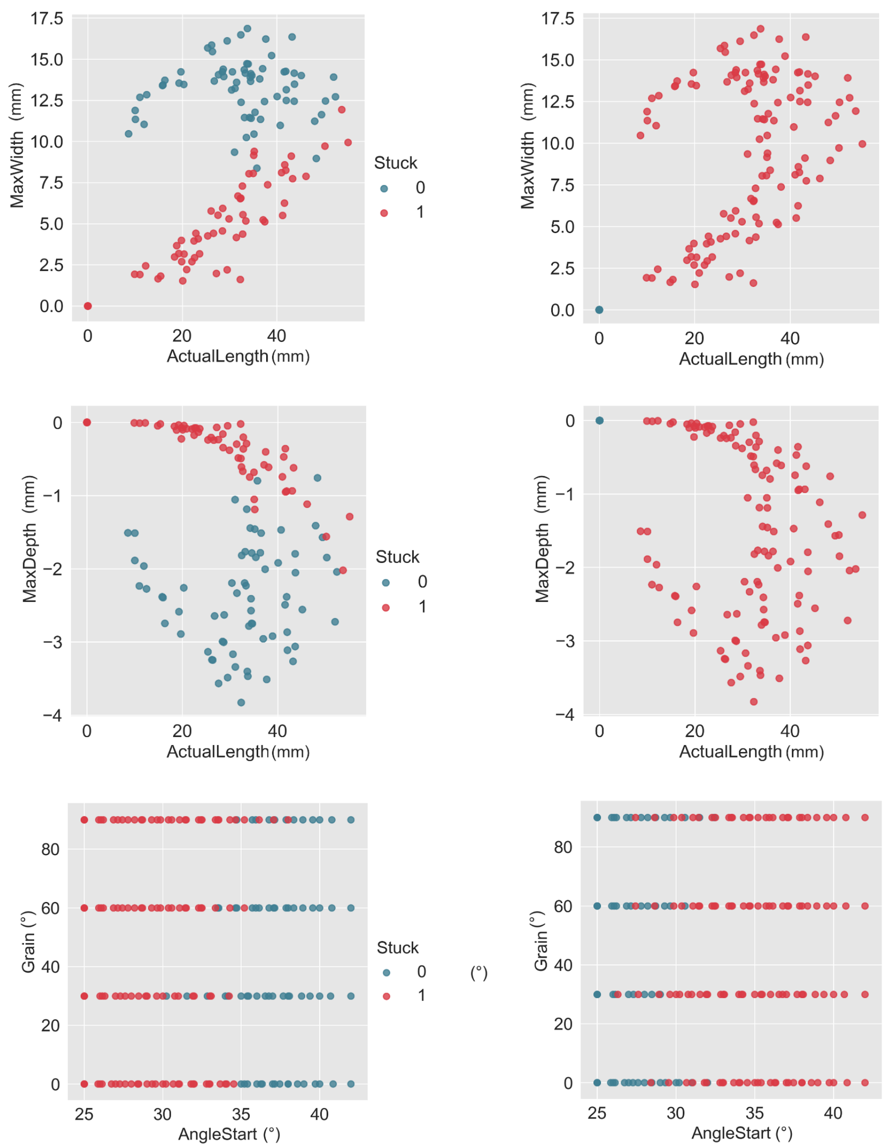


Figure 4.6 Pairwise analysis of the Pearson Correlation Coefficient across all the recorded features (global scale).

The calculation of the Pearson Correlation Coefficient is extended to a pairwise analysis of all the features (***Fig. 4.6***). As the previous heatmaps suggested, the most significant linear relationship is found between the input features of the Tool/Surface Angle and the output features describing the obtained cut: MaxDepth, EndDepth, MaxWidth, EndWidth. Furthermore, the heatmap presents strong correlations between the output features themselves, showing, for instance, a positive coefficient of 0.95 for Max Depth and Max Width.

The pairing of the input and output features in a series of scatter plots, in which each data point is coloured based on the event label, is used to get a qualitative description of the correlations presented in the heatmaps above (***Fig. 4.7***). Considering only a pair of features for each plot makes possible to identify, even from a visual point of view, the presence of two main, separable, groups. The learning objective for the binary classifier discussed in the next sections is to define a threshold function between these.



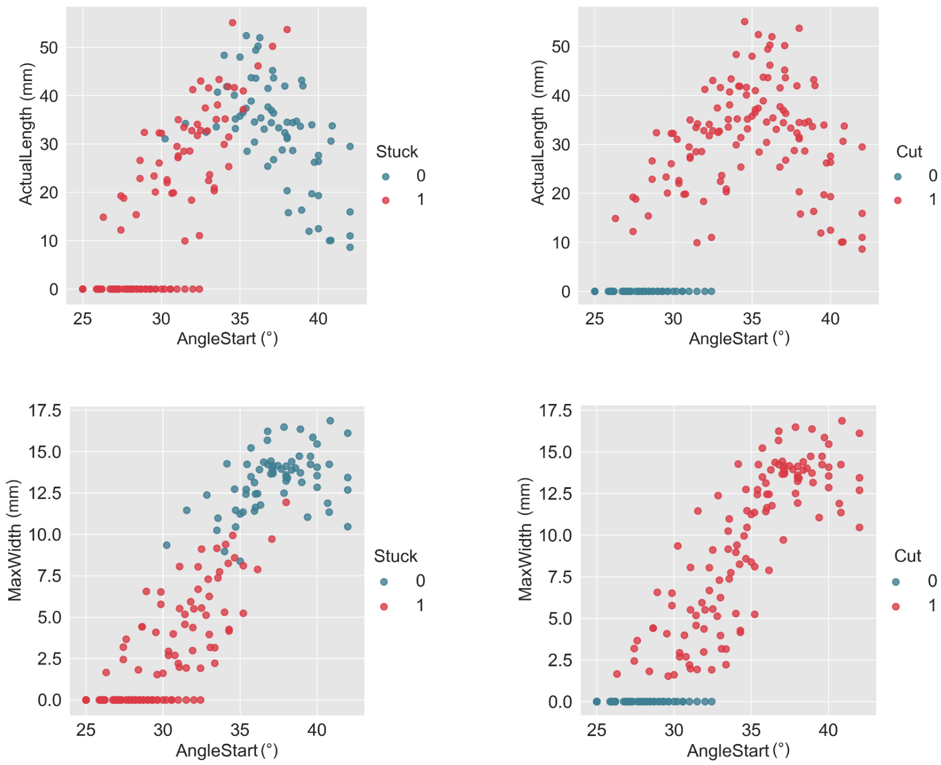


Figure 4.7 Scatter plots showing the distribution of the event labels (i.e. "Stuck" and "Cut") in relation to the recorded features.

4.2.2 Human Dataset Analysis

In this section, the analysis of manufacturing conditions occurring during the robotic data collection is compared to a dataset generated under identical conditions in terms of tools and wood species by a human expert demonstrator. The methods used to record human operations have been described previously in **Chapter 3** and relies on a combination of motion-capture cameras with real-time sensor data processing and subsequently photogrammetric reconstruction of the carving results.

The comparison between the two data acquisition methods is performed using the local scale dataset type as it provides a higher level of detail for each target frames composing the carving operation.

In ***Fig. 4.8*** the geometrical features of Depth, Length and Width for each frame of the robotic dataset are plotted, and to each data point is assigned a colour based on whether it belongs to an operation which overall resulted successful or unsuccessful, namely both event labels values were equal to 1. Such analysis presents two main findings: **i)** The data points are distributed as forming two distinct groups which appear evident even from a visual point of view, **ii)** there is a range of values for each geometric feature which never generates successful operations, therefore it would be beneficial to avoid them entirely already at a design stage.

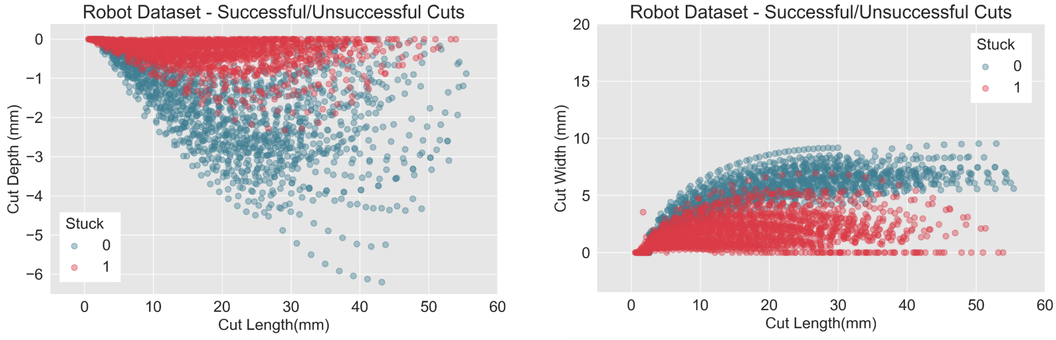


Figure 4.8 Analysis of the distribution of successful and unsuccessful operations in the robotic dataset based on output features of the carved geometry.

Based on these premises, the successful group of operations from the robotic dataset has been isolated and compared next to the entire dataset of operations collected from the human demonstration (***Fig. 4.9**-**4.10)***.

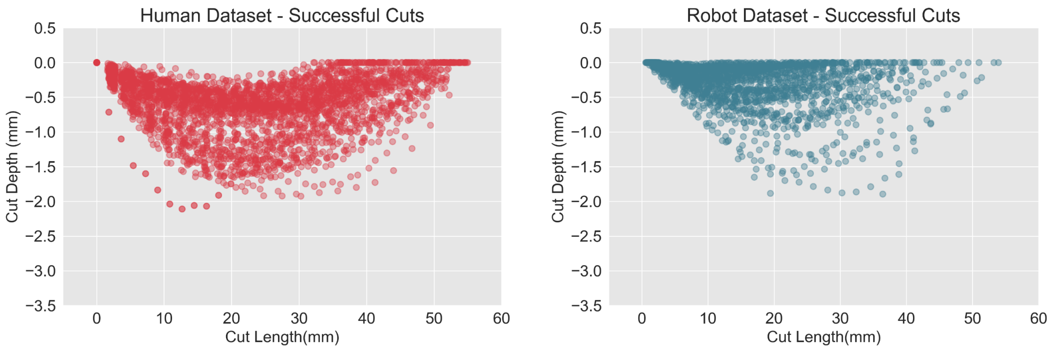


Figure 4.9 Depth feature - Comparison between the recorded successful operations of the robotic (left) and human (right) datasets.

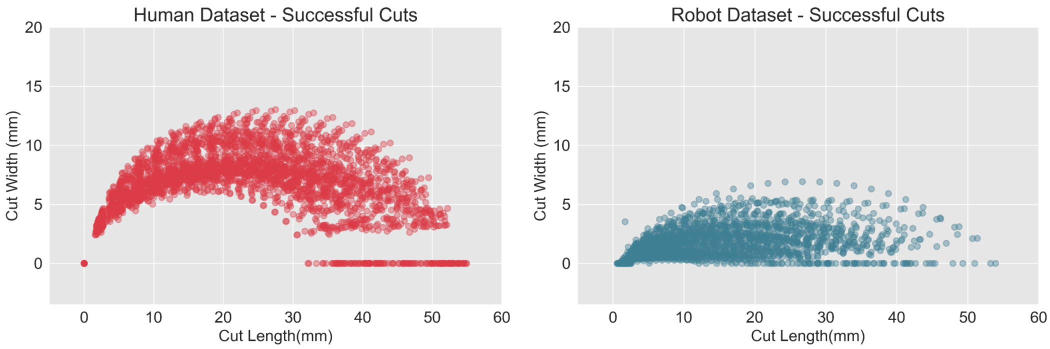


Figure 4.10 Comparison between the recorded successful operations of the robotic (left) and human (right) datasets.

The plots show that both datasets present a similar range of features values for successful operations, specifically between 2 to 13 mm for the Width feature and between 0 to -2 mm for the Depth feature. For both datasets, the prescribed range for the Length feature has been between 30 to 55 mm, however, the plots show that many robotic operations are significantly shorter and less deep than the original digital intention because of the lack of control on the deviation between digital inputs and physical outputs.

The main differentiator between the two datasets is represented by the ability of human craftsmen of intuitively navigating and anticipating, after training and experience, the range of possible successful operations. For this reason, a skilled craftsman is unlikely to execute dangerous or inefficient operations, as described in the previous section with the labels “Stuck” and “Cut”. Consequently, based on the two event labels considered here, it is not necessary to implement a binary classification filter between successful and unsuccessful operations for the human-based carving dataset.

4.2.3 Binary Classification: Individual Event Prediction

In this section, the individual binary prediction of the two manufacturing conditions, described by the categorical features “Stuck” and “Cut”, is assessed.

In a first instance, the task is approached with the training of a Logistic Regression (LR) model which represents a simpler, linear, model in comparison to the ANN model presented in the second part of this section using identical data and training conditions. LR is a binary classification algorithm whose aim is to linearly separate dichotomous classes within an N-dimensional dataset through an N-1 hyperplane. In simpler models, *e.g.* a 2-dimensional dataset, the separation boundary will be a straight line, while for a 3-dimensional dataset, it will be a 2D plane. To achieve this, LR models utilise the sigmoid function (or logistic function), which is an S-shaped function that maps any real number between 0 and 1, resulting particularly useful for transforming probability predictions into binary values:

$$\sigma(z) = 1/(1 + e^{-z})$$

where e is the Euler’s number and z is the value to transform.

The main reason to use such model, besides its more straightforward implementation, is to test whether the features dataset is linearly separable in the two groups describing the successful completion of the operation (0 or 1) in relation to the event considered.

The metrics used to evaluate the predictive abilities of the binary classifiers trained in this section, both for the LR and ANN models, are the following:

- **Accuracy (%)** is the percentage number of correct predictions made by a trained model in relation to the total amount of predictions.

- **Null Accuracy (%)** is the accuracy measure as a percentage value that a dummy model would score always predicting one of the two categorical features.

- **Confusion Matrix** is a table used to summarise the performance of the trained model describing the correct and incorrect predictions and type of errors, which the accuracy metrics alone is not able to provide. The four categories of the table are the following:

- **True Positives (TP):** Data point = 1 (True) and Prediction = 1 (True).
- **True Negatives (TN):** Data point = 0 (False) and Prediction = 0 (False).
- **False Positives (FP):** Data point = 0 (False) and Prediction = 1 (True).
- **False Negative (FN):** Data point = 1 (True) and Prediction = 0 (False).

Based on the Confusion Matrix results, the following scores are provided:

- **Precision** = TP / (TP+FP)
- **Recall** = TP/(TP+FN)
- **F-1 Score** = 2 * Precision * Recall / (Precision + Recall)
- **Support** is the number of actual occurrences of the class in the specified dataset.

The loss function used for the training progress is defined as *binary cross-entropy* function, or *log loss* function, and it is the define as:

$$C = \frac{1}{n} \sum_{x} [y \ \log(a) - (1 - y) \log(1 - a)]$$

where n is the total number of items of training data, the sum is over all training inputs, x, and y is the corresponding desired output and a is the prediction output (Nielsen, 2015). The main advantage of using such a loss function (***Fig. 4.11***), in comparison, for instance, to the quadratic cost function, is that the larger the error, the faster the model will learn, penalising especially those predictions that are confident and wrong (Loss Functions - ML Cheatsheet, 2017):

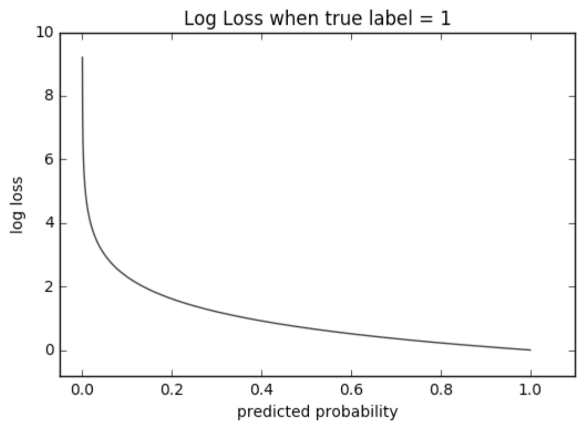


Figure 4.11 Log Loss Functions – Source: ML Cheatsheet 2017.

The examined dataset, consisting of 181 samples (*i.e*. carving operations), is subdivided into two subsets, a Training and Testing dataset, with a proportion of 75%:25%, corresponding to 135:45 samples. The total number of training epochs is 250.

The input feature vector has three dimensions: **1)** Tool/Surface Angle **2)** Tool/Grain Direction Angle **3)** Input Cut Length. The output categorical feature value to predict is a binary output (0 or 1) in relation to the individual event considered.

After the training, the LR model scores an Accuracy of 90% and 84.1% for the "Stuck" and "Cut" events respectively (***Fig. 4.12 - 4.13***). The null accuracy values for the "Stuck" model is 62.7 % and 67.7% for the "Cut" model.

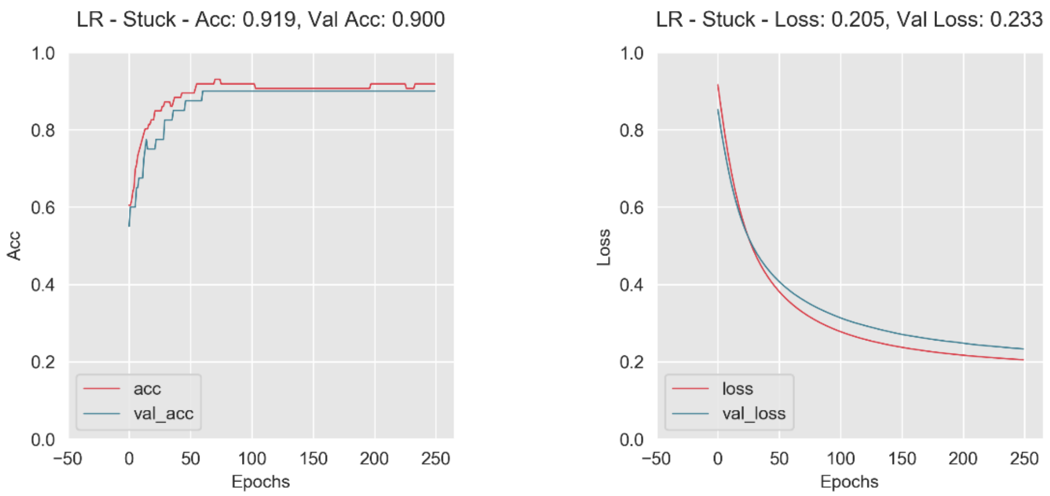


Figure 4.12 "Stuck" event label: Training history plots of the LR model.

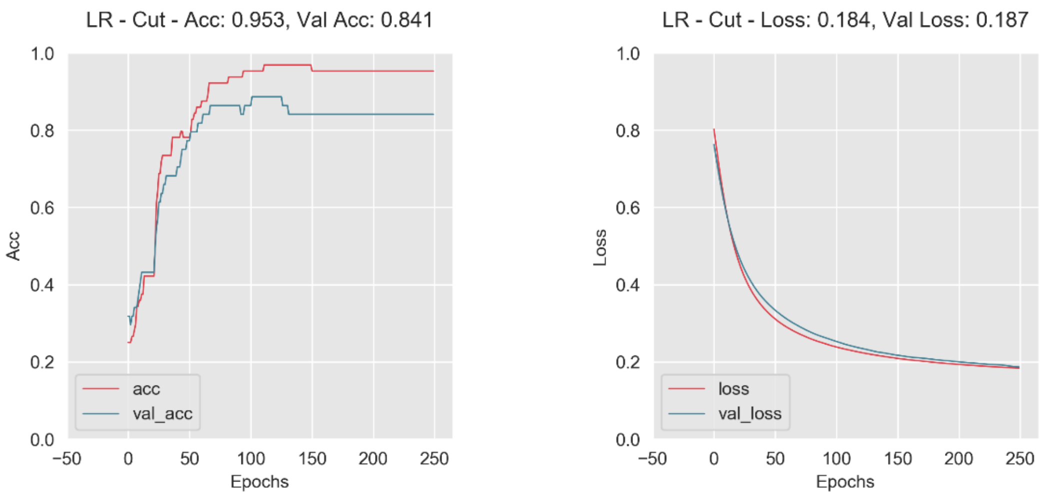
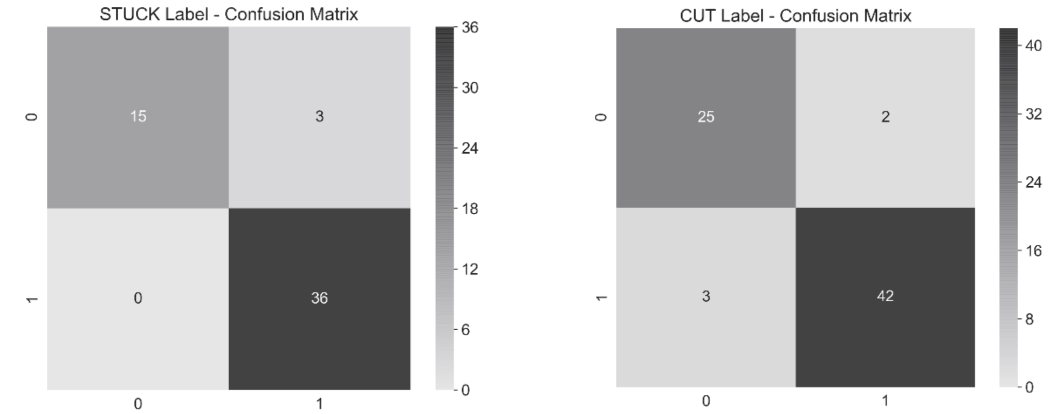


Figure 4.13 "Cut" event label: Training history plots of the LR model.

The predictive abilities of the model are evaluated plotting the predicted results for the Testing dataset in confusion matrices (***Fig. 4.14***). Different score measures are reported below each matrix. Overall, both LR trained models performs well with a Precision score of 0.96 for the "Stuck" event and 0.97 for the "Cut" event.

Following the analysis of the predictive performances of the LR model, an assessment of an ANN model addressing the same predictive task is presented below. The network topology is structured as *3:6:1*, with an input layer of *size* = 3 corresponding to the dimension of the input features vector, one hidden layer with *size* = 6 each and finally an output layer with *size* = 1. To compare the ANN model with the LR one, the training epochs number, *i.e.* 250, and the batch size parameter, *i.e.* 10, are the same.



Classes	precision	recall	f1-score	support
0	0.94	0.94	0.94	18
1	0.97	0.97	0.97	36
avg/total	0.96	0.96	0.96	54

Classes	precision	recall	f1-score	support
0	0.93	1.0	0.96	27
1	1.0	0.96	0.98	45
avg/total	0.97	0.97	0.97	72

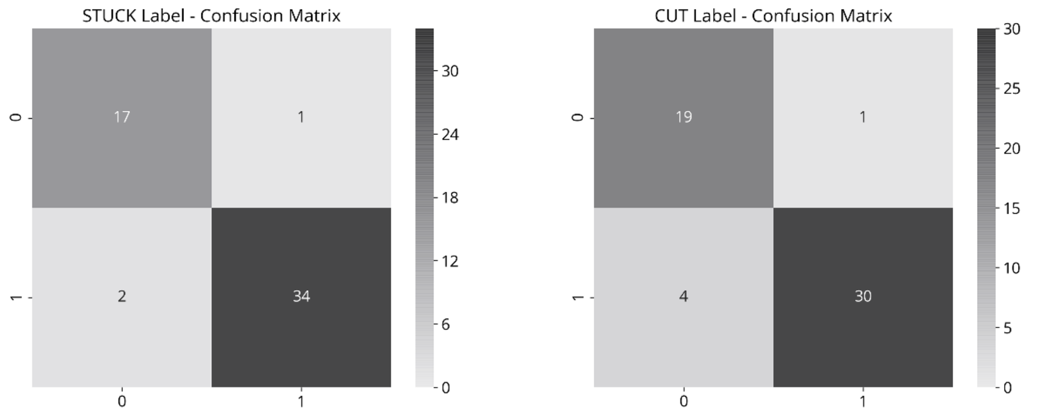
Figure 4.14 Confusion matrices for testing the prediction rate of the LR model - "Stuck" (left) and "Cut" (right) event labels.

At the end of the training, the "*Stuck*" model reached an accuracy score against the Validation dataset of 90.6%, in respect of a null accuracy of 62.7% (***Fig. 4.15***). The "*Cut*" model reached a Validation Accuracy score of 92.6%, in respect of a null accuracy of 67.7% (***Fig. 4.16***). Based on the training history plots, both accuracy scores converge quickly before the first 150 epochs and remain stationary until the end of the training.

Figure 4.15 "Stuck" event label: Training history plots of the ANN model.

Figure 4.16 "Stuck" event label: Training history plots of the ANN model.

The predictive abilities of the system are tested and plotted in the Confusion Matrices below (***Fig. 4.17***). Overall, both trained ANN models perform reasonably well with a Precision score of 0.95 for the "Stuck" event and 0.92 for the "Cut" event.



Classes	precision	recall	f1-score	support
0	0.89	0.94	0.92	18
1	0.97	0.94	0.96	36
avg/total	0.95	0.94	0.94	54

Classes	precision	recall	f1-score	support
0	0.83	0.95	0.88	20
1	0.97	0.88	0.92	34
avg/total	0.92	0.91	0.91	54

Figure 4.17 Confusion matrices for testing the prediction rate of the ANN model - "Stuck" (left) and "Cut" (right) event labels.

Comparing the LR and ANN models, the main takeaway is that the ANN model scores, for both event labels prediction, only a slightly higher accuracy value of a few percentage points. This finding suggests the dataset is linearly separable, for each event, in two distinct groups (0 and 1), as the LR model accuracy rate is above 90% in both cases. While the ANN performs slightly better than a linear model (LR), the latter, simpler, model appears sufficiently suitable for the task of a single event prediction.

4.2.4 Binary Classification: Combined Events Prediction

While it is possible to predict whether an undesired manufacturing condition will occur, this does not necessarily guarantee the overall success of the operation. For instance, the actual removal of material does not ensure that the tool will not get stuck, or the other way around, the completion of the tool movement does not imply that it will remove any material at all. The success of an operation depends on a series of factors which need to be considered simultaneously to confidently achieve the desired outcome. Furthermore, designers could have different opinions of what a successful operation is, not necessarily relying only on quantitative data but also on a qualitative or subjective analysis, for instance, perceived smoothness or other user-defined criteria (***Fig. 4.18***).

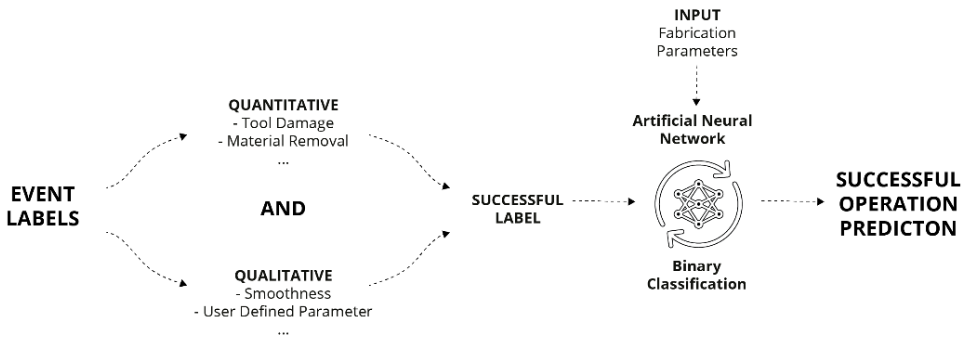


Figure 4.18 Successful operation prediction process – Diagram.

The definition of a Success label is, therefore, depending on the combination of individual single event labels. As all the event labels are structured with 0 as not successful, and 1 as successful operation in respect to a specific event, it is then possible to combine multiple of them using the AND Boolean operation. The plots in ***Fig. 4.19*** present the results of the Boolean intersection of the "Stuck" AND "Cut" events in relation to different pairs of dataset features.

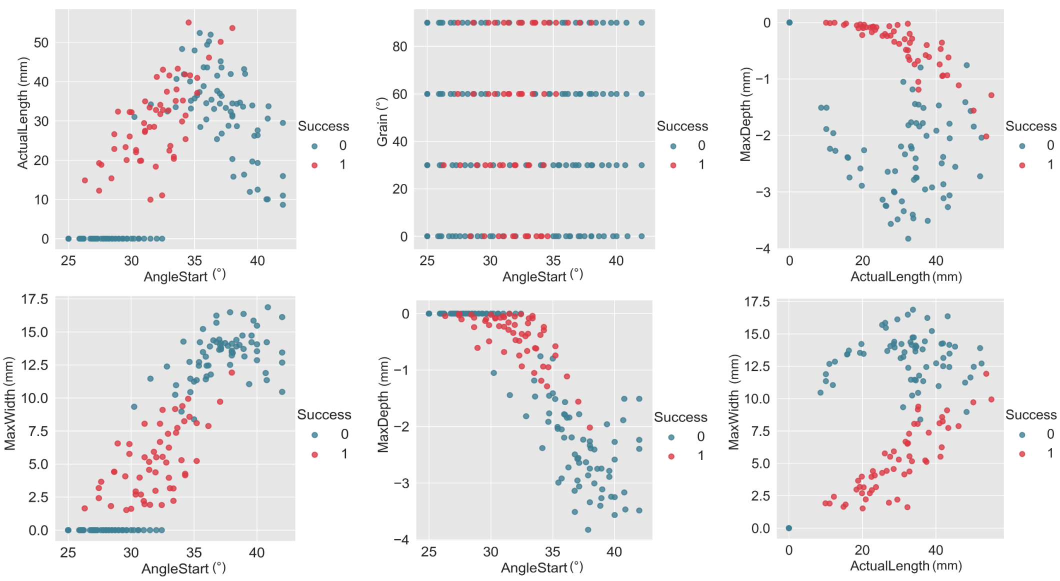


Figure 4.19 Scatter plots showing the distribution of the "Success" event label in relation to the recorded features.

Firstly, even if only pairs of features are plotted each time, drawing a line to separate the two groups is not as straightforward, at least visually, as in the individual-event case presented in ***Fig. 4.7***. As in the previous section, both LR and ANN model prediction performances are assessed in respect of the Success event label using the same configuration of features vectors, Train/Test Data split ratio and model parameters for comparison. During the training, the LR model scored a Validation Accuracy rate of 64.4% with a Validation Loss value of 0.672, which represents a poor performance, considering that such value corresponds to the null accuracy rate for that prediction task (***Fig. 4.20***). The result is further confirmed in ***Fig. 4.21*** by the confusion matrix and the classification report metrics which show how the model always predicted the same value (*i.e.* 0).

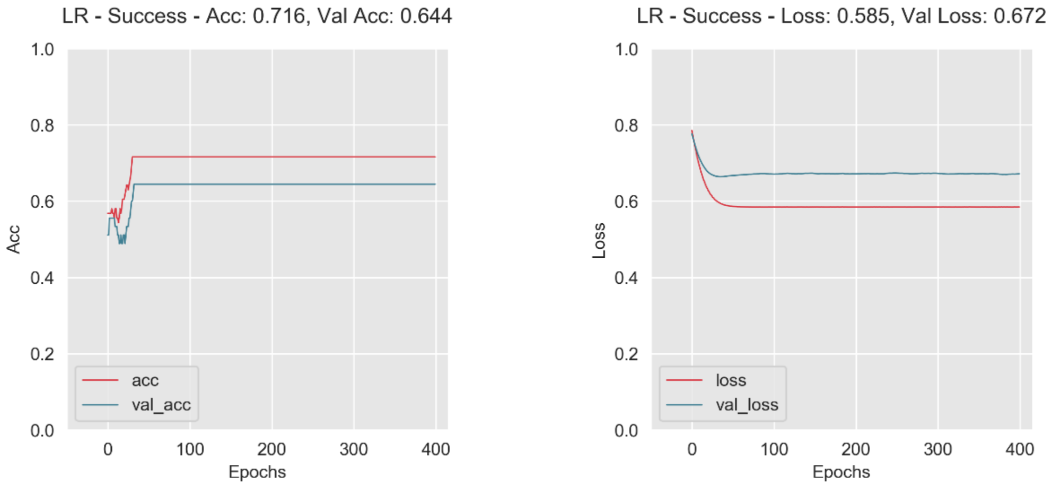
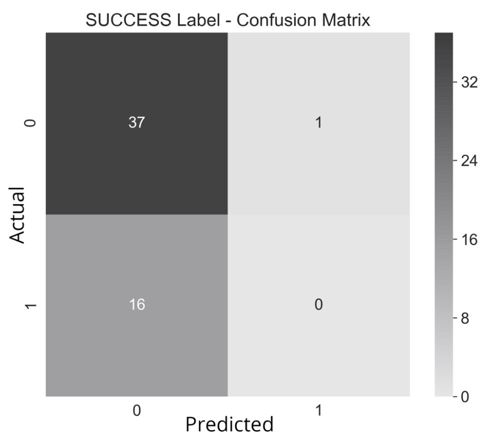


Figure 4.20 "Success" event label: Training history plots of the LR model.



Classes	precision	recall	f1-score	support
0	0.7	1.0	0.83	38
1	0.0	0.0	0.0	16
avg/total	0.5	0.7	0.58	54

Figure 4.21 Confusion matrix for testing the prediction rate of the LR model - "Success" event label.

Following the assessment of the LR model, the ANN model has been tested for the same binary prediction task. During the training, the ANN model reached a Validation Accuracy score of 94.7% and a Validation Loss value of 0.110 (***Fig 4.22***). Afterwards, the predictive abilities of the model have been tested against the Testing dataset, with a Precision score value of 87% (***Fig 4.23***).

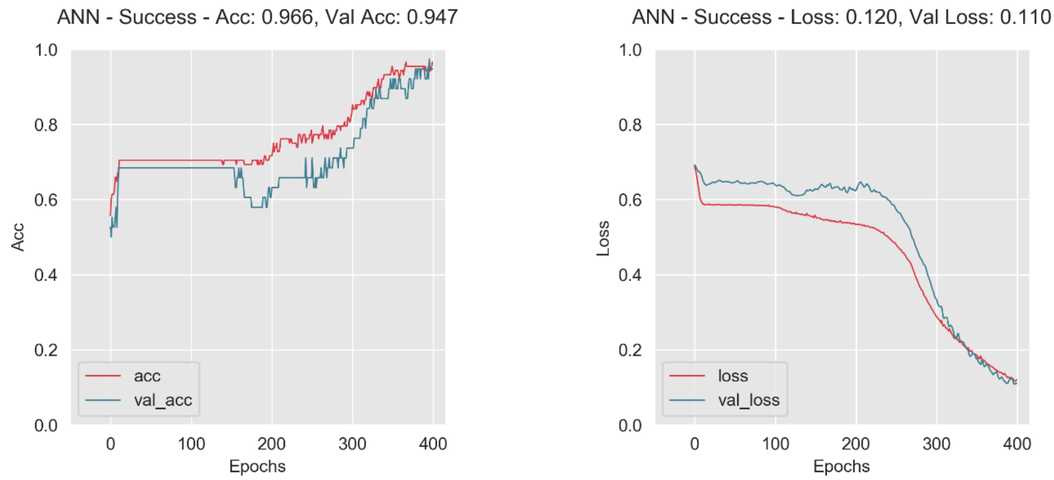
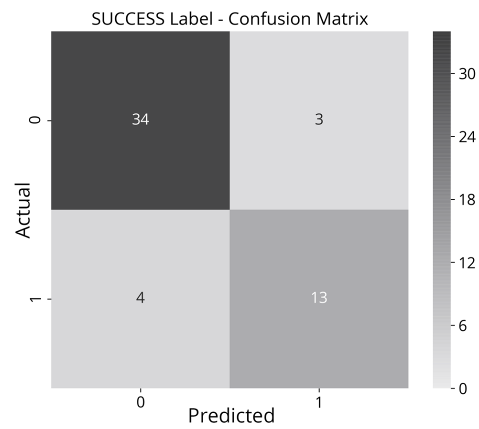


Figure 4.22 "Success" event label: Training history plots of the ANN model.



Classes	precision	recall	f1-score	support
0	0.89	0.92	0.91	38
1	0.81	0.76	0.79	16
avg/total	0.87	0.87	0.87	54

Figure 4.23 Confusion matrix for testing the prediction rate of the ANN model - "Success" event label.

Comparing the performances of the LR and ANN models, the results suggest that, while for the single event prediction, the LR model showed a similar prediction rate to the ANN, demonstrating that the dataset is linearly separable, for the combined event prediction, the LR model is inadequate to determine whether one operation would be successful or not. On the other hand, the ANN model proved to be able to correctly separate the two groups, performing reasonably well for the task requirements. As the prediction of the "Success" label is based on the combination of individual events (i.e. "*Stuck*", "*Cut*"), it could be framed as a typical XOR problem (Minsky and Papert, 1969), where the model is trying to define a region roughly in the middle between cutting too deep (and getting stuck) and cutting too shallow (and not cutting at all). This type of problems justifies the use of a hidden layer in the ANN model, as linear models are not sufficient to perform the prediction task, as demonstrated by the findings. Alternatively to creating a "Success" label and using an ANN model, it should be possible to assess whether an operation would be successful or not combining the individual predictions of linear classifiers for single events.

4.3 Geometric Features Prediction

Based on the binary classification process presented in the previous section, it is possible to identify which fabrication parameters will lead to a successful operation, excluding all those operations which are not effective or even dangerous. Nevertheless, the trained binary classifier does not provide sufficient information to geometrically reconstruct the outcome of the carving process.

The methods presented in this section seek to provide a geometrical approximation of subtractive operations informed by sensor-based data reconstruction of robotic operations performed during the recording sessions. As for the event prediction, this represents a supervised learning problem based on the pairing of fabrication parameters with material outputs. Specifically, it is a regression problem, as the model is asked to predict continuous output values (*e.g.* depth cut values) rather than categorical probabilities.

The learning objective is two-fold: **i)** To predict geometric output features values, such as actual Width, Depth and Length of the cut, based on a robotic toolpath and related fabrication parameters; **ii)** To reconstruct from a carved geometry the robotic toolpath that has generated it. Once the relationship between the two groups of data is established, it should be possible to utilise the predictive abilities of the system in both directions.

The goal of the strategy presented in this section is to significantly lower the deviation error between digital input geometries and robotically fabricated carving operations to a level which makes it possible to integrate such manufacturing technique as part of a design interface.

4.3.1 Robotic Dataset Analysis

As described in **Section 4.1.1**, the type of dataset used for the regression-based prediction of geometrical features is based on individual target frames arranged in a sequence of 20 frames in total. This level of analysis provides a detailed description of the operation both in terms of input and output features.

The training boards series from which the dataset is generated is the same utilised for the binary event prediction task in **Section 4.2**, however, as the operations are considered at the local target frames scale, the number of the samples, $n = 3780$, is much higher than the number of cuts (***Table 4.5***).

Dataset	Samples	Features	Wood	Robot	Tool
Frames	3780	11	Lime	ABB IRB1600	Stubai 9/20

Table 4.5 Robotic Dataset Info – Local Scale.

In ***Fig. 4.24***, a pair-wise features heatmap shows the Pearson correlation coefficient values, while in the three heatmaps in ***Fig. 4.25***, each output features to be predicted is analysed individually.

The three output features are positively and strongly correlated with each other: longer cuts show higher depth and width values. Furthermore, while in **Section 4.2.1** the Tool/Surface Angle feature presented high correlation values in respect to the categorical labels to be predicted, in this case, where only individual target frames are considered, the correlation coefficient values do not show a strong linear relationship.

Figure 4.24 Pairwise analysis of the Pearson Correlation Coefficient across all the recorded features (Local scale).

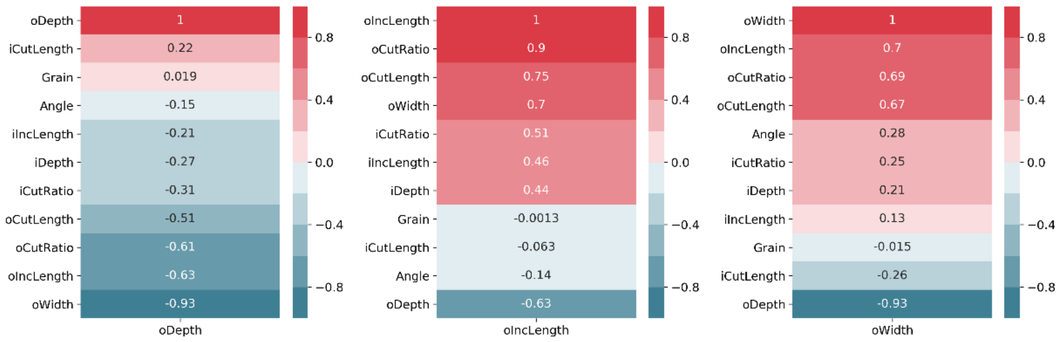


Figure 4.25 Pearson Correlation Coefficient analysis between individual geometric features of the cuts and the other recorded features.

4.3.2 Regression: Geometric Features Prediction

In this section, the prediction of the geometrical features necessary for the geometric simulation of subtractive operations is addressed using both an ANN model and a simpler linear model, called Linear Regression (LinR), for comparison.

LinR is a model for regression tasks which assumes a linear relationship between a set of continuous input variables and a single continuous output variable. While its architecture is similar to the LR model (used in **Section 4.2** for the binary prediction), it also differs for two main aspects: **i)** It does not make use of a Sigmoid function for splitting its prediction into two categories. **ii)** It uses the Mean Absolute Error (MAE) or Mean Squared Error (MSE) as loss function during the training and as metrics for the evaluation of the trained model.

Mean Absolute Error (MAE): measures the average magnitude of the errors in a set of predictions, without considering their direction. It is the average, expressed in the same unit of the dataset, over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |Y_i - \hat{Y}_i|$$

Mean Squared Error (MSE): It is the average of squared differences between prediction and actual observation. In comparison to the MAE, it returns an indication of the average magnitude of the error.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2$$

The dataset, consisting of 3780 samples (*i.e.* target frames), is subdivided into two subsets, a Training and Testing dataset, with a proportion of 75%: 25%, corresponding to 2835:945 samples. The input feature vector has five dimensions: **1)** Tool/Surface Angle **2)** Tool/Grain Direction Angle **3)** Input Unit Cut Length **4)** Input Incremental Cut Length **5)** Input Depth. The continuous output features to predict are **A)** Depth **B)** Length and **C)** Width values for each of the target frames describing the operation.

Plotting the performance score of the model during the training enables the in-progress evaluation of the system and identifying whether the model is over/underfitting. In ***Fig. 4.26***, the plots of the training histories of the LinR and ANN model are compared:

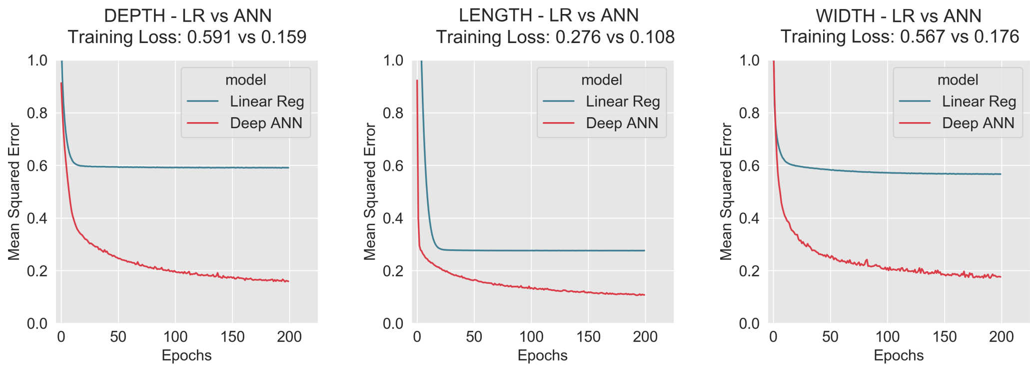


Figure 4.26 – Comparison between the LR and the ANN model – Training history plots.

The comparison summary is the following:

- **Depth**: The validation loss (MSE) with the LinR was 0.591 while with the ANN was 0.183, an improvement of the 222.9% in respect of the linear model.
- **Length**: The validation loss (MSE) with the LinR was 0.276 while with the ANN was 0.107, an improvement of the 157.9% in respect of the linear model.
- **Width**: The validation loss (MSE) with the LinR was 0.567 while with the ANN was 0.195, an improvement of the 190.7% in respect of the linear model.

The results demonstrate that the ANN model performs better than the LinR for the assigned task and that a linear model is insufficient to predict the output features of subtractive operation. For this reason, it will not be utilised in the subsequent studies. After the training, the predictive abilities of the ANN are tested using the testing dataset left out before the training process. In Fig. ***4.27***, the ANN predicted values are plotted against the actual ones:

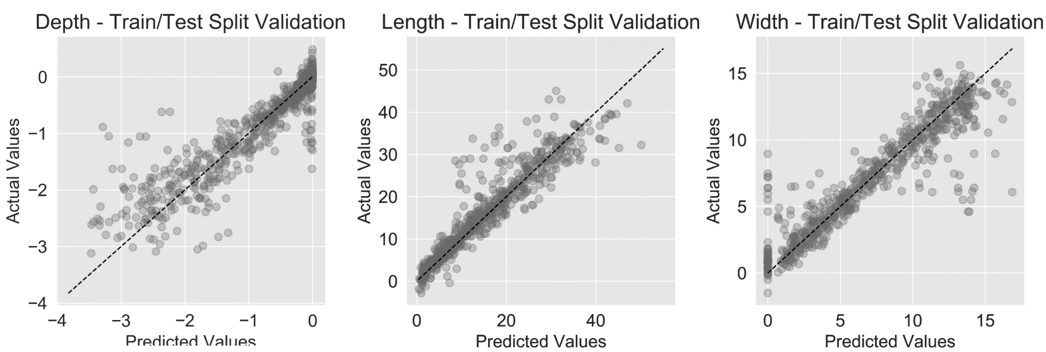


Figure 4.27 Train/test split validation for the prediction of the geometric features of the cuts (i.e. Depth, Width and Length of the cut).

The data points in the plots tend to align along the 45 ° bisecting line of the squared plots, showing the correct performance of the system. The Mean Absolute Error (MAE) and Standard Deviation (SD) for the prediction are the following: **a) Length**: MAE =

1.014 mm, SD = 0.293 mm; **b) Width**: MAE = 0.958 mm, SD = 0.106 mm; **c) Depth**: MAE = 0.921 mm, SD = 0.179 mm.

4.3.3 Regression: ANN Topology and Hyperparameters Search

The topology and hyperparameters of the ANN models presented in the previous section have been optimised for each individual feature prediction. The technique chosen to conduct such optimisation is a *grid search* method which is an exhaustive searching method for learning algorithms based on a manually defined set of hyperparameters and evaluated with a train/test split validation method.

The search has been set up in three passes. The first two passes were concerned with the topology of the network, defining the number of layers (*i.e.* 1 or 2) and the number of neurons for each layer, ranging from 2 to 30 with an interval of 2, for a total of 15 configurations tested for each pass.

In ***Fig. 4.28 - 4.30***, the validation results are plotted as grey points, while the results mean is plotted as a red dots-connecting line. The third pass, based on the results obtained from the previous two, focused on the optimisation of two key hyperparameters for the ANN model: i) the number of epochs and **ii)** the batch size. The hyperparameters search subsets utilised are: Epochs = {50, 100, 200, 400}, Batch Size = {5, 10, 20, 40}.

The results of the hyperparameter optimisation are plotted along with the first two topological optimisation searches in the shape of 2-D heatmaps with size 4x4, for a total of 16 configurations tested.

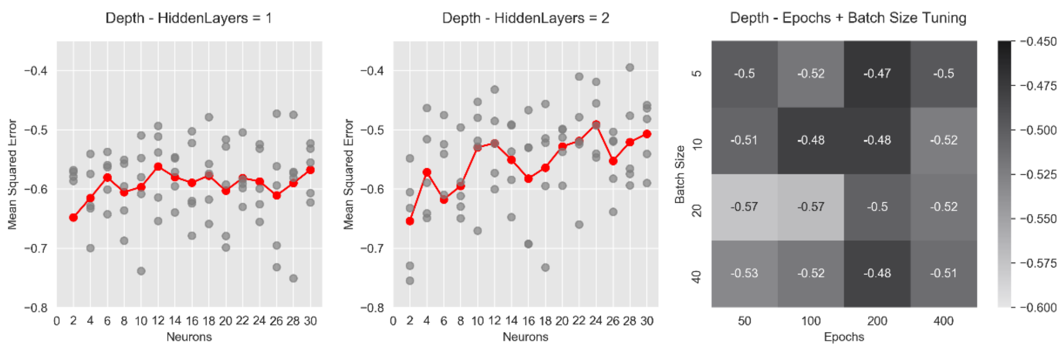


Figure 4.28 Depth feature prediction: optimisation of the ANN topology (i.e. the number of hidden layers and neurons) and hyperparameters (i.e. epochs and batch size).

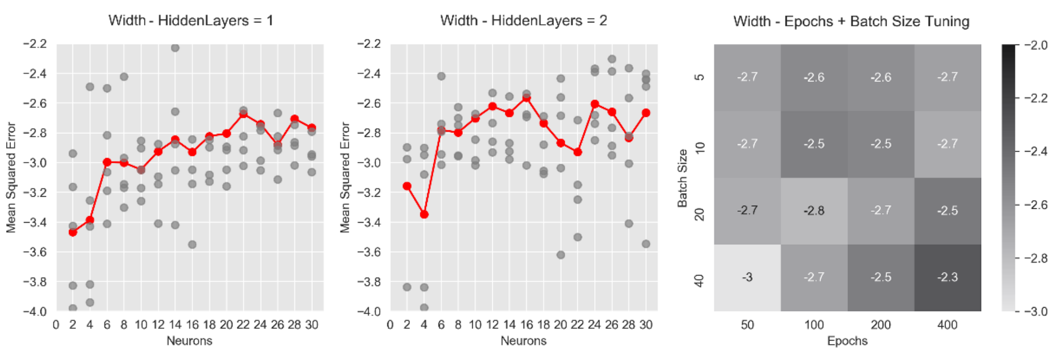


Figure 4.29 Width feature prediction: optimisation of the ANN topology (i.e. the number of hidden layers and neurons) and hyperparameters (i.e. epochs and batch size).

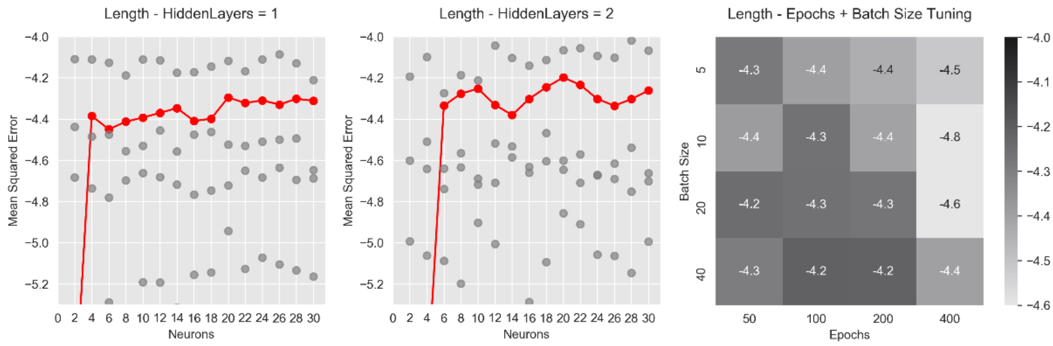


Figure 4.30 Length feature prediction: optimisation of the ANN topology (i.e. the number of hidden layers and neurons) and hyperparameters (i.e. epochs and batch size).

The summary of the best models found by the Grid Search optimisation is the following:

- **Depth**: First Hidden Layer Neurons = 12; Second Hidden Layer Neurons = 24, Epochs = 200, Batch Size = 5.
- **Width**: First Hidden Layer Neurons = 22; Second Hidden Layer Neurons = 16, Epochs = 400, Batch Size = 40.
- **Length**: First Hidden Layer Neurons = 20; Second Hidden Layer Neurons = 20, Epochs = 200, Batch Size = 40.

4.3.4 Regression: Fabrication Parameters Prediction

While in the previous section the models have been trained to predict the geometric features of the carving outcome from a combination of fabrication parameters, in this section, the learning objective is reversed: the models are trained to predict the fabrication parameters necessary to achieve a given carved geometry.

Such an application can be used for correcting the fabrication parameters to match a predefined desired geometrical outcome described as a digital Boolean operation or acquired through 3D scanning. The predicted fabrication parameters are used to reconstruct the robotic toolpath necessary to obtain the target carved geometry.

To achieve this, the configuration of input and output from the previous sections has been reversed. The predicted fabrication parameters are: **A)** Tool/Surface Angle **B)** Input Length. The input feature vector is 5-dimensional: **1)** Actual Unit Length **2)** Actual Incremental Length **3)** Actual Depth **4)** Actual Width **5)** Tool/Grain Direction Angle.

The ANN topology is 5:25:25:1 with Epochs = 200 and Batch Size = 20. These hyperparameters values have been defined following a Grid Search optimisation strategy as discussed in **Section 4.3.3**.

In ***Fig. 4.31*** and ***4.32*** are presented the ANNs training histories and train/test split validation plots.

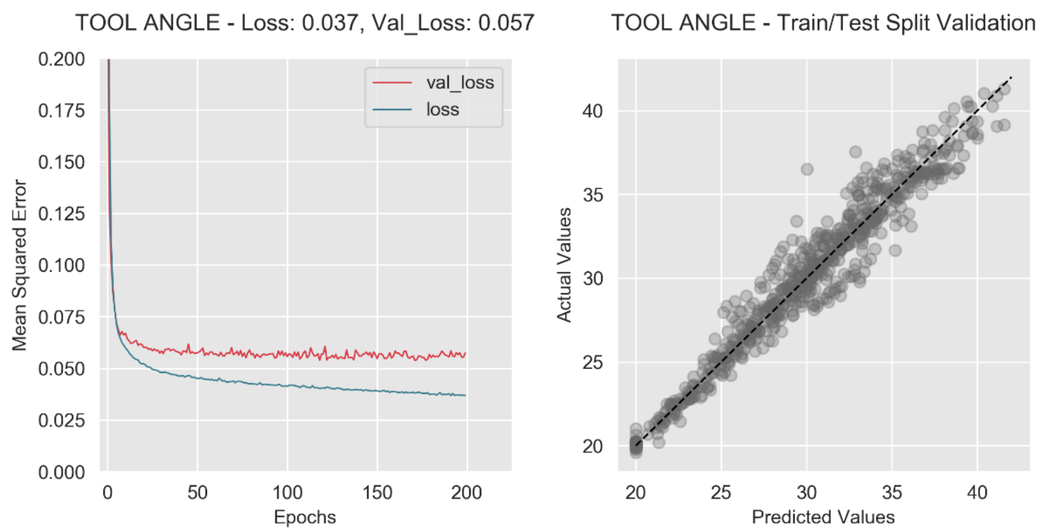


Figure 4.31 Tool/Surface Angle prediction: training history plot (left) and train/test split validation (right).

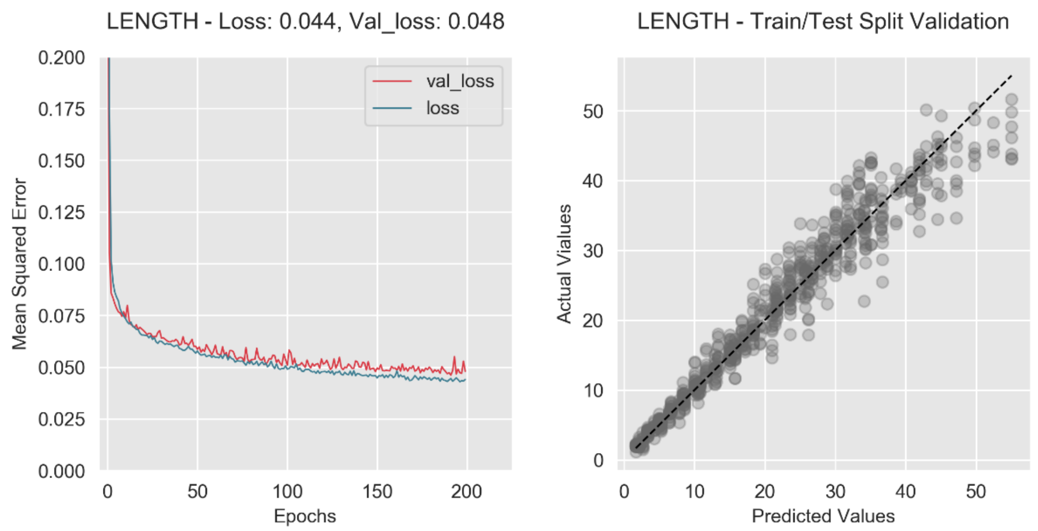


Figure 4.32 Input Cut Length prediction: training history plot (left) and train/test split validation (right).

The results of the training assessed using the Train/Test Split Validation methods are the following:

- **Tool Angle / Surface**: MAE = 1.174°, SD = 0.375°.
- **Input Cut Length**: MAE = 0.821 mm, SD = 0.124 mm.

These results, showing low error figures in the prediction, demonstrate that ANN models could also be used for the reconstruction of robotic operations alongside the simulation of geometric features.

4.3.5 Binary Classification + Regression: Optimized Training

In this section, the binary classifier for manufacturing conditions and regression prediction of geometric features are combined to improve the overall performance of the system. In the studies presented below is assumed that the binary classifier can predict with high accuracy, as previously demonstrated, whether a given set of fabrication parameters would generate a successful or unsuccessful operation. For this reason, the dataset utilised here to train the ANN exclusively consists of operations with attached a "Successful" label value. In this way, the original dataset size of 3780 is shrunk down to 1160 samples with significantly narrower boundaries of the feature's distribution (***Fig. 4.33***).

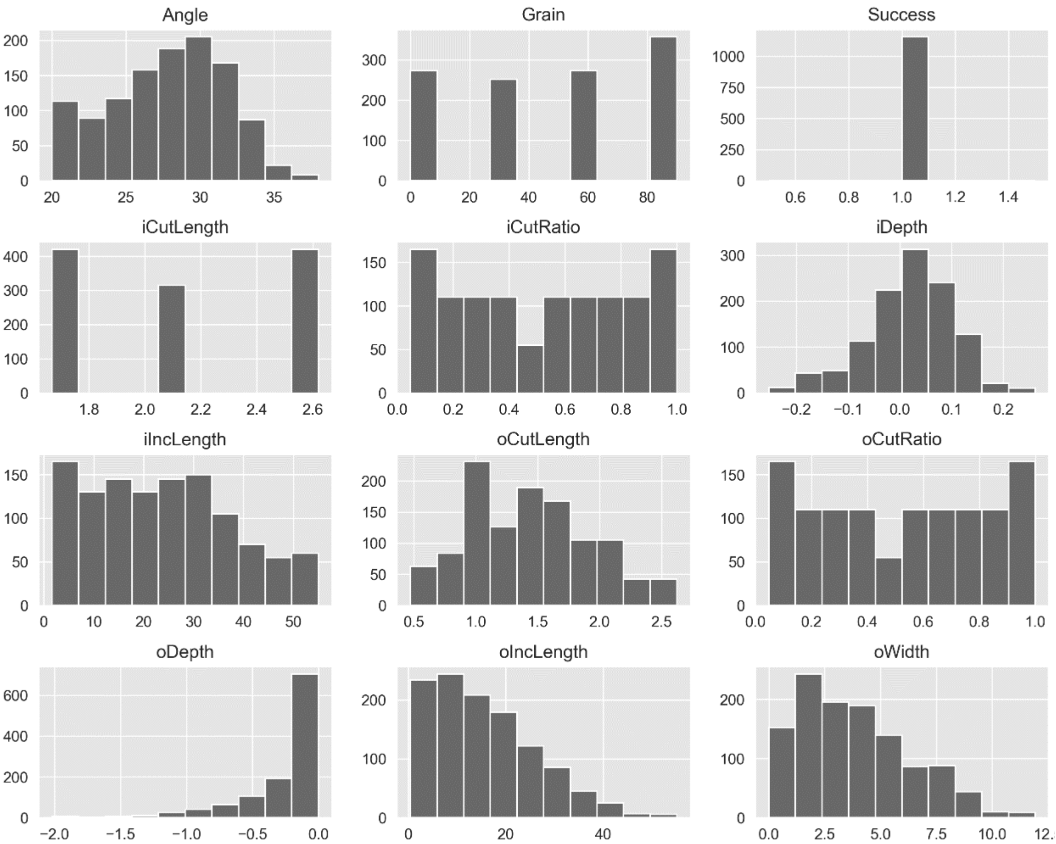


Figure 4.33 Individual features histograms of the dataset with only successful operations.

The input and output feature vectors, networks topologies and hyperparameters are unchanged in respect of those used in **Section 4.3.2**. As in the previous studies, ***Fig. 4.34 - 4.36*** show both the training history plots and Train/Test split validation plots next to each other for the prediction of the geometric features of Depth, Width and Length of the operation outcome.

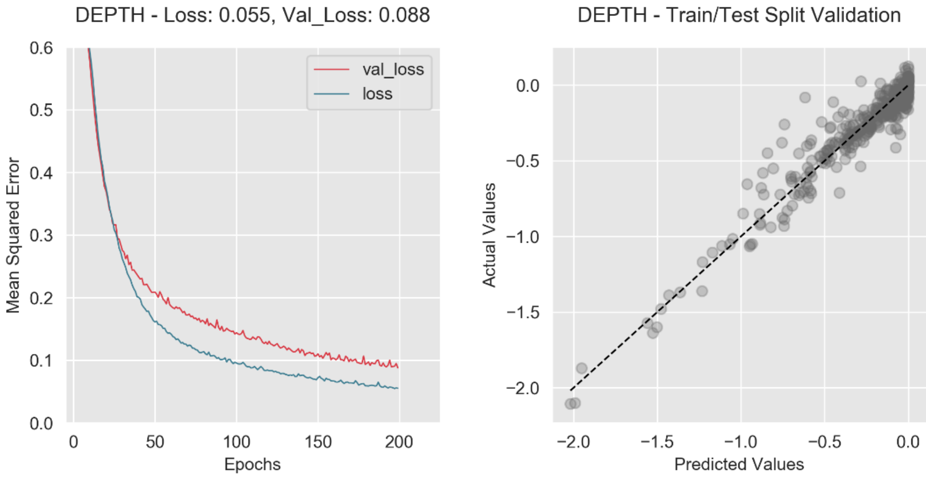


Figure 4.34 Depth prediction: training history plot (left) and train/test split validation (right).

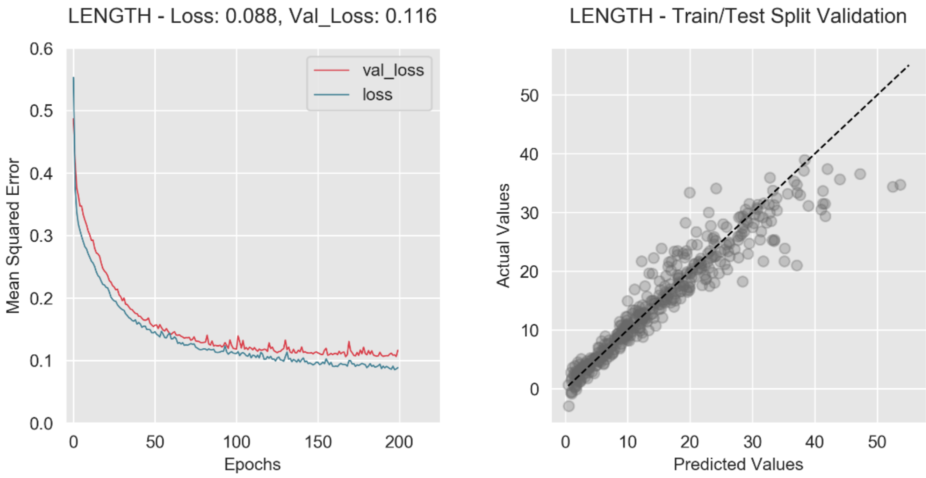


Figure 4.35 Length prediction: training history plot (left) and train/test split validation (right).

Figure 4.36 Width prediction: training history plot (left) and train/test split validation (right).

The results of the training assessed using the Train/Test Split Validation methods are the following:

- **Depth**: MAE = 0.462 mm, SD = 0.030 mm.
- **Width**: MAE = 0.733 mm, SD = 0.375 mm.
- **Length**: MAE = 0.681 mm, SD = 0.194 mm.

In ***Fig. 4.37***, the training histories of the ANN models assessed in this section (in red) are compared with the ones of **Section 4.3.2** which has been trained with both “Successful” and “Unsuccessful” operations (in blue):

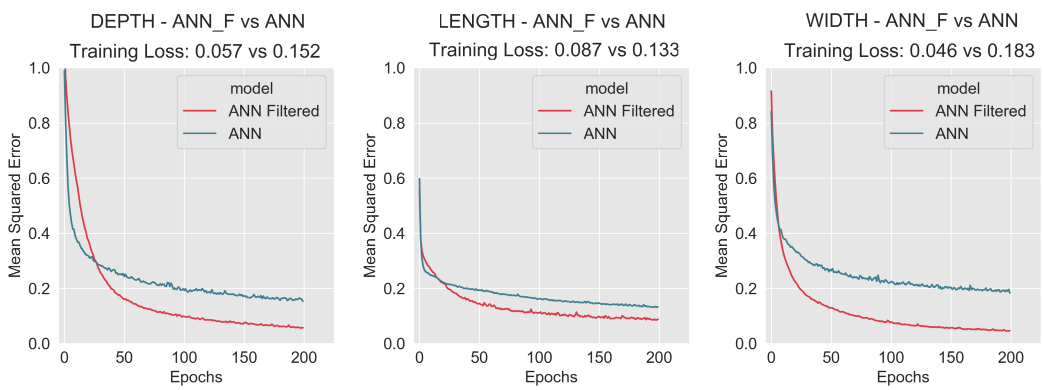


Figure 4.37 Training history plots comparing the prediction performance of the ANN model trained with only successful operations against the one trained with the full dataset.

In the Binary Filtered ANN training histories, the training loss value is decreased by 64.0% for the Depth, 74.1% for the Width and 31.2% for the Length prediction. Overall, the ANNs trained with only “Successful” operations outperform the ANNs trained on the full dataset. These results suggest that operations which are not “Successful” are more difficult to model by the trained system. One of the possible reasons is that manufacturing conditions which define the geometrical outcome of operations defined as “Unsuccessful” are not necessarily consistent. For instance, once a tool is stuck into the material, it is harder to predict the way is going to “break” the fibre structure to “get out” in comparison to a tool that smoothly cut through the fibre layers.

4.4 Results: Carving Operations Series

The predictive abilities of the models have been assessed at the end of every training session utilising a Testing dataset, demonstrating their ability to accomplish the assigned prediction task with low error values. This section presents an in-depth analysis of the application of the trained models to a series of carving operations and how the devised methods can be used to accurately simulate the deviation between the desired digital input and the physical fabrication outcome. The measure of the deviation between input and output is intended in geometrical terms, measured in mm, occurring in the features of Length, Depth and Width.

The series is composed of a total of 16 operations which have been robotically fabricated on a lime wood board and have not been utilised for the training of the system, representing "unseen" data suitable for evaluating the performance of the trained models. The critical aspect of these carving operations is that they are geometrically identical to each other as defined in the digital design environment and, consequently, the geometric input features, such as Length or Depth values, are the same for all the operations. The only non-geometrical parameter which changes throughout the series is the variation of the Tool/Surface Angle feature between the start and end of each cut, ranging from 45° to 25°. A summary of these parameters is reported in ***Table 4.6***:

Cut Series	Cuts	Samples	Tool Angle	Grain Direction	Input Length	Input Depth
A0	16	320	45°-25°	0°	55 mm	0.8 mm

Table 4.6 Carving Operation Series – Info.

The robotic operation outcomes are measured through a photogrammetric reconstruction of the board and their geometrical description is reported in ***Fig. 4.39*** in which the digital input (as dashed black line) representing the desired outcome is compared to the actual physical result (in red).

Firstly, it should be noted how each individual cut not only diverges to different extent from its respective desired digital input, but it also differs significantly from the rest of the operations in the series. Furthermore, a subset of cuts appears truncated due to the tool getting stuck in the material ("Stuck" label event), while, conversely, in another subset, no amount of material has been removed ("Cut" label event). This initial study shows, once again, that the interaction of carving tools with the properties of timber substantially affects the outcome of digitally-defined subtractive operations. In these regards, a measure of the deviation between digital inputs and physical outputs is presented below in ***Fig. 4.38***.

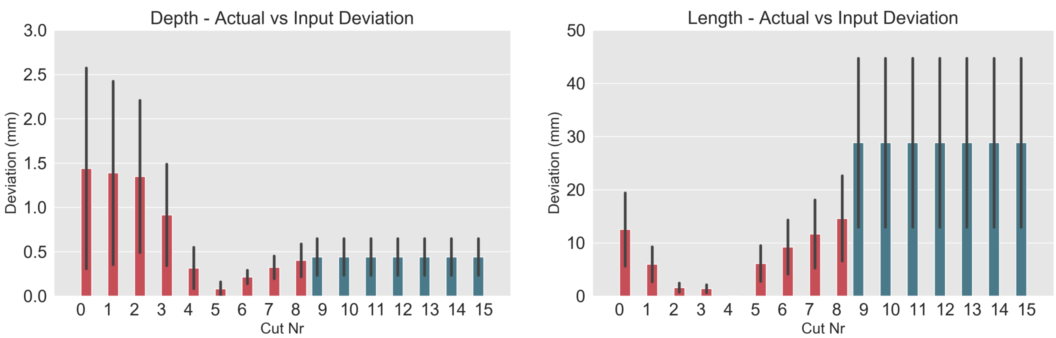


Figure 4.38 Deviation analysis (actual value vs input value) for the feature of Depth and Length of the cuts in the series. In red, the operations which removed any material volume.

Figure 4.39 Comparison between the input geometry (dashed black line) and the carved one (red). For each operation, top and side views are provided together with the deviation error.

Considering only the cuts which have removed material, the highest average value of deviation for the target frames composing the cut is found in Cut 01 for the Depth feature (1.43 mm) and in Cut 08 for the Length feature (12.55 mm). Analysing the whole cut rather than the single frame, the deviation from the original digital input is 411% and 56% respectively.

Following this initial deviation analysis, the methods described in this chapter have been applied to the same carving operations series to obtain a more accurate prediction of the fabrication outcomes. The trained ANN models utilised for the task are the ones presented in **Section 4.3** for the regression-based prediction of geometric features. The configuration of materials (*i.e.* lime wood) and carving tools (*i.e.* Stubai 9-20) is unchanged with respect to the training stage. The prediction results are reported in ***Fig. 4.40***, where is possible to compare in the same plot the ANN model prediction (in light blue), the actual fabricated geometry (as a red line) and the original digital input (as dashed black line). The operations which have not removed any material volume have been excluded from the comparison study.

Fig. 4.41-4.42 presents the deviation measure for the Length and Depth feature, comparing the actual values against the input values and the actual values against the predicted ones. This side-by-side comparison clearly shows a substantially lower deviation range between the digital input and physical output of carving geometries when the machine learning-based simulation is utilised instead of the conventional digital Boolean operations.

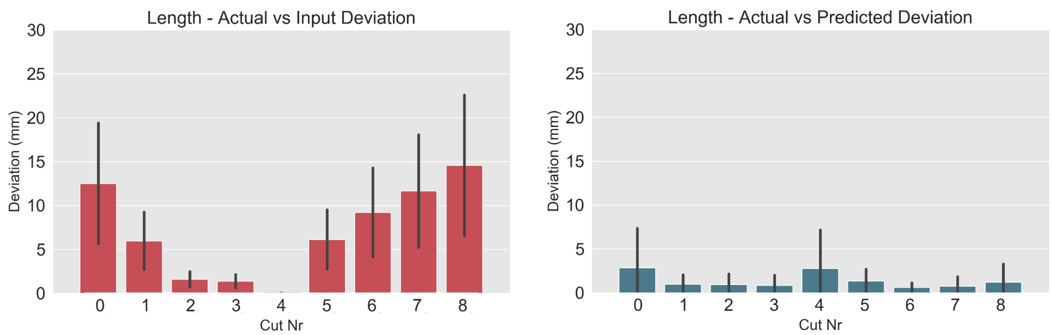


Figure 4.40 Deviation analysis for the Length feature: actual vs input value (left), actual value vs predicted value (right).

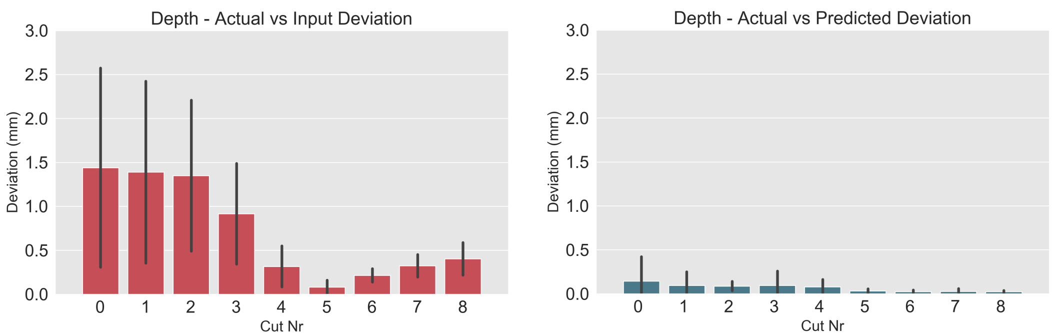


Figure 4.41 Deviation analysis for the Depth feature: actual vs input value (left), actual value vs predicted value (right).

To further support this claim, ***Table 4.7*** summarises the percentage deviation error for each cut presented in ***Fig. 4.40***, showing an improvement of several times (up to 11) in the accuracy of the outcome geometry. These results suggest that the integration of the devised methods into a design stage would enable to anticipate more precisely the outcome of the operation in a later fabrication stage, enabling the adoption of such a robotic manufacturing process previously unavailable due to its high variance determined by tools and material affordances.

CutNr	Actual/Input Depth	Actual/Pred Depth	Actual/Input Length	Actual/Pred Length
0	62.60%	6.20%	76.70%	13.50%
1	65.60%	7.90%	26.10%	4.60%
2	66.90%	8.40%	5.80%	3.90%
3	60.70%	9.00%	5.00%	3.00%
4	48.00%	25.20%	0.10%	8.10%
5	44.20%	28.00%	27.00%	7.40%
6	101.70%	19.60%	47.00%	4.40%
7	242.50%	31.30%	67.90%	4.60%
8	1110.70%	105.00%	102.40%	8.90%

Table 4.7 Percentage deviation errors for the features of Depth and Length of the cut.

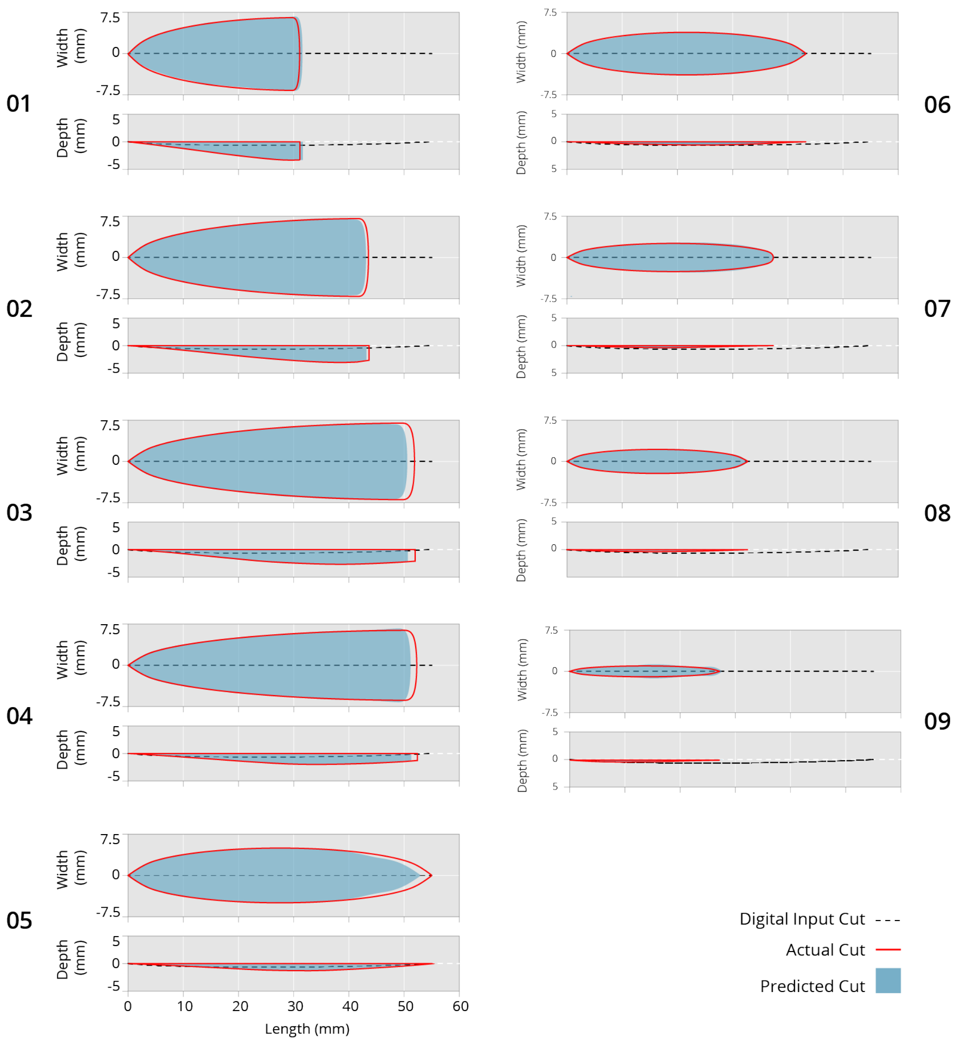


Figure 4.42 Comparison between the input (dashed black line), the actual (red line) and predicted geometry (light blue).

4.5 Results: Comparative Analysis of Trained Networks

The validation of the learning strategies in the previous sections allows performing a comparative analysis of multiple networks trained with different materials, tools and parameters. The goal of the study is to discuss the potential of fine-tuning a design-to-manufacturing workflow to a specific set of fabrication affordances and, potentially, create a library of trained systems to be deployed accordingly to the requirements of the design brief. For this purpose, the following studies aim to assess whether the devised methods are sufficiently versatile to synthesise knowledge from a wide variety of fabrication dataset.

The key driver of the comparative analysis is the concept of variance across the following categories:

i) Within the same wood species (*i.e.* different Tool/Grain direction angles).

ii) Across different wood species with the same carving tool.

iii) Within the same wood species but different carving tools.

In statistics, the term *variance* (σ^2) is defined as the measure of how far each value in the dataset (in this case, the predicted values) is from the mean. The variance for a dataset sample is mathematically described as:

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - m)^2$$

where N is the sample size, x_i is the sample and m is the sample mean. The square root of the sample variance is the Standard Deviation (σ) (SD) which has the advantage of being expressed in the same unit of the mean. The Relative Standard Deviation (RSD), or Coefficient of Variation (CV), calculated as $RSD = \sigma * 100/\mu$ (where μ is the mean), is useful to determine the extent of the SD in relation to the mean of the dataset expressed in percentage points (%).

The datasets utilised for such comparison have been collected through a series of robotic training sessions using different types of wood species (*i.e.* Lime, Tulip and Oak) and various carving tools (*i.e.* Stubai 9/20, 9/30 and 7/30). ***Table 4.8*** collects the main info about each dataset.

DATASET	Type	Cuts	Samples	Features	Wood	Robot	Tool
A	Cut Frames	181	3780	12	Lime	ABB IRB1600	Stubai 9/20
B	Cut Frames	138	2760	12	Oak	ABB IRB1600	Stubai 9/20
C	Cut Frames	213	4260	12	Tulip	ABB IRB1600	Stubai 9/20
D	Cut Frames	192	3840	12	Tulip	ABB IRB1600	Stubai 9/30
E	Cut Frames	136	2720	12	Tulip	ABB IRB1600	Stubai 7/30

Table 4.8 Description of the datasets used for the comparative analysis.

The datasets have been utilised for training the respective ANNs model for the prediction of the geometric features of Length, Depth and Width of the cut. The models have been evaluated using a train/test split validation method and the resulting MAE values have been reported in ***Table 4.9***. The low prediction errors showed in all the different trained models allow proceeding with the comparison between them in the following studies.

Dataset	Length - MAE	Depth - MAE	Width - MAE
A	0.684	0.462	0.733
B	0.545	0.593	0.802
C	0.732	0.446	0.679
D	0.402	0.522	0.584
E	0.564	0.604	0.546

Table 4.9 Prediction rates of the ANN models trained for the comparative analysis.

4.5.1 Wood Grain

As previously discussed, the fibrous structure of timber is the material feature affecting the most its mechanical performances, generating a significant variance in the outcome of identical carving operations executed in different locations and orientations on the same workpiece. Such behaviour is defined with the term *orthotropic* as it is characterised by three mutually perpendicular planes of symmetry: longitudinal direction along the fibres, radial direction towards annual rings and tangential direction to the annual rings (Hoadley, 2000).

One of the key skills in woodworking is the understanding of the influence of the wood grain and the ability to steer the carving tools accordingly to achieve the desired outcome in a constant dialogue with the material. While such an understanding is not present in current CAM environments, the studies of this section aim to demonstrate that is possible to train a system to quantify and model the influence of the grain structure in different carving configurations.

The training focused on a range of operations executed between 0° (*i.e.* along) and 90°, (*i.e.* across) in respect to the main grain direction, with intervals of 30°. The predictive abilities of the system have been assessed through 4 sets of operations, with each set presenting 4 identical operations executed on the same wooden board at angles of 0°, 30°, 60° and 90° (***Fig. 4.43 - 4.46***).

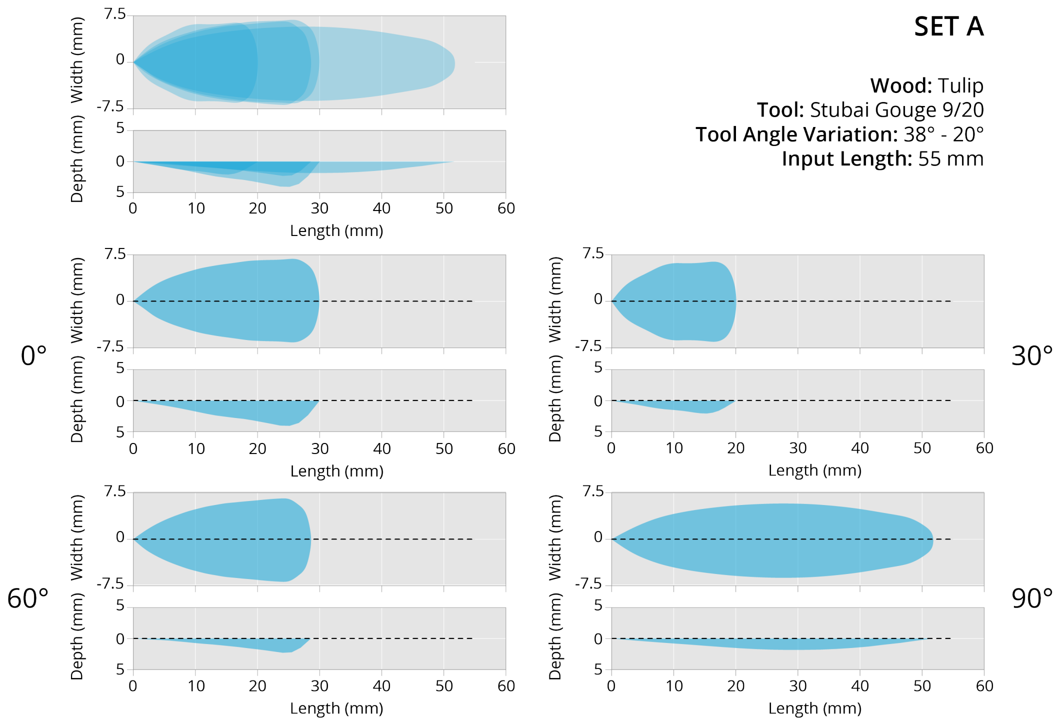


Figure 4.43 Set A - Wood grain direction – ANN-based prediction of the carving operation (light blue) against the digital input (dashed black line) - top and side views.

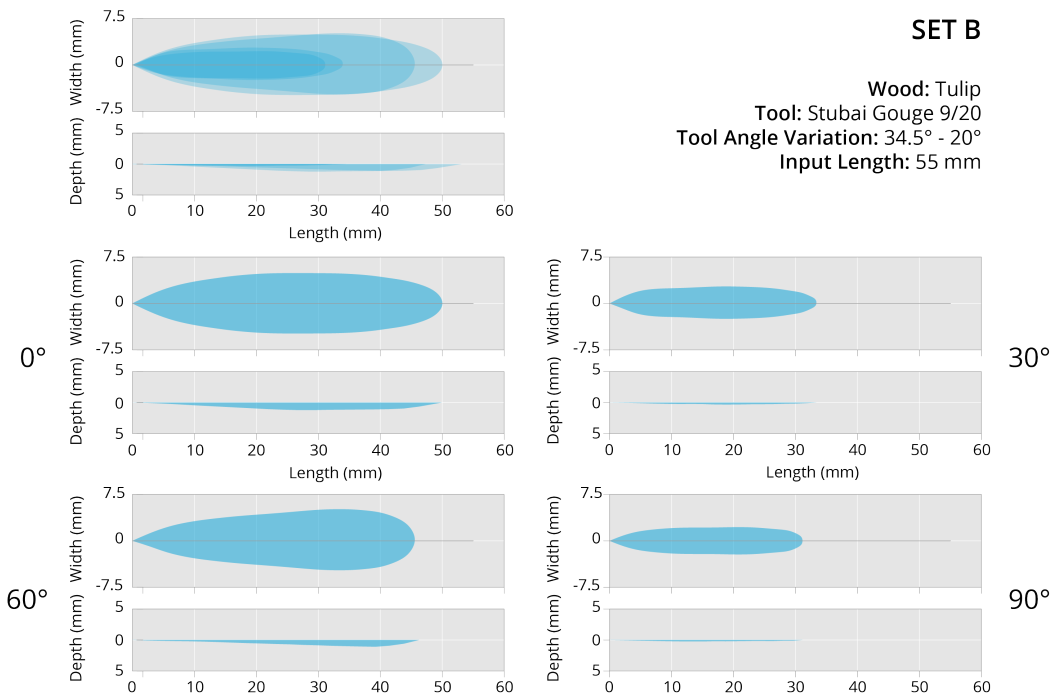


Figure 4.44 Set B - Wood grain direction – ANN-based prediction of the carving operation (light blue) against the digital input (dashed black line) - top and side views.

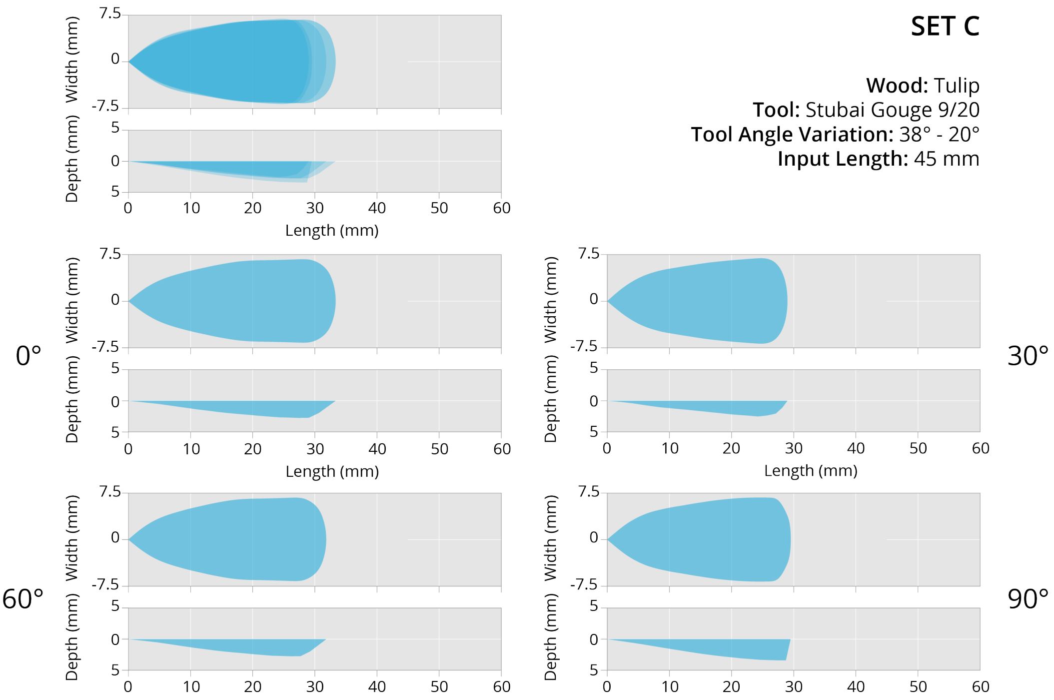


Figure 4.45 Set C - Wood grain direction – ANN-based prediction of the carving operation (light blue) against the digital input (dashed black line) - top and side views.

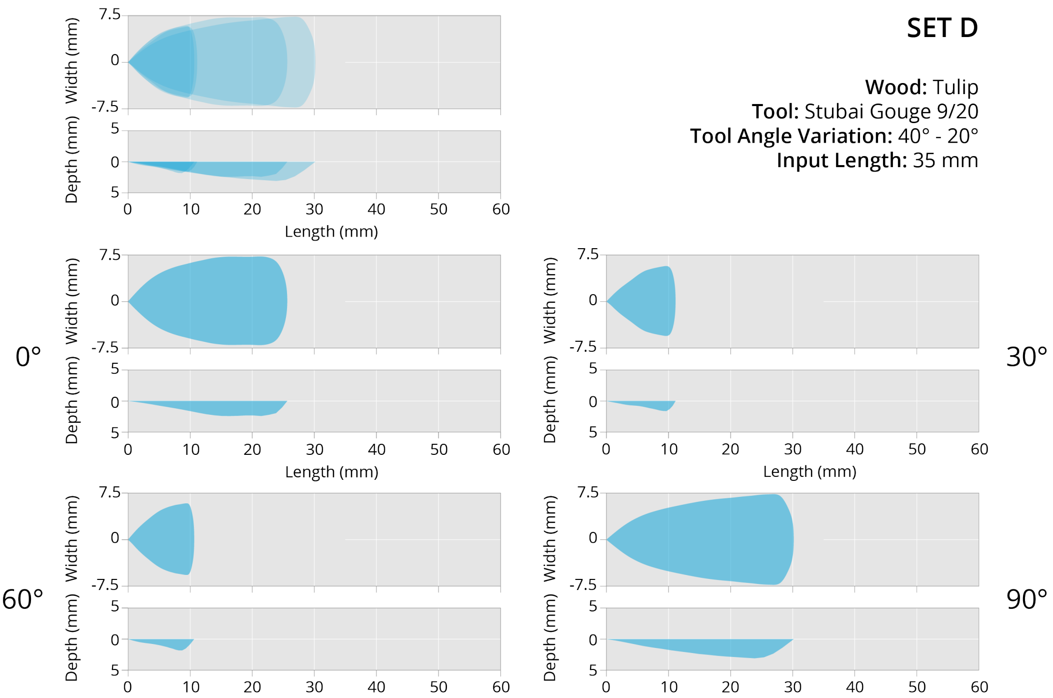


Figure 4.46 Set D - Wood grain direction – ANN-based prediction of the carving operation (light blue) against the digital input (dashed black line) - top and side views.

The plots in ***Fig. 4.47*** describe the variability in the carving outputs for the three main predicted output features (*i.e.* Total Length, Max Depth, Max Width) in relation to the different grain directions along which the same operation has been executed. The predicted feature for the four operations in each set, for a total of 4 sets, are represented as dark grey points connected with a dotted line. For the Length and Depth feature, the red points and dotted line show the input digital features of the desired geometry. The width of the cut is not used as input as it is defined by the previous two features and the tool specifications.

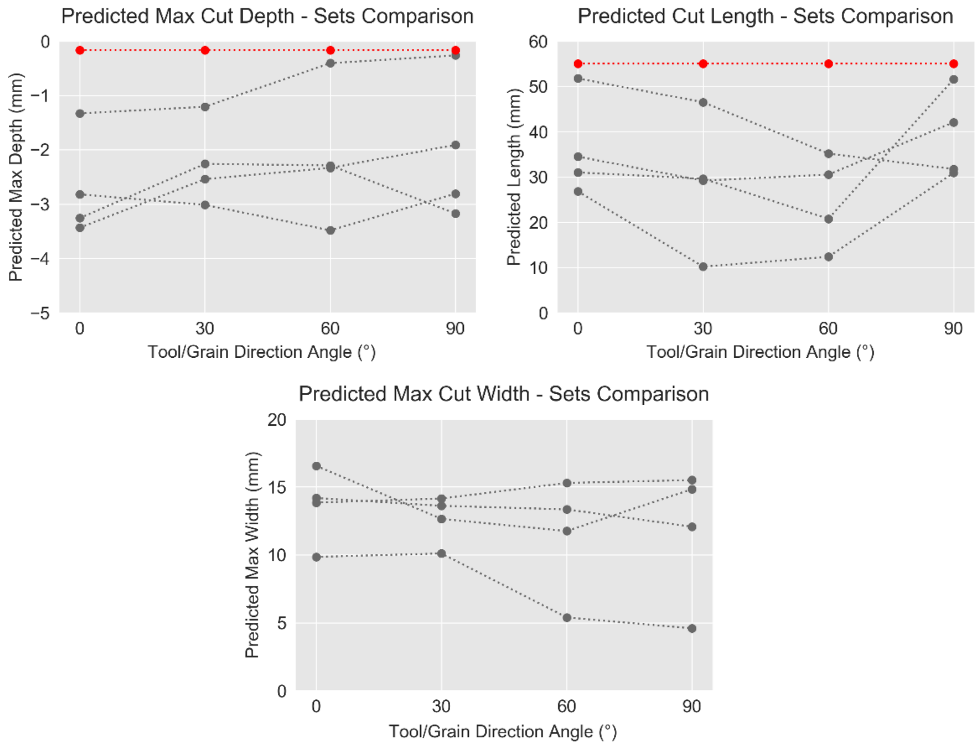
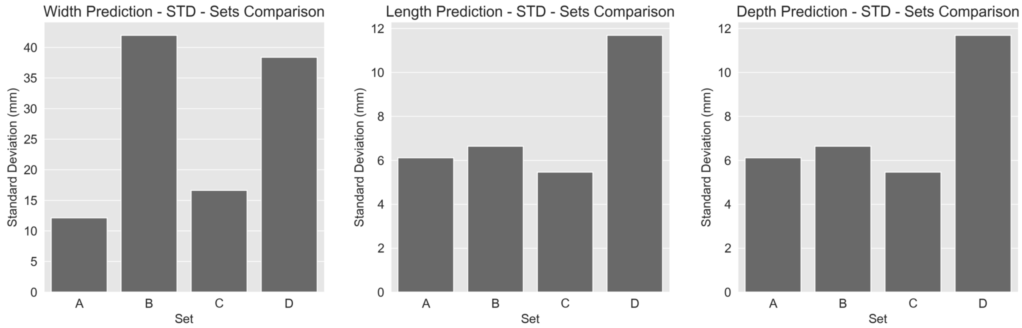


Figure 4.47 Comparison of the variability of the prediction output based on the Tool/Grain Direction Angle parameter across the four sets of operations.

In ***Fig. 4.48***, a measure of the Standard Deviation (σ) for each set is reported in relation to the three predicted features, while the tables below the graphs also include the measure of the mean and variance. The measure of the variance varies significantly across the different sets of operations generated by various configurations of fabrication parameters. Some operations appear less sensitive to changes determined by the different grain directions, while others are deeply affected. For instance, Set D shows variance $\sigma^2 = 136.71\ mm^2$, while Set C has a variance of only $\sigma^2 = 29.77\ mm^2$ for the Depth features prediction.



Set	Mean	STD	Variance
A	199.26	12.1	146.31
B	115.02	41.97	1761.52
C	224.02	16.62	276.39
D	196.62	38.37	1472.36

Set	Mean	STD	Variance
A	33.24	13.05	170.35
B	41.3	9.41	88.51
C	34.07	5.79	33.58
D	20.06	10.33	106.7

Set	Mean	STD	Variance
A	-26.72	6.11	37.28
B	-10.08	6.64	44.06
C	-36.41	5.46	29.77
D	-29.83	11.69	136.71

Figure 4.48 Comparison of the Standard Deviation (σ) and Variance (σ^2) across the four sets of operations for the Width, Length and Depth features.

4.5.2 Wood Species

The study of the previous section is here extended to different timber species to show how the trained system can model the influence of different grain arrangements and densities on the outcome of the fabrication task. The wood species analysed are the following:

- **European Oak** (*Quercus robur*): Average Density = 700kg/m³.
- **Lime** (*Tilia x europaea*): Average Density = 560 kg/m³.
- **Tulip** (*Liriodendrun tulipifera*): Average Density = 455 kg/m^3.

All the wood samples used have been kiln dried and presented a moisture content between 12-16%. The analysis is conducted with the same set of 4 operations presented in the previous section, now extended to a matrix of size 3x4 (*i.e. species x grain directions*) making possible to compare the influence of the wood grain directionality across multiple timber species (***Fig. 4.49 – 4.52***).

Fig. 4.53 reports the analysis of the variability of the geometric outcome features from the same set of input parameters as modelled by the trained ANN models. The plots provide a horizontal comparison across the four sets of operations considered for the study grouped based on the Tool/Grain Direction Angle feature (*i.e.* 0°, 30°, 60°, 90°) and respective wood species (*i.e.* Oak, Tulip, Lime). The study is complemented in ***Fig. 4.54*** with the presentation of the RSD values for each set of operations in a series of heatmap plots.

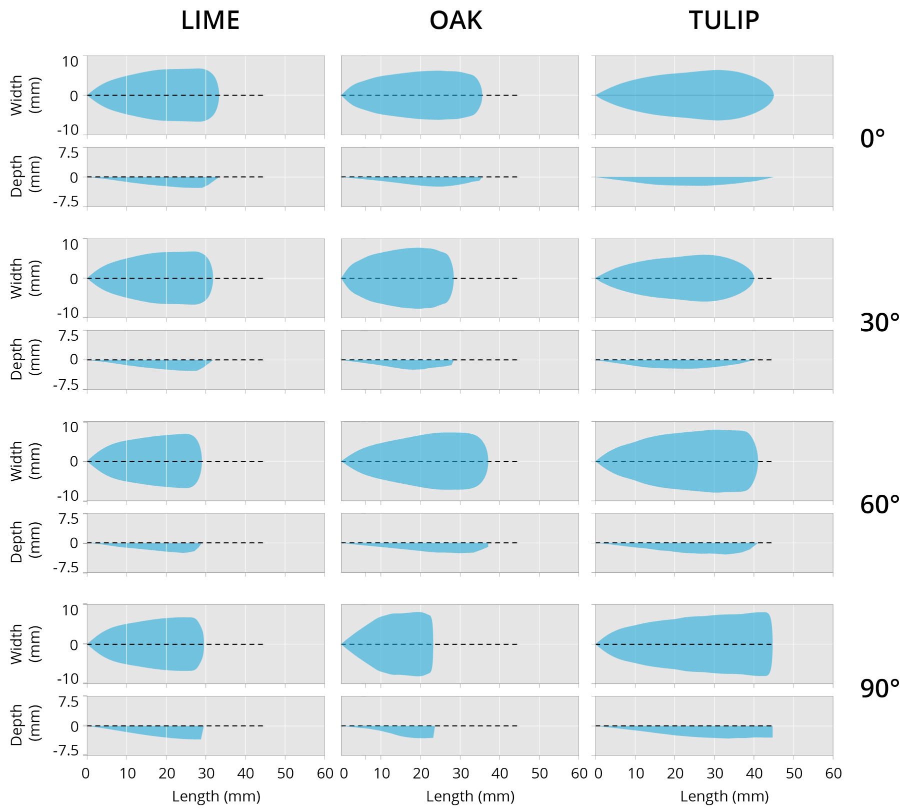


Figure 4.49 Set A - Wood species – ANN-based prediction of the carving operation (light blue) against the digital input (dashed black line) - top and side views.

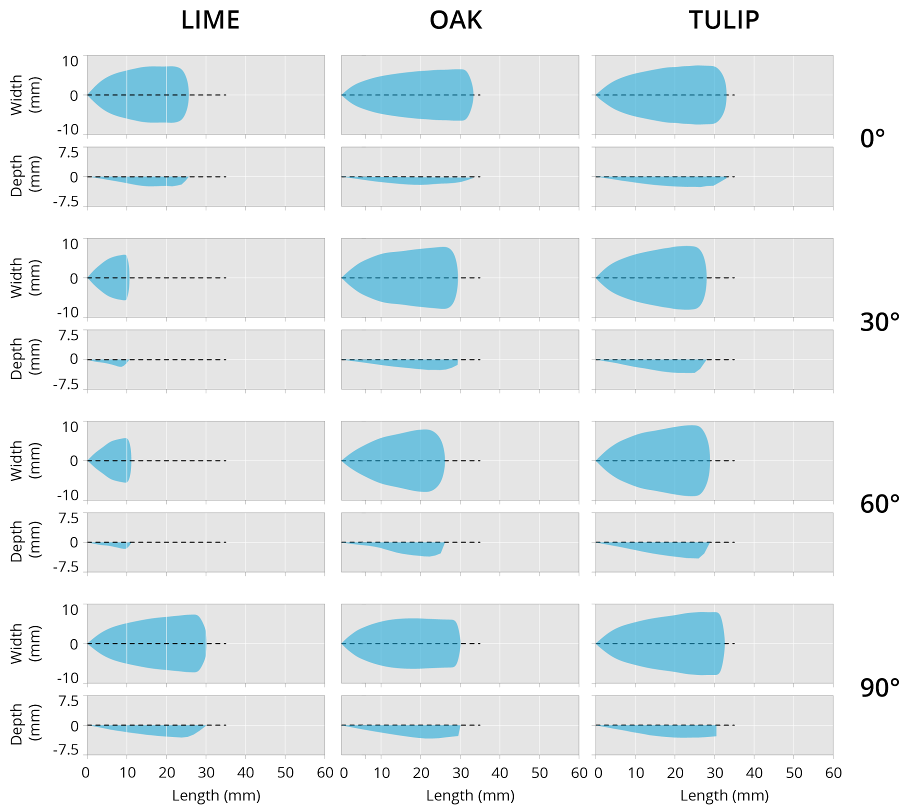


Figure 4.50 Set B - Wood species – ANN-based prediction of the carving operation (light blue) against the digital input (dashed black line) - top and side views.

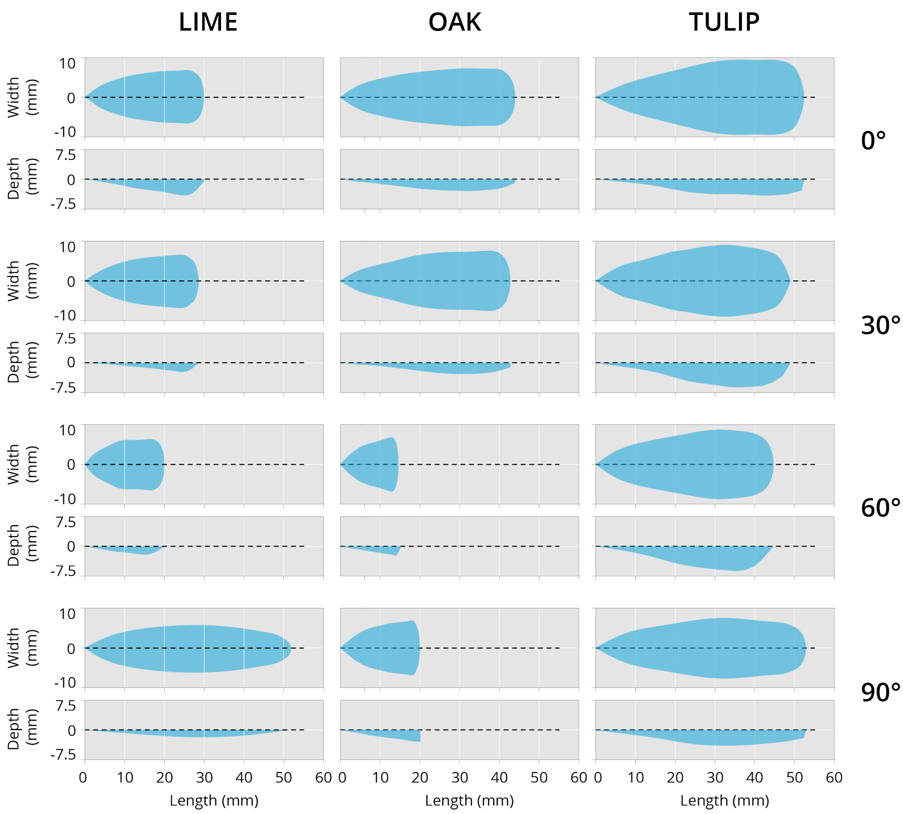


Figure 4.51 Set C - Wood species – ANN-based prediction of the carving operation (light blue) against the digital input (dashed black line) - top and side views.

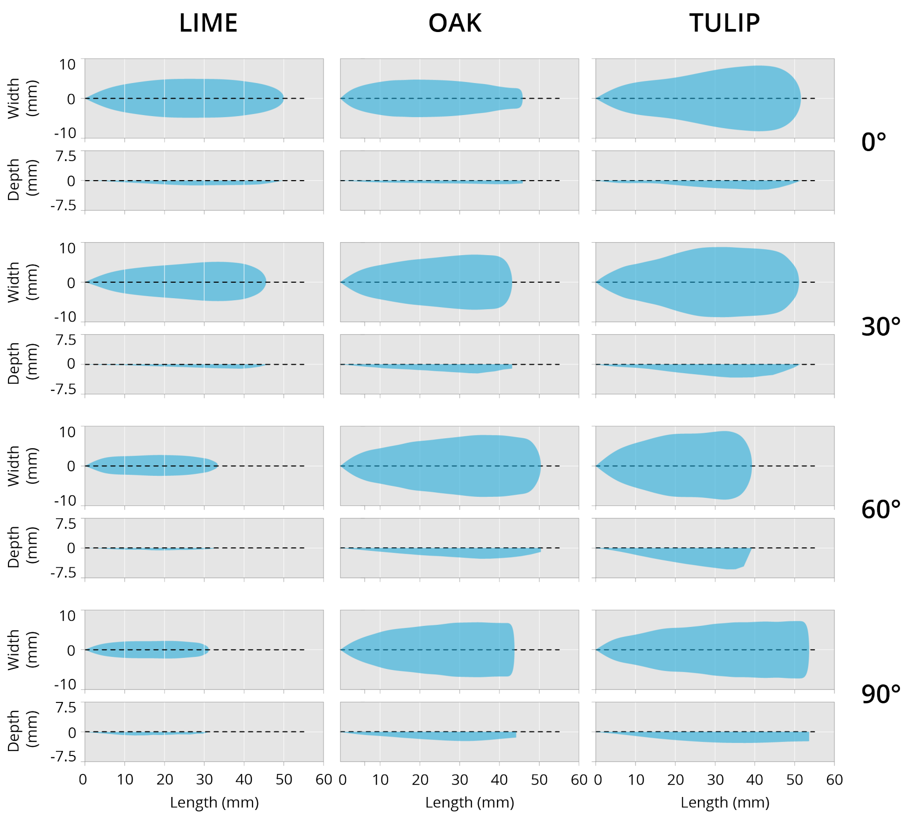


Figure 4.52 Set D - Wood species – ANN-based prediction of the carving operation (light blue) against the digital input (dashed black line) - top and side views.

In some of the material configurations, the deviation of the outcomes from the desired digital input seems to follow a similar trend across the different grain directions considered, although with different amplitudes (*e.g.* **Fig. 4.53**: Oak / Tulip – Max Cut Depth; Oak / Tulip – Max Cut Width). The trained models are able to predict not only whether a set of fabrication parameters will generate a successful operation but also the actual geometry of those cuts which have been included in the prediction despite being labelled as "unsuccessful". This is evident for the prediction of the Length feature, in which some of the cuts are interrupted as the tool is getting stuck into the material, generating a substantial variance for the same operation performed towards different grain directions but also different operations performed along the same grain direction (*e.g.* **Fig. 4.53**: Oak – Cut Length - Tool/Grain Direction Angle = 60° – Set A vs Set B). The prediction of the Max Width feature shows the lowest values for the RSD, meaning that is the features less affected in comparison to Depth and Length by operations performed towards different grain directions. The main reason is that the value of Max Width is usually reached in the middle of the cut, as both successful and unsuccessful operations could have similar values while for the Length that would be usually half or less.

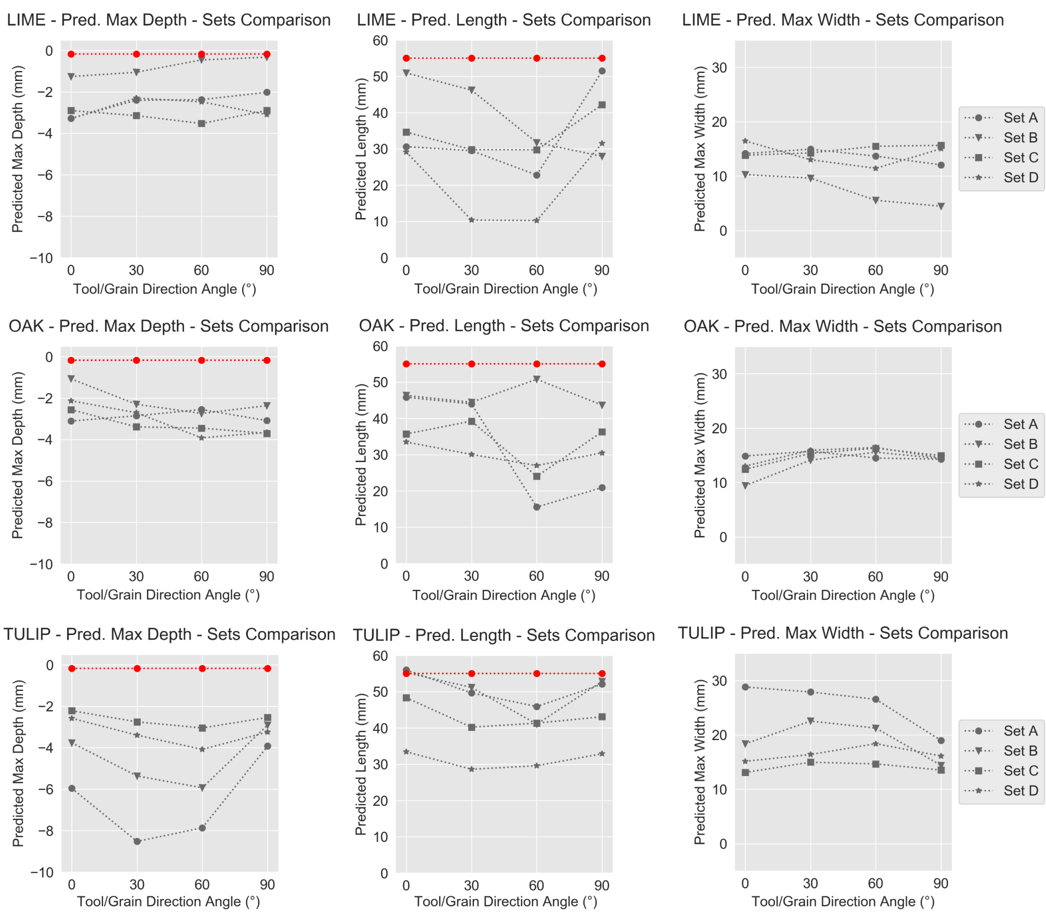


Figure 4.53 Comparison of the variability of the prediction output based on the wood species parameter across the four sets of operations.

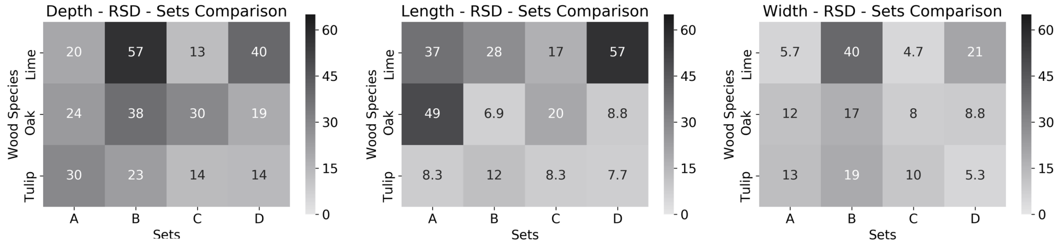


Figure 4.54 Comparison of the RSD across the four sets of operations for the Depth, Length and Width features.

4.5.3 Carving Tools

In this section, the trained network ability to model the interplay between tool affordances and material properties is presented. Intuitively, a change in tooling would necessarily determine a change in the obtained carved geometries. For a heterogeneous material such as timber, however, such variation in the outcome does not follow a linear relationship depending on tool specifications. This means that an increase of x in the width of the cutting profile will not necessarily increase the width of the obtained cut of x amount. As the affordances of the carving gouges are mediated by the specificity of the grain arrangement and direction, it seems necessary to assess the ability of the trained networks to model such non-linear relationship in the perspective of a fabrication process making use of multiple carving tools.

The gouges utilised in the study are Stubai 9/20, 9/30, 7/30. The first number represents an indexical sequence used by the company to describe the depth of the cutting profile, while the second number represents the width of the profile in millimetres. The selected species for the assessment is Tulip. In respect of the previous two sections, the analysis presented here uses four different sets of operations to accommodate fabrication parameters that would fit all the different tool sizes and shapes considered. Each set is composed of four identical operations, as in the previous studies, creating a 4x3 matrix (*i.e. carving gouges x grain directions*) (***Fig. 4.55–4.58***).

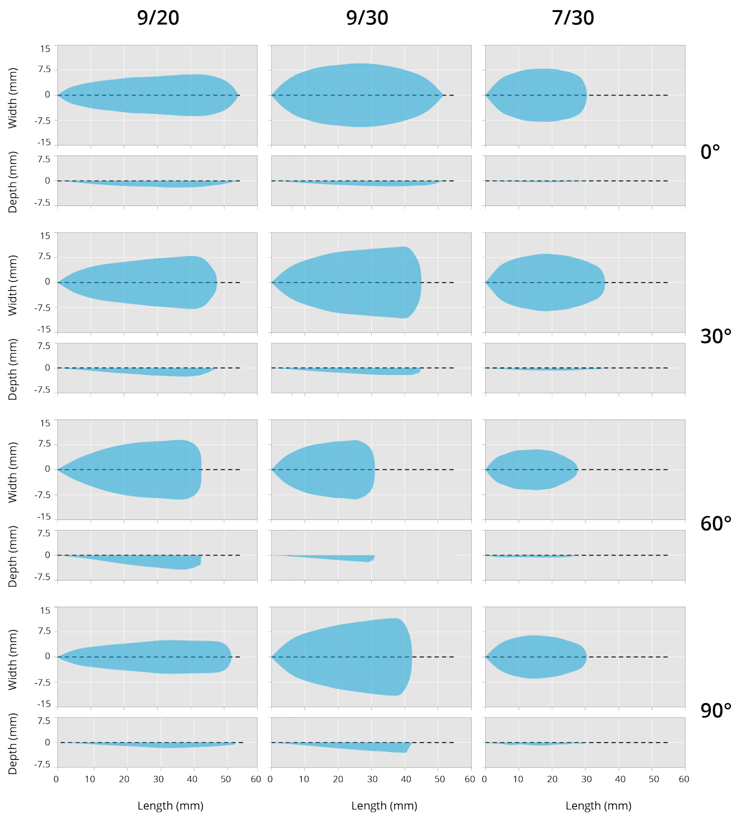


Figure 4.55 Set E – Carving tools – ANN-based prediction of the carving operation (light blue) against the digital input (dashed black line) - top and side views.

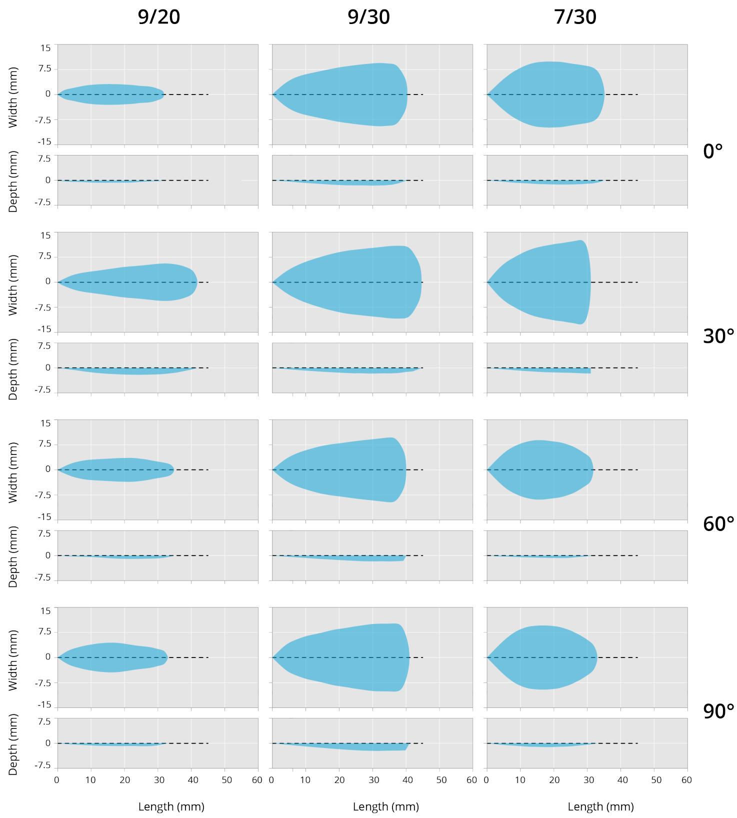


Figure 4.56 Set F – Carving tools – ANN-based prediction of the carving operation (light blue) against the digital input (dashed black line) - top and side views.

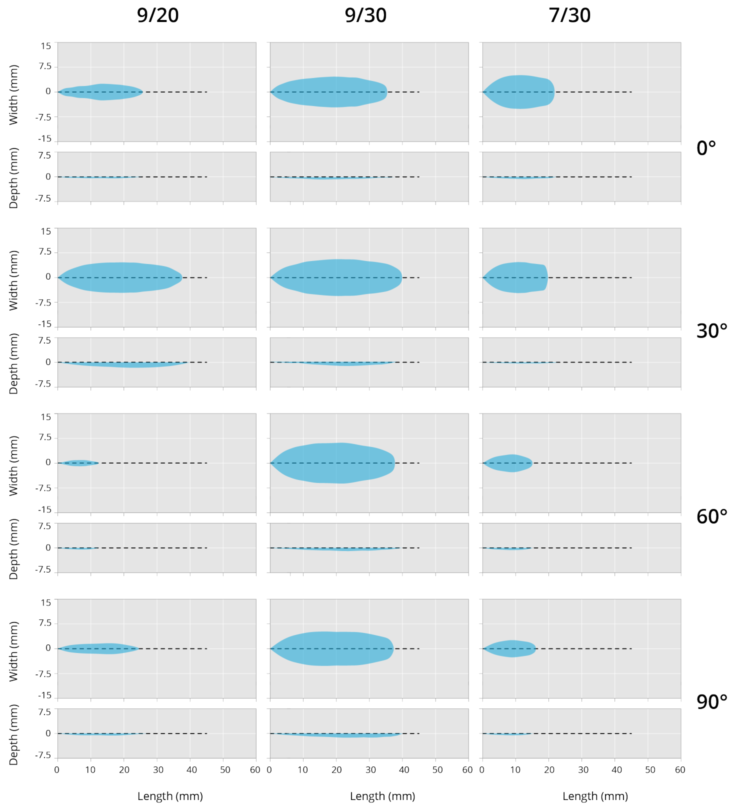


Figure 4.57 Set G – Carving tools – ANN-based prediction of the carving operation (light blue) against the digital input (dashed black line) - top and side views.

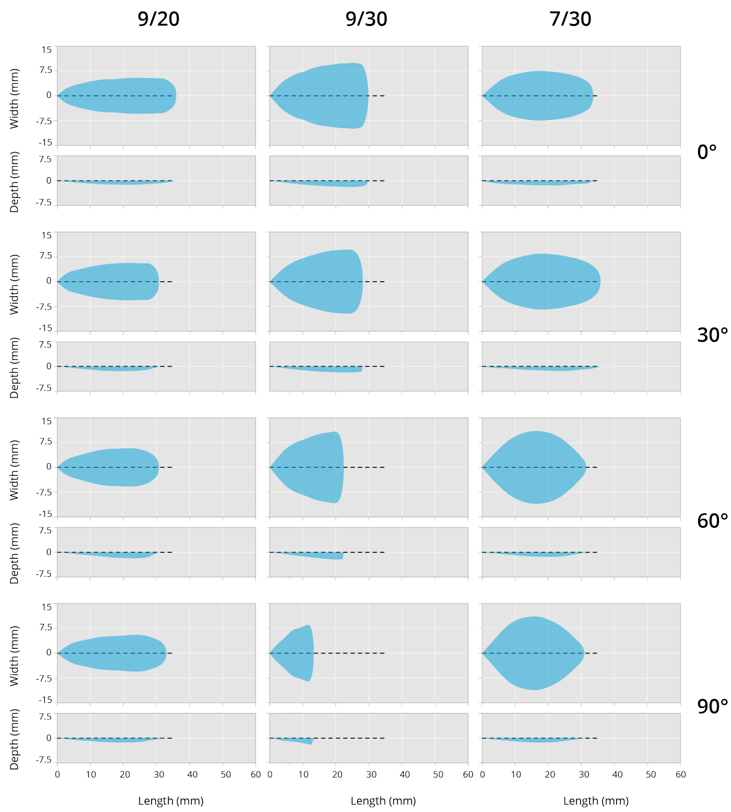


Figure 4.58 Set H – Carving tools – ANN-based prediction of the carving operation (light blue) against the digital input (dashed black line) - top and side views.

As in the previous studies with different wood species, the predicted geometric features for each operation performed with various tools are compared to each other (***Fig. 4.59***) to measure ***i)*** the variability between them and ***ii)*** their deviation from the prescribed input values. While the first is expected as the tools considered have different sizes, it is valuable to check whether operations performed with different tools follow or not a similar overall trend based on the grain direction of the cut. The measure of the RSD for each set shows that the carving direction plays a crucial role in the definition of the outcome geometry, showing substantial variance for the same operation which reaches values above 70% in some of the configurations (***Fig. 4.60***).

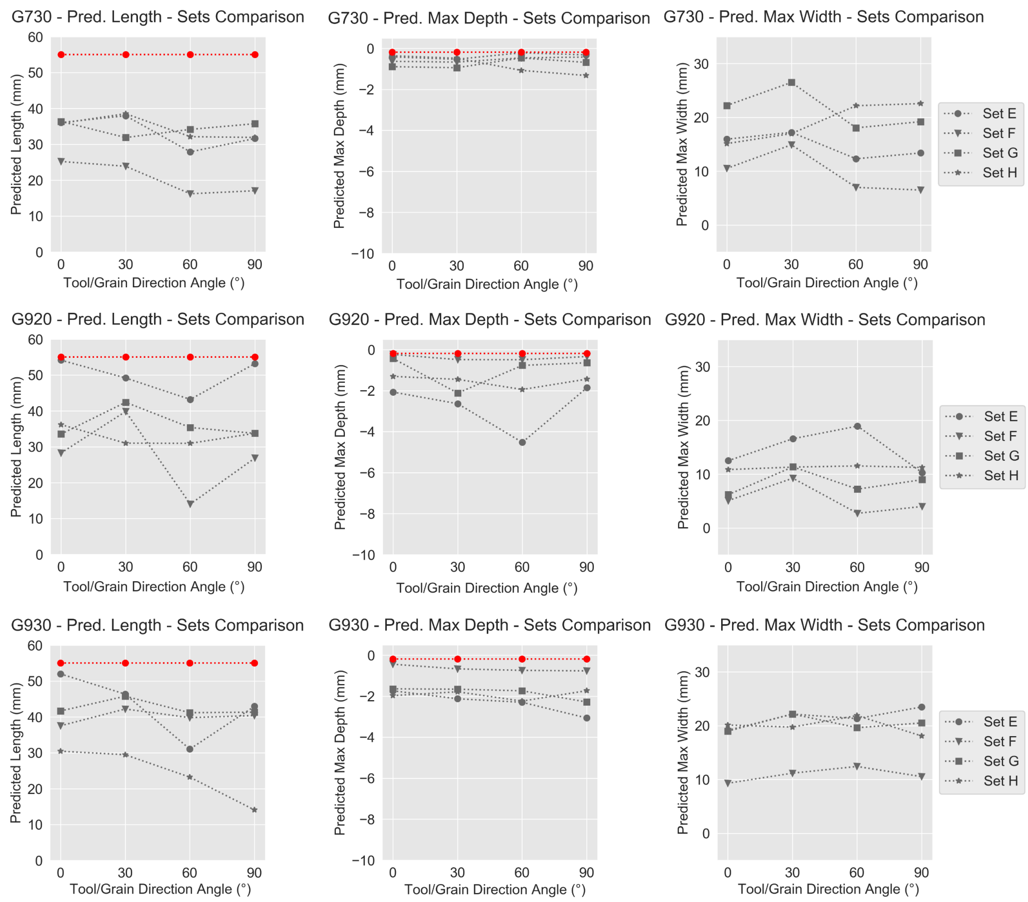


Figure 4.59 Comparison of the variability of the prediction output based on the carving tool parameter across the four sets of operations.

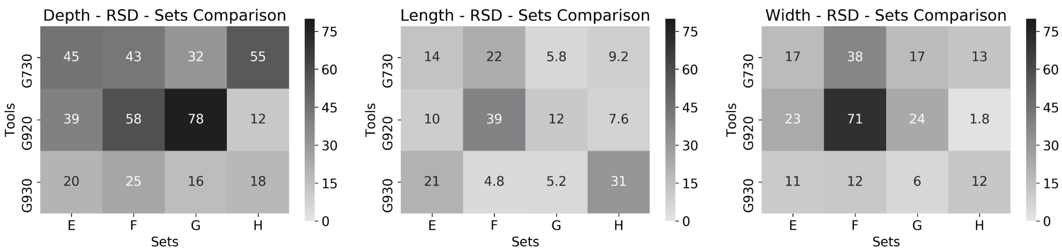


Figure 4.60 Comparison of the RSD across the four sets of operations for the Depth, Length and Width features.

4.6 Results: Summary

The chapter addresses **Hypothesis B** which claims that is possible to control the material variance in robotic carving operations and presents a series of simulation methods based on the training of machine learning models with real-world fabrication data. The assessment of the predictive abilities of trained models demonstrated that these methods successfully generate an accurate simulation of such operations, lowering the deviation error between the predicted and fabricated geometry to an acceptable range for its implementation into a design interface.

The structure of the training workflow in two main stages (*i.e.* **i)** binary classifier for prediction of manufacturing conditions or "events" **ii)** regression-based prediction of geometrical features necessary to reconstruct the carving operation proved to be particularly efficient as the filtering out of fabrication parameters leading to unsuccessful operations made possible to substantially improve (with a margin between 31.2% and 64.0%) the predictive performances of the system (**Section 4.3.5**). The event threshold prediction (**Section 4.2**) was assessed through the prediction of two different manufacturing conditions: the successful removal of material and the successful extraction of the tool. The prediction of individual event thresholds resulted suitable for a linear model, such as LR, as the two groups defining the occurrence of the event are linearly separable. For the prediction of combined events, however, a non-linear model such as the ANN outperformed the LR. The trained ANN proved to be able to predict reasonably well, with an accuracy of 87%, if an operation would be successful or not based on a set of fabrication parameters and design intentions.

The evaluation of the methods for prediction of geometric features of carving operations (*i.e.* Depth, Width and Length) based on a given set of fabrication parameters (**Section 4.3**) showed how the ANN model is more suitable for the task in comparison to a linear model, such as linear regression (LinR), which is not able to capture the non-linear relationships between inputs and outputs features. The predictive abilities of trained ANNs have been validated following a train/test split validation method, showing low error values (*i.e*. Depth = 0.462 mm; Length =0.733 mm, Width = 0.681 mm). These figures are particularly relevant for the support of **Hypothesis B** as they are all within the error thresholds (even the highest one of 2% deviation error) established in **Chapter 3**, demonstrating that the trained system can predict the result of carving operations with an accuracy sufficient for its deployment within a design workflow. To further test the performance of the system, the trained networks were utilised to simulate a series of carving operations (**Section 4.4**), providing a significantly more accurate simulation of the carving outcome considering the influence of material and tools properties in respect of the initially prescribed digital input. The comparative analysis of multiple ANNs (**Section 4.5**) trained with different combinations of affordances demonstrates that the devised methods can accurately model the variance occurring for identical carving operations performed across different combinations of material properties, wood species and carving tools.

5 Knowledge Integration

The methods and experimental results presented in the previous chapters focused on the synthesis of manufacturing knowledge based on the acquisition of real-world fabrication and their processing through a series of machine learning strategies. This chapter discusses the integration of such a knowledge as part of a simulation interface to support decision making procedures at an early stage of the design process, considering both fabrication constraints and opportunities.

The validity of the proposed methods has been assessed within the context of two industry secondments at ROK Architects (Zürich) and BIG (Copenhagen). Such collaborations provided the opportunity to apply the devised design-to-manufacturing strategies into the established workflow of design firms.

The focus of the secondments, each spanning for several months, was driven by **Research Question C** of this thesis which aimed to investigate *how the integration of manufacturing and material knowledge at an early stage of the design process affects the exploration and evaluation of design solutions for robotic carving operations.*

The main proposition behind such a research question is that the lack of information on material and fabrication affordances significantly limits the number of decisions that a designer can take during the design process and excludes from the search a substantial subset of design solutions. A standard hylomorphic model would not present, for instance, the effect of the grain direction on the carving process or the variance in the design outcome across two different wood species.

Following a case study methodology, the investigation implied, then, conducting experiments in the shape of full design-to-production cycles in a real-world context showing how their outcomes have been reached only following a multistep design process where the designer has been asked to make critical decisions based on a material and fabrication simulation provided by the trained system.

While the first two hypotheses, addressed in the previous chapters, deals with quantitative data as they focused on sensor-based recording session, material behaviour modelling and machine performances, **Research Question C** combines both quantitative and qualitative data as it aims to assess the interaction of different groups of design professionals with the devised design-to-production workflow.

The outcome of the industry collaborations was an extended catalogue of digital explorations and material evidence organised along a series of case studies which will be presented in the following pages to support each a specific set of findings. For this reason, the chapter is organised in three main sections: **5.2)** Separation Between Design and Making **5.3)** Fabrication as Design Curation Practice and **5.4)** Design Negotiation Platform.

5.1 Interface and Design Workflow

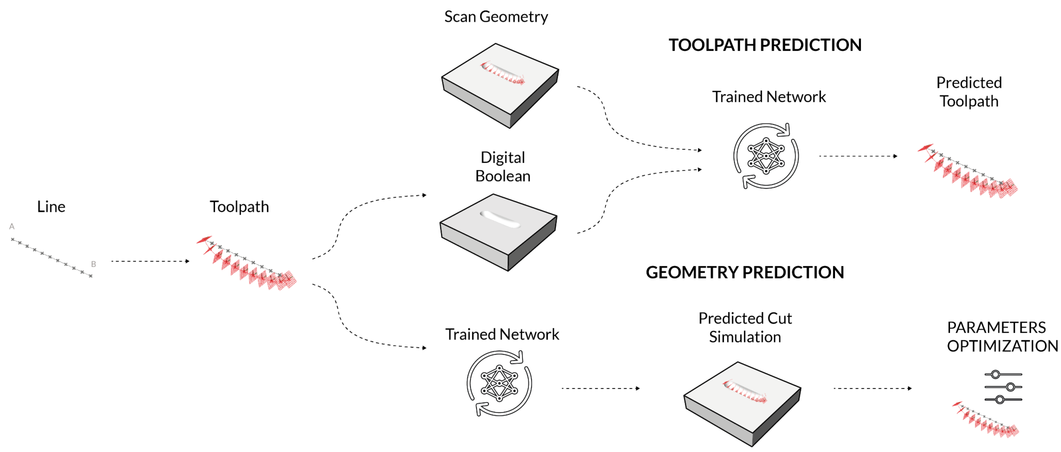


Figure 5.1 Different modes of integrating the trained system into design workflows.

The aim of encapsulating instrumental knowledge is its integration into a design interface which makes it accessible to designers and presents them with the opportunity of using materials behaviour into their design workflow as process drivers. Once the network has been trained and the correlations between fabrication parameters and carved geometries are established, it is possible to translate back and forth between the two sets of data and customise the ANN topology towards a specific design task (***Fig. 5.1***).

The three main modes of applications explored in the experiments are:

- *From robotic toolpath to the simulation of the carved geometry.* While conventional digital Boolean operations are insufficient in calculating the outcome of subtractive operations with non-standard tools on heterogeneous materials, the trained network provides a more accurate simulation based on actual material properties and tool affordances. Designers can directly test how individual fabrication parameters affect the resulting operation and evaluate how these could be tuned to match their design intention. The prediction could be applied to multiple cuts at the same time, each with different input parameters, and used to generate the overall simulation of the cutting pattern.

- *Individual parameters optimization.* Utilizing the same set of training inputs and outputs is possible to create labels (as Boolean flags) to predict a series of event thresholds based on sets of fabrication parameters, such as the successful removal of material or the correct extraction of the tool from the workpiece. Moreover, additional labels could be created by the designer to describe formal preferences (*e.g.* surface roughness, edges definition), curating the training dataset along a specific design direction. Such information can be used to tune individual fabrication parameters to maximise specific performances, such as material removal volume, without the risk of defining a dangerous or inefficient carving operation.

- *From carved geometry to robotic toolpath.* Extracting fabrication data out of the scanned model of a previously carved workpiece to reconstruct the robotic toolpath that has generated it. Alternatively, the same method could be applied to start from a digital geometry obtained through a subtractive Boolean operation as a way of matching a formal design intention in the fabrication stage

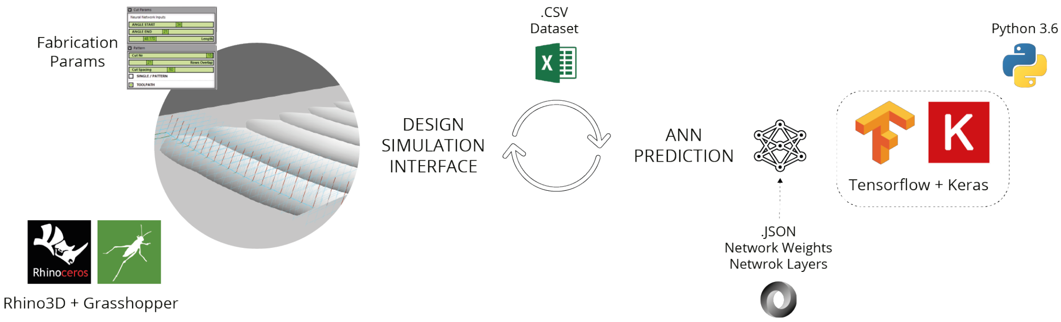


Figure 5.2 Software stack for the design simulation interface.

The trained networks have been made available to the designers through a digital interface in Rhino3D and Grasshopper where the user has been asked to model their design either geometrically or through the definition of a basic set of input parameters for the carving operations (***Fig. 5.2***). Such design data are structured into "features" according to the same process used for the training process and exported to a CSV (Comma Separated Values) file. From the design interface, it is possible to seamlessly call an external Python routine which requests to the ANN to produce a prediction based on its configuration of inputs and outputs. Utilising Google's Tensorflow framework and Keras as front-end is possible to save the ANN layers topology and weights distribution in a JSON file after the training. The main advantage of such a modular approach is the opportunity of flexibly loading within the same routine any desired trained network based on the specific design requirements. This could be, for instance, switching between wood species or quickly evaluating the effect of different carving tools in respect of a given grain direction.

5.2 Separation Between Design and Making

The collaboration with BIG in Copenhagen took place concurrently with the installation of two industrial robotic arms in their office spaces and provided the opportunity to assess the potential role of such technologies within their well-established design workflow. The chosen model for both industrial arms has been the ABB IRB 1600, whose specifications have already been described in **Chapter 4**. The robots were installed inside an industrial cell facing each other and with a medium-sized horizontal area between them where to position the workpiece. The fabrication cell was placed in the workshop area of the office dedicated to model making, mostly in foam and plastic materials.

This section addresses and analyses the established industry paradigm for the production of artefacts based on a linear workflow, as presented in **Chapter 2**, through the opportunity provided by the unusual proximity of the design team with robotic fabrication facilities which made possible to test the full design-to-production cycle. BIG is currently one of the leading firms in the architectural design industry with offices in Copenhagen, London and New York and hundreds of projects for renown public institutions and private clients. As a design firm, they deliver projects in the shape of drawings, specifications and reports and they are not directly involved in the manufacturing stage of the project.

The first opportunity to engage with the newly acquired fabrication facilities was the fabrication of a large landscape/urban model of Manhattan, New York, to present their linear park project for the city, the BIG U, as part of an exhibition at the Architectural Biennale di Venezia 2018 (***Fig. 5.3**, **5.4***). The main idea was to move away from the usual foam and plastics used for representational model and utilise solid wood to create a piece that would be more resistant and could be used in further occasions after the exhibition. The final U-shaped model at a scale of 1:750 covered an area including both the city waterfront and the Hudson River surrounding the city. For transportation reasons, the model was subdivided into 17 modules, each consisting of two parts for the city and water areas. The design and fabrication of the model were supervised both by the NY and Copenhagen office and took approximately three months.

Figure 5.3 – Completed BIG U model at the Biennale di Venezia 2018.

Milling, the process of removing material using a rotary cutter against a workpiece (Oberg *et al.*, 2016), was selected from the beginning as a well-established, industry-based, technique for achieving the task. An entry-level wood router (*i.e.* Kress 1050-FME-1) has been attached to the industrial robotic arm through a custom mount and configured as end-effector. This tool has been widely adopted by the maker community for its high price/quality ratio, however, it presents several limitations if compared to an industry-grade milling spindle, such as lack of a power inverter and digital speed control, low power (1050 Watts) and relatively small milling bits clamp of only 8 mm diameter.

The milling technique was developed and specifically optimised to operate within the industrial paradigm of a linear progression from the stage of design to fabrication. From this perspective, milling could be compared to the more recent 3D printing techniques as both promise to deliver exactly the original desired shape within very tight tolerances. As a way to exclude any material agency from the process, most of the time only industrially-graded homogeneous materials, such as metal or plywood, are utilised.

Figure 5.4 Robotic milling of one of the timber modules of the BIG U model.

The design-to-production workflow is described in **Fig. 5.5** and is organised in three main stages: **i)** the creation of the digital model, **ii)** the generation of the toolpath with a dedicated CAM software and processing of such for an industrial arm task and finally **iii)** the robotic fabrication task itself.

Each module was milled in one go within a fabrication time oscillating between 4 to 12 hours according to module size (in length) and material volume to be removed. Generally, the tool feed-rate has been kept to a conservatively low value to avoid overloading the tool and ensure a higher finishing quality. The chosen milling operation could be considered as part of a "*roughing*" strategy performed with flat end mill down-cutter of diameter = 8 mm. As the available tool was not able to cut beyond a certain depth, the timber blank had to be cut down to its final outer profile by an external contractor.

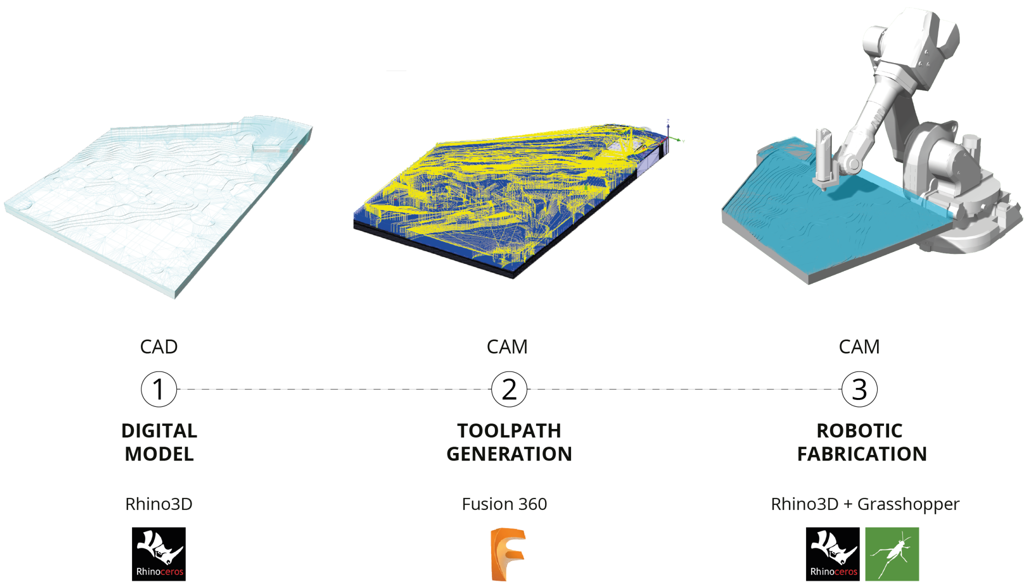


Figure 5.5 Design-to-production workflow of the BIG U model.

The transfer of a manufacturing technique such as robotic milling from the highly controlled environment of a factory/workshop to a design studio environment together with its application with a heterogeneous material, such as timber, highlighted a series of issues arising from the adoption of a conventional linear workflow based on the separation between the stages of design and making:

- A first issue was the distribution of the workload to create the digital model, in which the NY team has been responsible for defining the area to be represented and curate its content, while the Copenhagen team had the role of creating the model for its fabrication. The idea that is possible, or advisable, to separate the two tasks appears as a reflection of the established paradigm in the design industry: as the two teams focused on two different aspects of the project, one focusing on the design while the other on the production, it was particularly challenging to ensure the delivery and integrity of all the necessary information and the two teams ended up creating two different digital models serving two different purposes.

- From a conceptual level, the transfer of the representational model to a digital fabrication model showed a strong preconception deriving from previous experience of model making within the office applied to a different type of technology and material. The office established a technique to achieve three-dimensional landscape models via stacking together flat sheet material, such as cardboard or acrylic panels, cut to the right shape with an in-house laser cutter. Such layer-based logic has a strong influence on the visual appearance of the model, as any height difference is represented through right-angle small steps. The decision of the design team to apply a similar peculiar aesthetics to a model achieved with a completely different type of technology and material shows how individual manufacturing knowledge deeply affects design decisions (***Fig. 5.6***). In this case, a previous understanding of model-making techniques potentially limited the exploration of design opportunities which would fully exploit the tool fabrication affordances and timber properties. For instance, milling a smooth three-dimensional surface, resembling more closely the physical geographical configuration, would not be achievable with laser cutting. As a practical consequence of this design decision, the digital model had to be manually layered and each step had to be modelled as geometry rather than resulting from stacking flat-sheet material.

Figure 5.6 Layered design options for the landscape model.

- The lack of integration of specific manufacturing knowledge for milling operations with the design interface in such early stage of the process proven to be detrimental for the overall efficiency of the design-to-manufacturing workflow, requiring several post-rationalising adjustments which ended up in the necessity of the modelling the same object twice. To begin, the model had to be split up in separate modules of equal size, both for transportations, storage, fabrication working area and material availability of limited sizes rather than an indefinite large single piece. Furthermore, a series of geometric features determined by the fabrication technique and tools choice had to be implemented. For instance, it is not possible to achieve right-angle corners of a pocket and the corners will be necessary filleted based on the tool radius. Similarly, the router has a maximum reachable depth before collision defined by the length of the milling bits which results in the impossibility of achieving some type of geometries. Even in a compartmentalised workflow as the one described, the integration of initial manufacturability checks, similarly to the ones provides by online 3D printing services (*e.g.* wall thickness, steep angles…), concurrently with the design modelling would have made possible to avoid costly mistakes which would appear evident only at a later fabrication stage.

- While issues deriving from geometrical features and specificities of the chosen fabrication techniques were problematic for the overall process, the definition of material aspects of the project presented an additional set of challenges for the project. The digital models, even the one optimised for fabrication, carried no information regarding properties and behaviour of the specific material chosen to “materialise” the digitally-defined shape. Timber, more than other materials, presents specific challenges and requires careful planning as fabrication material. The choice of such material for the large landscape model significantly affected the choice made by the design team at an early stage when they had no information available about material features. The design solution space shrank considerably in relation to simple parameters, such as maximum length or thickness, in relation to the actual availability of the material. The chosen wood species was Lime for its light colour and relatively uniform grain arrangement. The information regarding the available dimensions for the boards of that species forced designers to readjust the size of the modules and remove part of the geometries which would not fit with the given thickness. Moreover, the blank for each module had to be put together glueing up 3 different boards to reach the width of 75 cm. This necessitated revising how the model was described digitally, taking into consideration an increased number of seams and the careful placement of individual boards in regards to the figuring determined by the grain arrangement. While in the digital environment each module appeared uniform and solid, in the physical version it was possible to notice the difference between different boards mostly because of subtle tone difference deriving from the differences in trees.

- The positioning of the workpiece inside the cell was measured using the precise coordinate system of the industrial arm and reconstructed in the digital design interface. The main issue with such method is that once the workpiece was correctly located, there was no strategy to take into account the shrinking and deformation of the blank determined by environmental conditions and in general higher tolerances given by using a natural material instead of an industrial one. Such a deviation between digital and physical model could go from several millimetres up to 1-2 centimetres for some of the largest modules. Furthermore, it was quite challenging to describe how this deformation has happened through the measurement of a few points within the robot coordinate system. As a consequence, geometrical features at the edges of the blank were either shifted or left unmachined. Cutting in different directions in respect of the wood grain loaded the tool differently, therefore, the machine had to be supervised to continuously monitor the sound and vibration level and the speed decreased accordingly.

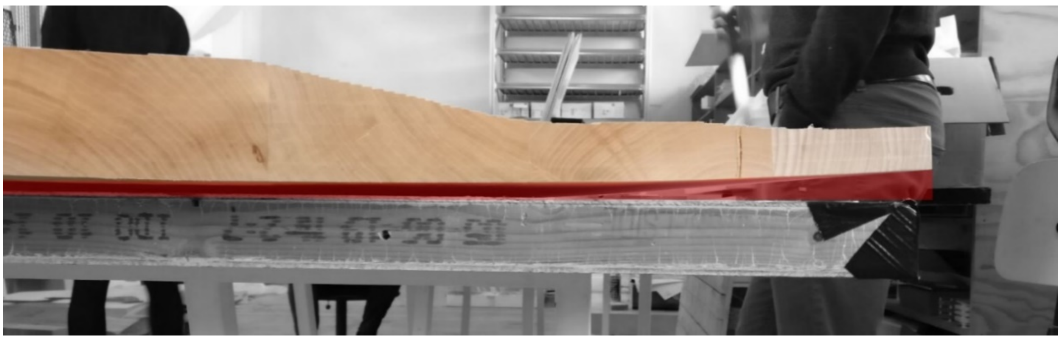


Figure 5.7 Warping of the timber model after the robotic milling operation due to changes in the internal stresses of the grain.

Finally, a few days after the fabrication, the asymmetrical release of the mechanical stress of the fibres, due to the removal of material on one side only, together with local environmental conditions generated significant warping in the milled boards. In some of those, it was necessary to apply stress release cuts on the bottom side of each component as the displacement reached a difference of several centimetres between the centre and the edges (***Fig. 5.7***). This posed a potential issue for the assembly of the modules in their final configuration.

5.2.1 Results: Summary

The project provided a series of valuable insights regarding the advantages and disadvantages of using a linear and compartmentalised workflow from the design to the fabrication stage:

- Utilising well-established fabrication techniques, such as robotic milling, allows seamless integration of the process within the current workflow of the design firm and generally has been received positively by most of the design professionals used to operate within a notation-based paradigm.
- The proximity of fabrication facilities, such as the industrial robotic arms cell, to the design team is not necessarily enough to encourage designers to engage with the fabrication tools and material properties. The predominant approach based on the "materialisation" of digital geometries, like in 3D printing processes, is mostly based on long-established workflows and lack of tool interfaces that would grant designers with manufacturing knowledge at an early stage.
- Even within a prescriptive fabrication workflow utilising robotic milling, timber material properties played a critical role which required to move several times back and forth between the stage of design and fabrication to reach a final design solution.
- Access to a material knowledge database, combined with data related to economic and resources availability within the local supply change, would be beneficial to the designer alongside formal considerations.

5.3 Fabrication as Design Curation Practice

In parallel with the design and fabrication of the BIG U model, the team of designers developed a series of robotic carving experiments focusing on the bottom-up exploration of material features through the integration of manufacturing knowledge at an early stage of the design process.

The training of the system, following the methods described in the previous chapters, implied the selection of the range of wood species, properties and carving tools to define the solution domain of the design exploration. This approach presents an opposite perspective compared to the previous case study as it moves from the physical domain of the fabrication stage to inform the exploration of design solutions in the digital realm. The shift from the physical to digital reject the conventional workflow presented in the previous section, where a model is defined digitally and “materialised”, as a sort of physical instance of an abstract shape. The perspective presented in this section frames the act of design as a curatorial practice where the designer is asked to specify, from the beginning, the physical domain of affordances through which directing her or his investigation. Whereas this might seem an unnecessary limitation, theoretically hindering the full exploration of the entire domain of solutions, the specification of the domain of the operations makes it possible to confidently map the complex combination of affordances and integrate effectively such knowledge as part of the digital interface. Such a knowledge base enables a series of solutions to be unlocked which would otherwise be unavailable in a purely digital hylomorphic space. Such an integrated base is not a crystallised entity, but it is constantly refined and expanded as more real-world data are collected. The curatorial process suggests instead of a monolithic approach, a modular and incremental approach, which can expand horizontally through the collection of multiple types of different affordances, and vertically, through collecting more information to create a more robust understanding of those properties and constraint. Furthermore, as discussed in the previous section, the lack ok of a knowledge base could be detrimental for the overall process where the chosen design might be unsuitable actual fabrication methods and constraints.

The following analysis is not focused on the specific comparison between milling and carving processes, which are too different both in methods and scope for a meaningful parallelism, but rather on the difference between the developed training methods and the conventional workflows and how these influence the design process.

5.3.1 Expert Systems and What-If Scenarios - Background

The “*What-If*” design approach, previously introduced in the Literature Review Chapter, provides designers with multiple scenarios based on different types of design alterations together with a series of DFM feedback necessary to support an informed decision to advance in the design process.

According to Vaneker and van Houten (2006), such methods aim to replicate the cognitive process of designers and engineers who are continuously asked to define and assess the combination of solutions that lies ahead together with the consequences of a specific choice on the overall outcome. The value of automating, at least partially, such a process is to support users in the navigation of sequential What-if stages which require to be informed in real-time by a multitude of information sources such as programs, databases or knowledge bases. Each of these sources acts as an expert system which provides contextual knowledge to structure the what-if investigation and generate the set of scenarios presented to the user.

Expert systems are defined by Lucas and van der Gaag (1991) as those “*systems which are capable of offering solutions to specific problems in a given domain or which are able to give advice, both in a way and at a level comparable to that of experts in the field*”. In their present-day formulation, expert systems are described as the combination of **a)** a knowledge base and **b)** an inference engine which is responsible for “*manipulating the knowledge represented in the knowledge base*” (***Fig. 5.8***).

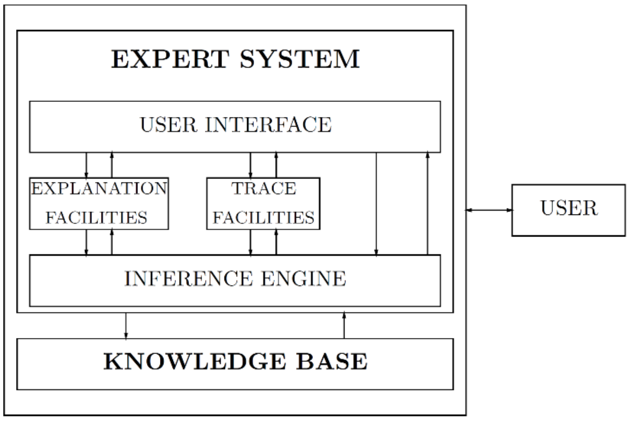


Figure 5.8 "Global architecture of an expert system" – Source: Lucas and van der Gaag, 1991.

The inference engine is encapsulated with a consultation system which represents the interface through which the user can interrogate the system.

As shown by several studies (Looney, 1993; Huang and Zhang, 1995; Goel and Chen, 1996; Medsker, 2012), ANN can be used successfully to create hybrid Expert Systems (ES) utilising their ability to build rules from the examples provided by the user. As Kottai and Bahill (1989) point out, one of the main differences with conventional ES is that the generation of the inference engine can be achieved with minimal external intervention as the "*network gradually takes over the task of the human expert*". Furthermore, ANN-based expert systems appeared more robust than conventional ones when provided with erroneous or incomplete data, still giving reasonable answers. Nevertheless, if compared to the original diagram proposed by Lucas and van der Gaag (***Fig. 5.8***), there are no explanation or trace facilities, since it is particularly challenging to reconstruct the reasoning behind the prediction of the ANN, appearing to the user/designer as a black box.

Within the thesis context, as discussed in the previous chapters, ANNs have been implemented as part of a strategy to synthesise material and instrumental knowledge based on data collected from directly recording human experts and robotic production sessions. The designer is not acting as an expert as she or he is not responsible for individuating the underlying relationships and patterns in the dataset but rather, through the curation of the training process, selecting the affordances and relative domain within which the design exploration is focused. While conventional expert systems are based on a set of rules established by human experts, in this case, the user setting up the ANN-based system does not need to know those rules or even explicitly formulate them. The inference engine represented by the trained ANN does not provide clues behind its reasoning and, as such, it does not increase the knowledge of the user but it instead provides a powerful source of knowledge which is possible to constantly query during the design process. As a result of the user curation process, the trained system does not provide access to universal knowledge about any timber subtractive manufacturing process, but rather to a specific subset of affordances coinciding with the one necessary to inform the what-if scenarios design strategy.

5.3.2 Training

The goal assigned to the team of designers was the exploration of a series of carving patterns for special surface treatments, generating interesting visual and tactile effects for a wide range of applications, from furniture pieces to building components of larger assemblies (*e.g.* façade or interior panels).

The exploration set out to investigate the influence of material qualities in the definition of the formal outcome of the design intention. For this reason, the designers started by selecting three substantially different wood species (*i.e.* Lime, Tulip and Oak) both in terms of aesthetic qualities and mechanical properties. The second focus of the investigation has been on the interaction of a set of different carving tools (*i.e.* Stubai 9-20, 9-30, 7-30) with the material properties, such as grain density and directionality (*i.e.* 0°, 30°, 60°, 90° from the main grain direction), of the selected wood species.

The aim of the training process was to map the complex interaction of the material and fabrication affordances to create a package of knowledge that could be integrated into the digital design exploration. The collection of the real-world fabrication data through robotic recording session had to be carefully arranged, balancing between the full range of the affordances available and the limited amount of time and resources available. A first step has been to select the relevant combinations. For each wood species, the collection of cuts has been performed using the three different carving tools in the fabrication toolset following four different carving direction with an interval of 30° between each. Within such selection, the following step has been to define the values range for each fabrication parameters (*e.g.* Tool/Surface Angle or Input Cut Length).

As discussed in **Chapter 3**, such operation could be performed either through a demonstration of a skilled human expert or an arbitrary definition of reasonable boundaries based on the designer's intuition. While the human's demonstration would have been more efficient, the second method has been chosen as it was relevant for this case study to identify both successful and unsuccessful robotic operations to avoid inefficient and dangerous configurations in the following design stage. In relation to the carving patterns exploration, the investigation has been limited to three main Input Cut Length intervals (*i.e.* 35, 45, 55 mm) which have been evaluated as providing enough meaningful variation in the pattern. Each length interval has been investigated through a selection of cuts between 9 to 13, each with a different variation of Tool/Surface Angle value, which represents a key parameter in the definition of the carving outcome as demonstrated in **Chapter 3**. The figure below (***Fig. 5.9***) summarises the structure of the curatorial process and how this defined the robotic training sessions.

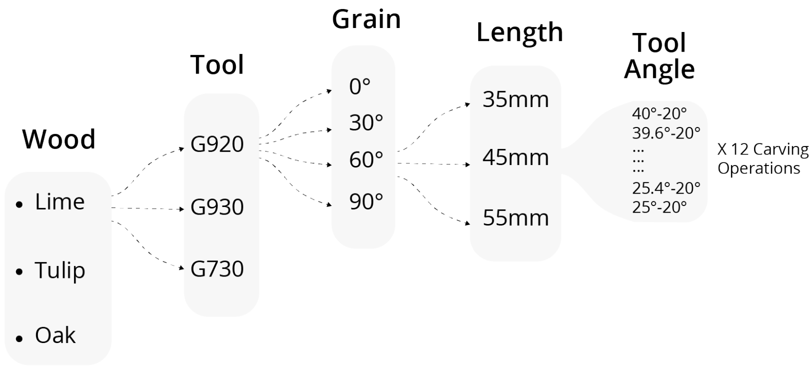


Figure 5.9 Selection of the parameters explored in the training session.

As a result of such structure, each wood species dataset counts between 430 to 460 robotic carving operations. Each training board (300x400x35 mm) counted between 32 and 36 cuts and took an average of 15 minutes to be produced, with the setting up (*i.e.* positioning, fixing and calibrating) being the most time-consuming part. Once these data have been collected and properly organised, the datasets have been used to train several ANNs based on the specific combination of wood species and tools utilised following the methods presented in the previous chapter.

The access to several carving simulations through the digital interface has been made possible through the seamless switch between different trained networks. Consequently, from the same set of input parameters is possible to receive back almost immediately multiple predictions and effectively compare them.

5.3.3 Design Explorations

As the designers had the opportunity to curate the domain of their design investigation, the team could confidently utilise the digital simulation interface as informed by the real-world fabrication data collected during the training sessions.

A series of pattern generation strategies have been developed with the aim of creating complex textures based on generative principles rather than manually defining each carving operation (***Fig. 5.10***). The key concept is the perturbation of a "field", in this case carving toolpaths arranged on a grid, performed by an external element such as an attractor/repulsion point, a curve or a grey-scale map. Following the positioning of the generating element, designers could define the type and range of modifications generated in the variation of the geometric and fabrication parameters of the toolpaths. These are open-ended and could be easily defined through the design interface and could include, for instance, variations in the cut length, depth, rotation or overlapping.

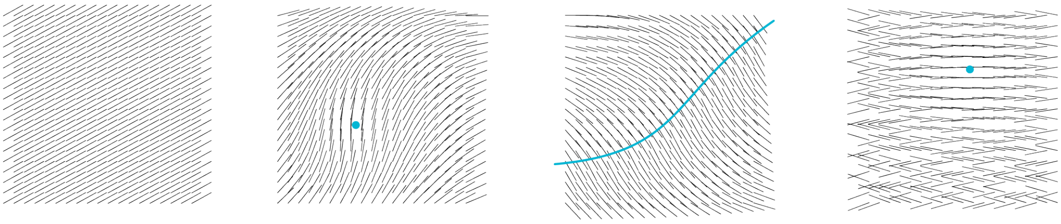


Figure 5.10 Procedural generation of carving patterns in the digital design environment.

Each toolpath of the generated pattern was fed to the trained ANN which returns a simulation of the collection of carving operations based on the selected material and fabrication parameters. The advantage of such method is not only, as discussed in the previous chapter, to access a more accurate prediction of the fabrication outcome, but also to seamlessly evaluate the influence of different fabrication affordances in generating different outcomes from the same set of input parameters. As such methods enable the assessment of multiple combinations at a digital level, it substantially reduces the need for robotically fabricating each generated pattern, making the process more efficient and reducing material waste.

Such a workflow was utilised to generate several designed/fabricated carved panels to evaluate the effectiveness of the developed methods. Design explorations followed a what-if scenarios structure organised through multiple stages in a tree-like structure whose branches eventually culminating with the actual robotic fabrication of that design iteration. At each stage, the available combinations of material and fabrication affordances, based on the collected data during the training, could result unpractical to navigate in terms of solutions space. As a more effective way to advance the design process, each stage required the choice of one specific set of affordances to explore, with the others inherited from the previous stage. Such analysis could explore geometric pattern variations, wood species and density, grain directionality, carving tools and specific fabrication parameters, such as Tool/Surface Angle, which would significantly affect the resulting length, depth and width of the cut.

The opportunity to access the ANN simulation of multiple fabrication simulations had to be combined with the designer's intuition of evaluating whether the specific iterations would respect her or his design intention and what to explore in the following stage to steer the overall process. Alongside qualitative evaluations, it has been very important to provide designers with a series of quantifiable measure that would support the decision-making procedure at each stage such as the number of cuts, fabrication time and resulting geometric parameters.

5.3.4 Design Case Study

This section discusses one of the several design explorations performed by the team of designers. The focus is to present the tree-like evolution of the investigation, the set of affordances considered at each stage and the evaluation of the fabricated panels. The structure of the what-if scenarios sequence is summarised below in ***Fig. 5.11***.

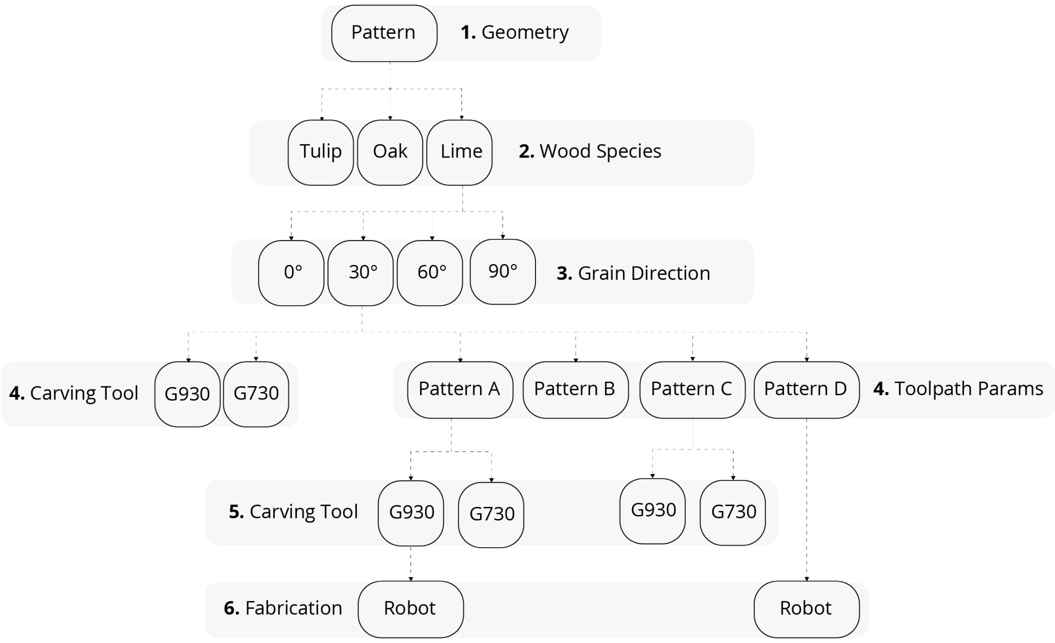


Figure 5.11 Tree-like structure of the what-if stages explored during the design process.

Behind each fabricated panel, several digital designs were explored through the ANN-based simulation of the outcome geometry. The design evolution is presented through a smaller portion of the overall carving pattern for one larger panel (***Fig. 5.12***).

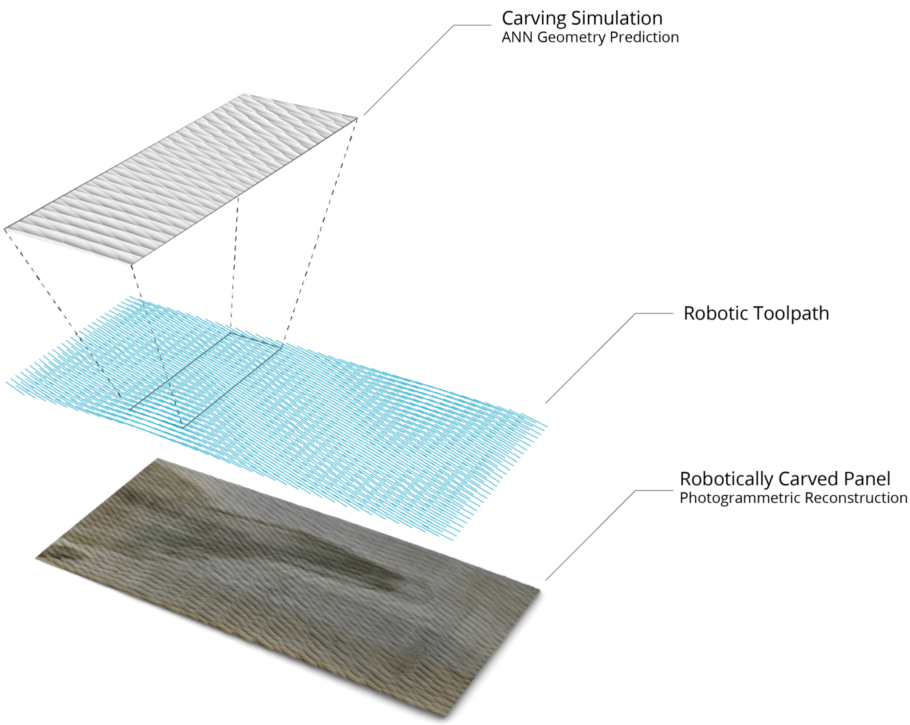


Figure 5.12 The ANN-based simulation represents the interface between the digital robotic toolpath and the final carved panel, enabling the evaluation of multiple design solutions before moving to the production stage.

1) **Geometry Pattern (*Fig. 5.13*):** The original geometric pattern is generated following the methods described above, utilising a curve as the perturbating element of a grid of carving toolpath. Based on the distance from the curve, the toolpaths have been subject to a rotation between -30° to 30° and variation in length between 35 to 50 mm.

1. Geometry Pattern

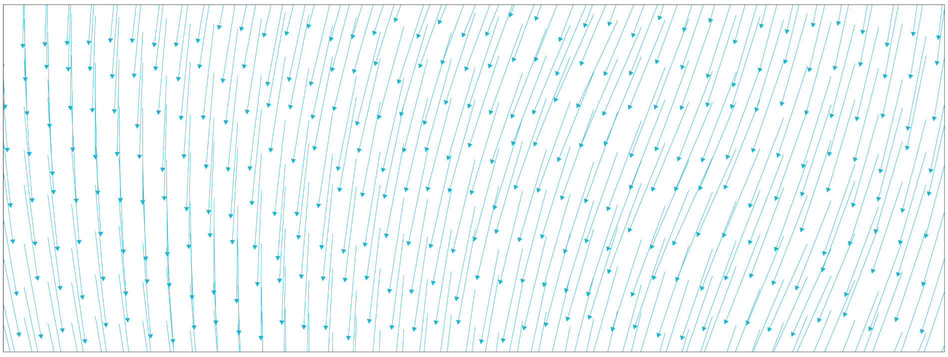
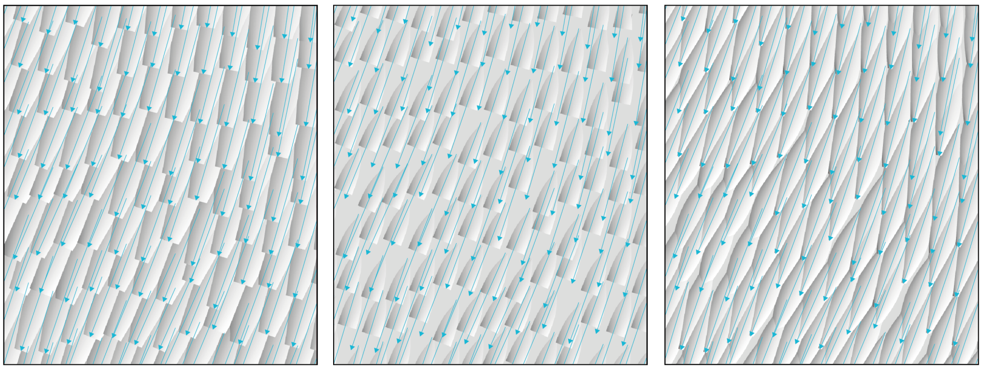


Figure 5.13 Stage 1: Geometric pattern generation.

2) **Wood Species (*Fig. 5.14*):** The generated pattern was simulated using a series of arbitrarily defined fabrication parameters across different wood species to understand their impact on the fabricated outcome. Please note that the selection of the wood species was not determined only by the geometric prediction, as the input params exploration was still minimal at this early stage, but also by qualitative consideration from the designer's team, such as the surface colour of a specific species (*i.e.* "*oak is too dark*").

2. Wood Species



Wood Species: Lime
Grain: 30°
Tool: G920

Wood Species: Oak
Grain: 30°
Tool: G920

Wood Species: Tulip
Grain: 30°
Tool: G920

Figure 5.14 Stage 2: Wood species comparison (i.e. Lime, Oak, Tulip).

3) **Grain Direction (*Fig. 5.15*):** Once tulip was chosen as preferred species, the necessary following step has been to assess the influence of the grain structure and direction in relation to the carving toolpaths. The carving pattern was oriented along four main grain directions (0°,30°,60°,90°) which added to the rotation applied during the pattern generation (*e.g.* 60°+12.4° = 72.4° is the actual angle between the toolpath and grain direction).

3. Grain Direction

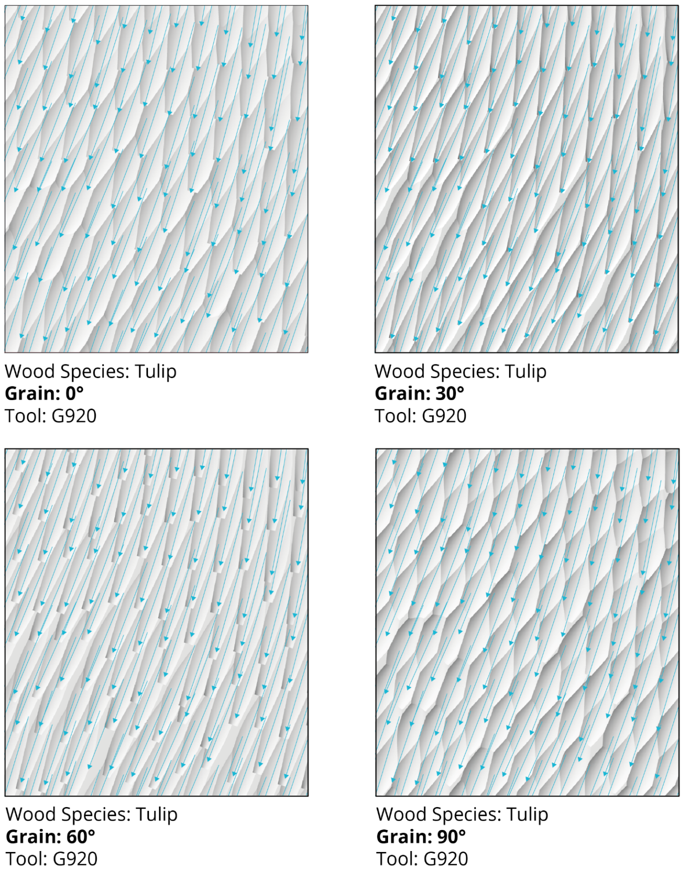


Figure 5.15 Stage 3: Grain direction (i.e. 0°, 30°, 60°, 90°)

4.1) Carving Tool (Fig. 5.16): The what-if scenario scenarios made possible to quickly evaluate alternative solutions for the same pattern generated by different fabrication tools curated during the training process. In this case, once defined the wood species and angle in respect to the grain structure, it was possible to assess the simulation of the same pattern carved with a Stubai 9-20 and 7-30 carving gouge.

4.1 Carving Tool

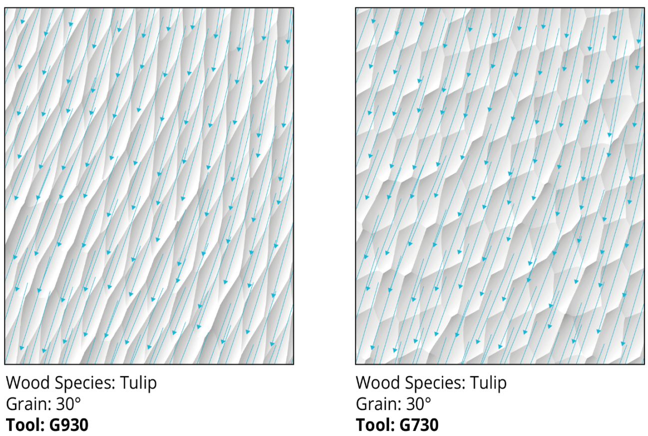


Figure 5.16 Stage 4.1: Carving gouges (i.e. Stubai G930, G730)

4.2 > 5) Carving Pattern Params > Carving Tools (*Fig. 5.17*): The second what-if scenario revolving around the selection of different carving tools was combined with substantial modifications of the geometric parameters in three different alternatives (Pattern A, Pattern B, Pattern C). Different amount of operations and overlapping factor were explored to understand what would work best with carving tools of different sizes.

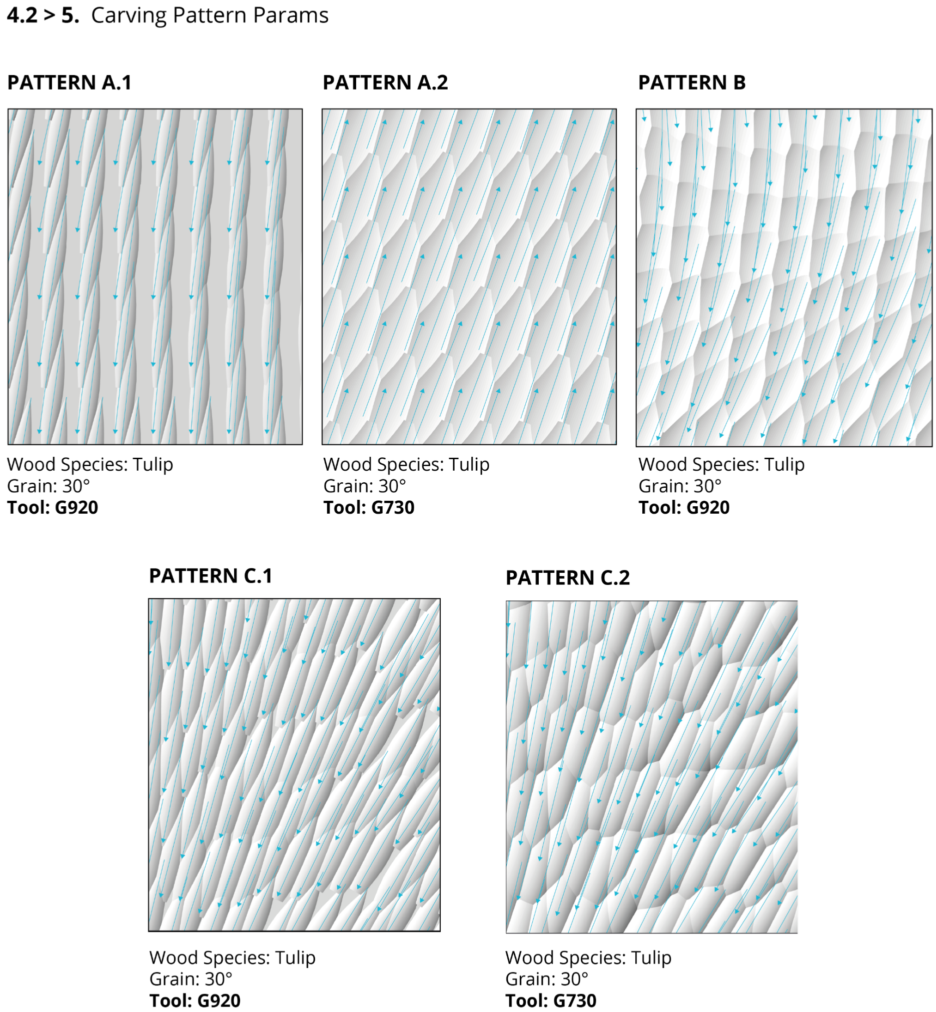
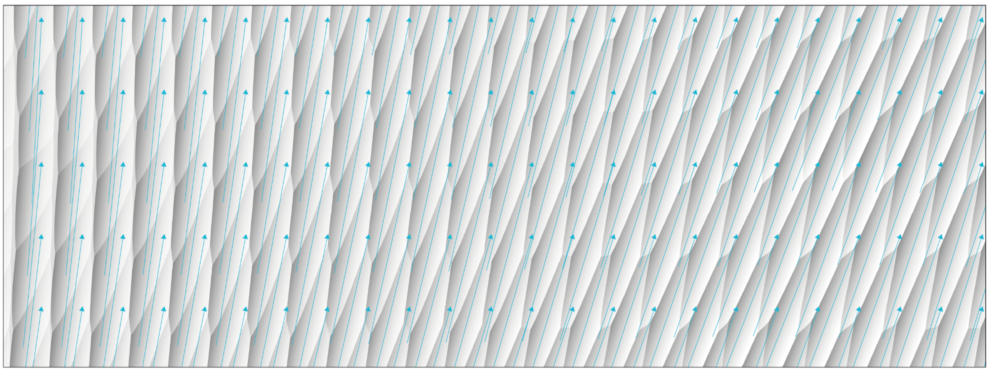


Figure 5.17 Stage 4.2: Geometric variations of the original pattern (Stage 1).

6) Fabrication Stage (*Fig. 5.18-19*): The final stage of the exploration is the robotic fabrication of a series of carved panels which results from the sequence of what-if scenarios examined by the design team (***Fig. 5.20-21***). For this exploration, two digital patterns were selected for the fabrication stage. Both were manufactured on ulip boards following the main grain direction (0°). Pattern A was carved with a Stubai 9-30 and focused on the toolpath rotation with minimum overlap between cuts. Pattern D was carved with a Stubai 9-20, a smaller carving tool, and utilised a fixed grid orientation with a higher number of cuts which resulted in a larger overlap and a subtler texture. The photogrammetric reconstruction of the carved panels was compared to the ANN-based prediction and the deviation between the two was used to generate colour gradient mapping.

6. Fabrication Stage

PATTERN A.3 - ANN PREDICTION

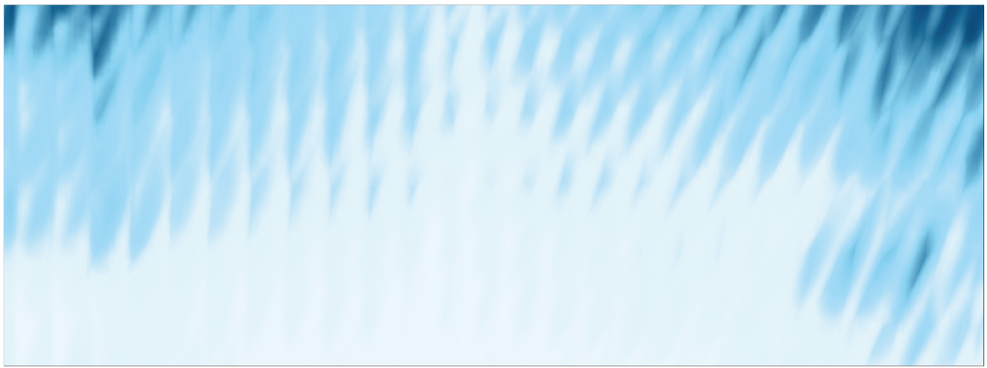


Wood Species: Tulip - Grain: 30° - Tool: G920

PATTERN A.3 - CARVED PANEL (PHOTOGRAMMETRIC RECONSTRUCTION)

Wood Species: Tulip - Grain: 30° - Tool: G920

PATTERN A.3 - PREDICTED VS ACTUAL DEVIATION

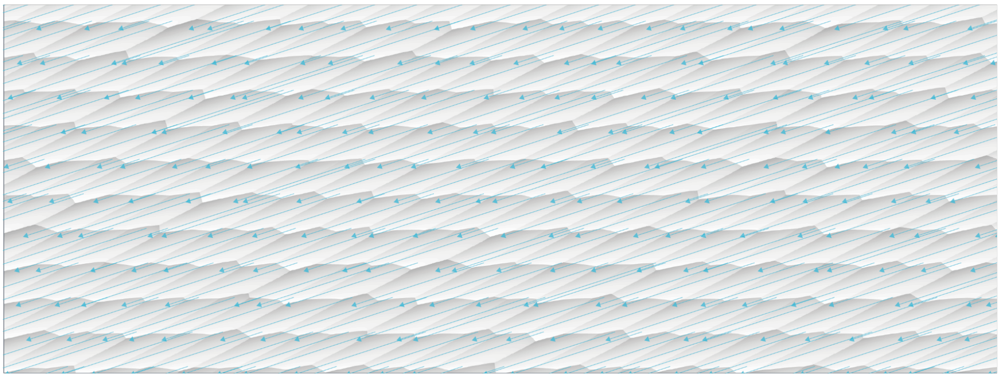


Wood Species: Tulip - Grain: 30° - Tool: G920

Figure 5.18 Stage 6, Pattern A.3: Fabrication and analysis of the outcome. ANN-based digital simulation (top), photogrammetric reconstruction (middle), deviation analysis map (bottom).

6. Fabrication Stage

PATTERN D - ANN PREDICTION

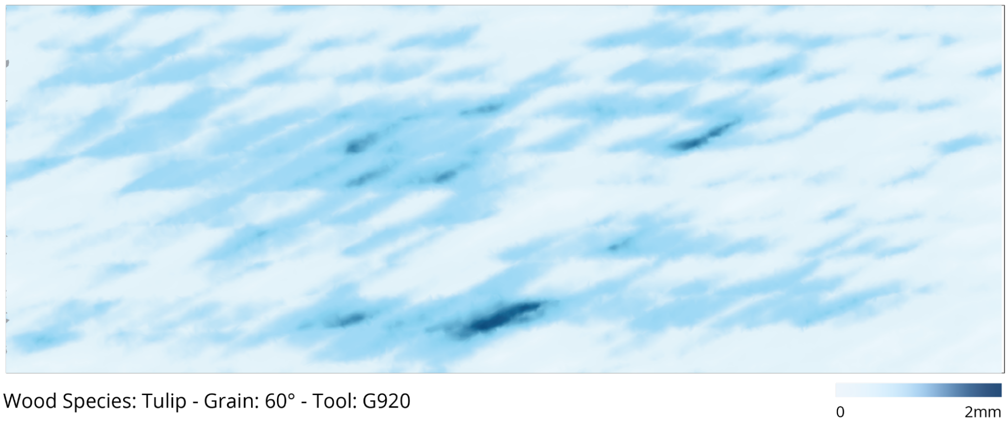


Wood Species: Tulip - Grain: 60° - Tool: G920

PATTERN D - CARVED PANEL (PHOTOGRAMMETRIC RECONSTRUCTION)

Wood Species: Tulip - Grain: 60° - Tool: G920

PATTERN D - ANN PREDICTION



Wood Species: Tulip - Grain: 60° - Tool: G920

Figure 5.19 Stage 6, Pattern D: Fabrication and analysis of the outcome. ANN-based digital simulation (top), photogrammetric reconstruction (middle), deviation analysis map (bottom).

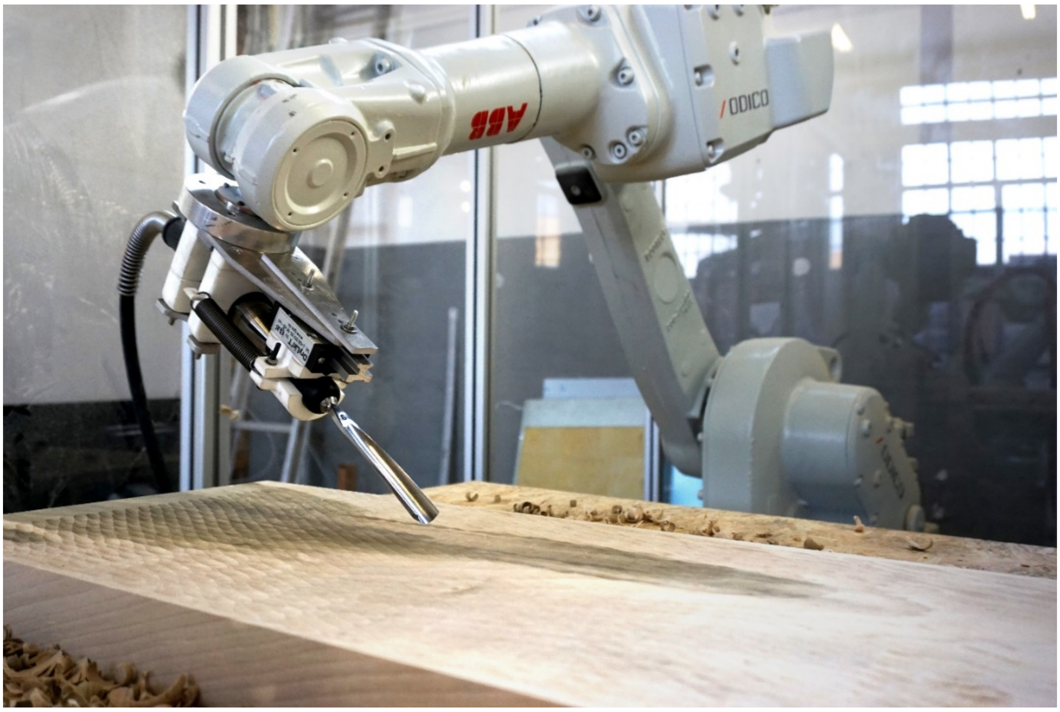


Figure 5.20 Robotic carving operations during the secondment at BIG.

Figure 5.21 Detail of a robotically-carved texture fabricated during the secondment at BIG.

5.3.5 Results: Summary

The discussion of a typical design to fabrication exploration based on a sequence of what-if scenarios describe the workflow utilised by the design team for producing several carved panels. The following findings could be derived from such catalogue of material evidence and digital experiments performed within the secondment timeframe:

- The final fabrication stage of a specific what-if scenario does not represent necessarily the end of the design process, but it becomes instead the starting point for another set of digital explorations which can build upon the initial fabricated evidence. As the tree-like structure of the presented case study suggested, the design to fabrication process is rarely linear and choices made at an early stage can always be revised, especially if new material data is included in the process.
- While the prediction of any single carving operation is highly accurate within a fraction of millimetres, as demonstrated in the previous chapter, the analysis of complex fabricated patterns shows a higher deviation between the ANN-based prediction and the photogrammetric reconstruction of the carved board. The main reason for this is likely due by the combined effect of overlapping cuts whose interaction generate mechanical conditions which are not present in the single cut configuration. For instance, a carving operation performed where only one side of the cut find the resistance of the material, while the material has already been removed on the other side by the previous operation, is a specific condition which has not been modelled during the training stage. Nevertheless, the overall accuracy of the ANN-predicted pattern is more than acceptable for design purposes and it has been proved to be able to correctly capture the impact of different material and fabrication affordances on the fabricated geometrical outcome.
- The curation of the fabrication process through the definition of the training stage and material affordances explored represents the keystone of the design process. The search domains defined at an early stage through the selection of the wood species, relevant material properties, carving tools and fabrication parameters directly the determine the range of solutions available in the digital design stage.
- The exploration of what-if scenarios driven by material affordances would not be possible using conventional methods based on purely geometric considerations rather than on the collection of real-world fabrication data. As a consequence, the evaluation of the impact of choices such as the selection of a specific wood species enables to unlock a series of design opportunities otherwise unavailable and support a better-informed decision-making process.

5.4 Design Negotiation Platform: Top-down Decisions and Bottom-up Fabrication Affordances

Figure 5.22 "Kizamu", a research demonstrator realised as part of the collaboration with ROK Architects.

The integration of material and fabrication affordances provide designers with the opportunity to evaluate their effect on their original design intention. As the trained ANN provides an accurate simulation of the fabrication outcome, the designer could either decide to embrace the agency of materials and tools on the design or, conversely, use such information to adjust the robotic fabrication parameters accordingly to obtain the original design. In most cases, such decision is not binary and implies to carefully balance between top-down design requirements and bottom-up material features. Consequently, the developed methods, once integrated within a design-to-manufacturing workflow, provide the opportunity to negotiate between these two different positions.

The secondment at ROK Architects set out to evaluate the impact of the machine-learning-based design tools if used as a negotiation platform for the design and fabrication of a large furniture piece for a gallery space (***Fig. 5.22-24***). The demonstrator is named Kizamu, Japanese for "carving", and should serve as an exhibition platform for several smaller art items. The aesthetic appearance of the carving process and material is supporting the focus on the item on each platform. The focus on a specific design brief from an actual client made possible to test the developed tools within a real-world scenario with a specific timeframe, resources availability and costs. While at the building scale it is challenging to develop and test different design-to-fabrication workflows due to strict legislation that regulates the different stages, the interior furniture project allowed more freedom in proposing alternative pathways to production which did not necessarily rely on a notational form of the object.

Figure 5.23 The demonstrator is composed of a series of robotically-carved wooden platforms to exhibit art objects.

Figure 5.24 Details of the carved flutes of one of the wooden platforms of the demonstrator.

5.4.1 Top-Down Constraints and Design Choices

The design brief and its requirement posed a series of constraints which needed to be integrated as part of the negotiation platform. These considerations included the number of “exhibition spots” needed together with the overall dimensions, display height and orientation in relation to the gallery space. Alongside such requirements, designers had the opportunity to project their design intention at different scales, through a series of top-down choices having a significant impact on the final result.

Pattern Parameters (*Fig. 5.25*): As previously discussed, there are several combinations of geometric and fabrication parameters which play a crucial role in the creation of a carved texture. One of the key design choices has been to focus on a pattern made of parallel carved flutes which could vary in their number, orientation, overlap and the number of cuts in which they were subdivided. Each cut composing a carved flute could be shifted forward or backwards in relation to the next one to change the overlap between the two. Finally, fabrication parameters for each operation have been randomised within specific ranges, for instance with Input Cut Lengths between 40 and 80 mm and Input Cut Depth between 1 to 6 mm. The combination of these choices at the local scale made possible to create variation within an, initially, very simple parallel arrangement of operations.

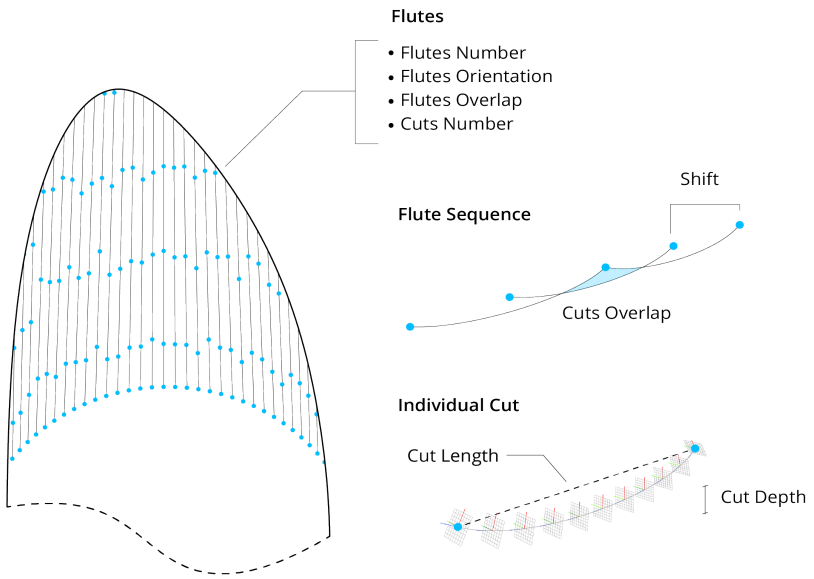


Figure 5.25 Carving pattern parameters – Diagram.

Board Parameters (*Fig. 5.26*): At the medium scale of the individual board, the critical top-down decisions taken by the designers were the overall profile of the board and the relationship between the carved and uncarved areas which would define the arrangement of the art pieces exhibited. Furthermore, the three-dimensional definition of the boards, with a difference of several centimetres in the levels between the two areas, required shifting from two-dimension carving patterns toward a more complex configuration of the fabrication process.

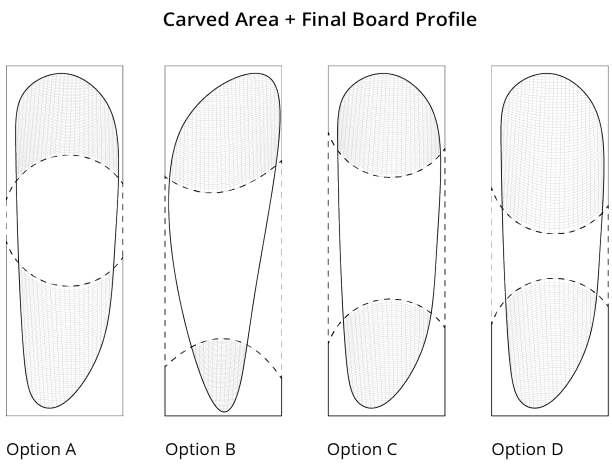


Figure 5.26 Boards Parameters – Diagram.

Global Parameters (*Fig. 5.27*): From the beginning, the design team oriented its preference toward lime wood as preferred wood species due to its light, warm, colour, and its excellent machinability. The overall configuration of the piece was driven by the concept of a carved landscape made of different boards with organic and smoothen shapes, with the art pieces positioned in a central position of these carved podia.

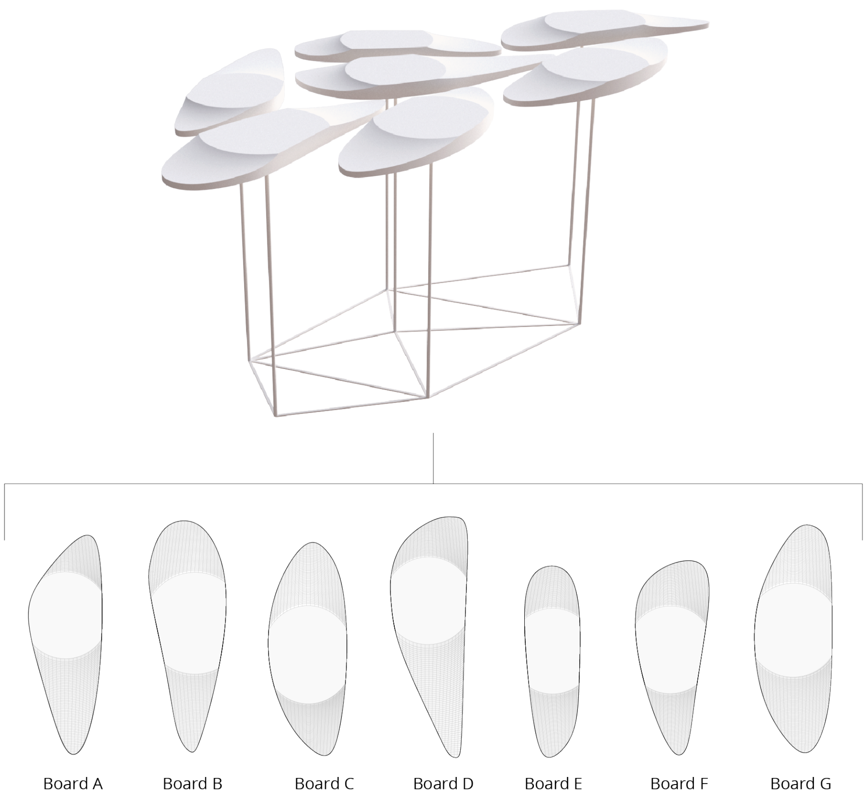


Figure 5.27 Global design parameters - Diagram.

5.4.2 Bottom-Up Features

Each carved board composing the furniture piece, while following a similar design logic to the others, presents individual local features and changes in the pattern arrangements of parallel flutes, due to the combination of input design parameters and material features related to the chosen wood species, such as grain density and arrangement.

Similarly to the previous case studies, a training session has been set up to obtain an ANN-based simulation of the effect of these on the fabrication outcome. The networks have been trained using Lime wood and a set of three different carving tools (*i.e.* Stubai 9-20, 9-30, 7-30). The design exploration focused on the variation of top-down design parameters and how these are affected in a non-linear and unexpected way by the properties of material and tools. Even within fixed design parameters boundaries, such choices generate a significant variation in the outcome. The opportunity to seamlessly explore such a domain, before moving to the fabrication stage, appears beneficial for the efficiency of the overall workflow. Several design iterations have been generated following a what-if scenarios strategy, simultaneously proposing multiple alternatives at the variation of one individual parameter or fabrication condition.

In the following pages, three different studies are presented as examples of the application of the developed methods for such design brief. The input fabrication parameters are reported on the side of the top view of the toolpaths arrangement and related carving simulation. Study A (***Fig. 5.28***) shows the effects of changing a fabrication parameter at the local scale of the individual cut with a variation of the Input Cut Length between 14.3 and 60.19 mm and decreasing the total number of cuts from 653 to 431. Study B (***Fig. 5.29***) focuses on the variation at the pattern level with a variation of the number of flutes from 18 to 32. Study C (***Fig. 5.30***) is concerned with the effect of different carving tools operated with the same design parameters. Linear changes in the size of the tools are not necessarily reflected in the obtained patterns, which show significant variations among the different cuts even within the same sample.

The evolution of the design through a series of what-if scenarios allows evaluating simultaneously aesthetic and functional requirements together with material and fabrication considerations, negating the linear progression of conventional production workflows. Consequently, the design team could focus on exploring multiple solutions and receiving back for each a series of qualitative and quantitative DFM feedback to support or dismiss their choices.

CUT LENGTH
Prediction 01

Pattern
Min Cut Length = 14.3 mm
Max Cut Length = 40 mm
Nr Flutes = 36
Nr Cuts = 653

Cut
Tool Angle Start = 36°
Tool Angle End = 20°
Grain Direction = 0°

CUT LENGTH
Prediction 02

Pattern
Min Cut Length = 17.9 mm
Max Cut Length = 46.1 mm
Nr Flutes = 36
Nr Cuts = 538

Cut
Tool Angle Start = 36°
Tool Angle End = 20°
Grain Direction = 0°

CUT LENGTH
Prediction 03

Pattern
Min Cut Length = 17.9 mm
Max Cut Length = 60.4 mm
Nr Flutes = 36
Nr Cuts = 431

Cut
Tool Angle Start = 36°
Tool Angle End = 20°
Grain Direction = 0°

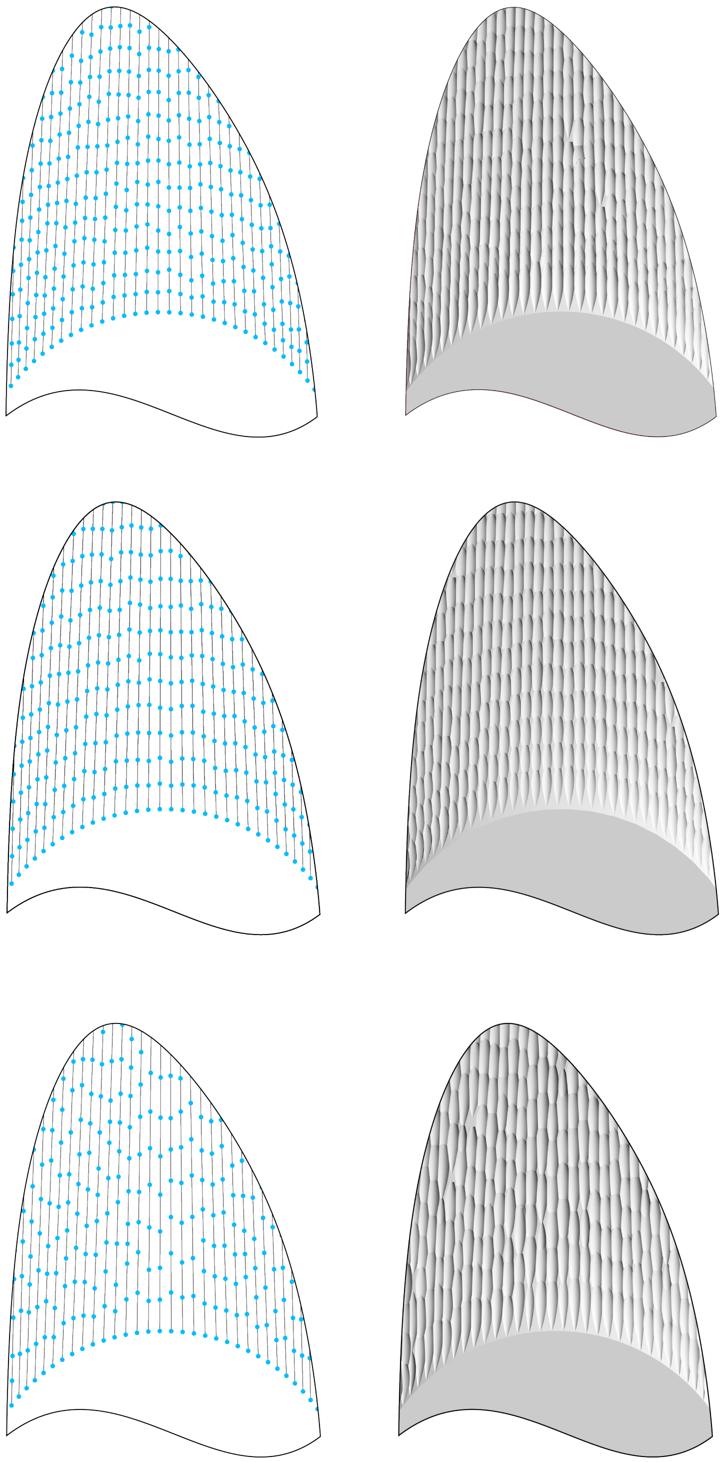
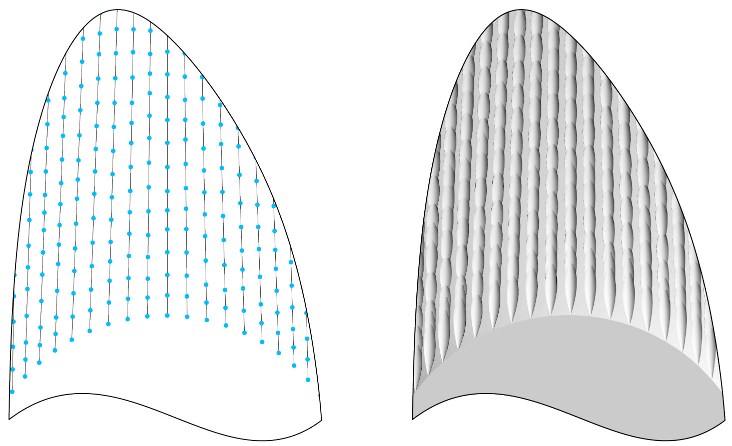


Figure 5.28 Study A: Local variation in the cutting length of the carving operations.

FLUTES
Prediction 01

Pattern
Min Cut Length = 14.3 mm
Max Cut Length = 40 mm
Nr Flutes = 18
Nr Cuts = 653

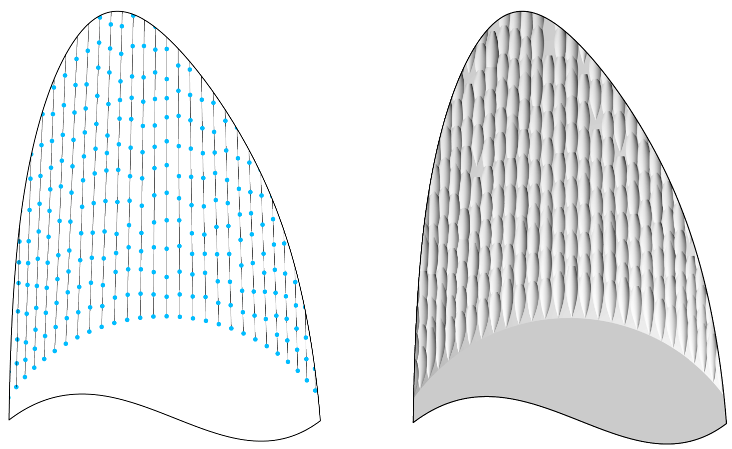
Cut
Tool Angle Start = 36°
Tool Angle End = 20°
Grain Direction = 0°



FLUTES
Prediction 02

Pattern
Min Cut Length = 14.3 mm
Max Cut Length = 40 mm
Nr Flutes = 27
Nr Cuts = 653

Cut
Tool Angle Start = 36°
Tool Angle End = 20°
Grain Direction = 0°



FLUTES
Prediction 03

Pattern
Min Cut Length = 14.3 mm
Max Cut Length = 40 mm
Nr Flutes = 46
Nr Cuts = 653

Cut
Tool Angle Start = 36°
Tool Angle End = 20°
Grain Direction = 0°

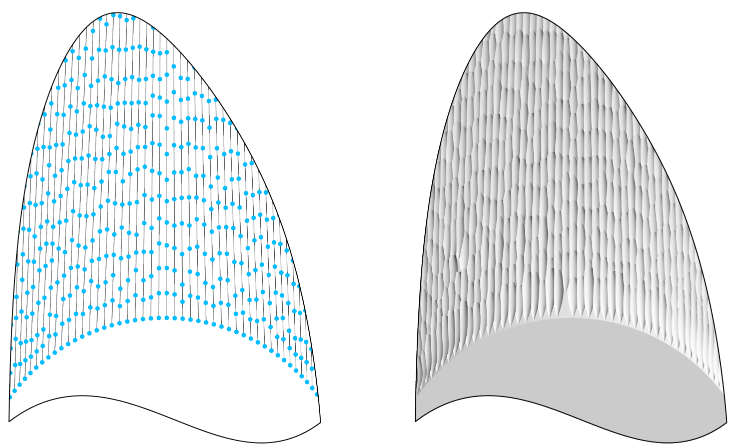


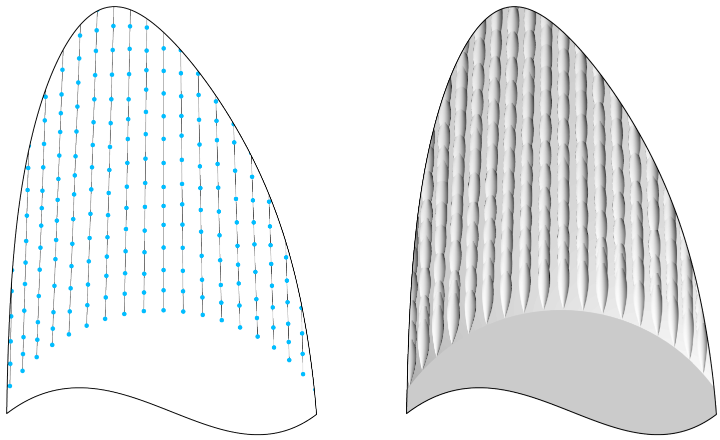
Figure 5.29 Study B: Variation in the arrangements of carved “flutes”.

CARVING TOOLS
Prediction 01

Tool = G920 Gouge

Pattern
Min Cut Length = 14.3 mm
Max Cut Length = 40 mm
Nr Flutes = 36
Nr Cuts = 653

Cut
Tool Angle Start = 36°
Tool Angle End = 20°
Grain Direction = 0°

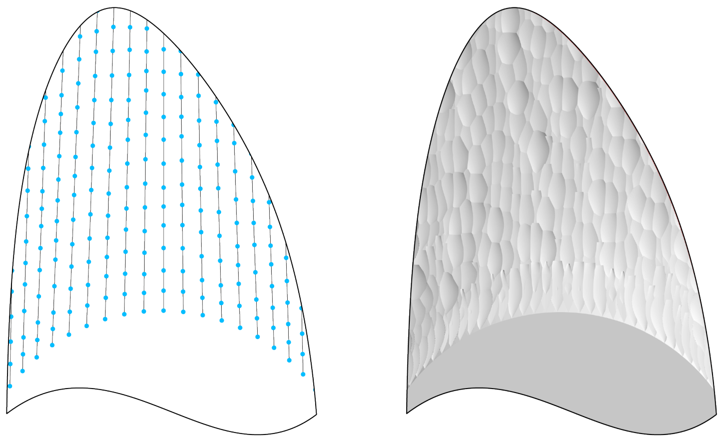


CARVING TOOLS
Prediction 02

Tool = G930 Gouge

Pattern
Min Cut Length = 14.3 mm
Max Cut Length = 40 mm
Nr Flutes = 36
Nr Cuts = 653

Cut
Tool Angle Start = 36°
Tool Angle End = 20°
Grain Direction = 0°



CARVING TOOLS
Prediction 03

Tool = G730 Gouge

Pattern
Min Cut Length = 14.3 mm
Max Cut Length = 40 mm
Nr Flutes = 36
Nr Cuts = 653

Cut
Tool Angle Start = 36°
Tool Angle End = 20°
Grain Direction = 0°

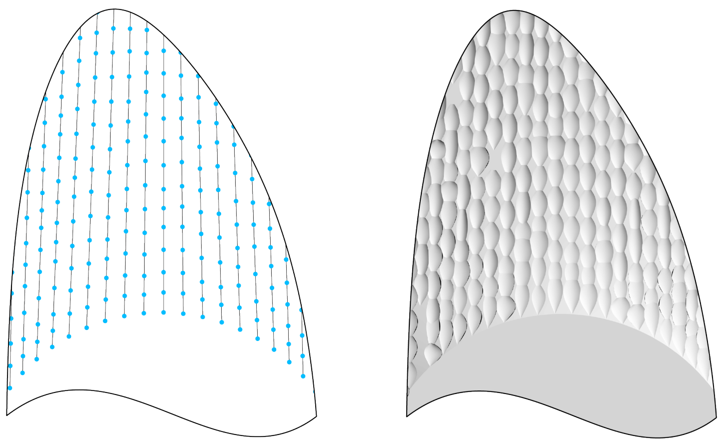


Figure 5.30 Study C: Variation in the carving gouges used.

5.4.3 Fabrication

The robotic fabrication of each board required several carving passes to achieve the desired final shape. The number of these passes ranged from 12 to 30, depending on how much material was needed to be removed. For each of these fabrication steps, the trained ANN generated a simulated instance of the carving outcome to evaluate at each step the successful combination of parameters would align with the design intention (***Fig. 5.31***). The amount of material removed at each cut has been maximised using the binary event threshold method described in the previous chapter (**Section 4.2**) to cull out unsuccessful operations.

The fabrication has been performed with the same industrial robotic arm (*i.e.* ABB IRB 1600) used in the previous case studies equipped with the carving effector and the set of gouges selected during the training (***Fig. 5.33-34***). The rectangular boards were fully carved in their final shape and only afterwards trimmed down to their final edge profile using a standard 3-axis CNC router. While this might be inefficient time-wise, it provided the opportunity to test the system and collect valuable insights for the robotic carving process.

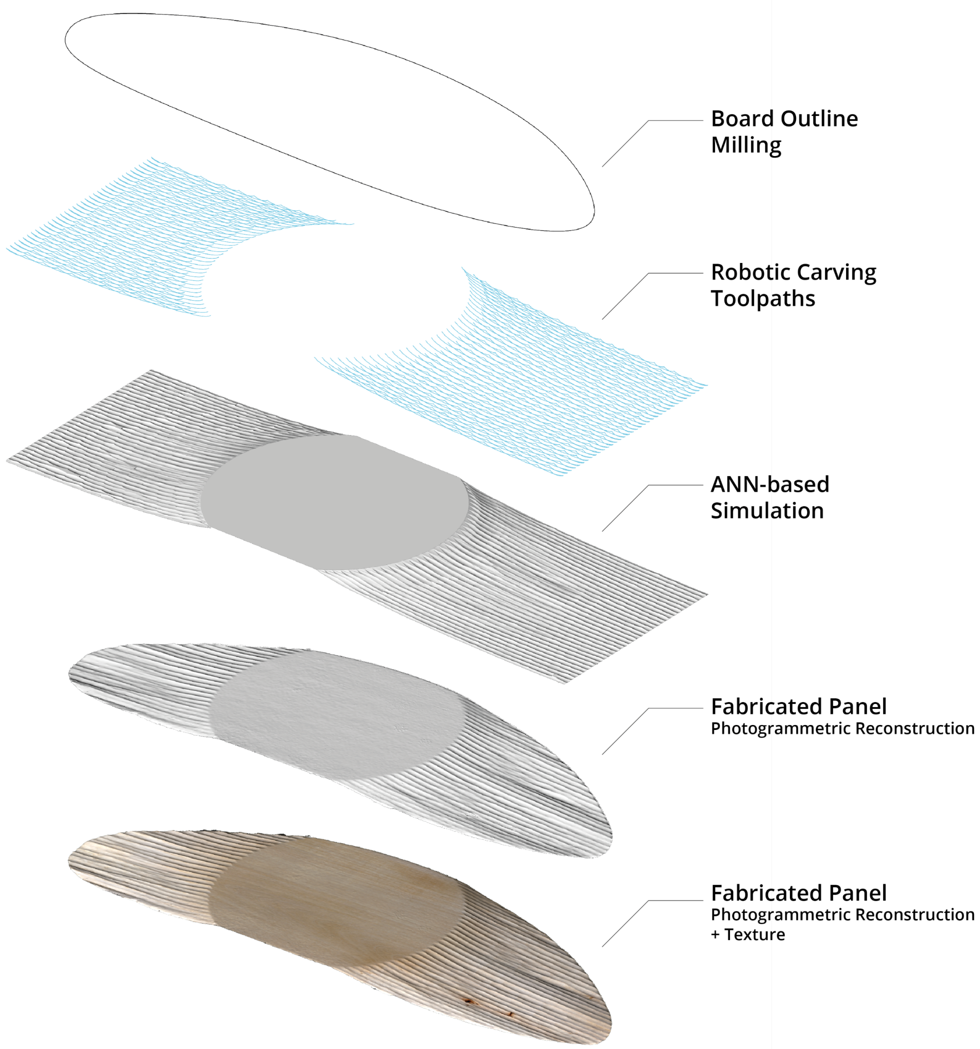


Figure 5.31 Layers of information used for the design, production and analysis of the robotically-carved boards.

Each carved board was reconstructed digitally through photogrammetry and compared to the ANN-based prediction, generating a gradient-based mapping of the deviation between the two (***Fig. 5.32***). This analysis was critical to validate the tool and assess the impact of its application as a core element of the digital design process. While the overall simulation is accurate to a tolerance below 1 mm, it should be noted that some area of the carved board shows a higher deviation value than the average. This is probably due to local material conditions, specific to the specific wooden sample, with mechanical properties that slightly differ from the rest of the grain of structure. Such behaviour can be caused by several conditions related to the tree growth, the presence of features such as knots or different hygroscopic response to the internal moisture content.

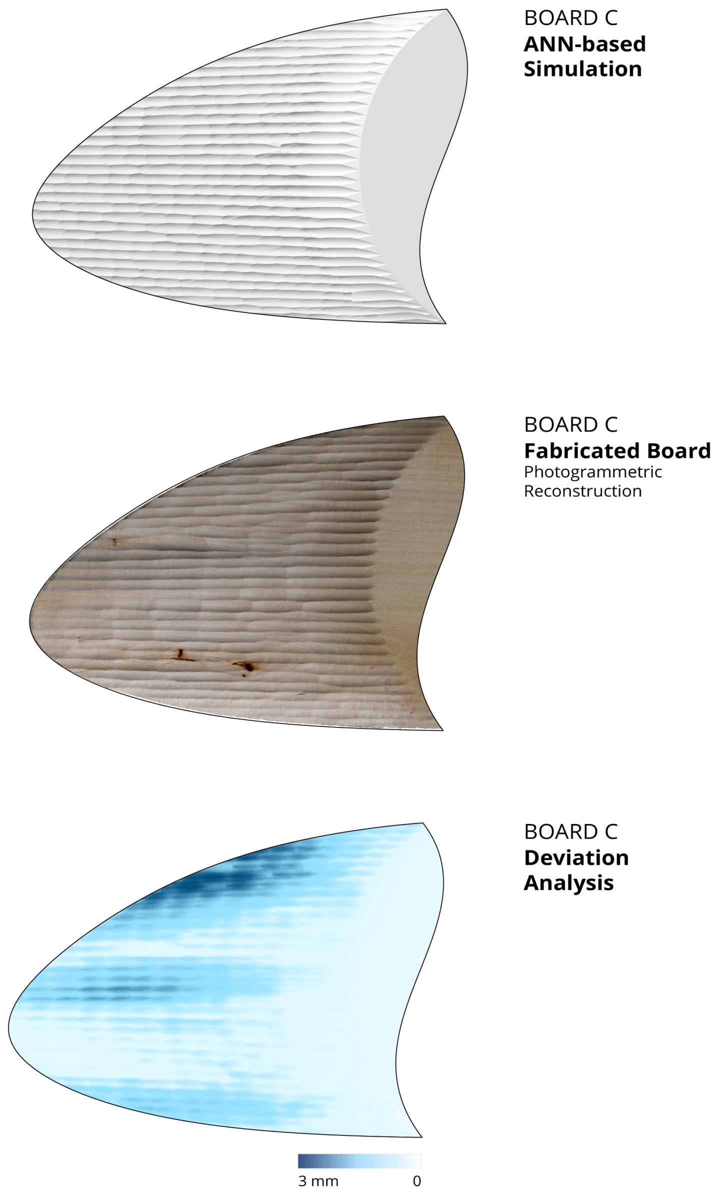


Figure 5.32 Deviation analysis of the robotically-carved boards. ANN-based digital simulation (top), photogrammetric reconstruction (middle), deviation analysis map (bottom).

Figure 5.33 Robotic carving process of one of the demonstrator's components.

Figure 5.34 Close-up detail of a robotic carving operation.

5.4.4 Results: Summary

The design and robotic fabrication of Kizamu focused on the application of the developed methods within a real-world project commission as a negotiation platform among a selection of relevant criteria that drive a typical design-to-manufacturing workflow.

- The integration of instrumental knowledge enabled the assessment of the constraints and opportunities provided by the material and tool affordances on top-down design decisions. Access to a specifically trained manufacturing knowledge base is beneficial to the evolution of the design process as it becomes possible to assess simultaneously, at an early stage when key decisions are taken, both design and fabrication considerations.
- The simulation can be used to easily explore material-aware solutions ahead of the fabrication stage, however, the physical fabrication of the carving patterns is still necessary for evaluation of qualities related to optical (e.*g.* colours, light reflections and shadows) and tactile (*e.g.* smoothness) aspects. In this case, the trained system makes it possible to reduce the number of necessary fabrication iterations to reach the final design.
- The combination of complex pattern configurations, in comparison to individual carving operations, and the three-dimensional shape of the final boards appeared to be a challenging scenario for the ANN-based simulation. While the overall digital result is still very accurate, as shown through the deviation map analysis, the combined effect of multiple operations is difficult to model and would require the collection of further data.
- The introduction of material and fabrication affordances as design drivers needs to be carefully balanced with the more conventional top-down, geometric-driven, design approach. A promising strategy for this specific project was clearly defining the areas and domain within which both would lead the design process. The carved portions of each board were not modelled digitally beforehand but resulted from the digital explorations informed by the collected real-world fabrication data. Within this context, the developed tools can be used to choose between the optimisation of individual fabrication parameters to achieve the original design intention or, potentially, follow a more open-ended trajectory where material and fabrication affordances act as design drivers.

6 Discussion

The research investigates the synthesis and integration of manufacturing and material knowledge at an early stage of the design process to enable the exploration of novel design opportunities informed by the affordances of non-standard tools (*i.e.* carving gouges) and heterogeneous materials (*i.e.* timber).

In the previous chapters, the developed methods, experiments and related results have been presented along two main conceptual strands:

i) **Technology**: Development of a robotic training workflow based on the acquisition of real-world fabrication data and utilisation of machine learning models to obtain an accurate simulation of subtractive operations.

ii) **Design**: Implementation of the trained system as part of the established workflow of design firms to inform the design and fabrication of a catalogue of digital experiments and material evidence.

In this chapter, the relevance of the main findings in relation to the thesis hypotheses and how these relate to the body of work from the literature are discussed together with an assessment of their impact, methodological constraints and further outlook.

For this purpose, the two strands have been here woven together as they reciprocally support each other in highlighting the knowledge contribution of this research. Such integration of the technology-led and design-led component of the work is horizontally present in each of the three sections of this chapter:

i) **Embracing Material Variance** discusses the modelling and integration of the agency of materials as a key component to enable holistic design feedback and support decision-making processes.

ii) **Learning Tools** presents the vision of designer curating her/his own custom design-to-production process in dialogue with a tool which can be iteratively trained and optimised to accomplish tasks.

iii) **Knowledge Exchange** discusses the generation, transfer and augmentation of manufacturing knowledge between machines and human experts in the context of automation.

6.1 Embracing Material Variance

While the literature review has shown the primary role of materials and their agency in design and manufacturing practices, either to exploit or suppress it, the starting point of the research has focused around the acquisition of data to specifically measure the variance generated by the heterogeneous properties of timber in carving operations. The findings collected during the experiments support **Hypothesis A** and demonstrate that the heterogeneous qualities of materials such as timber substantially affect the outcome of operations performed with different carving tools, hindering their utilisation within current design workflows. The application of a DOE methodology has been used to demonstrate that such variance not only is measurable, but it appears to be significantly affected by the direction of the carving in respect of the main grain direction and the structural arrangement of the fibres across different wood species.

From this position, the research has shown how translating back and forth between geometric modelling and robotic manufacturing parameters makes it possible to seamlessly explore the landscape of material affordances provided by the system through the continuous consultation of an integrated knowledge base aimed to inform design decisions at every stage. The findings demonstrate that an alternative to the dominant hylomorphic approach in the industry is feasible in which heterogeneous materials such as timber are not transformed into inert and homogeneous media but, through a combination of sensor data and machine learning strategies, it is possible to effectively train our tools to adapt to the nature of materials, fully embracing their heterogeneity and yet maintaining control over the entire design process.

6.1.1 Successful and Unsuccessful Operations

Machine learning models based on binary and multi-labels classification are currently used in the manufacturing industry for machine and tools monitoring purposes (Sun *et al.,* 2004; Phillips, 2015; Susto, 2015). This research made use of similar methods beyond the diagnostic scope applied only at the fabrication stage, providing an understanding of the relationship between shape features, manufacturing constraints and material affordances at an early design stage. In comparison to the industrial applications, the prevention of tool damaging, for instance, is considered as a key design requirement that needs to be satisfied by the design solution itself rather than using a corrective approach at a later stage based on decreasing machining performances, such as reducing speed or material removal rate. Furthermore, as the threshold is based on the combination of individual labels describing specific manufacturing and design conditions, it is possible to search for operations which satisfy multiple requirements defined accordingly with the design brief and final product specifications.

Interestingly, the assessment of the training methods showed that linear regression models for binary classification provide comparable performances to the ANNs for individual labels prediction, while they are outperformed by the latter for the combined events prediction which ultimately defines the successful operation threshold. What this seems to indicate is that the two groups of successful and unsuccessful operations, based on sets of individual manufacturing conditions, are not linearly separable and ANN models are more suited to identify complex non-linear patterns among the recorded data.

6.1.2 Geometric Features Prediction

In the field of subtractive manufacturing, the application of machine learning models is mainly confined to the optimisation of individual parameters to increase performances and reduce costs at the fabrication stage (Pontes *et al., 2*010; Zain, Haron and Sharif, 2009; Bernardos and Vosniakos, 2002; Stark and Moon, 1999; Tsai, Chen and Lou*,* 1999).

The results of the training suggest a novel range of applications for ANNs within design-to-manufacturing workflows where an early integration of manufacturing knowledge is used for the reconstruction of the geometric features of carving operations as informed by fabrication and material affordances. This makes it possible to evaluate multiple design solutions before moving to the production stage and avoid late adjustments which are inevitably limited and inefficient.

The validity of the methods has been demonstrated in **Chapter 4** through a series of experiments using different carving gouges and wood species, where the trained networks have been successfully deployed to model the influence that the variance of tools and material properties have on digital carving geometries. Furthermore, the findings show that ANN networks trained on datasets with only successful operations, filtered out by the binary classifier, perform significantly better (even above 70%) than networks trained with both successful and unsuccessful operations. One possible explanation could be that that specific manufacturing conditions, such as the breaking of grain fibres following the tool getting stuck, exhibit a more complex behaviour which is harder to identify and model. This indicates that the combination of the two strategies, the binary classifier and the geometry regression model, is highly advisable as it determines an increase of the prediction performances for simulation purposes.

6.1.3 Material Feedback

As manufacturers are contractually obliged to deliver products which comply with their notational description provided by design firm within agreed tolerances, the outcome variance determined by materials and tools properties is mostly regarded as a risk rather than an opportunity. This challenge has been addressed during the collaborations with the two industry partners of the project, ROK Architects and BIG, which provided the opportunity to apply the devised methods into the established workflows of design firms and develop a catalogue of design explorations for a wide range of applications, from furniture to building components of larger assemblies.

As previously identified in the literature review, the lack of knowledge-based tools is central to the issue of linear design-to-manufacturing workflows based on separate stages without feedback information. The research demonstrated that is possible to establish a simulation framework supported by real-world fabrication data to better support design explorations providing an accurate geometrical description which considers material properties and behaviours, reducing the uncertainty of the outcome in the fabrication stage. The access to a validated simulation framework able to provide feedback at any stage of the workflow presented, in a practical case study such as robotic carving, what is described by Maxwell and Pigram (2012) as the shift from a geometric-driven to a process-driven approach to design. Material knowledge that would be usually available only through direct engagement with fabrication processes over an extensive period (Sennet, 2008; Ingold, 2013), it is here used to guide the choices of designers who benefits from such knowledge through receiving manufacturability feedback in real-time despite being physically and timely detached from the actual carving process. In comparison to CAPP strategies (Park, 2003) relying on standard materials and features specified for individual industries (*e.g.* aeronautics, automotive...), the advantage of the devised methods is to give designers the opportunity of actively participating in the definition of their custom design-to-manufacturing workflow, extending the range of processes and materials beyond industry conventions to better fit the diversity of design briefs and their requirements.

The devised methods are not dissimilar in their practical application to other analysis and simulations frameworks, such as Finite Element Analysis (FEA) or Computational Fluid Dynamics (CFD), as they provide designers with the opportunity of evaluating the results of a proposed specification before actually building (or fabricating) it. However, they also differ substantially from those as they propose an alternative to the dominant hylomorphic approach as discussed in **Chapter 2**, representing the material with more sensitivity towards **i)** its heterogeneity and anisotropic behaviour and **ii)** the chosen manufacturing method and fabrication tools. The research focused on providing designers with a simulation of the effect of material properties, such as the wood grain direction, on a digital model to enable the exploration and comparison of multiple options otherwise unavailable within a hylomorphic context.

Based on the validation of this approach, as presented in the experiments discussed in **Chapter 5**, it is possible to envision a potential outcome of such a simulation tool in which it is not only used to anticipate the material outcome of the desired design intention but also to proactively modify that original intention to follow better the peculiarities of the material (*e.g.* a local grain condition determined by a knot). A version of this is represented by the, previously discussed, work of the artist Giuseppe Penone as he did not prescribe the position and orientation of the cuts performed with the carving gouge, but he instead followed, step by step, the branches inside the log without knowing where they would lead. This type of application, where the agency of material plays an active role in shaping the design outcome, should be possible to achieve already with the current version of the training process as it is based on the requirement of knowing the relationship between the robotic carving action and its respective material outcome. At the same time, this would require two additional components: **i)** the specification of design or fabrication goal (*e.g.* follow the branches inside the tree log) **ii)** sensor feedback providing local material feedback information as the fabrication process unfolds (*e.g.* specific grain arrangement around a knot).

Although the research strategically focused on a specific application such as robotic carving with timber, the developed methods have the potential to be applied to a broader variety of non-trivial robotic manufacturing tasks requiring dexterity and a high-level understanding of the constraints. For those processes where fabrication and material affordances play a crucial role in the definition of the design outcome, it is necessary to establish a simulation strategy that will integrate their effect from an early stage. For instance, the modelling of the spring back factor for the bending of steel rods based on real-world data would lead to reducing the tolerances necessary for the assembling of multiple parts. This means that the machine would not execute the bending action accordingly to the exact digital geometric notation expressed in angle values (°), but it would instead adaptively compensate for the resistance of the metal. In concrete 3d printing, the material shrinkage during the curing process affects significantly the final geometry of the printed component and having access to a model of such behaviour could be used to better organise the timing of the fabrication process and identify which shapes and features work best given a specific concrete composition.

The ultimate potential of training procedures for extracting manufacturing knowledge through the collection of fabrication and material data is their inherent scalability. As more relevant data are provided to the system, the better the network will be able to approximate the assigned process or behaviour and, therefore, support the decision-making process of designers and manufacturers. The bottleneck of the data acquisition stage necessary to train these models could be overcome coordinating the training of multiple robots and machines communicating with each other through an online interface and sharing the same fabrication data repository. Recently, Google successfully explored this approach through the parallel training of 14 industrial robots, learning through a reinforcement learning strategy with over 800,000 total attempts to pick up random objects (Levine *et al.*, 2016). Such a distributed strategy for knowledge acquisition and synthesis makes it possible creating libraries of material knowledge condensed in discrete packages that could be easily implemented into any design-to-manufacturing workflow.

6.2 Learning Tools

6.2.1 Designers, Toolmakers and Curators

The research investigated the role of designers as active curators of their design tools as a way to extend their authorship to the entire design-to-manufacturing workflow and fluently move between the design and fabrication stages, enabling the access to novel design solutions.

Historically, the dynamic bidirectional relationship between tools and their output has been a critical factor in driving our understanding of the world: as we made tools to better understand and shape our surroundings, the same tools shaped us and defined the boundaries and scope of our knowledge. Andrew Witt (2010) traces this throughout the discipline of architecture, starting with Brunelleschi who was not only designing buildings, "but al*so the instruments to construct these building*" such as hoists and pulleys, and continuing with Giambattista Suardi's "*geometrical pen*" that enabled the drawing of complex curves by employing compound motion, and thus enabling new creative expressions in the architecture. Digital design tool-making can be traced back to the 1960s with the early developments of the original CAD systems (Aish, 2013). These early systems and subsequent developments continuing right up to the present have provided the foundations for expressing creative and technical intentionality evident in all contemporary design processes.

In the same way, access to digital fabrication technologies is leading to a radical reconsideration of the scope of design-to-manufacturing workflows and their influence on the built environment. Nevertheless, the collaborations with the industry partners of the project showed that the direct access and proximity to manufacturing facilities (*i.e.* industrial robotic arms) is a necessary but insufficient condition alone for designers to engage with materials and fabrication processes. The separation, physical and chronological, between design and making is deeply rooted in the established culture and workflows of design firms. This linear progression is further reinforced from the lack of tools acting as interfaces to share feedback information across the different stages of the processes and stakeholders involved.

One of the main limiting factors of existing tools for designers is their difficult customisation which makes it particularly challenging to adapt them to the specific needs of each project. Designers, frustrated with the opaqueness of their software, are turning to develop their own digital tools, making extensive use of coding, readily available libraries and the support of a growing open-source community of developers (Miller, 2010; Deutsch, 2017; Deutsch, 2019). While the figure of designer as toolmaker, along the path initiated by Brunelleschi (Carpo, 2011), is undoubtedly fascinating, especially in academia, the exposure to the design industry has also shown its limitations as most designers do not currently possess the expertise necessary to develop their own software and, consequently, they are forced to use the generic tools provided by their firm.

The novel approach proposed in this research has been to provide the team of designers with a customisable design-to-manufacturing interface communicating fabrication and material feedback in relation to a specific selection of desired geometric features, wood species, tools and carving techniques. The advantage of such a curatorial approach is that designers can adapt their design tools through the iterative acquisition and processing of material and fabrication data rather than explicitly coding software from scratch. The access to manufacturing knowledge, synthesised with machine learning strategies from the curated data, supported the choices of designer along each stage of the design development, from the initial choice of the wood species to the impact of a specific geometric feature on the overall fabrication speed.

The trained tool represents an expert system (Lucas and van der Gaag 1991) curated by the designers themselves which actively supported the explorations of novel design solutions driven by fabrication and material affordances as modelled from the provided data. For this reason, the acquisition and curation of such information played a key role in the design process as it directly defined the domain of solutions that would have been later available in the digital simulation interface.

As such knowledge is accessed through digital geometrical simulation, it enabled designers to immediately evaluate the results of their design intention once expressed through the material medium, simultaneously comparing multiple scenarios. These findings support the argument put forward by Hanna (2007) and Tamke, Nicholas and Zwierzycki (2018) for the use of machine learning models within design workflow to support decision-making procedures for complex fabrication processes.

Further advantages of this approach highlighted from the industry collaborations have been:

- **Open-ended Modularity**: Multiple networks trained with different wood species and carving tools have been integrated into the same design interface to compare simultaneously different combinations of fabrication affordances. This can be used to easily extend the capabilities of the simulation interface through the addition of more trained modules and include, for instance, new wood species or carving techniques.
- **Flexibility / Scalability**: The accuracy of the simulation of carving operations directly depends on the amount and quality of the provided data. As the

design brief evolved throughout the process, it has been possible to organise further recording sessions to acquire new data which would reflect more closely its requirements in terms of materials and geometric features.

Based on these premises, it can be speculated that, in the future, further iterations of similar learning tools would be able to perform the assigned task increasingly well over time as more "experience" is provided in the form of curated fabrication and material data, likewise a craftsman learns over years of experience. As already argued by Nicholas Negroponte (1970), these trained systems could eventually rise to the role of actual partners in the design process, actively proposing novel solutions and establishing a fruitful dialogue with their human counterpart.

6.2.2 Counterpoint: Designer NOT Maker

One of the critical challenges discussed during the industry collaborations has been the scalability of the devised design-to-manufacturing process for timber carving operations beyond the prototyping stage to the actual production. Whether the fabricated object is an architectural component or a furniture piece, there is no guarantee that manufacturing contractors would be able and willing to adopt a production strategy devised by someone else not considering their specific workflow structure and machines' capabilities.

Design projects evolve through a complex web of technical, economic and social interactions generated by the multitude of different stakeholders involved. Within such a multi-stages negotiation process, the key element necessary to support such interaction is the access to a common knowledge base which should provide a shared understanding of the opportunities and constraints available at any stage of the process. In response to this, the research proposed a series of methods to integrate portions of manufacturing knowledge into a transmissible form that can be shared and used to steer design decisions.

In this perspective, it might be beneficial to reconsider the relationship between the role of designer and fabricator as two separate professional figures, where the latter is the actual developer of the material-driven manufacturing workflow and provides the former with a machine learning-powered simulation environment which allows an integration of fabrication knowledge from the beginning of the design process.

Designers not willing to engage with the physical dimension of making and the exploration of material behaviours can still access such knowledge directly through an interface which provides the necessary constraints set to efficiently drive their design. This means that once the design solution is finalised, the manufacturer can confidently move to production knowing that the project has been developed within the framework of affordances initially provided.

One critical issue that could be overlooked during the technical developments of tools, but it appeared to be central for design firms, is the quest for originality and the exploration of novel design and fabrication methods as a way to achieve it. In this regard, the main issue with using tools developed by other designers or manufactures is the over-constrained aesthetics outcomes that such methods allow. One example of this is the "ROBmade" system and its software plugin "BrickDesign" developed by Keller Systeme AG for the design and robotic fabrication of brick façade elements

(Source: *https://keller-systeme.ch/en/robmade-facades*). The system has been developed in collaboration with the architects Fabio Gramazio and Matthias Kohler who have been the first to explore such fabrication methods in the architecture field (Gramazio and Kohler, 2008). Despite the potentially infinite variations made available by the system in terms of complex brick patterns, the overall outcome is strongly attached to the architect's aesthetic and the series of projects previously developed by their firm. For this reason, while the tool has been demonstrated as a compelling design-to-manufacturing framework, its impact has been fairly limited in the construction industry.

The main risk is then to incorporate a large part of the design decisions within the tool itself, allowing only for a limited variety of parameters and heavily defining the aesthetic outcome. The approach presented in the thesis mitigates such an issue providing an understanding of fabrication-specific parameters and material features rather than constraining the design search to a limited number of formal solutions. The material variance addressed by the tool is not subjectively selected by another author (*i.e.* the toolmaker) recognizing qualities, as Pye (1968) would argue, based on her/his assessment but rather determined by objective properties of the material which do not compromise the designer's authorship. This strategy, together with the opportunity of finely tuning the design/fabrication system to a particular set of manufacturing conditions, makes possible to establish a better interface between fabricator and architect and a broader acceptance of fabrication-based design tools in practice.

6.3 Knowledge Exchange

6.3.1 Human Knowledge Integration

The recording of human demonstrations performing carving operations revealed the ability of the skilled expert to intuitively navigate the range of successful operations and avoid dangerous or inefficient manufacturing conditions.

The analysis of any of the robotically generated training datasets shows the presence of a geometric threshold which defines the range of possible operations available in that specific system configuration. The comparison with the human dataset collected in similar conditions, in terms of tools and materials, demonstrate the human's ability to anticipate the failure threshold.

This initial finding suggested the potential of using human demonstrations to efficiently generate an initial knowledge base to be used to further inform the robotic recording sessions. This has been further supported by several case studies in literature (Kikuchi *et al., 2014;* Ng *et al.,* 2014; Kalt, Monfared and Jackson, 2016; Steinhagen *et al., 2016,* Prahbu *et al., 2017;*) where human demonstrations have been utilised to inform subtractive fabrication tasks, for instance, polishing and grinding operations.

The approach has been assessed in a series of experiments which have demonstrated two main benefits:

i) Efficient exploration of the robotic fabrication parameter's space from a set of operations which have been already defined as successful, avoiding proceeding by trial-and-error which, especially in the field of manufacturing, could be costly and dangerous.

ii) Curation of the training process toward specific sets of solutions through the direct definition of a series of design features and shapes obtained using the intuition, experience and skills of a human expert.

Knowledge bases in machining are created through the externalisation (Nonaka and Takeuchi 1995) of machinist's tacit knowledge into a series of machine and tooling parameters recorded in large databases within a CAM framework. In the developed methods, the collection of knowledge is not dependent on the ability of the craftsman to describe the process and identify its key aspects but rather on the unfiltered recording of the operation through sensor data.

Although falling outside the scope of this research, a more in-depth study and comparison of different expertise levels in human craftsmen would have probably revealed valuable insights leading to different grades of knowledge repositories. In reference to Pye's argument (1968) for which the recognition of material qualities is subjective and dependent on individual knowledge in opposition to the objective properties of materials, it could be assumed that datasets collected from different craftsmen would show unique features, a sort of "*signature*" determined by their personal experience, intuition and skills.

Beyond the advantages to the field of automated manufacturing, such differentiation of knowledge sources could be used in an educational context where the robotic carving system trained with data coming from an expert could be used for the training of many inexperienced human apprentices, overcoming the problem of lack of skilled craftsman willing to spend time transferring their skills through extensive teaching.

6.3.2 AI and Knowledge Synthesis

In the description of Expert Systems (ES), Lucas and van der Gaag (1991) highlight the importance of its "*explanation facilities*", namely the possibility of asking at any moment during the consultation with the system how certain conclusions were arrived at. He further describes the use of "*trace facilities*" through which "*the reasoning behaviour of the system can be followed one inference step at a time during the consultation*". While the creation of a knowledge base for an ES makes use symbolic models and explicit rules to capture the behaviour of a group of experts to replicate it, ANN models automatically identify patterns in the provided examples through optimisation of their weight values over many iterative cycles.

Extracting explicit rules for knowledge base creation is particularly challenging as most of the knowledge, especially expert one, is implicit and difficult to communicate. Furthermore, conventional rule-based ESs are not able to extract knowledge from experience in the shape of collected manufacturing and material data (Yoon, 1994). The integration of ANNs models in ESs have been used in literature to overcome those limitations (Zeng *et al.* 2002), however, the lack of explicit rules determines the impossibility of tracing how a specific conclusion has been reached. For this reason, ANNs have been often described as "black-boxes" (Benítez, Castro and Requena, 1997). The research made use of physical sensor devices and a series of ANNs to acquire, synthesise and integrate manufacturing knowledge in a design workflow for robotic carving operations in timber. The designer can consult the expert system through a conventional 3D modelling interface which returns material and fabrication feedback based on design choices as a geometric simulation of the results of the carving operations.

In knowledge-based software for metal machining, the knowledge usually resides in an extensive database with explicit information created from empirical data which is possible to consult and update with new information. On the opposite, the ANNs developed in this research perform the function of automated "*oracles*" (Vanmali, Last and Kandel, 2002), able to produce a solution (*i.e.* geometry simulation) for a given problem (*i.e.* carving operation) without the possibility of tracing their reasoning to check whether they are right or not. The validation of the oracle happens at the end of the training stage and, once validated, it should be trusted by the error range measured during the validation.

While there is a number of studies (Benitez, Castro and Requena 1997; Boger and Guterman 1997; Hinton, Vinyals, Dean 2015) demonstrating that is possible to partially extract knowledge from ANNs, such strategies were beyond the expertise level of the designer-users interacting with the interface and were not applied during the industry collaborations. Nevertheless, the results indicate that the teams of designers had successfully accessed the knowledge encapsulated in the tool and used it to drive the design process supported by feedback information steering their choices throughout sequential what-if scenarios. The opaqueness of the ANNs did not affect the practical use of the trained tool in the design applications observed during the industry collaborations. In a similar way, very few designers interrogate themselves about the calculus-based mathematics behind each NURBS surface they create in their preferred 3D modelling environment. However, If the ANN is able to predict whether a set of fabrication parameter will generate a "dangerous" operation with an accuracy of 90%, as demonstrated in **Chapter 4**, to what extent should designers integrate their knowledge and intuition to confirm or refute such a prediction? What happens if designers do not have that specific knowledge? To what extent should the 10% error influence their design decisions?

The knowledge encapsulated in the ANN appears to be a different form of tacit knowledge, accessible but just as difficult, if not impossible, to communicate, as the experience gathered throughout the years by a skilled human craftsman. It is relevant to note that throughout all the different stages of recording data from human and robotic sessions, training of the machine learning model and integration into the design interface, this knowledge, has always been transmitted across different stages without being made explicit. The critical difference between the tacit knowledge encapsulated in a human and the trained model, is not then its traceability or understanding but rather its accessibility that enables the latter to be easily packaged, transmitted, integrated and most importantly, always consulted without any concerns regarding scalability, which conversely is the most severe drawback of personal tacit human knowledge.

6.3.3 Automation and Traditional Crafts

During the development of this research, one of the most recurring questions asked during presentations and lectures has been whether the developments of AI and automation technology would gradually erode until completely substituting traditional crafts. Debating over broader socio-economic scenarios is beyond the scope of this research, however, the project findings suggest a few reflections relevant for such discussion.

The Arts and Crafts movement, begun in England in the second half of XIX Century, strongly opposed the upcoming Second Industrial Revolution and put forward the moral superiority of hand-made traditional crafts. To these were attributed the value of "honesty" and imperfections were celebrated as an expression of humanity's uniqueness. Similarly, in the second half of XX Century, David Pye distinguishes between the workmanship of certainty in industrial production and the workmanship of risk in traditional crafts, where the quality of the outcome of the making process is constantly at risk and subject to the unique human's judgement and dexterity (Pye, 1968).

Nevertheless, the series of design projects developed for this research challenge such understanding of "imperfection" as an exclusively human trait, as the carved geometries fabricated by the robotic arm show a range of variation which was not programmed, although simulated and anticipated, and originated not by human action but rather from allowing, in a controlled way, the interaction between tools and material properties such as the influence of the wood grain direction in steering the depth of the cutting profile of the gouge. The carved panels do not show the usual repetitiveness of industrial production processes and could be easily confused as human-made.

The celebrated "imperfections" of traditional craft practices then are not the exclusive result of prescribed human ingenuity but rather emerge from the complex interactions between the carving tools driven by human actions through the landscape of affordances offered by the material medium. This follows the same argument put forward by Herbert Simon (1969) discussing the origins of complex animal behaviour, including humans. He argues that the apparent complex behaviour shown by an ant does not depend from superior cognitive abilities of the animal but rather from following simple behavioural rules in a complex environment: *"Viewed as a geometric figure, the ant's path is irregular, complex, and hard to describe. But its complexity is really a complexity in the surface of the beach, not the complexity in the ant."*

If a robot is able to produce an artefact seemingly indistinguishable from one made by a human, showing the unique "imperfections" traditionally attributed to human making, the role of traditional crafts will probably need to evolve to remain relevant in the light of these novel fabrication processes. Whether human expertise will be replaced or augmented by these technologies remains an open discussion to which this research wanted to contribute proposing, through a specific case study, a possible way of linking together the domain of human making to robotic manufacturing.

As shown in **Chapter 4**, a demonstration of a skilled human expert represented the starting point for the training of the robotic system, reducing significantly the time and resources necessary to complete the task. While, on the one hand, it could be argued that human's intervention is not necessary after the initial interaction with the fabrication system, on the other hand, as human's ingenuity and cognitive abilities remain, for now, unsurpassed, it could be advantageous to frame the relationship between human and the machine as an unfolding, open-ended, dialogue, rather than a linear process. The abilities of skilled human experts could be then augmented (for instance, in precision or speed) by the ongoing training of the fabrication tools available to a craftsman, iteratively widening the scope of the fabrication process in terms of novel materials, tools and techniques. As the system is trained based on the data provided by the craftsman, the trained tool would be unique and match her/his subjective dimension and idiosyncrasies alongside the objective properties of tools and materials.

Furthermore, the encapsulation, at least partial, of human tacit knowledge into a transmissible form could address the issue of knowledge scalability and distribution, as discussed in the previous section, of traditional crafts which are slowly fading away as there are increasingly fewer skilled experts able to transmit the knowledge to the next generation. In this regard, it does not seem unlikely a future scenario where craftsmen apprentices all around the world would learn, for instance, how to carve timber using a chisel from a robotic fabrication system trained with the combined knowledge of multiple human experts.

6.4 Limitations

The devised strategy focused on a narrow set of materials and processes to develop a compelling application with the necessary depth to support the validity of the research investigation. The extent to which the methods could be applied to different applications was not demonstrated in this thesis. It only could be assumed that these should be valid, at least partially, for a broader range of design-to-manufacturing workflows than the ones directly investigated, utilising different sets of heterogeneous materials and non-standard fabrication methods. This claim is supported by the growing evidence in the literature on the versatility of machine learning models for manufacturing applications, where complex and diverse tasks are successfully modelled based on the identification of key correlations in the provided data.

The devised training workflow also showed a series of technical limitations. While the prediction of carving operations is highly accurate and suitable for design purposes, the deviation analyses of carving patterns show higher deviation values in comparison to the prediction of single cuts. This suggests that the sequence of operations determines complex mechanical interactions between individual operations, falling outside the current predictive capabilities of the system, therefore, it would be beneficial to train the ANNs with multiple cuts configurations to successfully model such behaviour. Furthermore, one of the limitations of the research has been considering exclusively quantitative types of data, *i.e.* tool damaging and null material removal rate, for the prediction of manufacturing events, while one of the key potentials of the devised method could be combining measurable conditions with subjective evaluations based on designer's judgement and sensibility defining, for instance, tactility (*e.g.* surface smoothness) or optical features.

While different carving tools and wood species were utilised for the training process, the data collected from the human demonstrations is not as diverse, as it focused on a fairly narrow range of carving of operations and, perhaps more importantly, skillset level. The recording methods have only been tested with just a few craftsmen and their subjective dimension remained marginal to this thesis to rather focus on the main research proposition. Admittedly, it would have been wise to spend more resources on this aspect to further prove the strength of the devised strategy to capture human knowledge and transfer it to the domain of robotic manufacturing and digital design interfaces.

Finally, the case study-based methodology adopted to investigate the design component of this research made it possible to devise a series of compelling applications within the living laboratory context of the Innochain Research Network. Nevertheless, such a research component presents a constraint shared with other projects developed within a similar framework, namely the drawing of general statements and valid conclusions from a necessarily limited range of case studies. While the two industry partners of the projects were quite diverse in terms of scope and scale of operations, it hasn't been possible to engage with a broader range of design practitioners and firms due to resources and time constraints. Nevertheless, despite the limitations in the number of case studies addressed, the industry collaborations were key for situating the project within a real-world context, making it possible to develop the design and fabrication workflows based on actual industry needs and requirements, while, at the same time, providing a framework within which evaluating the outcome of these collaborations.

6.5 Further Research

Within the scope of the thesis, three key areas worthy of further research were identified:

- **Data acquisition**: The recording of the task is strictly dependent on the limitations of the sensor devices utilised to capture the event information. The sensor strategy adopted in the research made use of different types of cameras operating in the visible and infrared light spectrum. This configuration made it possible to successfully reconstruct the carving operations examined, nevertheless, the introduction of different type of sensor devices not based on vision could be used to define a more comprehensive description of the task. For instance, a force-torque sensor applied on the end-effector would make possible to precisely measure the cutting force along the different axis, while a tomographic scan of a wooden workpiece would return an incredibly detailed description of the grain structure that can be used to establish more precise material correlations. The collection of a more diverse range of sensor data is reflected in the generation of a more extensive set of input features which would improve the robustness of the trained model. Furthermore, such an integration of sensor data would made possible to precisely control in real-time the robotic actuation to account for local conditions of the material and complement the early-stage material simulation provided by the trained model.

- **Learning Strategy**: One of the main limitations emerged during the results discussion has been the lower predictive performances of the trained models when applied to complex combinations of carving operations in comparison to individual predictions. For this reason, further research is necessary to address the non-linear influence that previously executed operations have on the following operation in the fabrication sequence when considered as part of an overall carving pattern geometry. To achieve this, it might be beneficial to adopt a combination of different learning strategies modelling the carving task from different types of datasets other than numerical features values. For instance, the use of 2D image samples describing the neighbourhood condition between operations could be used to feed a Deep Convolutional Neural Network model which could be integrated as part of the presented workflow.

- **Design Workflow Integration**: One of the advantages of the approach proposed in this thesis is the scalable and open-end dimension of the devised methods which would enable the creation of manufacturing and material knowledge modules ready to be deployed in the workflow of any design firm. For this reason, it would be worthwile to broaden the sample of firms exposed to the devised strategy to better understand the different use cases across a more diverse selection of design firms with different requirements and type of operations. Further investigation is needed to assess the integration of the methods at a larger scale based on the coordination of multiple data acquisition strategies, parallel models training and knowledge sharing between different fabrication machines through an online interface.

7 Conclusion

7.1 Hypotheses Response

7.1.1 Hypothesis A

> **Hypothesis A**: T*he heterogeneous qualities of materials such as timber substantially affect the outcome of operations performed with different carving tools, hindering their utilisation within current design workflows*.

The findings in support of **Hypothesis A** were presented in **Chapter 3** through a series of studies based on the acquisition of manufacturing and material data collected during human and robotic carving sessions recorded with a combination of different sensor devices.

The Factorial Design of Experiment (DOE) proved to be an efficient method to explore combinations of factors and identify their relation to the observed phenomenon (*i.e.* the carving operation), confirming its primary role for the analysis manufacturing processes as stated by several previous studies (Benardos and Vosniakos, 2002; Athreya and Venkatesh, 2012; Antony, 2014; Montgomery, 2017). In this specific research, the combination of experimental data collected both by human experts and robotic recording sessions has shown to be particularly beneficial as it reduced significantly the range of each factor-level, therefore reducing time and use of material necessary to achieve statistically valid results. The developed sensing strategy presented in **Section 3.1** made it possible to successfully reconstruct each operation to a high level of details (± 0.2 mm) necessary to measure variance levels within a range suitable for design applications.

In **Section 3.3**, the results of the DOE strongly support **Hypothesis A** as material properties such as grain arrangement, density and carving direction determine a significant deviation between the digitally prescribed operation and its actual physical result on the material. In the specific, the hypothesis is supported by the fact that deviation error is, in most cases, substantially above the defined tolerance threshold for design purposes, hindering the use of the robotic carving process in any practical application. Such deviation is not constant and its amplitude changes across the different material conditions, wood species and carving tools analysed. Specific sets of factors-levels have consistently shown lower deviation values, suggesting that there are optimal combinations of parameters for which the agency of material aligns with the desired design intention. In most cases, however, the agency of the examined timber properties is not overridden by the fabrication process and pure geometrical Boolean operations do not provide a satisfying digital simulation of the resulting geometry. Furthermore, the quantification of the agency of material behaviours in carving operations supports the argument for which materials are active participants in the genesis of forms rather than mere inert receptacles and should be involved in a mutual dialogue with the design process (Deleuze and Guattari, 1980; DeLanda, 2002; Ingold, 2013).

7.1.2 Hypothesis B

> **Hypothesis B***: Given input parameters of (a) measurable properties of the given material, such as wood grain structure and density, and (b) tool affordances, a prediction can be made of (c) the geometrical outcome of the fabrication procedure to a level of accuracy sufficient for design purposes.*

Resting on the validity of **Hypothesis A**, **Hypothesis B** focused on the necessity of establishing a series of methods to accurately model the relationship between the digital design input and the fabrication outcome of carving operations. As analytical models for complex manufacturing tasks are particularly difficult to generate (Luttervelt *et al.,* 1998), the chosen methodology to investigate the hypothesis has been an inductive approach aimed to identify complex patterns and correlations among the recorded fabrication dataset through the training of a combination of machine learning models (Lu, 1990).

The evidence in support of **Hypothesis B** have been collected both after the training of each predictive models using a Testing dataset and in their further applications in a series of comparability studies:

- The results presented in **Section 4.2** suggest that is possible to predict with high accuracy (*i.e.* 87%) whether a set of fabrication parameters would generate a successful or unsuccessful operation according to a set of evaluation criteria defined by the user. The identification of dangerous or inefficient operations supports early-stage design decision-making procedures based on tools and material affordances before moving to the prediction of carved geometries. Designers can identify which sets of geometries are suited for the chosen manufacturing process and efficiently narrow-down the design exploration boundaries towards a range of successful operations.
- The findings in **Section 4.3** show that an ANN model trained on collected fabrication data can accurately map from robotic fabrication toolpaths to carved geometries and opposite direction with a similar low error rate in the prediction. The comparison between the prediction results of the trained network with the digital Boolean operations method shows a significant improvement in accuracy up to one order of magnitude. In particular, the degree of tolerance in the prediction rate is below 1 mm (*i.e*. Depth = 0.462 mm; Length = 0.733 mm, Width = 0.681 mm) and, therefore, within the tolerance threshold as defined in **Chapter 3**, demonstrating that the devised system makes possible using the robotic carving process on timber for design purposes.
- In **Section 4.5**, comparability studies between models trained on different fabrication conditions show that **i)** material properties, wood species and tool specifications play a primary role in the definition of the final carved geometry, further supporting **Hypothesis A**; **ii)** the trained ANNs are sensitive to such variance and able to accurately model the influence of different manufacturing conditions on the carving outcome. It is interesting to note that

the variance analysis performed for different sets of fabrication parameters indicates that some cuts are more sensitive than others in respect to changes in the material conditions such as wood grain directionality or material density.

As discussed in **Section 6.1**, the successful demonstration of the validity of **Hypothesis B** is particularly relevant beyond the practical utilisation of the simulation framework as it shifts the idea of material variance from a detrimental and unpredictable component towards a controllable dimension of the agency of tools and materials potentially enriching the overall design process.

7.1.3 Research Question C

Research Question C: *How does the integration of manufacturing and material knowledge at an early stage of the design process affect the exploration and evaluation of design solutions for robotic carving operations?*

Research Question C was addressed through a series of case studies, presented in **Chapter 5,** performed in collaboration with the industry partners of the project where the integration of material and manufacturing knowledge at an early stage of the process made possible to unlock a series of novel, otherwise unavailable, design opportunities and support a better-informed decision-making process.

The findings from the first case study, discussed in **Section 5.2,** provided valuable insights on the established workflows and culture of design firms and indicated that one of the main reasons for the current separation between design and making is the lack of interfaces that would grant designers with manufacturing knowledge, providing feedback along the way to guide the design process. At the current state, the variance of heterogeneous materials such as timber and non-standard fabrication methods determine a significant deviation between the prescribed digital notation and the fabrication outcome, preventing their utilisation for any practical application. Nevertheless, the findings from the industry collaborations demonstrate that the integration of a simulation framework supported by real-world fabrication data can be used for evaluating the constraints and opportunities provided by wood properties and carving tools on top-down design decisions, reducing the uncertainty of the outcome in the fabrication stage. For this reason, the access to a specifically-trained manufacturing knowledge base is particularly beneficial for the advancement of the design process as it becomes possible to assess simultaneously, at an early stage when key decisions are made, both design and fabrication considerations.

As discussed in **Section 5.3**, the exploration of solutions organised through what-if scenarios (Vaneker and van Houten, 2006) driven by material affordances would have not been possible using conventional methods based on purely geometric considerations rather than on the collection of actual fabrication data. The workflow entails the analysis of geometric pattern variations, wood species and density, grain directions, carving tools and specific fabrication parameters (*e.g.* Tool/Surface Angle) which significantly affect the resulting geometric features (*i.e.* Length, Depth and Width) of the cuts. The final fabrication stage of a specific what-if scenarios sequence does not necessarily represent the end of the design process, but it could become instead the starting point for another set of digital explorations which can build upon the fabricated evidence. Following a tree-like structure, the design to fabrication process is rarely linear and choices made at an early stage can always be revised, especially if novel material evidence is included in the system.

Each industry case study unfolded in an extended catalogue of robotically fabricated components and multiple digital design iterations supported by the ANN-based simulation tool trained by the team of designers to fit the specific scope of the design brief. The benefits provided by the open-ended modularity, flexibility and scalability of the system have been discussed in **Chapter 6** based on the collected findings. One of the main takeaway is that the active role assumed by the team of designers in the curation of the training of the system was successfully justified with the access to a brief-specific, yet previously unexplorable, domain of fabrication-informed solutions already at the initial design stage.

As addressed in **Section 5.4**, the choices taken by the designer interacting with the simulation framework are usually concerning a negotiation between top-down design decisions and the, now accessible, interaction that these have with specific sets of tools and materials. The devised strategy opens up a new way of approaching the issue of the deviation between digital and physical, offering a negotiation platform where designers could choose between the optimisation of individual fabrication parameters to achieve the original design intention or following a more open-ended trajectory where fabrication affordances act as design drivers (Menges, 2012).

7.2 Contribution

The contribution to knowledge of the research is to the fields of robotic fabrication technologies and digital interfaces for design-to-manufacturing applications as it focused on utilising sensor data to train material-sensitive fabrication systems and integrating them as part of design workflows.

Although the research strategically focused on a specific application such as robotic carving with timber, as previously discussed in **Chapter 6**, the developed methods could potentially apply to a broader variety of design and robotic manufacturing tasks requiring a high-level understanding of the different fabrication affordances involved in the process.

Part of the novelty of the approach proposed in this research lies in transposing established industrial methods for optimising robotic manufacturing tasks into the workflow of creative practices to augment and support the abilities of designers providing feedback information to guide the evaluation of design solutions.

The successful development of a series of methods to collect, process and encapsulate manufacturing knowledge and its application within a design environment demonstrated the benefits of interacting at an early stage with fabrication tools and material affordances to make better-informed design decisions and enable the exploration of novel design opportunities.

7.2.1 Designing Through Material Affordances

The research presents, through a practical application, an alternative framework to the hylomorphic paradigm for the design and making of physical artefacts dominant in current design practices (DeLanda, 2002).

Heterogeneous materials, such as timber, are not transformed into inert and homogeneous media: through a combination of sensor data and machine learning models, it is possible to effectively train our tools to adapt to the nature of materials, fully embracing their heterogeneity and yet maintaining control over the entire design process (Fure, 2011; Weston, 2012).

The research found context within an increasingly prominent component of the current architectural discourse focused on a renew sensibility towards tools technologies and materiality, within which simulation and robotic fabrication are regarded as enabling frameworks to establish information feedback loops driving design and production processes (Maxwell and Pigram, 2012; Dörfler, Rist and Rust, 2012).

The access to a validated simulation framework able to provide feedback information from an early stage of the workflow made possible the shift from a geometric-driven to a process-driven approach to design, bridging between the digital and physical realm (Gramazio and Kohler, 2008; Menges, 2012).

The creation of design hypotheses in the form of digital models which are tested within a simulation environment was proven as a promising strategy to anticipate and exploit the variance of complex material properties before moving to the actual production stage.

Material knowledge that would be usually available only through direct engagement with fabrication processes over an extensive period (Sennet, 2008; Ingold, 2013; Sharif and Gentry, 2015), it is here used to guide the choices of designers who benefits from such knowledge through receiving manufacturability feedback in real-time despite being physically and timely detached from the actual carving process.

The encapsulation of knowledge made possible to shift the approach to digital design processes more closely to the "thinking through making" (Ingold, 2013) approach of crafts practices based on heuristics and trial-and-error, here combined with the advantages of speed and scalability of digital design environments (Carpo, 2015).

7.2.2 Design Curation & Learning Tools

The novel approach proposed in the thesis is based on providing the team of designers with a customisable design-to-manufacturing interface communicating fabrication and material feedback in relation to a specific selection of desired geometric features, wood species, tools and carving techniques. The advantage of such a curatorial approach is that designers can adapt their design tools through the iterative acquisition and processing of material and fabrication data rather than explicitly coding software from scratch. The access to manufacturing knowledge, synthesised with machine learning strategies from the curated data, supported the choices of designer along each stage of the design development (Vaneker and van

Houten, 2006), from the initial choice of the wood species to the impact of a specific geometric feature on the overall fabrication speed.

The trained tool represents an expert system (Lucas and van der Gaag 1991) curated by the designers themselves which actively supported the explorations of novel design solutions driven by fabrication and material affordances as modelled from the provided data. For this reason, the acquisition and curation of such information play a key role in the design process as it directly defines the domain of solutions that would have been later available in the digital simulation interface.

As such knowledge is accessed through digital geometrical simulation, it enables designers to immediately evaluate the results of their design intention once expressed through the material medium, simultaneously comparing multiple scenarios. These findings support the argument put forward by Hanna (2007) and Tamke, Nicholas and Zwierzycki (2018) for the use of machine learning models within design workflow to support decision-making procedures for complex fabrication processes.

In comparison to CAPP strategies (Park, 2003) relying on standard materials and geometric features specified for individual industries (*e.g.* aeronautics, automotive…), the advantage of the devised methods is to give designers the opportunity of actively participating in the definition of their custom design-to-manufacturing workflow, extending the range of processes and materials beyond industry standards to better fit the diversity of design briefs and their requirements.

7.2.3 Knowledge Acquisition, Synthesis and Integration

The research successfully addressed the challenge of acquiring and integrating manufacturing knowledge to validate simulation frameworks necessary for the development of digital interfaces that would enable designers to engage with the affordances of production processes.

A key contribution of this research lies in weaving together the perspectives of design practices, traditional crafts and industrial manufacturing around the central role of knowledge in the making of physical artefacts, highlighting overlaps and strategies that could be translated across these different domains to overcome such a challenge.

In doing so, the research put forward a practical example of how knowledge from the domain of human making could be captured and transferred in a robotic manufacturing environment to efficiently train a fabrication system.

The demonstration required the development of a sensing strategy and experimental data collection process based on a combination of human expert demonstrations and robotic recording sessions which was proved to be particularly beneficial to narrow down the mapping of the parameter space explored, saving time and material resources.

This further support the findings of previous case studies in the literature (Kikuchi *et al., 2014;* Ng *et al.,* 2014; Kalt, Monfared and Jackson, 2016; Steinhagen *et al., 2016,* Prahbu *et al., 2017;*) where human demonstrations have been utilised to inform a range of subtractive fabrication tasks, such as polishing and grinding operations.

The research presents an example of a transition process from an *information-intense* to a *knowledge-intense* system for design and manufacturing (Whitehall and Lu, 1991; Monostori, 2002; Hansson et al., 2016), where the devised strategy has not only been used to record and retrieve information but, more importantly, to synthesis such information into knowledge to support decision making (Lu, 1990).

The focus on subtractive manufacturing allowed the reintroduction of traditional carving tools, such as chisel and gouges, within the realm of robotic manufacturing applications with timber, unlocking this way a series of techniques with peculiar expressive qualities, now made available to a larger segment of users beyond traditional human craftsmen. In this way, the research suggests a possible strategy to preserve and distribute human making knowledge, infusing new life into the currently declining scope of traditional crafts through their reconciliation with contemporary design practices.

The successful development of a strategy to synthesise and integrate knowledge presented in this research is particularly valuable for all the different stakeholders involved along a typical design-to-manufacture workflow.

From the perspective of designers, the access to packages of instrumental knowledge extends the range of materials and manufacturing techniques available as the trained models bring a significant increase in the simulation accuracy of non-standard fabrication processes. Designers willing to engage with the curation of the training process have the opportunity of creating customised design-to-manufacturing workflows validated by feedback data and statistical models. At the same time, the trained system does not require the designer to be a manufacturing expert, computer scientist or a skilled craftsman to engage with the production process as feedback information is provided through a familiar geometrical interface. In this case, the access to material and manufacturing knowledge could be compared to the specialised knowledge made available within other simulation frameworks (*e.g.* FEA, CFD) to a larger group of design professionals, enabling the evaluation of complex structural or environmental analysis.

Finally, for manufacturing companies, the research demonstrates a strategy for encapsulating manufacturing knowledge and making it available to all the stakeholders involved in the design workflow, ensuring from the beginning a fruitful communication between the different parts and avoiding inefficient decisions which could be very expensive and challenging to adjust at a later stage of the process.

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