Proceedings of the Canadian Society for Mechanical Engineering International Congress 2021
CSME Congress 2021
June 27-30, 2021, Charlottetown, PE, Canada

Mass Optimization of 3D-Printed Composites using Topology Optimization and Artificial Neural Network

Burak Yenigun
Department of Mechanical Engineering
York University
Toronto, Canada
byenigun@yorku.ca

Ahmed Elsayed Moter
Department of Mechanical Engineering
York University
Toronto, Canada
moter@yorku.ca

Mohamed Abdelhamid
Department of Mechanical Engineering
York University
Toronto, Canada
mahamid@yorku.ca

Aleksander Czekanski
Department of Mechanical Engineering
York University
Toronto, Canada
alex.czekanski@lassonde.yorku.ca

***Abstract*—Additive manufacturing is a crucial new trend that is steadily taking over traditional methods. Despite its many advantages, the anisotropic nature of the produced parts of most additive manufacturing methods is a significant disadvantage. Of the methods that suffers from this anisotropy drawback is the fused filament fabrication (also known as fused deposition modeling). As a result of this anisotropy in the mechanical properties, a need arises to define the optimum direction of printing to be used for a certain loading condition.**

Topology optimization is a great numerical design tool for weight and material savings. It's basically used to determine where to put material to optimize a certain objective function under specific constraints. The design variables in a topology optimization are typically chosen as the densities of the finite elements. Adding the printing direction as an additional design variable complicates the problem further. This eventually gives rise to a huge selection of local minima and further increases in the computational costs.

In this work, we attempt to utilize artificial neural networks to tackle this problem. Selected results of mass minimization problems run in ANSYS are used as input data for the neural network model, which is used to predict the fiber angle that has the minimum mass under specific stress constraints. Results so far are promising with small errors considering the computational savings achieved.

***Index Terms*—Topology Optimization, Artificial Neural Network, Additive Manufacturing, Anisotropy, Composites**

I. Introduction

Additive **M**anufacturing (AM) has started to be used extensively in many different industries due to the cost of AM reaching acceptable levels. It enables the production of complex shapes that are not produced by traditional manufacturing methods [1]. Since AM also does not require any mold or machining tools, the part is printed in the desired final shape with minimal waste [2]. In addition, AM is capable of printing in a wide range of different materials, including polymers, ceramic, composites, metallic or hybrid composites [3, 4]. Although AM has valuable advantages, it also has some disadvantages such as energy consumption, long printing time, and non-isotropic properties of the printed parts. **F**used **f**ilament **f**abrication (FFF) - also known as fused deposition modeling, a material extrusion AM technique - is one of the most popular AM methods in the market for both hobbyists and professionals. Due to its material extrusion nature, it's highly anisotropic, where the mechanical properties along the fiber orientation are much better than in the other directions. This property puts additional limitations on the design of parts to be manufactured using this method [5]. One of the solutions to address such a problem is using numerical design tools such as topology optimization.

Topology **o**ptimization (TO) is a freeform design approach that does not require a priori assumption of the final layout. It is frequently used as a design-for AM because it can produce novel, effective design solutions [6–8]. TO has different methods; the modified **s**olid **i**sotropic **m**aterial with **p**enalization (SIMP) is the most popular approach due to its ease of implementation and robustness [9]. Most, if not all, commercial simulation packages that include a topology optimization module typically utilize the SIMP method.

Recently, the research focus shifted from optimizing only the topology of additively-manufactured parts to optimizing the printing angle (i.e. fiber angle) as well. Adding the printing angle as a factor in the optimization problem formulation enhances the optimized output significantly [8–11]. So far, this is performed using gradient-based optimization methods, which have proven to be robust and effective. However, the computational overhead increases dramatically with the size of the problem (i.e. the design domain). From this perspective, **a**rtificial **n**eural **n**etworks (ANN) - one of the most widely used prediction models in AM - can be a viable alternative [12]. ANN presents practical and cost-effective solutions for complicated engineering problems. It is capable of capturing obscure input/output nonlinear correlations from numerical and/or experimental results, where a clear mathematical model is missing or too complex [13].

In this work, we demonstrate - as a proof of concept - how artificial neural networks can be combined with topology optimization methods to minimize the mass of a composite part under stress constraints. The presented numerical example is solved using standard available tools; the engineering analysis software ANSYS for performing topology optimization and the programming environment MATLAB for running the ANN mode [14, 15]. It is worth noting that this work doesn't include any significant in-house proprietary code.

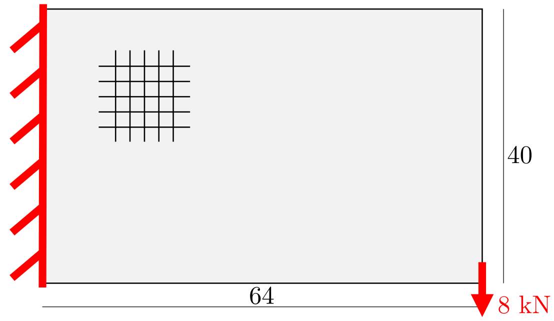

Fig. 1. A cantilever beam of dimensions 40×64 mm is fixed from the left side with a load of 8 kN applied to the bottom right corner.

II. Materials and Methods

A. Material

The material of choice in this study is a glass/epoxy composite. Although such material is not typical for FFF methods, its high anisotropy makes it a great candidate for this study as we emphasize the significance of the fiber direction in the produced part. The 2D properties of this material, where the fibers are aligned with the x-axis, are as follows [16]:

$$\begin{aligned} E_x &= 38.6 \text{ GPa}, \\ E_y &= 8.27 \text{ GPa}, \\ \nu_{xy} &= 0.26, \\ G_{xy} &= 4.14 \text{ GPa}, \\ \rho &= 1,800 \text{ kg/m}^3. \end{aligned} \tag{1}$$

The maximum stress constraint is set to $\sigma_{max} = 9$ MPa. This arbitrary value represents the maximum global von Mises stress to be experienced in the optimized structure.

B. Topology Optimization

TO is performed on ANSYS using its topology optimization module [14]. The problem of choice is a 2D cantilever beam - a standard benchmark problem - with dimensions of 64×40 mm (cf. Fig. 1). A depth of 1 m is assumed, so the problem is considered plane strain. It is fully fixed at the left edge, and a load of 8 kN is applied to the lower right corner. Note that in this work, the whole structure is assumed to have the same printing angle (i.e. fiber orientation) symbolized by θ. The mass minimization problem can be stated as follows:

$$\begin{aligned} \min_{\boldsymbol{\rho}} \quad & M(\boldsymbol{\rho}, \theta) = \sum_{e=1}^{N} \rho_e. \\ \text{s. t.} \quad & \sigma_{\text{vM}} \leq \sigma_{max}, \\ & \mathbf{K}(\boldsymbol{\rho}, \theta)\mathbf{U} = \mathbf{F}, \\ & \mathbf{0} \leq \boldsymbol{\rho} \leq \mathbf{1}. \end{aligned} \tag{2}$$

where M is the mass of the structure, $\boldsymbol{\rho}$ is a vector representing the density of each finite element, θ is the fiber orientation (i.e. printing angle) of the whole structure, N is the number of finite elements, ρ_e is the density of element e, $\mathbf{K}$ is the global stiffness matrix, $\mathbf{U}$ is the global displacement vector, and $\mathbf{F}$ is the global force vector. We opted to consider the mass minimization problem instead of the more popular compliance minimization problem due to the fact that the former is less well-behaved and takes more iterations to converge than the later and hence a more suitable candidate for ANN.

The constitutive matrix for a composite material with a density variable is defined as follows :

$$\mathbf{C} = \begin{bmatrix} \frac{\rho^p\, E_1}{1-\nu_{12}^2} & \frac{\rho^p\, E_2\, \nu_{12}}{1-\nu_{12}^2} & 0 \\ \frac{\rho^p\, E_2\, \nu_{12}}{1-\nu_{12}^2} & \frac{\rho^p\, E_2}{1-\nu_{12}^2} & 0 \\ 0 & 0 & \rho^p\, G_{12} \end{bmatrix}. \tag{3}$$

The print direction (i.e. fiber angle) θ is implemented in the constitutive matrix as follows [17]:

$$\boldsymbol{\sigma} = \mathbf{C}'\boldsymbol{\epsilon}, \tag{4}$$

$$\mathbf{C}'(\theta) = \mathbf{T_1}(\theta)^{-1}\mathbf{C}\mathbf{T_2}(\theta), \tag{5}$$

$$\mathbf{T_1} = \begin{bmatrix} c^2 & s^2 & 2cs \\ s^2 & c^2 & -2cs \\ -cs & cs & c^2 - s^2 \end{bmatrix}, \tag{6}$$

$$\mathbf{T_2} = \begin{bmatrix} c^2 & s^2 & cs \\ s^2 & c^2 & -cs \\ -2cs & 2cs & c^2 - s^2 \end{bmatrix}. \tag{7}$$

where c and s represent $cos(\theta)$ and $sin(\theta)$, respectively. In order to calculate the updated engineering constants (i.e., E'_x, E'_y, ν'_{xy}, and G'_{xy}) after each rotation, the compliance matrix $\mathbf{S}'$ (i.e., inverse of the constitutive matrix $\mathbf{C}'$) and the engineering constants are extracted as follows [18]:

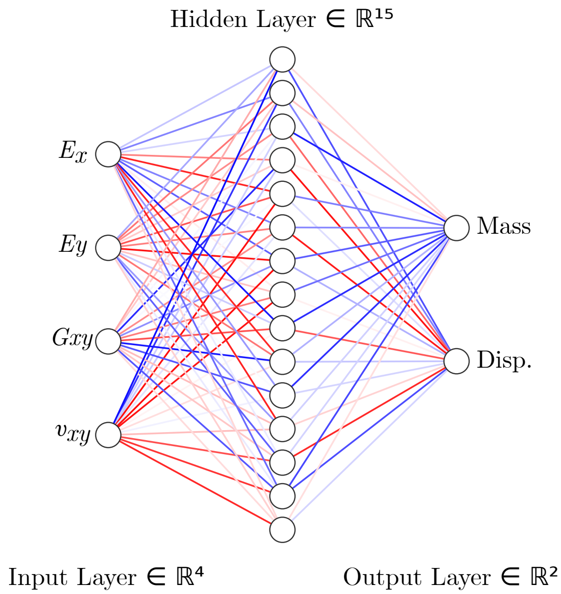

Fig. 2. The artificial neural network model implemented in this study.

$$\mathbf{S}' = \mathbf{C}'^{-1} = \begin{bmatrix} S_{11} & S_{12} & S_{13} \\ S_{21} & S_{22} & S_{23} \\ S_{31} & S_{32} & S_{33} \end{bmatrix}. \tag{8}$$

$$E'_x = \frac{1}{S_{11}}, \tag{9}$$

$$E'_y = \frac{1}{S_{22}}, \tag{10}$$

$$\nu'_{xy} = -\frac{S_{21}}{S_{11}}, \tag{11}$$

$$G'_{xy} = \frac{1}{S_{33}}. \tag{12}$$

A parametric study is performed in ANSYS where the updated engineering constants are used as input with increments of 5° in θ (i.e., from 0° to 180°). Then a mass minimization problem is solved under the predefined formulation (cf. Eq. 2). The mass and maximum deformation are collected from ANSYS to be used as output for training the ANN model.

C. Artificial Neural Network

In this study, a two-layer feed-forward network with 15 hidden neurons is used for the ANN model. The network was trained with the Levenberg-Marquardt back propagation algorithm (cf. Fig. 2). Generally, in literature, 70% of the available data are used for training, 15% for testing, and 15% for validation [13], hence the same rates are used in this study. The elastic moduli in the x and y directions, the shear modulus in the xy plane as well as Poisson's ratio in the xy plane are defined as inputs, and optimized mass and displacement at the load point are defined as outputs.

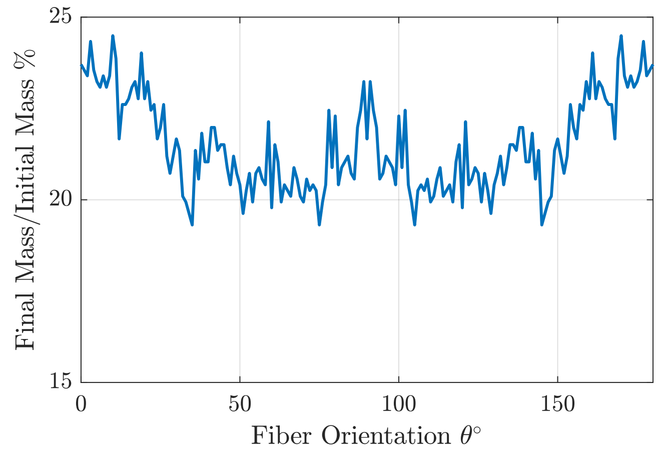

Fig. 3. Final mass percentage of the initial mass for the optimized designs at fiber angles 0° to 180° with 1° increments.

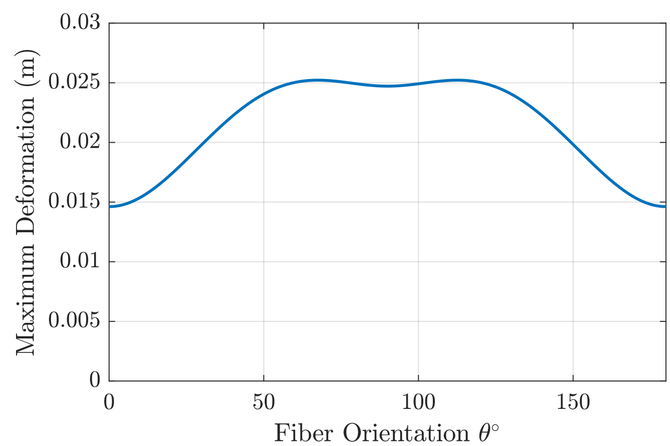

Fig. 4. Maximum displacement of the optimized designs at fiber angles 0° to 180° with 1° increments.

III. Results and Discussion

A. Finite Element Results

In this subsection, FEA results are discussed before running the ANN model. It's worth noting that although ANSYS is used to extract information at fiber angles 0° : 180° with 1° increments, only those at 5° increments are used for the ANN model. The remaining data points are used for verification purposes after the ANN model is run. It is clear from Fig. 3 that the maximum mass savings occur at fiber angles 35° and 75° and by symmetry at 105° and 145° as well. Good mass savings are also achieved at fiber angles 51° and 129°. Figure 4 shows the maximum displacement vs. fiber angles, where it can be seen that the behavior of the maximum displacement is more well-behaved than the final mass.

B. Results of the ANN Model

Considering that the computational cost of running a topology optimization case in ANSYS ($\approx$ a few minutes) is much

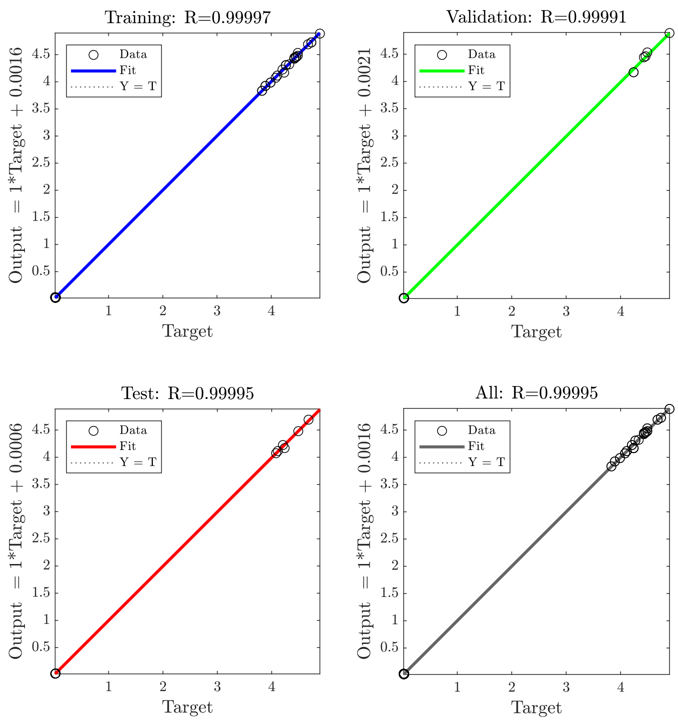

Fig. 5. Regression performance of the ANN model.

larger than that of running the ANN model in MATLAB ($\approx$ a few seconds), we only consider the former while discussing the computational costs. The regression performance of the ANN model is given in Fig. 5, which shows high correlation between simulation data and prediction data. A comparison of the final mass and total deformation for fiber angles at 1° increments is shown in Fig. 6. The percentage error in the final mass doesn't exceed 15%, which seems reasonable when considering that the ANN model results only utilized 20% of the computational cost (i.e., running ANSYS at 1° vs. 5° increments). As for the total deformation, due to its well-behavior in the original problem (cf. Fig. 4), the ANN model shows a much better prediction with the maximum error not exceeding 1% (cf. Fig. 7). The minimum predicted mass from the ANN model occurred at 34° and 74° (and through symmetry at 106° and 146° as well) with final mass errors of 1.8% and 6.4% respectively. The local minimum at 51° was not captured by the ANN model.

IV. Conclusions

In this study, a neural network model is utilized to predict of the final mass and maximum displacement in a topology optimization problem of composites with the fiber angle as an additional design variable. The input data are topology optimization cases run in ANSYS with a fiber angle of 0° to 180° with a 5° increment. The 1° increment data is utilized after the ANN model is run to verify the results manually. ANN predictions showed maximum mass savings at 34° and 74° with small errors. Overall, we consider the results

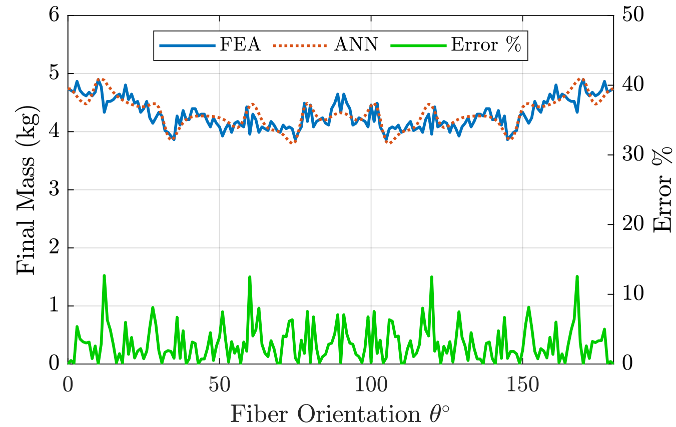

Fig. 6. Regression performance of the ANN model.

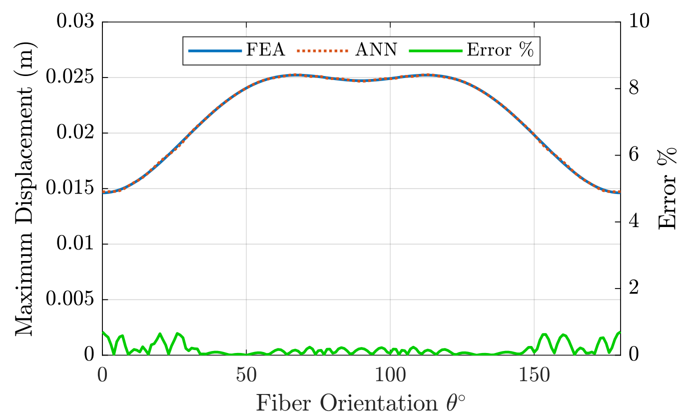

Fig. 7. Regression performance of the ANN model.

promising given that the savings in computational costs are 80%.

Future work includes modifying the increment in the fiber angle design variable from a constant value (5° in this study) to a varying value that could be defined from initial output data from the ANN model. We also plan to extend the complexity of the model by including the direction of the load as an additional design variable.

A note-worthy remark on this particular example is in order. It's a valid suggestion to tackle this problem as a topology optimization case with both the finite elements' densities as well as the fiber orientation as design variables. However, from our experience and the literature's, this problem is not well-behaved and tends to produce local minima depending on the initial guess and the optimizer settings. Also, including any additional design variables or constraints tends to complicate the problem ever further.

References

[1] Carmita Camposeco-Negrete. Optimization of printing parameters in fused deposition modeling for improving part quality and process sustainability. *The International*

Journal of Advanced Manufacturing Technology, 108(7-8):2131–2147, jun 2020. ISSN 0268-3768. DOI:10.1007/s00170-020-05555-9.

[2] Junhui Wu. Study on optimization of 3D printing parameters. In *IOP Conference Series: Materials Science and Engineering*, volume 392, page 062050. Institute of Physics Publishing, aug 2018. DOI:10.1088/1757-899X/392/6/062050.

[3] Syed A.M. Tofail, Elias P. Koumoulos, Amit Bandyopadhyay, Susmita Bose, Lisa O'Donoghue, and Costas Charitidis. Additive manufacturing: scientific and technological challenges, market uptake and opportunities. *Materials Today*, 21(1):22–37, jan 2018. ISSN 13697021. DOI:10.1016/j.mattod.2017.07.001.

[4] N. Shahrubudin, T.C. Lee, and R. Ramlan. An Overview on 3D Printing Technology: Technological, Materials, and Applications. *Procedia Manufacturing*, 35:1286–1296, jan 2019. ISSN 23519789. DOI:10.1016/j.promfg.2019.06.089.

[5] M. Somireddy, C. V. Singh, and A. Czekanski. Analysis of the Material Behavior of 3D Printed Laminates Via FFF. *Experimental Mechanics*, 59(6):871–881, jul 2019. ISSN 0014-4851. DOI:10.1007/s11340-019-00511-5.

[6] Tomás Zegard and Glaucio H. Paulino. Bridging topology optimization and additive manufacturing. *Structural and Multidisciplinary Optimization*, 53(1):175–192, jan 2016. ISSN 1615-147X. DOI:10.1007/s00158-015-1274-4.

[7] Jikai Liu, Andrew T. Gaynor, Shikui Chen, Zhan Kang, Krishnan Suresh, Akihiro Takezawa, Lei Li, Junji Kato, Jinyuan Tang, Charlie C. L. Wang, Lin Cheng, Xuan Liang, and Albert C. To. Current and future trends in topology optimization for additive manufacturing. *Structural and Multidisciplinary Optimization*, 57(6):2457–2483, jun 2018. ISSN 1615-147X. DOI:10.1007/s00158-018-1994-3.

[8] Josephine V. Carstensen. Topology optimization with nozzle size restrictions for material extrusion-type additive manufacturing. *Structural and Multidisciplinary Optimization*, 62(5):2481–2497, nov 2020. ISSN 1615-147X. DOI:10.1007/s00158-020-02620-5.

[9] Delin Jiang, Robert Hoglund, and Douglas Smith. Continuous Fiber Angle Topology Optimization for Polymer Composite Deposition Additive Manufacturing Applications. *Fibers*, 7(2):14, feb 2019. ISSN 2079-6439. DOI:10.3390/fib7020014.

[10] Aaditya Chandrasekhar, Tej Kumar, and Krishnan Suresh. Build optimization of fiber-reinforced additively manufactured components. *Structural and Multidisciplinary Optimization*, 61(1):77–90, jan 2020. ISSN 1615-147X. DOI:10.1007/s00158-019-02346-z.

[11] Martin-Pierre Schmidt, Laura Couret, Christian Gout, and Claus B. W. Pedersen. Structural topology optimization with smoothly varying fiber orientations. *Structural and Multidisciplinary Optimization*, 62(6):3105–3126, dec 2020. ISSN 1615-147X. DOI:10.1007/s00158-020-02657-6.

[12] Muhammad Arif Mahmood, Anita Ioana Visan, Carmen Ristoscu, and Ion N. Mihailescu. Artificial Neural Network Algorithms for 3D Printing. *Materials*, 14(1):163, dec 2020. ISSN 1996-1944. DOI:10.3390/ma14010163.

[13] Burak Yenigun and Erol Kilickap. Prediction of the Tensile Load of Drilled CFRP by Artificial Neural Network. *Applied Sciences*, 8(4):549, apr 2018. ISSN 2076-3417. DOI:10.3390/app8040549.

[14] ANSYS Mechanical User's Guide, 2020. https://www.ansys.com/, Accessed on 2021-02-01.

[15] MATLAB Online Documentation, 2020. https://www.mathworks.com/, Accessed on 2021-02-01.

[16] S. Adali, J. C. Bruch, I. S. Sadek, and J. M. Sloss. Simultaneous design/control optimization of symmetric cross-ply laminates of hybrid construction. *Engineering Optimization*, 17(1-2):123–140, feb 1991. ISSN 0305-215X. DOI:10.1080/03052159108941065.

[17] Carl T. Herakovich. *Mechanics of Fibrous Composites*. Wiley, New York, first edition, 1998. ISBN 9780471106364.

[18] Mohamed Abdelhamid and Aleksander Czekanski. Impact of the Lattice Angle on the Effective Properties of the Octet-Truss Lattice Structure. *Journal of Engineering Materials and Technology*, 140(4):1–11, oct 2018. ISSN 0094-4289. DOI:10.1115/1.4040409.