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CALIBRATING A FORMFINDING ALGORITHM FOR SIMULATION OF TENSIONED KNITTED TEXTILE ARCHITECTURAL MODELS

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Abstract. This paper presents an optimization-based calibration process for tuning a digital formfinding algorithm used with knitted textile materials in architectural tension structures. 3D scanning and computational optimization are employed to accurately approximate a physical model in a digital workflow that can be used to establish model settings for future exploration within a knit geometric typology. Several aspects of the process are investigated, including different optimization algorithms and various approaches to data extraction. The goal is to determine the appropriate optimization method and data extraction, as well as automate the process of adjusting formfinding settings related to the length of the meshes associated with the knitted textile behavior. The calibration process comprises three steps: extract data from a 3D scanned model; determine the bounds of formfinding settings; and define optimization variables, constraints, and objectives to run the optimization process. Knitted textiles made of natural yarns are organic materials and when used at the industrial level can satisfy DSG 9 factors to promote sustainable industrialization and foster innovation in building construction through developing sustainable architectural systems. The main contributions of this paper are calibrated digital models of knitted materials and a comparison of the most effective algorithms and model settings, which are a starting point to apply this process to a wider range of knit geometries. These models enhance the implementation and further development of novel architectural knitted systems.

Keywords. Tensioned Knitted Textiles; Computational Design; Formfinding; Calibrating; Optimization, SDG 9.

While knitted fabrics are not common in architecture, recent improvements in CNC knitting and computational design have increased their viability, leading to increasing interest (Tamke et al., 2020; Thomsen et al., 2016; Ahlquist & Menges, 2013; J. E. Sabin, 2013). Knitted textiles offer many potentials, which makes them a perfect material for developing more sustainable architectural systems and building

construction. This research positions itself in the Sustainable Development Goal 9 [SDG 9] sector which aims to build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation ("HLFP Thematic Review of SDG-9," 2017). Knitted textiles made of organic yarns enable architects to apply these materials for making sustainable structures. Additionally, knitted textiles because of their specific structures allow for integration of different materials such as conductive yarns into their structures. When used as architectural structures these materials can collect energy and be used as a source of electricity. Much more can be added to the list that support the need for more in-depth investigation of these materials for architectural application. Successful design and fabrication of knitted textiles in architectures requires developing a digital model parallel to physical experiments that represents the behavior of the material accurately.

However, developing digital models for architectural knitted textiles is often a challenge, especially in early design. While tools such as Kangaroo 1 and 2, which use Dynamic Relaxation and the Projective Constraint method respectively, are immensely powerful for explorative formfinding of flexible materials, they require the user to specify lengths and stiffnesses or related model properties to get an accurate representation of the tensioned shape. Especially for knitted structures, a specimen might have substantially different properties in different directions or regions of the textile, making these settings tedious to model correctly. Making digital models thus requires an iterative process of experimentation with real materials, learning from the physical modeling, and translating material logic to simulation settings in the digital environment. Yet converting material behavior into numerical data has challenges that stem from the range of simulation inputs required to accurately represent a tensioned shape. Such manipulations include translating non-linearity in the behavior of the knitted textile in different directions depending on yarn types, patterns, and knitting setting used for making knitted structures, as well as boundary conditions, and stabilizing applied forces.

In connection to ongoing research for developing formfinding methods of knitted tensioned structures (Oghazian, Farrokhsiar, & Davis, 2021), the authors of this paper implement and test optimization methods as tools for tuning a digital formfinding algorithm to aid in the design of architectural knitted tension structures.

1. State-of-the-Art

Formfinding and simulation of architectural tension structures made of real materials with complex characteristics are challenging. Although some researchers emphasize that the formfinding process is a geometrical problem and material independent (Dutta & Ghosh, 2019), others argue that in working with specialized materials, the characteristics of the material along with the geometry inform particular behaviors (Oxman & Rosenberg, 2007). This research positions itself in the second category, where the geometry and material characteristics are both informative in formfinding process. However, for materials such as knitted textiles used in architectural tension structures, working with the material properties requires an iterative learning process. This learning process is a feedback loop that synthesizes information from physical models and manipulates digital formfinding algorithms.

In design and fabrication with knitted textiles, three scales can be recognized in

their structure: micro-scale (one stitch or loop), mesoscale (combination of stitches in patterns), and macro-scale (overall form) (Oghazian & Vazquez, 2021). Knitted textiles possess some uncertainty in their behavior, derived from how they were formed at these varying scales. No matter the yarn type, different knit structures affect the elasticity of the textile. Therefore, when combined with the complex irregular architectural forms not common in textile design, predicting and simulating the exact shape and behavior of the knitted material is challenging. Many research studies in the literature tried to remove the extra elasticity added because of the structure of the textile by using yarns with the least elasticity, such as Dyneema, and patterns that add minimum elasticity to the textile (Tamke et al., 2020). In order to limit stretchability, techniques such as in-laying yarns are incorporated during the manufacturing process (Pal, Chan, Tan, Chia, & Tracy, 2020).

Calibrating digital models based on the results of a physical model is not new in architecture. However, in many studies, the calibration process is not elaborated. The simulation result is not compared with the actual physical models, especially with materials that possess some uncertainty in their behaviors, such as knitted textiles. In a study by Cuvilliers, Yang, Coar, & Mueller (2018), two common algorithms of Kangaroo1 and 2 are compared regarding the reliability, speed, and accuracy of the formfinding process by defining numerical calculation from physical model measurements and comparing them with the form found models. Their main argument is that it is not clear how the available algorithms can be calibrated to get meaningful results in physical units. Specifically for knitted textiles, in calibrating the simulation process for a piece of knitted textile by Schmeck & Gengnagel (2016), the authors explored the cyclic manipulation process to make their algorithm correspond to certain characteristics of the material. However, complete accordance has yet to be achieved.

While simulating and calibrating a digital model of a square shape of knitted textile that is deformed to a conical shape by applying force in the middle of the textile, Baranovskaya, Tamke, & Thomsen (2020) used a genetic algorithm through Galapagos to calibrate the digital model. The meshes represent graded knitted textiles with different stiffness characteristics manipulated to obtain a digital model close to the physical 3D scanned shape of the knitted textile. In connection to this last study, in our research, we propose a procedure and examine different optimization tools as a method of calibrating digital formfinding algorithms for conical 3D knitted tension structures. The goal is to speed up the calibration process by systematically limiting the number of data points and selecting the most reliable algorithms.

2. Introducing Workflow, Case Study, Challenges, and Research Goals

In this research, 3D scanning captures the overall shape of a physical knitted textile structure to compare it with the digital models. The selected shape is a conical form with 48 stitches in the course and wale direction in the conical part. The cone is selected because it is common in tensile architectural structures. Seamless knitting allows to knit tube and cones easily. While simple, there are challenges in simulating the exact behavior of the conical shapes to avoid a bottle-neck effect around the tip of the cone and wrinkles over the stretched surface. Figure 1 shows some of projects that used conical knitted textile shapes for architecture. The formfinding procedure implemented by Oghazian, Farrokhsiar, & Davis (2021) is used as a starting point. The formfinding

uses Kangaroo 2 and a simplified quad-based mesh representing the knitted textile structure.



Figure 1: Case studies of projects made of conical knitted textiles. Left: Hybrid Tower (Thomsen et al., 2015). Right: Fabricating Networks, Flower Antenna Sculpture (Davis, 2021)

Usually in the formfinding process the mesh settings should be modified to obtain a shape that corresponds to the physical model. A more accurate model will have smaller geometric differences between the digital and physical artifacts as measured by the method in Section 3.1. Accurate models are critical because designers use them for feedback during rapid iteration, and a final product that looks substantially different is undesirable. The tedious task of calibration requires looking at the model repeatedly and determining the length and stiffness of the mesh edges in formfinding components. In this paper, we use optimization methods to automate this calibration process. Pre-requirements for the calibration process include first overlapping the formfound and 3D scanned mesh, considering the upper and lower boundaries as the fixed points (Figure 2). The distance between two meshes is then minimized through calibration process. The cumulative distance is considered as an objective function for optimization, while the length for seven mesh edge categories are the variables. These mesh categories will be explained in more detail in section 4.2. The same process can be used for tuning formfinding simulation of other soft and knitted textile materials and forms. However, the mesh categories might differ based on the overall form used.

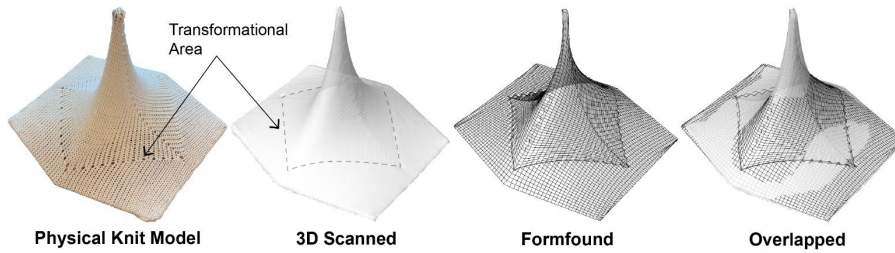


Figure 2: Physical Knit Model, 3D scanned, Formfound Models, and 3D scanned/Formfound Overlapped meshes

In the conical shape selected in this study, two critical parts can be recognized: the cone and the planar surface. After post tensioning the connection between these two parts is more consistent. Since the stitch effect is different in Transformational Area, as it is shown in Figure 2 over the Physical Knit Model, we can use it as a qualitative criterion to determine the performance of the optimization algorithms.

3. Process

The main questions we address in this research are: what are the best data extraction methods from the 3D scanned model that represent the overall form and behavior of the tensioned knitted textiles? What are the most appropriate optimization algorithms that can assist architect designer for tuning formfinding algorithms? The calibration process includes a series of steps. The first step is to extract data from the 3D scanned model that is being used as a test case, and the second step is to determine the range for springs length in the formfinding algorithms based on the results of the physical modeling. Once the simulation problem has been established, the third step is to set the optimization constraints and repeatedly run different combinations of data extraction and optimization settings to determine the most effective method.

3.1. DATA EXTRACTION

A 3D Systems SENSE 2 3D Scanner was first used to scan the knitted samples. The output of the 3D scanning process is a 3D mesh. The formfound model also includes many points associated to the corners of the mesh faces/stitches. To determine the distance between two meshes, the points from formfound model can be projected vertically or perpendicularly to the 3D scanned mesh (Figure 3).

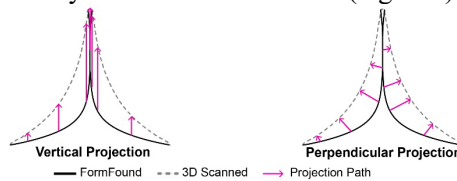


Figure 3: Projection methods

While both were attempted, the perpendicular projection method is used because it produces better results regarding the curvature fit between the models. Vertical projection was also problematic for the points near the tip of the cone, where the projection lines were almost tangent to the mesh, or not touching the other mesh at all.

Next, the set of points for distance measurement had to be selected. Three individual approaches are explored: Random Points, Section Points, Transformation Area Points (Figure 4A). Except for the Random Points the other methods are selected because of the specific geometry of the overall model. Combinatorial approaches are also explored by combining the individual strategies to investigate the combined effect on enhancing the performance of the optimization process (Figure 4B).

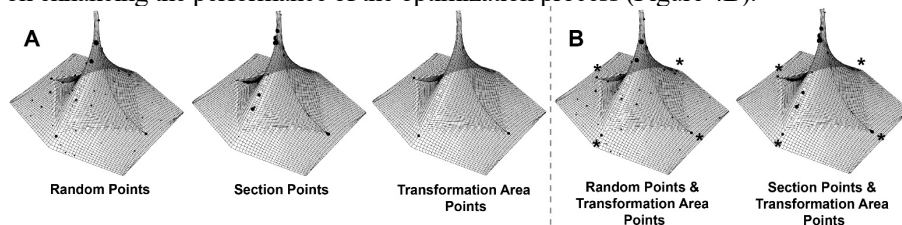


Figure 4: Data extraction approaches A: Individual Approaches. B: Combinatorial Approaches (Weighted /not Weighted. The weighted points are labelled with *)

3.2. MESH EDGES AND MESH LENGTH FACTOR BOUNDS

Once the points are selected for comparison, the formfinding process was implemented using Kangaroo 2. The main steps for any formfinding process are 1) defining the initial mesh, 2) determining the boundary conditions and external forces, 3) converting the mesh edges to the springs considering the mesh length and strength, and 4) running the formfinding solver. The central activity of this paper is Step 3, where we convert mesh edges to springs and input characteristics of the knitted textiles. Studying physical conical models used in this study show, while characteristics and size of the stitches are similar before applying the tension, their behaviors are varied at different sections of the conical tensioned structures. As illustrated in Figure 5A, the mesh lines are divided into seven categories to have better control over the shape change of different parts of the model.

Another critical element is the length criteria. This element determines the length change during formfinding. Here, initial mesh lengths are multiplied by a length factor to determine the length change. These length factors are used as variables in the optimization process. To adequately reflect the size change of the mesh edges, the bounds of the length change associated with each of these categories are limited to reliable bounds as presented in Figure 5A.

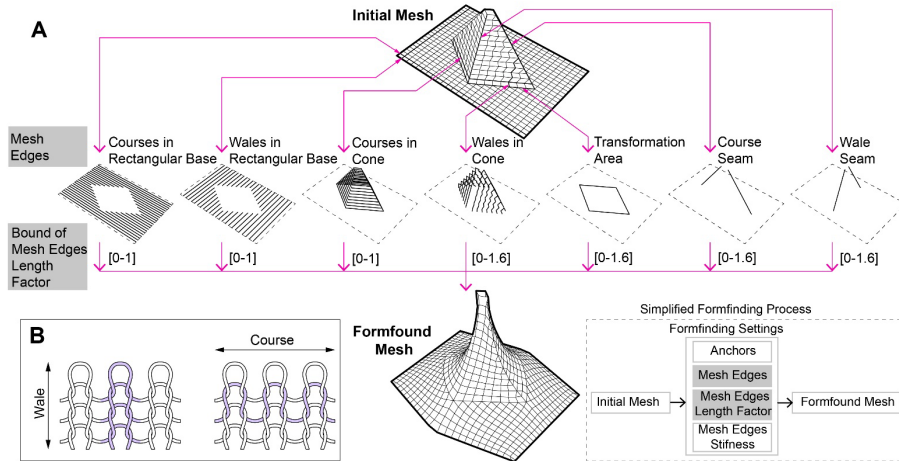


Figure 5: A: Seven categories of mesh edges and associated length factors, B: Wale and Course

In general, two main directions can be recognized in knitted textiles structures, and these are course and wale (Figure 5B). In the physical model used in this study, the initial knitted model is attached to the boundary frame, keeping the overall length and width around the rectangular head as it was knitted and without stretching. Therefore, the elongation only happen in the wale direction, which is the direction of the exterior force. Consequently, the stitches in course direction mainly shrink.

3.3. OPTIMIZATION

For optimization, the plugins Radical and Opossum are selected. Radical is a tool in Design Space Exploration (DSE) that incorporates algorithms for constrained,

gradient-based optimization for numerical and geometric design variables (Brown, Jusiega, & Mueller, 2020). Opossum is a black-box optimization tool applicable for time-intensive architectural problems (Wortmann, 2017).

After an initial test period, we selected nine promising algorithms that performed better on minimizing the differences between the simulated and physical structure. There are six algorithms from Radical DSE including: SBPLX, GN_ORIG_DIRECT, GN_ORIG_DIRECT_L, ISRES, LN_BOBYQA, LN_COBYLA. There are three from Opossum including: RBF, CMAES, and CMAES_Random. All algorithms in Radical are from the NLOpt library (G. Johnson, 2020), which can be consulted for more information about each one. The algorithms from Opossum are from RBFOpt, an open-source library for black-box optimization (Costa & Nannicini, 2018). The starting point for all the algorithms is setting the length factor to zero, which can be the start of a generalized process. Figure 6 graphically illustrates the starting point.

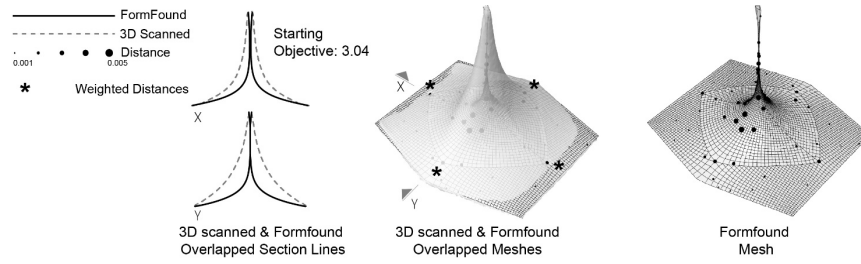


Figure 6: Starting point in optimization process where all the variables are set to zero

3.4. RESULTS OF OPTIMIZATION PROCESS

The results of the optimization processes for different data extraction methods and algorithms are provided in this section. Figure 7-left illustrates the performance of different algorithms for the three individual data extraction approaches. The Random Points and Section Points techniques both give better results considering the shape of section lines. But the Transformation Area Points technique did not yield curves in the formfound model that completely followed the 3D scanned model shape. GN-ORIG-DIRECT-L Radical is the best solver for both approaches. In the Transformational Area Points method, because the distance between the four points in this approach was less than the other approaches, the distance is multiplied by 25. Transformational area lines in the formfound model completely overlap the 3D scanned model. However, none of the algorithms yield section lines that are close to the 3D scanned model. Based on these observations we decided to combine the four-point Transformational Area Points strategy with the Random Points and Section Points approaches as a combinatorial approach (Figure 7_Right). In this approach we added the four Transformational Area Points with and without weight.

In general, adding weight to the four critical points of the Transformational Area in combinatorial approaches does not improve the performance of the algorithms. Almost all the algorithms will give better section lines in unweighted strategies. Performance of the algorithms regarding the Transformational Area shape is a bit better in weighted strategies, but it is not significant.

LN_BOBYQA and LN_COBYLA usually stopped at the earlier stages of the optimization process for either individual or combinatorial approaches and not giving good results regarding the objective of the project. GN_ORIG_DIRECT_L, which is a global optimization algorithm that works through systematic division of the search domain into smaller hyperrectangles, is the most reliable algorithm for different types of the data extraction such as Random, Section Points, and Random Points & unweighted Transformational Area Points. 1077 seconds is the minimum, and 3750 s is the maximum time for optimization of the models that ran for all 400 iterations. However, some algorithms were able to obtain their best results faster and within less than 100 iterations such as SBPLX.

4. Conclusion and Contribution

This study explores the potentials of using optimization strategies for calibrating the digital model out of the formfinding process and automating the process of adjusting formfinding settings in simulating architectural knitted textiles. The results of our study, a contribution of this paper, show that among different individual and combinatorial data points, we found the Random Points and Random Points & Not Weighted Transformational Area Points technique to provide good data points for a calibration process. The number of data points obtained from the 3D scanned models are many and if all of them are used to minimize the distance between the 3D scanned mesh and formfound mesh, it increases the computational process during the optimization process. Therefore, we limited the data to the minimum critical points to obtain the desired results.

The performance of different optimization algorithms in Grasshopper plug-ins was then investigated for tuning a simulation process of conical knitted tensioned structures. Another contribution is that GN-ORIG-DIRECT-L from the Radical plugin was one of the best algorithms for this research problem. To speed up the calibration process during the design process, it was important to understand which kinds of data, variables, and optimization tools should be selected at the first step.

While this research uses small conical models as a case study, the whole process of calibrating the formfound model can be applied to other projects and other tension structure shapes that use similar materials. Researchers can benefit from the detailed calibration process introduced here that include 3D scanning the model and extracting the essential data, Determining the bounds of formfinding settings, and setting the optimization process and minimizing the distance between the target surface and initial surface. The procedure can be adopted as a method to automatically determine the length factor settings for the mesh edges during the formfinding and design process.

Acknowledgement

The authors are grateful for the support of ICDS Seed Grant at Penn State University 20212022.

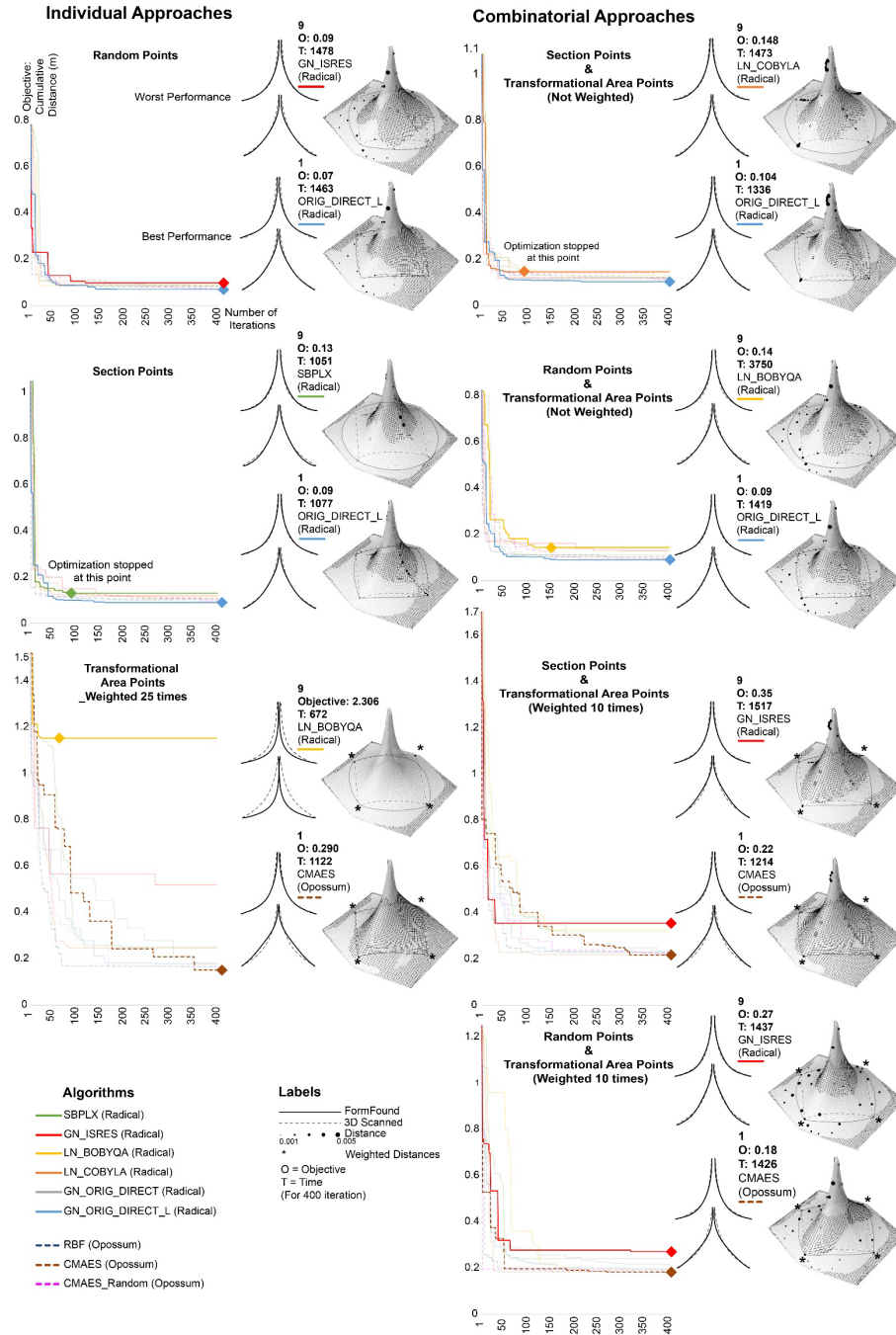


Figure 7: Comparison of individual and combinatorial data extraction strategies for different Radical and Opossum algorithms (Left: Individual approaches. Right: Combinatorial approaches)

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