Robotic Constraints Informed Design Process

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Pradeep Devadass
Tobias Heimig
Sven Stumm
Ethan Kerber
Sigrid Brell-Cokcan

Chair for Individualized Production, RWTH Aachen University Germany

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1 'Twisted Arch' Project

ABSTRACT

Promising results in efficiently producing highly complex non-standard designs have been accomplished by integrating robotic fabrication with parametric design. However, the project workflow is hampered due to the disconnect between designer and robotic fabricator. The design is most often developed by the designer independently from fabrication process constraints. This results in fabrication difficulties or even non-manufacturable components. In this paper we explore the various constraints in robotic fabrication and assembly processes, analyze their influence on design, and propose a methodology which bridges the gap between parametric design and robotic production. Within our research we investigate the workspace constraints of robots, end effectors, and workpieces used for the fabrication of an experimental architectural project: "The Twisted Arch." This research utilizes machine learning approaches to parameterize, quantify, and analyze each constraint while optimizing how those parameters impact the design output. The research aims to offer a better planning to production process by providing continuous feedback to the designer during early stages of the design process. This leads to a well-informed "manufacturable" design.

Keywords: Robotic Fabrication and Assembly, Mobile Robotics, Machine Learning, Parametric Design, Constraint Based Design.

INTRODUCTION

In recent projects, some of the constraints of parametric design based methods for robotic fabrication processes have been addressed, explored, and achieved at various experimental and architectural scales. In the project *Robotically Assembled Spatial Structures* by ETH (Gandia 2018), the design of a steel structure was optimized based on reachability constraints of the robot. This was done by digital simulating the robotic production and analyzing for collisions. The algorithm was then optimized to adjust the position of the steel bar component and ensure the robot could achieve a valid collision-free path. Similarly, the project developed by Aarhus School of Architecture, Israel Institute of Technology, and ETH Zurich (Søndergaard et al. 2016), has proven the value of integrating optimization for cutting the angles of assembly components order to achieve successful robot reachability. Additional projects demonstrate the optimization of design based on tool constraints. Projects such as *The Research Pavilion-2011* of ICD Stuttgart (Schwinn 2012), *Timber Folded Plate Shells* (Robeller 2016), and the *Adaptive Fabrication Aware Form Finding* (Pigram 2016), each used bespoke robotic milling process for the full-scale fabrication of complex timber structures and found ways to inform their designs based on specific tool constraints. The *Lightweight Timber Plate Shells* project optimizes the panel sizes and angles based on the available workpiece/raw material dimensions (Krieg 2014).

It is this research's goal to build upon the lessons learned though such state-of-the-art projects in order to develop an explicit process which comprehensively addresses:

- Robot, tool, and workpiece constraints
- Influences of the fabrication process parameters
- Reciprocal relationships between fabrication and design

To overcome the gap between design and production, we introduce a process which is driven by a continuous feedback and the integration of production constraints in three unique steps. First, all constraints—including the robot, tool, and workpiece constraints of the fabrication and assembly process—are identified and parametrized. This is done by developing a parametric model of the entire design to fabrication process in Rhinoceros and Grasshopper 3D, a visual programming environment. Second, the critical parameters of the design are selected and simulated for training a machine learning dataset. This dataset enables learning methods to understand manufacturability of the components in the design. Finally, this learned network of the parameter's influence is stored and mapped for machine learning prediction so that optimization of future design parameters is made greatly more efficient. This methodology is demonstrated through design and construction of *The Twisted Arch* project, a 1:1 scale prototype made of complex space frame timber structures. The outcome of this research results in the creation of an intelligent computational program, which provides visual guidance for the user during the design process and optimizes the fabrication through machine learning prediction of robotic parameters. Within *The Twisted Arch* project, the process flow consists of the following steps:

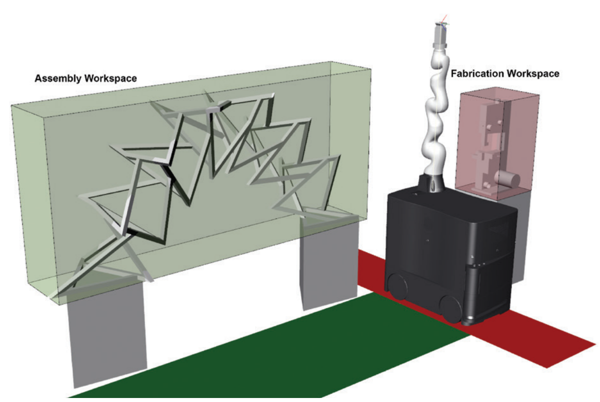
- Global Design defines the overall design of the structure
- Local Design defines the joinery design of components
- Fabrication Process is informed by local design where the component is manufactured using a band saw and robot
- Assembly Process is informed the global design where each component is assembled through human-robot collaboration

Parametric Design Constraints

The first step from design to production (fabrication and assembly) is to consider the various workspaces of the production resources which include the tools and machines involved to identify the work flow and layout of the robotic setup (Figure 2). For *The Twisted Arch*, the setup consists of a KUKA-iiwa with a 14kg payload and an electrically activated gripper as an end-effector. The robot is mounted to a KUKA Mobile Robotic (KMR) platform.
A standard workshop band saw is mounted to a workstation which is at a raised height of 500mm due to the limited reachability of the robot. For the same reason, the base of the arch are raised with a box of 500mm in height on either ends.

Workspaces

In robotic fabrication, the robot's workspace is defined by the maximum functional volume which the Tool Center Point (TCP) can successfully reach considering all necessary given target positions and orientations. The robot



2 Workspace

workspace differs from working envelope of robot because the workspace takes the robots TCP into account; this not only includes the Cartesian coordinates (XYZ), but also the orientation (ABC) at the target position (Aggarwal 2014). Methods for pre-determining the workspace of a robot has been demonstrated through 3d visualization of the manipulability distribution of six degree of freedom (6DoF) kinematic chains as addressed in previous research inquiries (Vahrenkamp 2014; Zacharias 2007).

The workspace does not depend only on the robot's kinematic chain and the tool/end-effector used. The tool extends the kinematic chain, and parameters—such as the workpiece's shape, size, form, position, and its environment—act to directly influence the viability of the tool-path. To comprehend and implement the parameter space within which fabrication and assembly can be successfully carried out, the effective workspace of each production resource (robot, end-effector, workstations/external tools, and material) is analyzed.

These analytical results are combined to create a process model that considers the interrelationship between all parts of the production process. There are two types of workspaces based on the process: 1) Fabrication Workspace which is a combination of robot workspace (KMR + iiwa) and tool workspace (band saw); 2) Assembly workspace which is combination of robot workspace and prototype components, i.e. *Twisted Arch*.

The fabrication workspace can be described as a collection of robot's TCP positions for cutting the timber workpiece, which is depended on the robot and tool constraints. The robot arm has a maximum reach of 840mm. This constraint defines the maximum volume or the working envelope within which the robots can reach. The band saw has with a maximum cutting depth of 110mm within which the timber component needs to be placed for fabrication. This volume defines the tool, and in this project, the band saw workspace. The intersection of the robot working envelope with end-effector and band saw workspace defines the fabrication workspace. By establishing this fabrication workspace, it is possible to test the manufacturability of a component.

The intersection of robot and end-effector with various TCP positions for assembly of all components in the prototype define the assembly workspace. The sequential assembly order of the timber components must be considered and understood so that the robot does not collide with the already assembled components.

With this workspace defined, we can inform the design within the volumetric constraints of the position of the band saw, robot, and assembly station. While this workspace provide a basic guideline for the design, the manufacturability of a component is questionable at this stage of the process. On the other hand, each process is clearly defined by the boundaries of fabrication and assembly workspaces, which are placed orthogonally to each other so that the mobile platform can freely operate to resolve reachability issues without any collisions.

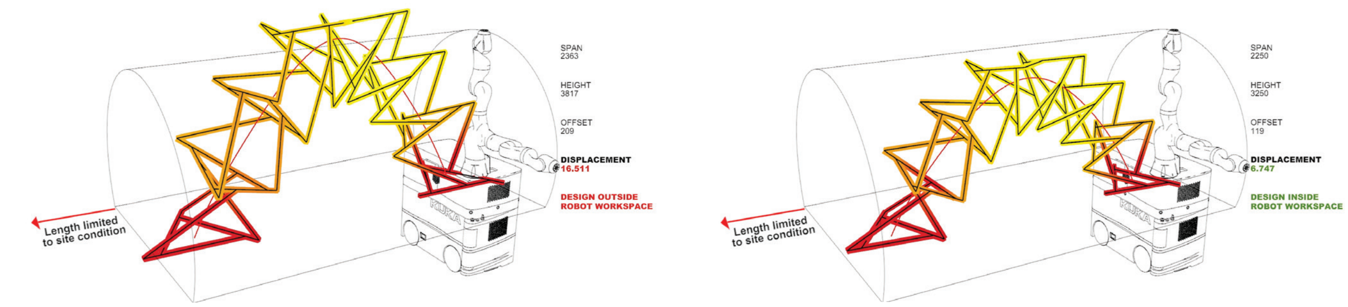
Global Design

The design of the prototype is based on a catenary arch comprised of a complex triangular space frame system of timber elements. The triangular space frame system is generated along the cantenary arch, and its geometry can be controlled by the designer using the various control points of the curve, allowing the designer to explore different design variations. Alternatively, the curve of the cantenary arch can also be controlled parametrically in the Grasshopper 3D interface where span, height, and offset of the catenary arch are defined as the parameters. The modification of the control points or the parameters, in turn, radically changes the space frame design and subsequently changes the length and joinery angle of each timber component while still maintaining the configuration of the system.

The controls points or the parameters are modified so that the design is bounded within the limit of the derived workspace. This is ensured through an algorithm that informs the user through visual graphics if the design is outside or inside the robot's workspace. However, sometimes even if the design is within the workspace of the given setup, there are instances when the robot is not able to manufacture a part due to other fabrication constraints or is not able to assemble the component due to reachability constraints. Although this design process is tested only with a simple curve (cantenary arch) and a triangular space frame system, the same methodology can be scaled up for more complex processes given that the complex processes are modeled parametrically so the optimization can be automated.

Local Design

After several iterations of the optimization process the design is finalized, and the algorithm creates butt joinery between connecting components from the centerlines of the space frame system. Butt joinery is generally used to connect two or more timber pieces and consist of flat cuts at specific angles for alignment. The flat faces of the butt joints are fastened using timber screws. The butt joinery results in compound angles of specific connections due to complexity of the design. The sectional dimensions of the



3 Optimization of the design guided by the fabrication and assembly workspace

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timber stock are 35x35mm. To avoid loss of the strength, considering the limited sectional size of the timber, each timber component is restricted to only one connection at each end. The output from the algorithm is the final geometry, which needs to be fabricated from the given stock material. The length of each component is limited to a certain size depending on the maximum reach of the robotic arm or the robots working envelope. This constraint is ensured to avoid collision between the timber material and the robotic arm or the environment (later explain under fabrication constraints). As the timber is gripped by the robot only at the center, the lengths of the timber pieces are also limited to avoid extensive vibrations are the end of the stock material.

PARAMETRIC PRODUCTION CONSTRAINTS

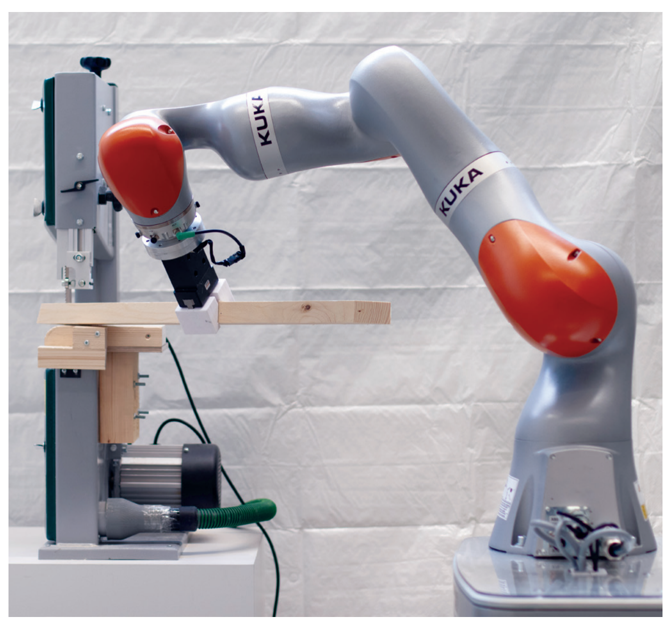
Robot Trajectory Optimization for Fabrication

While manually cutting timber using a band saw, tremendous amount of forces are exerted by the band saw blade on the workpiece. Therefore, the workpiece must rest on the band saw table so that the vibration forces are mostly absorbed by the table. This allows the fabricator to easily guide the workpiece at the required direction and angle without being affected by the forces. Similarly, while using the robot, in order to ensure a minimal amount of forces are transferred to the robotic arm, the workpiece is required to rest on the band saw table during the cut (Figure 4). This prerequisite becomes a major robot trajectory challenge, as the robot not only has to place the workpiece at the required orientation and position, but also to ensure the workpiece rests on the band saw table.

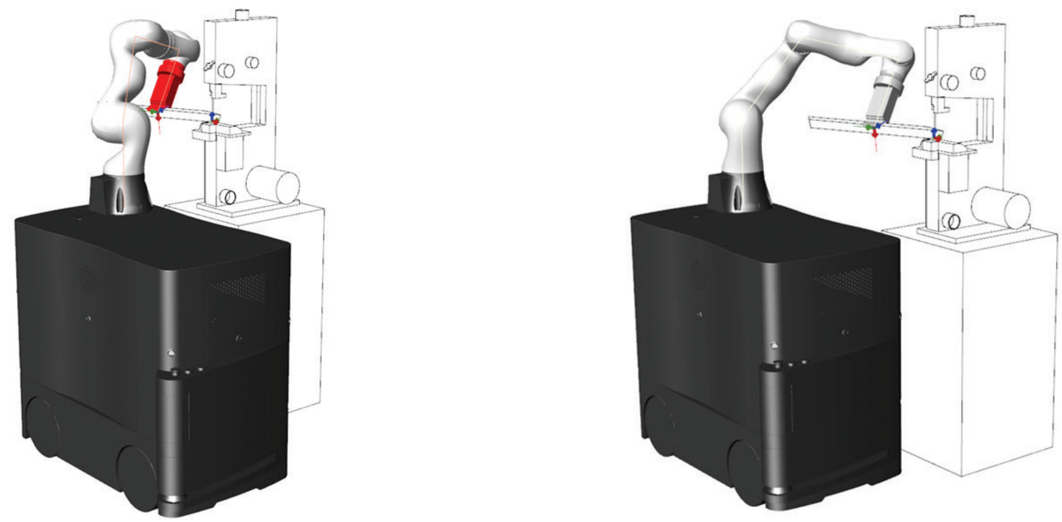
Therefore, to achieve robot reachability for the above complex trajectory devoid of any collisions, we move the KUKA mobile platform, which in turn changes the base position of the KUKA iiwa robotic arm, and therefore, enables different axis configuration in the robotic arm movement (Figure 5). This optimization of the base position of the robot is conducted until a suitable trajectory is obtained that is free from collisions and well within the reach of the robot. The optimization movement of the KUKA Mobile Robot for fabrication is only along the Y-coordinate of the Robot Base Plane. The distance between the starting position and the optimized position of KMR mobile robot is referred to as the 'safe distance.' The algorithm uses inverse kinematic solver, namely KUKA|prc (Braumann 2012), which checks for reachability, collisions, and singularities of the robot simulation.

Robot Trajectory Optimization for Assembly

Current work flows only consider design-informed fabrication, while complex assembly requires more consideration of sequence planning. Similar to fabrication, to resolve reachability issues during assembly the base position of the mobile platform is optimized (Figure 6). The optimization movement of the KUKA Mobile Robot for assembly is only along the X-coordinate of the Robot Base Plane. There are instances where the robot is still unable to reach the target position. Since the geometry plane is placed along the centerline of the geometry, we can rotate it into four different configurations, which leads to the robot gripping



4 Resting the work piece on the band saw table using the robot during fabrication



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5 Optimizing the mobile robot position for fabrication

6 Optimizing the mobile robot position for assembly

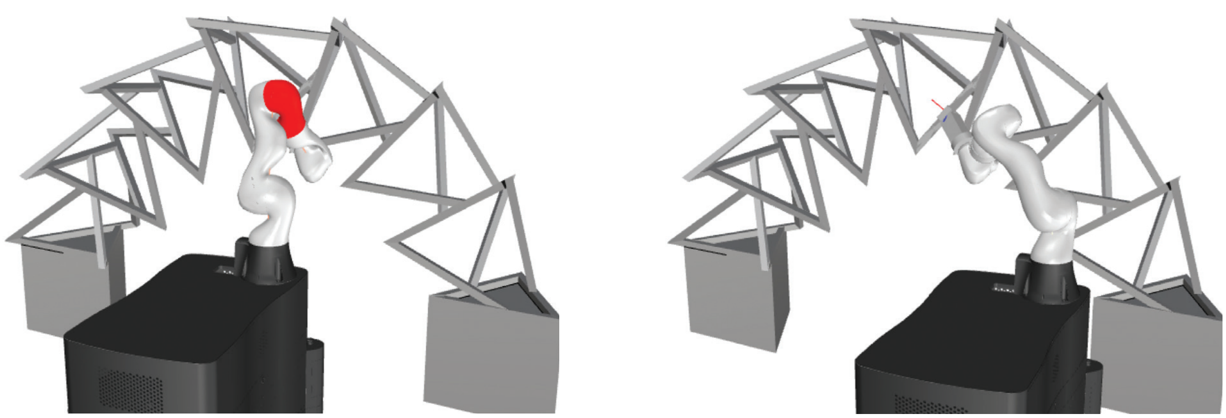
the part from 4 different directions. This also changes the robot's configuration while keeping the geometry in the same place. In order to compensate for these deviations, the robot connects the assembly component to the existing butt joint of its predecessor.

Optimization through Machine Learning

An evolutionary algorithm—that assesses and improves the manufacturability of a design of the *The Twisted Arch* project by iterating through all possible robot trajectories and determining the best possible path—could still result in a sub-optimal design process that is not efficient. This is because every change in design results in a unique set of components, requiring a re-evaluation of the evolutionary algorithm. This requires a significant amount of time and leads to a complex analysis due to a very high number of parameters.

To create a more efficient design to production process, this research uses machine learning (ML) techniques to achieve a real-time prediction of the best parameters for robotic fabrication of the design part. By creating a statistic model to analyze the production parameters and constraints this process is able to predict the ideal robotic path for fabrication. This is more efficient than evolutionary algorithms because the training simulation for machine learning is stored in the computer's memory. Rather than having to recalculate the ideal solution after every design change, as in the case of the evolutionary approach, the machine learning approach significantly improves the time required to optimize robotic fabrication processes.

In the case of this project, the challenge was to optimize and visualize the numerous parameters involved in the process. The solution for this can be found in dimensionality reduction allowing to plot an ***n***-dimensional parameter



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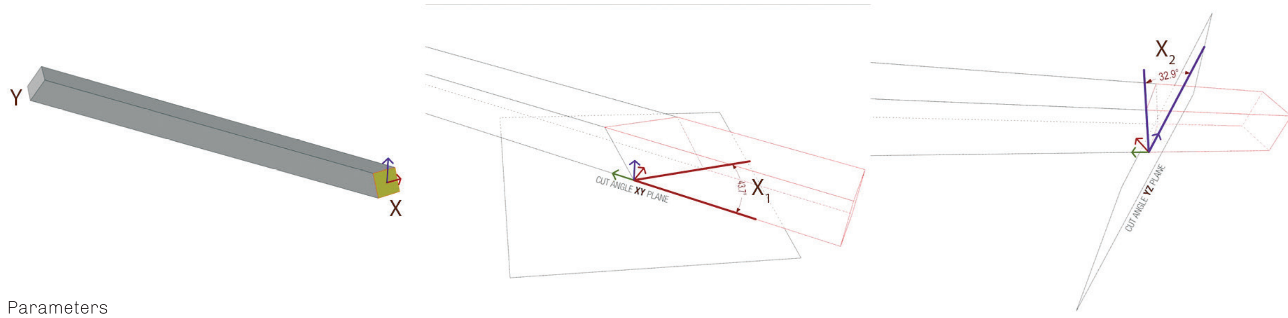


7 Parameters

space in a lower ***m***-dimensional parameter space. John Harding describes the advantages of dimensional reduction for the exploration of design parameters spaces in architecture in “Dimensionality Reduction for Parametric Design Exploration” (Harding 2016), and suggests "Self-Organizing-Maps,” a non-supervised machine learning approach for clustering and dimensionality reduction developed by Teuvo Kohonen (Kohonen 1982; 2001).

The result of the self-organizing-map (SOM) methodology has an equal or lower dimensionality than the input data describing the complete parameter space. This results in an abstraction of the dependencies of the parameters (Kohonen 2001). In addition, the basic concept described by John Harding in the second step of the SOM process incorporates a “secondary feature.” These features are post-processed values associated with the neurons of the SOM. As such, the SOM approach differs from other neuronal network based ML techniques.

Neurons can be described as models trying to fit the parameter space the SOM is analyzing (Kohonen 1982). After the initial analysis, the self-organizing-map results in several neurons, each describing a generalized model where the parameters space represents the most suitable input data. In the case of the catenary *Twisted Arch*, the angles of the two planes which define the compound angle of the timber are considered as the primary feature. The secondary features are the planes X1, X2 and Y1, Y2 on each side of the timber component. These represent “Neurons” in the SOM process (Figure 7). Safe Distance, the parameter which alters the position of the KMR to optimize the robot trajectory was also considered as the secondary feature.

Machine Learning Process

In this project, ML was used in two different stages. In the first stage, the Self-Organizing-Maps (SOM) was used to analyze and map relationships between input parameters of the design such as the cutting angle of the work piece, the resulting production information and its constraints.

In the second stage, additional ML methods were used in addition to the SOM approach. Supervised learning algorithms - k-nearest neighbors (KNN) (Altman, 1992) and backpropagation (Goodfellow 2016, 196) – were also used to develop a reliable model for real-time prediction.

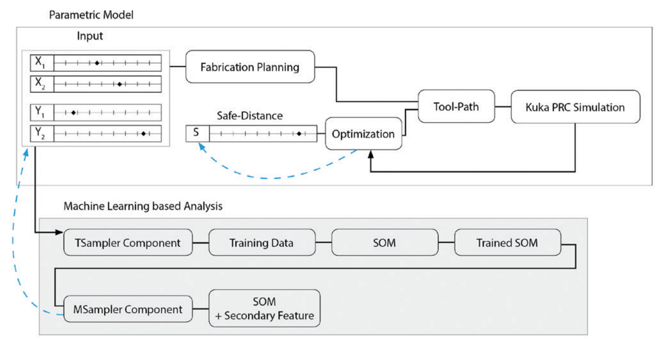
In Machine Learning, a larger training data-set leads to a more reliable output. While the parametric modelling methods of Grasshopper can generate significant amount of training data, the process for generating appropriately large data-sets for machine learning is still challenging. To realize this approach the standard parametric model for production was extended by implementing the following processes:

- Crow (Grasshopper 3D Plugin) created by Fabian Felbrich was used to allow access of artificial neuronal networks in Grasshopper
- Three bespoke C# components, Evolutionary Solver, TSampler-Component, MSampler Component developed by the authors for solving the generation and completion of datasets.

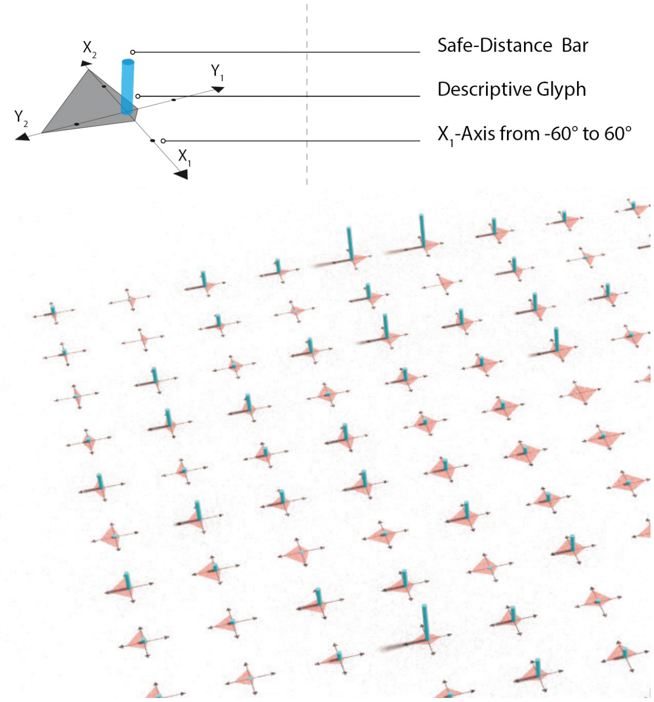
Evolutionary Solver: This was created to optimize the “Safe-distance” of the KMR platform for the given design. The algorithm also allowed for testing of multiple design models which was made possible due to custom start, stop triggers buttons for optimizations. This was not possible with the currently available evolutionary solver plug-ins like Galapagos or Octopus.

TSampler-Component: This was implemented to resolve the problem of generating a high quantity of data sets for machine learning training. The component works by generating random normally distributed datasets, processing them in the parametric model, and saving the results. The generated results were later used as target vector for supervised learning and displaying meshes for visualization.

MSampler Component: To expand the SOM with a “secondary feature” a second sampler component was implemented similar to the TSampler-Component but



8 Machine learning process diagram 8



9 Visual representation of the Neurons and Self Organizing Map 9

with the focus not on training data but on the neurons of the processed SOM. Similar to the second step of the T-Sampler-Component, the sampling component for map data (MSampler-Component) iterates over a set of given input samples and processes the parametric model to save the corresponding results and display mesh. This differed from the TSampler-Component as the MSampler-Component does not generate a set of random samples but instead uses the neurons of the processed SOM. This allows to the process to save a display mesh and a corresponding "secondary feature" for each neuron.

Machine Learning Process

Using the custom algorithm, 10,000 samples of training datasets were generated by the T-Sampler-Component. As a typology for the Self-Organizing-Map a 2-dimensional map with 15x15 (225) Neurons on a square grid was chosen. After processing the learning of the map in 10,000 cycles the second sampler component for mapping members was used to process each neuron and calculate the 'Safe Distance' as a secondary feature and crease an associated map of the data.

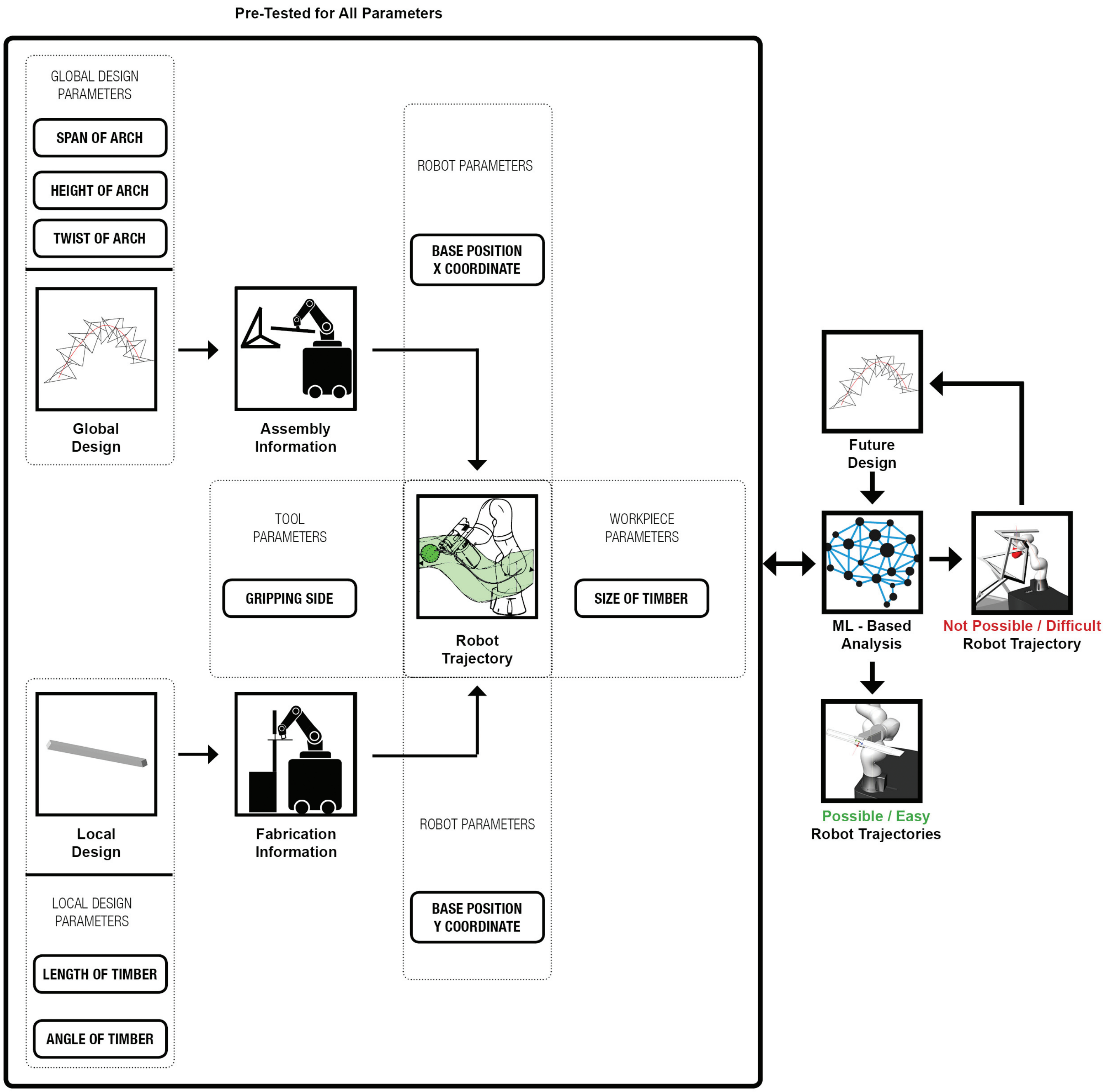
The resulting map consists of 225 neurons representing meaningful examples of the parameter space - storing the elements X1, X2 and Y1, Y2 of the compound angle X and Y. These parameters are arranged so that the change between neighbored neurons is as smooth as possible. Each neuron is associated with the corresponding Safe Distance as a secondary feature.

The visual representation of the data and abstraction of the angles is represented as a 4-sided polygon on a Coordinate System with 4 axes chosen to support the comparison. The Safe Distance as a secondary feature is visualized as a bar in the third dimension (Figure 9).

The goal of the second stage was improved accessibility for the designer of the ML models results and advantages. To create a reliable statistic model for the fabrication process was the main challenge of the second stage and will be continued in future research. Especially the neuronal net trained using Back propagation showed a high reliability even with a relatively small number of 10,000 training samples. It turned out that the quality of the optimization has a significant influence on the quality of the training data.

A relatively small accuracy in optimization seems to result in a higher scattering in the fabrication information. This adds a further factor that causes fuzziness in the relationships and dependencies of input data. The primary and secondary feature did not corelate with each other continuously, which increases the complexity of the clustering. A deep learning based clustering of parameters for a more fuzzy distinction using convolution neural networks would require a higher sample number. Even though the back propagation method showed promising results all three approaches were not able to create a reliable model for the prediction of fabrication information.

Even though the introduced models did not achieve a suitable reliability, they showed a huge potential of ML to close the gap between design and production by speeding up the feedback from production simulations and even predicting fabrication parameters for deviating designs. To improve the accuracy of the design feedback in the future, larger sets of training data created with a higher optimization quality are required.



10 Methodology

DESIGN IMPACT AND CONCLUSION

This process establishes a new methodology in the field of architecture, where every design decision is continuously informed and controlled by the parameters of fabrication in real-time due to the use of ML approach. The process results in multiple options where every design is completely manufacturable but with slight modifications in its overall appearances from the one initially envisioned by the designer. Within the larger context, the work flow establishes a new methodology in architectural design where the designer understands and is aware of the potentials and limitation of the fabrication process. The designer is always informed during design and construction through continuous designing and redesigning before and during the construction process. Thus, this methodology also allows the designer to have complete control throughout the project. Another feature of this methodology is that any production setup or design can be integrated, through which we can evaluate the manufacturability of the design or limitations of the production setup.

11 Robotic Production

The biggest drawback of this method is that the algorithm does not indicate which exact parameters are to be modified and how much change is required to achieve a manufacturable design. Although the constraints are identified and parameterized in this research, in future work an interface will be developed that would result in providing the above-mentioned feedback to the designer. Next steps will also include the development of an algorithm to find the best suitable robot setup for tool- and assembly-workstations. This would result in an alternative approach, which optimizes the process layout based on the created design.

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Pradeep Devadass is an architect, computational designer, and robotic fabrication specialist. He holds an M.Arch from the Architectural Association and is currently working as a researcher at The Chair of Individualized Production, RWTH Aachen University on innovative robotic fabrication methods for architectural applications, developing a 'smart' programming environment to bridge the gap between design and fabrication. Pradeep is one of few recipients of the prestigious MAK-Schindler Residency Program Award. He has extensive experience at leading research organizations including Bristol Robotics Laboratory (UK), MAK (USA), Archi-Union (China), and RSP (India).

Tobias Heimig is a Master degree student at the RWTH Aachen, specializing in robotics and programming. His research ranges from parametric design to digital fabrication. Previous projects have included investigations into parametric path planning for welding and Metal Additive Arc Welding (MAAW).

Sven Stumm is a computer scientist with extensive experience in electrical and mechanical engineering. He is currently leading the robotic programming and outdoor robotics research team at the Chair for Individualized Production in Architecture at RWTH Aachen University. Sven Stumm submitted the first PHD Thesis at the Chair for Individualized Production in Architecture (IP) in 2018 titled "Interconnecting Design Knowledge and Construction by Utilizing Adaptability and Configurability in Robotics," which was graded summa cum laude. His research focuses on accessibility of robotics through human robot collaboration and sensor-based adaption with *a priori* knowledge.

Ethan Kerber is a computational designer working at the intersection of architecture, engineering and construction. Ethan has a Master of Industrial Design from the San Francisco State University and a Master of Engineering in Computational Design and Construction from the Hochschule Ostwestfalen-Lippe. He has experience in metalwork and digital fabrication with public sculptures permanently installed in Washington, D.C. and Arlington, Virginia. Ethan is currently a researcher at The Chair of Individualized Production, where he is developing a doctoral dissertation on the Optimization and Automation of Steel Structures.

Sigrid Brell-Cokcan is the founder and director of the new Chair for Individualized Production in Architecture at RWTH Aachen University and co-founded the Association for Robots in Architecture in 2010. She is currently board member of EU-Robotics and coordinating the new topic group for construction robotics.

The Chair for Individualized Production in Architecture (IP) founded by Prof. Sigrid Brell-Cokcan in 2015 focuses on the use of innovative machinery in material and building production. In order to create an environment that allows the efficient, individualized production of lot size one, new and user friendly methods for man machine interaction are developed. IP employs researchers from different fields of robotics and building production to streamline the necessary digital work flow from the initial design to the production process; shaping the construction site of the future via intuitive, easy-to-use interfaces.