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ADVANCEMENTS ON THE STRUCTURAL TIMBER OPTIMIZER (STO)

Johannes Belz[1], Benjamin Kromoser[2]

ABSTRACT: While wood-based building materials can help reduce emissions in the construction industry, their increased use impacts forests and ecosystems. To address this, the Structural Timber Optimizer (STO) was developed to minimize material usage in wood-based building components by increasing structural utilization. This paper aims to validate the functionality of the STO in finding the optimal solution for optimizing the stiffness of a wall-like beam (wlBeam) under bending, by comparing the deflection of the solution with a known near-optimal reference. Additionally, the influence of different parameters affecting the result and performance of the optimization were tested and quantitively assessed. This study also presents insights into the newly developed segmented discrete modeling approach as well as advancements in the optimization process such as the implementation of an initial population. The results show that optimization parameters constraining the diversity of the population e.g. mutation rate and the use of a fine mesh in finite element analysis improve the overall performance in finding the best solution. With this study the effectiveness of the STO process can be confirmed, demonstrating its ability to identify the optimal solution for the wlBeam problem.

KEYWORDS: topology optimization, shape optimization, genetic algorithm, finite element analysis, engineered wood

1 – INTRODUCTION

To limit the environmental impact of the construction industry, the reduction of material-related emissions through the increased use of bio-based building materials and the high utilization of structural elements is a promising solution. Structural optimization methods for anisotropic material, such as laminated composites, enhance stiffness and overall structural performance by optimizing material orientations within structural elements [1]. While structural optimization techniques found in high tech industries, e.g. aerospace or automotive industries, are becoming more advanced, implementations in the construction industry are still limited, especially in relation to building components made from wood-based materials [2]. Studies have demonstrated material reductions of 15-20% by optimizing the cross-sectional width along the length of glue-laminated timber beams [3] or through topology optimization of the middle layer in cross laminated timber slabs [4]. Recent research on implementing orthotropic materials such as timber and bamboo in a topology optimization approach show promising advancements [5]. However, studies validating these methods through practical testing, such as all-wooden trusses [6] or mass optimized cross laminated timber panels [7], remain underrepresented. This gap can be attributed for one to the limited accessibility of code and for another to the failed transition from theoretical research to practical testing and industry use cases.

To address this research gap, the authors at BOKU University developed the Structural Timber Optimizer (STO) as an accessible and user-friendly framework [8]. This framework integrates the state-of-the-art commercial finite element (FE) software ABAQUS [9] with its extensive capabilities and high accuracy of its FE solver forming the foundation for the structural analysis in the STO. With a large user base and well-documented resources, ABAQUS is an accessible solution that supports interactive processes through its native Python scripting interface. In the STO framework, ABAQUS commands are encapsulated as functions within larger Python scripts, which can be executed via command-line arguments.

The other side of the framework is the optimization algorithm controlling the iterative change of variables with the aim of finding the best solution to a given objective. STO utilizes a genetic algorithm (GA), implemented through the Python package PyGAD [10],

[1] Johannes Belz, Institute of Green Civil Engineering, University of Natural Resources and Life Sciences, Vienna (BOKU University), Austria, ORCID 0009-0007-8172-4092

[2] Benjamin Kromoser, Institute of Green Civil Engineering, University of Natural Resources and Life Sciences, Vienna (BOKU Univer-sity), Austria, ORCID 0000-0003-3416-8146

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iteratively changing the optimization variables to reach the optimal fitness. GAs mimic natural selection by evolving a population of solutions over generations. Each individual is represented by a genome defined by optimization variables and its fitness is evaluated based on the objective function. Through selection, crossover, and mutation, the best genes propagate, gradually converging toward an optimal or near-optimal solution [11]. GAs are probabilistic optimization methods, meaning they do not guarantee finding the best solution, even with unlimited computation time. However, unlike deterministic methods, GAs can handle black-box problems without requiring explicit problem formulation. This flexibility makes them well-suited for the STO, allowing application to various structural optimization problems, including different load cases and optimization objectives. To facilitate the optimization of various dimensions and types of structural elements the STO implements a 3D model generation through the python package CadQuery [12].

2 – ADVANCEMENTS OF STO

2.1 MODELING

Since the development of the accessible framework STO [8] several advancements such as the modeling approach have been made. While the general optimization approach of STO could be implemented for a variety of use cases, advancements were made considering the use case of a multi-layered wall element made from oriented strand board (OSB). As shown in Figure 1, the first development of the STO considered an element-based approach with a continuous domain in each layer of the wall element. This continuous domain was then meshed, allowing each finite element to be assigned individual material orientations. However, this approach proved to be limiting in several ways. While a continuous panel with varying material orientations and material grades would likely increase the structural utilization of the element, current OSB manufacturing methods make this approach not of practical use at present.

Therefore, a new modeling approach has been developed segmenting the continuous domain of a layer into discrete parts allowing the individual material definition of each part including its interaction to the neighboring elements.

To segment the continuous panel into discrete parts, the STO makes use of the ABAQUS meshing algorithm. After generating the mesh, used for finite element analysis, the nodal data of each finite element is exported as a list of x, y, and z coordinates that can be further processed into a multi part 3D model using the CadQuery python package.

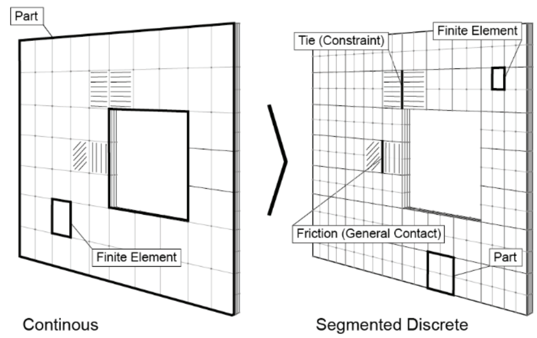

Figure 1:Continuous vs. segmented discrete modeling approach.

The segmented discrete parts can then be imported into ABAQUS as a step file making the structural element fully parametric in the material definition of each part. Additionally, individual parts can be excluded from the simulation enabling the use of variables to control their mass (mass = 1, no mass = 0).

As the continuous domain is split into several parts and the orientation of the parts can be independently changed by the optimizer, corresponding logic interactions between parts should be modelled accordingly. While the interlayer bonding in a multilayered OSB element is modelled as a tied contact (constraint), the contact areas between the sides of the individual parts must adapt according to their orientation. Within this logic, equally oriented parts are considered as continuous, enforcing a tie constraint between them. For all further interactions a general contact domain with a normal and tangential behavior is generated. Due to the high number of interactions, the complexity as well as the nonlinear behavior of the model increases. For these reasons and the high displacement of some of the solutions, the ABAQUS explicit dynamic solver was chosen. While this further introduces time as a variable in the structural model the loading rate can be cautiously increased to a quasi-static problem, reducing calculation time. The material behavior was modeled using an elastic material defined through the engineering constants E_1: 6780 MPa, E_2: 2680 MPa, E_3: 1000 MPa, G_{12}: 1090 MPa, G_{13} / G_{23}: 60 MPa, as found in EN 12369 [13] and ν_{12}: 0.128, ν_{13}: 0.211, ν_{23}: 0.433 as found in Li et.al [14]. To determine whether a structural element has exceeded elastic plastic deformation, a failure model is required. For this, two applicable methods were identified. While an integrated failure model (damage criterion), as shown in Figure 2, yielded better results within the optimization, a penalty constraint implemented

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outside of ABAQUS presented a viable alternative. When returning the fitness value, the stress values of the element would indicate an element exceeding the strength of the material resulting in the application of a penalty to the fitness value accordingly. While this penalty constraint eliminates the need for complex material definitions in ABAQUS, inaccurate weights of the penalty can lead to a distorted search space for the optimizer. As ABAQUS does not provide an applicable failure model for wood when using volumetric elements, a ductile damage was implemented using fracture strain with an instant damage definition.

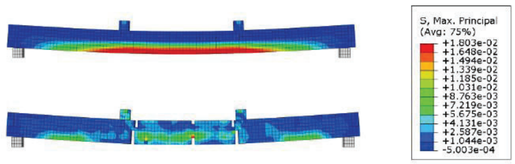

Figure 2: ABAQUS material model testing on 4-point bending beam.

2.1 OPTIMIZATION

With the aim to reduce runtime and convergence, an initial population was introduced. When using a probabilistic method like the GA, the starting point significantly influences the outcome of the optimization. Instead of randomly creating an initial set of variables, in this case orientation values, a predefined set of solutions is passed to the GA as the starting point for optimization. Studies have shown that principle stress lines can be applied to topology optimization problems [15] and, in the case of continuous fiber placement, can enhance the maximum load bearing capacity compared to unidirectional fiber placement [16]. STO makes use of the principle stresses in the initial population as follows: (1) In ABAQUS, an isotropic material is assigned to the segmented discrete model and analyzed under the same boundary conditions as the final optimization model. (2) The stress tensors (s_{11}, s_{22}, s_{12}) are exported from the odb file through the xy Data option for each finite element of the model. (3) The 2D stress tensor (σ) is constructed and solved for the eigenvalue (λ) and eigenvector (v). (4) The eigenvalues are sorted in descending order to identify the maximum principal stresses, and the orientation angle (θ) is calculated using the arctan2 function. (5) To ensure consistent orientations, the direction is adjusted if s_{12} is a negative value ($\theta = 180° - \theta$). (6) To complete the extraction of the principal stress orientations, the orientations are averaged across all finite elements in each segmented discrete part and returned as a list of orientations. (7) As the GA works with discrete orientation variables, the orientation values need to be interpolated to the selected orientations. While the principal stress orientations are interpolated to their closest possible orientation the generation of the initial population introduces an additional randomness that allows adjacent parts to influence the interpolation as well as its starting point. This is needed to provide a diverse set of solutions for the initial population and can be controlled via the initial population randomness variable.

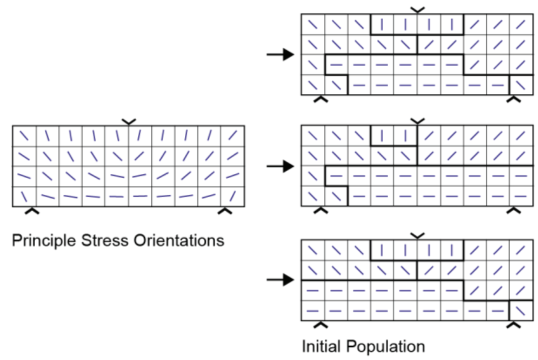

Figure 3: Processing and interpolation of principle stress orientation to initial population.

As multi-objective optimization algorithms, such as NSGA-2, are also available in the pyGAD package, efforts were made to implement this function in the STO. The STO returns now the maximum displacement values, maximum stress, and the mass of the element from ABAQUS, which can be used as single or multi objective. This combined with the possibility of eliminating individual parts within the structure, a topology optimization can be implemented. In the case of multi-objective optimization of mass and displacement, the variable space for the GA is extended by an additional value outside of the value range of orientations. This value can then be used as the identifier for zero mass parts without doubling the variable count for the GA.

3 – VALIDATION AND INFLUENCIAL PARAMETERS

To validate the optimization approach, a three-point bending test setup was selected using a wall-like beam (wlBeam) as the test specimen, optimized to maximize stiffness. The choice in setup and specimen dimensions was primarily motivated by the given boundary conditions of the Zwick Roell 250 kN universal testing machine, which would be used within full-scale testing, and the desire to maintain an aspect ratio representative of a wall element. The wlBeam was discretized into 48

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segments, each of which could be oriented at either 0° or 90°, as shown in Figure 4.

Prior to the optimization, an analytical solution was calculated to establish an optimal or near-optimal reference configuration, where all three layers of the wlBeam were positioned horizontally (0°), resulting in a deflection of 15.05mm.

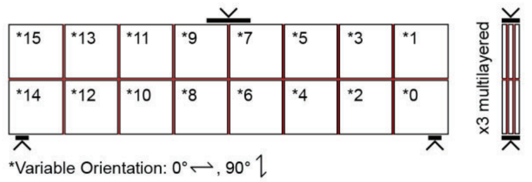

Figure 4: Segmented discrete parts and variables of wall-like beam (wlBeam) under bending.

To evaluate the impact of the different parameters (Table 1) on the optimization algorithm, the deflection of the best overall solution from the STO was compared to that of the reference configuration. This deviation, expressed as a percentage in Figure 5, indicates whether the optimization achieved a better solution (smaller deflection - positive value) or remained below the known "best" solution (larger deflection -negative value).

Since the initial population has a randomness when generated, it varies with each run, influencing the starting point of the optimization. To account for this variability, the best overall solution was also compared to the best solution from the initial population. This comparison provided additional insights into the optimizer's rate of convergence.

The optimization parameters, listed in Table 1, were systematically varied, with the baseline (*bl*) serving as the initial setup to examine the effects of increasing or decreasing the parameters. In addition to the parameters defined in Table 1, the mutation type was set to "random," the crossover type to "single point," and the parent selection type to "tournament."

Table 1: Parameters assessed within the optimization using the STO of the wall-like beam (wlBeam)

GA Parameter	Baseline (bl)	Low (l)	High (h)
numGenerations (G)	18		
populationSize (P)	60	30	120
initPopRandomness (PR)	0.3	0.15	-
numParentsMating (PM)	18	6	-
mutationNumSolutions (M)	3	1	-
tournamentSize (T)	12	-	24
crossoverProbability (C)	1	0.5	-
meshSize(MS)	250	83	-

Most parameters was assessed in four separate optimization runs, while *bl_P(l)* was subjected to three, *bl_T(h)* and *bl_C(l)* to two, and *bl_MS(l)_M(l)_PR(l)* to one. The best-performing result of each category was used within the following comparison.

As shown in Figure 5, the most noticeable impact on the optimization outcome and convergence rate was achieved by decreasing the mesh size. While this parameter does not directly affect the genetic algorithm (GA), it improves the accuracy of the ABAQUS simulation, leading to more predictable and precise fitness values.

A general trend of improved performance was observed when certain optimization parameters were when constrained. Reducing randomly mutated solutions in each generation from three to one solution showed an overall better solution as well as higher convergence rate. Similarly, decreasing the number of parents "mating" for the next offspring showed a higher convergence rate.

Reducing the randomness of the initial population resulted in a better overall solution but diminished the relative improvement from the initial population. Constraining the population size led to the lowest solution overall, while doubling the population size yielded a better solution, with no improvement in the convergence rate in either case.

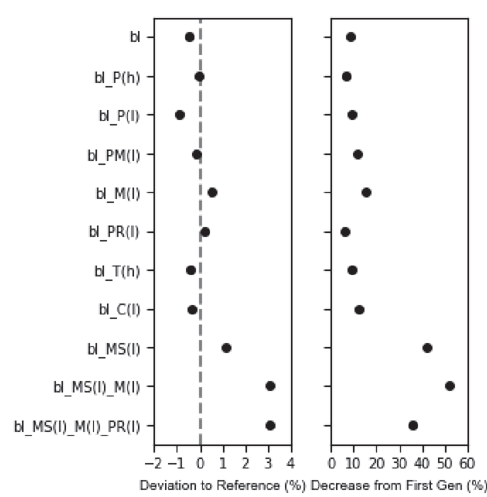

Figure 5: Influence of optimziation parameters on the best solution (deviation to reference configuration) and rate of convergence (decrease from best solution of the first generation).

The solutions of the last parameter test *bl_MS(l)_M(l)_PR(l)* were evaluated and the distribution of the fitness value within every generation plotted using the kernel density estimation (KDE), shown in Figure 6.

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In unfavorable configurations, failure was prone to occur, leading to extreme displacements as the remaining elements collapse without support. To improve the readability of Figure 6, the extremely high displacements were capped at 50 mm deflection.

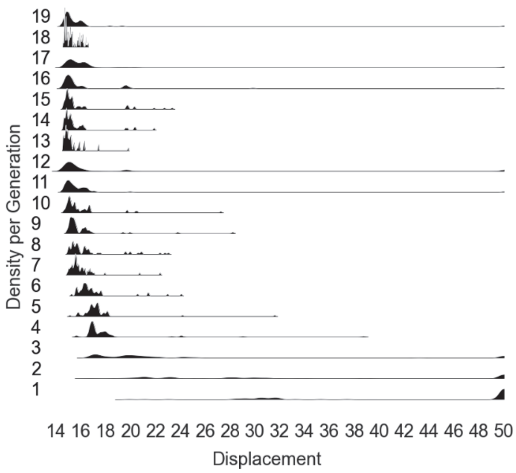

Figure 6: Distribution of the populations fitness values (displacement) of each generation using the kernel density estimation (KDE).

The distribution of fitness values across generations shows a steep increase in the first three generations, after which all configurations of the 4th generation successfully withstand the applied load, and the highest density of samples is found between 16mm and 18mm of maximum deflection. While new best solutions were found until the overall best solution was reached in generation 13, with 14.59mm of maximum deflection, the rate of convergence decreased at a high rate after the first generations. Over the generations, a shift in population distribution, i.e., diversity, was observed. In generations with a high percentage of "good" individuals, the diversity increased in the following generations. A higher proportion of individuals with higher displacement values appeared, which contributed to the broader spread of solutions.

4 – DISCUSSION AND CONCLUSION

The advances in the Structural Timber Optimizer (STO), as outlined in this paper, enable a practical and versatile approach for the structural optimization of wood-based building components. The segmented discrete modeling approach allows for individual assignment of any material properties such as orientation or material grade as well as the removal of individual parts of a structure. Advances in the ABAQUS model have been made, including the implementation of failure criteria facilitating a precise structural response of the component. While the segmented discrete modeling approach provides several advantages, the increased complexity of the structural problem in ABAQUS made the optimization computationally more expensive. While ABAQUS standard solver showed good convergence in the continuous model approach, the current analysis can only be performed using the explicit solver. While the structural model in ABAQUS provides an accurate representation of the structural behavior, the time per calculation (around 50 seconds) lowers the performance of the algorithm. Therefore, increasing the rate of convergence of the algorithm and quality of the best solution is key to an efficient optimization using the STO approach. To facilitate an ideal starting point for the optimization this paper outlines the principal stress orientation approach to generate a set of solutions as the initial population.

In this study some of the influential optimization parameters were systemically assessed to validate the overall optimization approach as well to set initial parameters for further optimization. The case of the wlBeam under bending was optimized to maximize stiffness, with 48 variables each allowing 90° and 0° as possible values resulting in 48^2 possible solutions. It was shown that a population size of 60, with a low mutation rate of 1 individual and reduced randomness in the initial population, produced good results, with the optimal solution found in 13 generations. The results suggest that constraints on the population diversity (i.e. high selection pressure) result in better performance. However, balancing the diversity of the population throughout the optimization is crucial to avoid premature convergence while ensuring effective exploration of the search space. The observed shift in population diversity can serve as a reliable indicator of whether the diversity is properly balanced. In the case of the wlBeam optimization this positive impact of recombining a more diverse population can be observed between the generation 7 and 13 where the diversity of the population increased leading to the best solution in generation 13 (low diversity).

While advancements in the initial population and sensitivity analysis of optimization parameters positively impacted the efficiency of the optimization algorithm, further studies could explore the use of “smart” recombination techniques to replace the stochastic one-point crossover methods. This can be archived using reinforcement learning for decision making during the crossover or by utilizing the large amount of available data from ABAQUS, e.g. stresses in each part to determine whether it is fully utilized or not. In addition to displacement as an objective, the ultimate load-bearing capacity could also serve as a practical optimization objective and warrants further exploration.

4 – ACKNOWLEDGMENTS

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5 – DATA AVAILABILITY

The code is available from the corresponding author upon reasonable request.

6 – REFERENCES

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