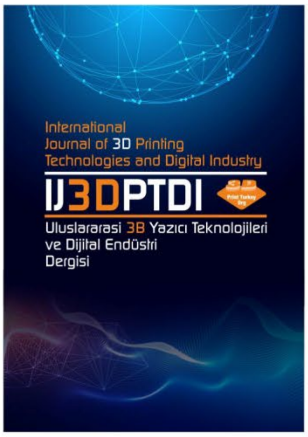

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2D LATTICE GENERATION BY COMPUTATIONAL DESIGN METHOD

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ABSTRACT

Designers often face the challenge of getting stuck with rigid and dogmatic ideas, leading to a limited number of design options being produced. While experience and talent can help overcome this, it can still take a significant amount of time and effort. This study proposes a repeatable, dynamic process that transforms all design components into parameters, creates a structural analysis model, and performs an optimization process that integrates design and structural analysis. Thus, by leveraging the power of technology, designers can generate a larger number of high-quality design options quickly and efficiently. The article evaluates the effectiveness of this proposed method in generating 2D lattice design concepts and highlights its ability to improve the quality of the design options generated and simplify the idea and concept generation process. The novelty of this method lies in its ability to create a flexible and dynamic approach to design, enabling designers to move beyond dogmatic ideas and generate a larger number of innovative design options. Another purpose of this article is to explore the potential of computer-aided computational design software in generating new and innovative design concepts.

Keywords: Computational design, Generative design, Design Optimization, Lattice structures.

1. INTRODUCTION

The creation of a parametric design model through the combination of mathematically expressed design elements in an algorithm has become commonplace in engineering works that require structural performance and low weight [1-2]. These models offer advantages such as automation, speed, and increased variety in geometry. These features of parametric design have special importance in the design of lattice structures. Because of their lightness and strength, lattice structures made of truss or cellular structures are a popular design element in architecture, construction, and mechanical design [3].

Recent advancements in Additive Manufacturing (AM) have provided a new avenue for designing and producing lattice geometry. AM enables the fabrication of structures with micro-dimensions and areas that cannot be produced using traditional manufacturing methods, resulting in structures with superior mechanical properties such as strength, stiffness, and energy absorption [4-5]. Additionally, AM methods offer a wide working field for parametric design, allowing for a high strength-to-volume ratio and an ideal geometry by changing the material distribution in the entire volume [6-7].

The optimization of geometry and shape using parametric, computational, and generative design methods has become a popular area of study. These methods provide an autonomous structural analysis tool in the early design process, allowing for the generation of good/optimal design alternatives quickly and economically [7]. Moreover, it enables the determination of the design option that meets the design and engineering needs while requiring the least revision.

Several studies have explored the application of parametric and computational design methods in different design fields [3]. In architecture, these methods have been used to optimize building shapes for energy efficiency, to create lightweight structures with high structural performance, and to generate form variations with similar functions [8-9]. In machine design, these methods have been used to optimize the design of mechanical components for better performance and reduced weight [10]. Additionally, several studies have examined the use of parametric and generative design methods in the design of lattice structures, focusing on improving their mechanical properties and thermal conductivity [11]. In conclusion, the integration of parametric and computational design methods has become an essential tool in all design fields and activities, providing advantages such as automation, speed, and increased variety in form and geometry. The use of these methods, combined with advancements in AM, has opened up new possibilities in designing lattice geometry with superior mechanical properties. The application of these methods in various design fields has shown promising results and is expected to continue to develop in the future.

2. BACKGROUND

2.1. Computational Design

Computational design involves incorporating design parameters into a design algorithm with advanced computer technology. Computer software creates and evaluates design options with some mathematical operations. Computational design algorithms; create a dynamic, repeatable, and sustainable process. Different from the traditional design process, the use of time and resources is optimal here, as the designer is independent of his knowledge and intuition. Computational design tools break down the overall design structure into meaningful subunits and processes. The input-output relations between these subunits are made with visual programming.

With an interest in computational design, different techniques have been developed over time. Some of these are parametric and generative design concepts/techniques that are often used interchangeably. Although they do not have clear boundaries, they have important differences. First, the parametric design creates an interactive process by establishing semantic relationships between the elements (size, angle, volume, position, etc.) that make up the building. A change to a parameter causes other associated parameters to change automatically. Parametric models enable alternative design exploration with real-time editing capability. On the other hand, generative design is an iterative design technique that can create an infinite number of alternatives with the help of artificial intelligence and cloud technologies according to predetermined design goals. Here, unlike parametric design, design evaluation criteria (weight, amount of material used, manufacturability, strength) are also included in the generative design algorithm. The ideal design is reached by making changes to the design parameters by trial and error. Thus, the design geometry is determined according to the current production method, and it is optimized in terms of strength and material used.

2.2. Design Optimization

Firms/manufacturers try to make economical production that saves material and cost to maintain market competition. In addition, it is aimed that the products produced are robust and long-lasting [12]. All these requirements have caused shape, size, and topology optimization problems in engineering design [13]. Size optimization adjusts material cross-sections and thicknesses to create designs with better performance. Shape optimization, another type of optimization, makes partial changes to the outer geometry of the part. Topology optimization, however, tries to provide the intended physical strength by using the least material under certain load and volume limitations [14-15].

In engineering design, some optimization and artificial intelligence techniques (evolutionary algorithms, swarm intelligence, artificial neural networks, machine learning, etc.) are used for ideal sizing, reshaping, weight, and cost reduction. These techniques have also been used to develop optimum truss and lattice structures. Raina et al. used a deep learning-based design support system for a lattice design problem in one of these studies. This system aimed to create an ideal lattice structure by following the mental processes after sequential design stages [16]. Zhengtong et al. proposed the use of a Particle Swarm Optimization (PSO) algorithm for multi-plane lattice problems with different layout and design configurations [17]. Caferi et al. integrated Cultural Algorithm (CA) into PSO to create an efficient hybrid algorithm for optimal lattice structure design [18]. In addition, algorithms such as Genetic Algorithms (GA), Simulation Annealing (SA), and Differential Evolution (DE) are also widely used in lattice design problem solutions [19-21].

3. MATERIAL AND METHOD

This study proposes a process that will design a lattice structure with maximum energy absorption ability. "Grasshopper," a commercial computational design software, was used to solve the identified problem. Grasshopper is a visual programming language that offers parametric modeling and coding on Rhino CAD [22-23]. Model creation, structural analysis, and optimization can be done with various plug-ins in this software.

There are many unique tools for the operations mentioned above and the like. One of them, Karamba3D enables engineers and designers to perform various structural analyzes and optimizations within the platform. Karamba3D creates more efficient and high-performance designs by considering factors such as material usage, weight and structural integrity [24]. It can be used actively in optimization processes with its integration with other plugins. Another popular plugin, "Galapagos," is a single-purpose shape optimization tool. Optimizing two or more parameters (genome) provides a fitness function that expresses the maximum or minimum numerical value.

The Galapagos plugin includes two different solvers, Evolutionary Algorithm and Simulated Annealing. The Evolutionary Algorithm starts with a certain number of randomly generated populations. Population variation is achieved by creating different genomes over several generations. Each generation's high-performing members (parents) are determined according to their fitness function. New members (children) are formed by crossing the parents. Members with a low fitness value are prevented from being passed on to the next generation. In addition, the entire solution space is scanned with the mutation applied to randomly selected members. This iterative process continues until the specified stopping condition is met [1-2].

The simulation annealing algorithm starts with a random initial solution. Due to its structure, the algorithm avoids local optima by navigating the solution space at the beginning. In the final stages, a precision search is performed to approach the fitness function [25]. It tries to find solutions that meet or are close to the objective function [26]. The simulation annealing process is stopped when a certain number of iterations or the run time has elapsed. Like other heuristic search algorithms, there is always the possibility that the best solution may not be found.

4. RESULTS

This study proposes a computational design process to create 2D lattice geometries with high energy absorption capability. In the first stage of this process, all structures/beams forming the lattice geometry are parametrically modeled in the Grasshopper environment. The numerical range and boundary conditions that the parameters can take are also determined at this stage. A parameter's minimum and maximum value range are arranged so that it does not affect other parameters. The workflow for the study is shown in Figure 1.

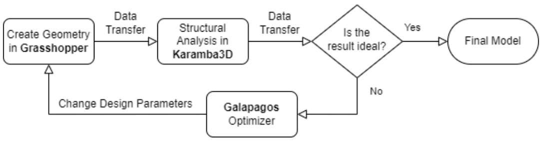

Figure 1. Computational design flowchart

The parametric lattice model used in this research is one of 8 axially equally divided parts of a square. Beam length, position, and angles are determined on one of these equally divided parts. As seen in Figure 2, three different parameters are created to obtain different lattice geometries. A slider is used to set these parameters manually. The sliders here allow dividing a beam length into 100 equal parts and bringing the connection points to the desired position. In the next step, the symmetries of this geometry are created around a diagonal axis. In the last stage, all of these geometries are reproduced by rotating them around a center. The resulting geometry is the unit lattice cell bounded by a square (Figure 3).

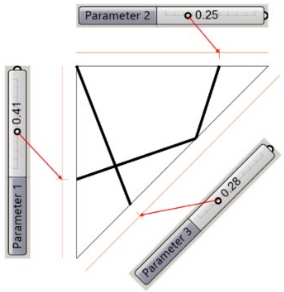

Figure 2. Unit geometry and parametric control representation

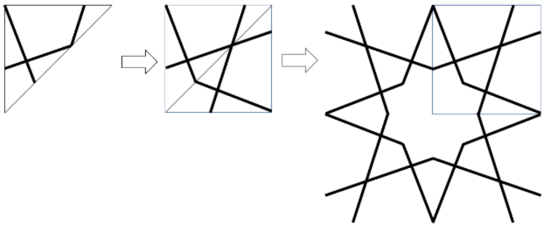

Figure 3. Parametric design steps and lattice unit cell

In order to perform structural analysis on the parametric model, the geometry must be converted to a structural analysis model. The Karamba3D plugin mentioned in the previous section was used in this conversion and analysis Process [24]. In order to determine the relationship of the lattice cell with other lattice cells, a 2x2 periodic structure is first created. In the next step, all beam and connection locations to be analyzed are determined. Then, the support coordinates and support forms to which the structure will be fixed are defined. In order to test the ability of this lattice structure to absorb energy and flex, the direction and magnitude of the loads and forces to be applied are regulated accordingly. After the material and cross-section of the lattice structure are determined, the structural analysis model is completed [24]. The created structural analysis model is shown in Figure 4. Here, the red arrows indicate the position and magnitude of the applied loads, while the green arrows indicate the reaction forces at the support points. The yellow and green markings in the lattice geometry (stress intensity decreases from yellow to green) indicate stress intensity.

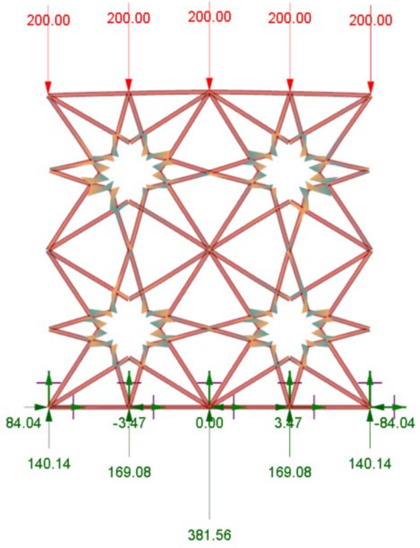

Figure 4. Structural analysis model of Lattice geometry

Since the comparison will be made between Lattice cells, the beam cross-section, size, material, numerical value, and unit of the applied force are unimportant. This study aims not to determine the energy absorption ability but to determine the lattice geometry with the highest energy absorption ability.

At the last stage of the computational design process, the lattice geometry with the highest energy dissipation ability was tried to be determined with the Galapagos optimizer. For this purpose, Input variables such as the value of the applied load, support positions, material, and cross-sectional area are kept constant. Galapagos iteratively performs the structural analysis processes with different combinations of three design parameters defined within certain rules. Here, two different optimization algorithms, Evolutionary Algorithm and Simulated Annealing are used [2, 25]. The ideal design concepts and energy apsorbtion capabilities suggested by the algorithms are shown in Figure 5.

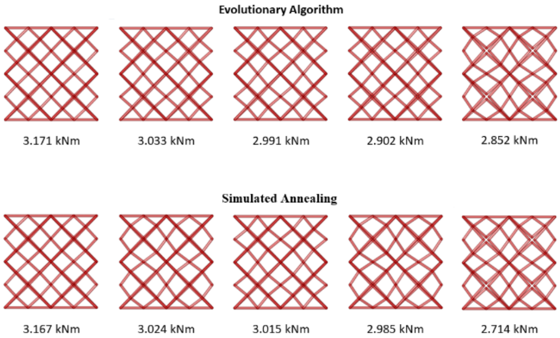

Figure 5. Design concepts generated by Evolutionary Algorithm (top) and Simulated Annealing (bottom)

5. DISCUSSION

This study highlights the effectiveness of the computational design process in detecting lattice geometries with superior energy absorption capabilities. By combining modelling, structural analysis, and optimization techniques, the method facilitates a thorough examination of the design landscape, generating a variety of lattice geometries.

Utilizing the Karamba3D plugin streamlines the structural analysis process and ensures precise evaluations of the lattice geometries. Moreover, developing the 2x2 periodic structure enables a more authentic assessment of the energy absorption potential of the lattice configurations

[24]. The Galapagos optimizer, on the other hand, is instrumental in identifying the lattice geometry with the most efficient energy dissipation capacity. Although the Evolutionary Algorithm and Simulated Annealing yielded comparable outcomes [27], neither has a clear advantage over the other. However, the fact that these two algorithms achieve similar results strongly indicates that the potential global best has been reached [21, 28].

Future investigations could broaden the design scope and enhance the performance of lattice geometries by incorporating additional design parameters and constraints. Integrating alternative optimization algorithms or multi-objective optimization techniques may offer a more in-depth understanding of the compromises between distinct performance metrics and uncover innovative high-performing lattice designs.

6. CONCLUSION

In conclusion, this study presents a computational design process for generating 2D lattice geometries with high energy absorption capabilities. The parametric modeling, structural analysis, and optimization processes were carried out within the Grasshopper environment using the Karamba3D plugin. By defining a set of parametric design rules and constraints, various lattice geometries were generated, analyzed, and optimized to find the optimal geometry with the highest energy absorption ability. The Galapagos optimizer was employed in the final stage of the computational design process, using two different optimization algorithms, Evolutionary Algorithm and Simulated Annealing. Although the best design concepts produced by both algorithms exhibited similar energy dissipation capabilities, the study found that neither algorithm provided a clear advantage over the other in this specific context. Nevertheless, the design concepts generated by these optimization algorithms show promising potential for being global best concepts.

This research demonstrates the power and flexibility of computational design methods in developing innovative and efficient lattice geometries for solving similar design problems. The insights gained from this study can be further explored and applied to various fields, such as architecture, engineering, and materials science, to develop advanced structural solutions that address specific performance requirements. Moreover, future research can expand upon the presented methodology by incorporating additional design parameters, constraints, and optimization techniques, to develop even more effective lattice geometries for energy absorption and other applications. In addition, similar computational design processes can be developed for all outputs obtained with structural analysis models, such as weight, strength, volume, energy absorption, displacement, and Poisson's ratio of the designs produced.

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