A DATA-DRIVEN WORKFLOW FOR MODELLING SELF-SHAPING WOOD BILAYER

Utilizing natural material variations with machine vision and machine learning

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Abstract. This paper develops a workflow to train machine learning (ML) models with a small dataset from physical samples to predict the curvatures of self-shaping wood bilayers based on local variations in the grain. In contrast to state-of-the-art predictive models, specifically 1.) a 2D Timoshenko model and 2.) a 3D numerical model with a rheological model, our method accounts for natural and unavoidable material variations. In this paper, we only focus on local grain variations as the main driver for curvatures in small-scale material samples. We extracted a feature matrix from grain images of active and passive layers as a Grey Level Co-Occurrence Matrix and used it as the input for our ML models. We also analysed the impact of grain variations on the feature matrix. We trained and tested several tree-based regression models with different features. The models achieved very accurate predictions for curvatures in each sample (R^2>0.9) and extend the range of parameters that is incalculable by a Timoshenko model. This research contributes to the material-efficient design of weather-responsive shape-changing wood structures by further leveraging the use of natural material features and explainable data-driven modelling and extends the topic in ML for material behaviour-driven design among the CAADRIA community.

Keywords. Data-Driven Model; Machine Learning; Material Programming; Smart Material; Timber Structure; SDG 12.

1. Introduction

Natural materials like wood uniquely show anisotropic changes in shape in response to changes in moisture combined with impressive structural and ecological properties

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(Rowell, 2005). The swelling and shrinking in wood occurs mainly perpendicular to the stiff cellulose microfibrils upon water uptake and loss, whereas the microfibrils prevent most swelling parallel to their orientation. This hygroscopic property can be utilized in "smart" weather-responsive shape-changing natural fibre composites materials such as a double-layered build-up of cross-laminated timber composite (bilayer) (Rüggeberg and Burgert, 2015) to create specific bending effects from flat to curved with various applications in architectural structures (Menges and Reichert, 2012; Wood et al., 2016; Wood et al., 2018). In bilayer, one layer serves as the actuator through shrinkage (active layer), while the other turns the motion into bending (passive layer).

A material behaviour-driven shaping method allows the construction of structurally efficient, form active, curved wood structures with minimal waste and labour, and little formwork or machining (Wood et al., 2020). However, the advantages of using wood as a self-shaping material come with the challenges of working with the imperfections of a naturally grown material and its often high levels of variation in structuring even under ideal conditions. The most influential parameters in predicting how wood hygroscopic shape changes are dependent on the arrangement of the fibrous structure and the orientation of the grains within the standardised board geometries.

In contrast to the material characteristics, methods of modelling self-shaping wood currently rely on simplified material models: either a 2D analytical model based on Timoshenko's theory (Rüggeberg and Burgert, 2015) or a combination of rheological models and a 3D non-linear numerical model (Grönquist et al., 2018). Even though these models were good at predicting the behaviour of a wood board, they always assume reduced variability on each wood board while, in reality, each wood board has a different range of properties and feature variations. These models also have a limitation on simulating only certain bilayer configurations and unaccountability for more complex designed variations in the layouts and layups of the laminates.

Besides the simplified modelling methods, the industry is capable of collecting highly specific and high-quality variable material features data from each wood board using machine vision technology (Olsson and Oscarsson, 2017; Wimmer et al., 2021), but the main focus is on grading and elimination (Ramage et al., 2017) which creates waste and material resource inefficiency (Barber et al., 2020). This acquired material features data opens the opportunity to better integrate material uncertainties as a material behaviour-driven agency in modelling and design.

Recent projects in computational design and fabrication use machine learning (ML) models to understand material uncertainties. Artificial neural networks predicted inconsistent spring back in robotic metal forming using a small dataset from physical samples (Zwierzycki et al., 2017; Rossi et al., 2019). Fragkia et al. (2021) trained a generative adversarial network to predict the geometry of self-shaping single-layer wood veneer strips but only focused on designed grain variations by the layup setup. Vasquez (2021) trained a deep convolutional neural network with paired images from serial events in a robotic concrete sheet forming to predict non-linear deformation behaviour. He et al. (2021) used a synthetic dataset to train a Gaussian mixture model convolutional operator that predicts the geometry of self-shaping textile.

We propose a data-driven workflow to predict the final shape of self-shaping wood bilayers using ML algorithms with a small dataset from physical samples to complement the state-of-the-art predictive models. In this paper, we focus on local grain variations as the main driver of variable curvatures in small-scale wood bilayer samples made of European beech veneers. Figure 1 illustrates our main contributions in this paper as follows: 1.) an experimental method to build a dataset from wood bilayer samples, 2.) data augmentation and features generation for ML-ready data using machine-vision approaches, and 3.) the development of ML-based predictive models using various tree-based regression algorithms.

2. Methods

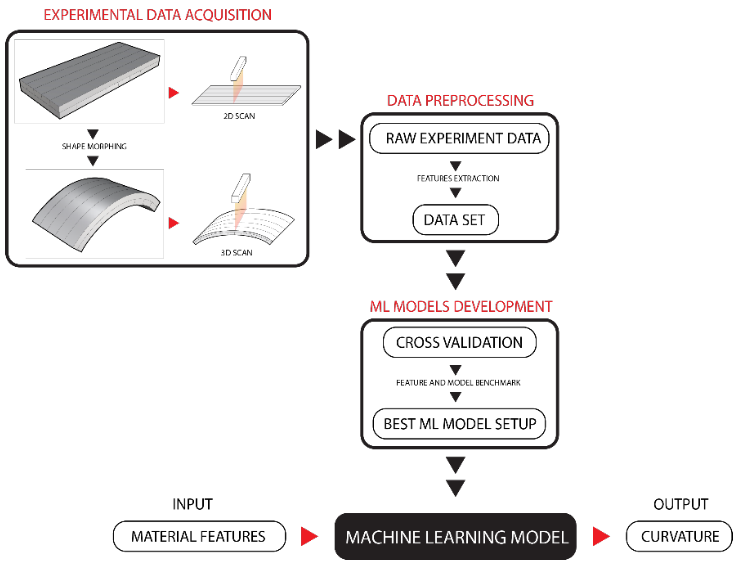

Figure 1. A flow chart of data-driven modelling for predicting self-shaping behaviour of wood bilayer. It includes bilayers sample production and data acquisition, data pre-processing, and ML models development.

2.1. SAMPLE PRODUCTION AND DATA ACQUISITION

We produced 30 small-scale wood bilayer samples using European beech veneers with visible natural variations in the longitudinal (L) axis of the sheets and variable growth ring inclinations. We equalized the active layer sheets inside a moisture-controlled chamber for adsorption at 95% RH to achieve a wood moisture content (WMC) of 20±2%. We used one thickness ratio of $h_1 : h_2 = 1 : 1$ (passive : active) with a total thickness of 4mm. We laminated both layers perpendicularly using 1cPUR adhesive (HB S309 Purbond, Henkel & Cie. AG, Switzerland). We cut the sheets into smaller bilayer strips with a uniform size (width: 60 mm and length: 180 mm) and stored them again inside the moisture-controlled chamber for re-equalization.

We acquired data in both flat and curved states. We used a flatbed scanner to scan the surface grain of both active and passive layers right after removing the samples from the chamber. We relocated the samples to 26±2% RH and room temperature for actuation. We measured each sample's weight several times during the acclimatization period (120 hours) to make sure that the samples are fully equalized. Finally, we 3D scanned each actuated sample using a laser scanner.

2.2. DATA AUGMENTATION AND PRE-PROCESSING

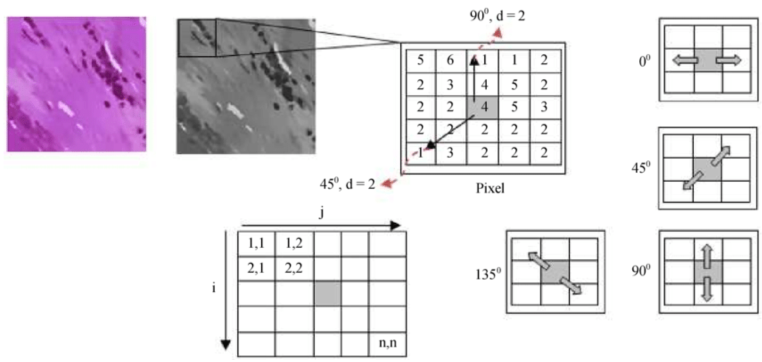

Figure 2. Illustration of GLCM with various angles (0, 45, 90, and 135) and distance (d = 2) orientation from the reference pixel (Haryanto et al., 2020).

To prepare ML-ready data, we did two consecutive steps to the physical samples data which are data augmentation and pre-processing. We augmented the data from 30 to 120 data points by flipping, mirroring, and rotating the grain images and 3D point clouds. We pre-processed both active and passive layer grain images to extract their features (Figure 2). We converted the grain images into greyscale images and enhanced the contrast using an exposure equalization algorithm. We extracted texture features from each image, known as Haralick features (Haralick & Shanmugam, 1973). Each feature is calculated as a Gray Level Co-occurrence Matrix (GLCM), a histogram of co-occurring grayscale values in neighbouring pixels at a given offset with a specific distance and angle over an image. In this paper, we used one distance (2 px) and three angles for each layer (active: 0°, 45°, and 315° and passive: 45°, 90°, and 135°) to extract six main features: contrast, dissimilarity, homogeneity, ASM, energy, and correlation. We combined these processes in a custom python-based image analysis workflow using Scikit-image (van der Walt et al., 2014). Using Rhino and Grasshopper, we reconstructed each 3D point cloud into a surface to compute the principal curvature that is parallel to the L axis of the strip. For each feature, we built a dataset that contains six values calculated from different angles for both layers and the curvature of the bilayer strips

2.3. MACHINE LEARNING MODELS DEVELOPMENT

We first split the dataset into a training set (90 data points) and a test set (30 data points). We trained four tree-based regression algorithms: Random Forest (RF), Decision Tree (DT), Gradient Boosting (GB), and Extra Tree (ET) which are very good at learning from non-linear data (Lundberg et al., 2019) and understanding how the model uses the input features to predict by visualizing the decision path of the tree (Lundberg & Lee, 2017). Using six-fold cross-validation, we calculated the coefficient of determination (R^2), which is the degree of variability a model explains, to benchmark various combinations of input features and ML algorithms. The benchmark also helps to study the possibility of using a minimum amount of input features to reduce ML models' complexity. We used the implementation of these algorithms in Scikit-learn (Pedregosa et al., 2011).

We also calculated the curvature using the adaptation of Timoshenko's theory (Timoshenko, 1925) in Rüggeberg and Burgert (2015) which is subjected to a WMC change $\omega - \omega_0$ where h_1 and h_2 denote layer thicknesses, α_1 and α_2 are the differential swelling coefficients taken from references (Hassani et al., 2015), and E_1 and E_2 are the stiffness in the corresponding fibre orientation of each layer, taken from Hering et al. (2012) (Equation 1). We calculated a range of curvatures using three different angles for Radial/Tangential (RT) grain (0°, 45°, and 90°) to differentiate the material parameters of the active layer (E_2, α_1 and α_2) since it was impossible to measure from the active layer.

$$\frac{1}{\rho} = \frac{6(1+m)^2}{(3(1+m)^2+(1+mn)(m^2+\frac{1}{mn}))}\frac{(\alpha_2-\alpha_1)(\omega-\omega_0)}{h} = k\frac{\Delta\alpha\Delta c}{h}, \mathrm{m} = \frac{\mathrm{h}_1}{\mathrm{h}_2}, n = \frac{\mathrm{E}_1}{\mathrm{E}_2} \quad (1)$$

Finally, we compared the prediction accuracy of the best ML model with the Timoshenko model to the curvature measured from physical samples.

3. Results and Discussion

Our GLCM implementation produced efficient and effective inputs for the ML algorithms. We managed to encode the local grain variations in each sample into a small number of vectors without over-simplification. Table 1 shows our analysis on the influence of grain variations on the values of six main Haralick features (contrast, dissimilarity, homogeneity, ASM, energy, and correlation) for different angles from the grain images of active and passive layers of each sample (active: 0°, 45°, and 315° and passive: 45°, 90°, and 135°) after contrast equalization as shown in Figure 3. We used the data to identify the orientation of medullary ray spindles and growth rings in each strip. The data shows that the direction of medullary ray spindles is indicated by the highest values for homogeneity, ASM, energy, and correlation as well as the lowest values for contrast and dissimilarity. We also found that the deviations between the main angle variables for the GLCM indicate the orientation difference between the medullary ray spindles with the annual growth ring texture.

Figure 4 compares two samples with parallel and non-parallel relationships between the medullary ray spindles and the annual growth ring texture that are shown on the surface of the European beech veneer strips. Table 2 shows that the standard deviation in the data is smaller in non-parallel textures. This information may indicate the veneer sample's cutting orientation that can be advantageous for our research.

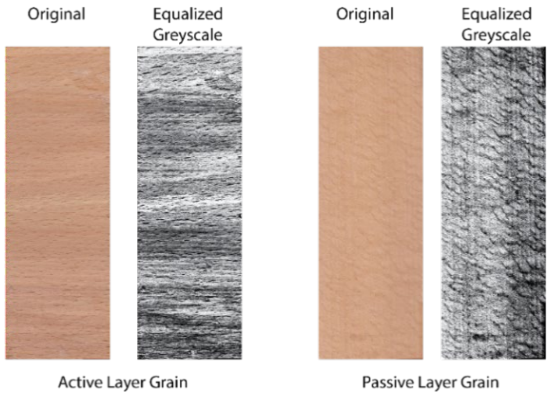

Figure 3. The active and passive layer grains from sample no.6 and the equalized grayscale images.

	Active			Passive		
	0°	45°	315°	45°	90°	135°
Contrast	**3354,672**	7543,229	7213,122	**5882,220**	6627,176	7202,329
Dissimilarity	**42,737**	67,839	66,331	**59,372**	63,448	66,708
Homogeneity	**0,039235**	0,018837	0,019352	**0,022476**	0,021648	0,019135
ASM	**3,3653E-05**	1,8177E-05	1,8521E-05	**2,0292E-05**	1,9653E-05	1,8167E-05
Energy	**0,005801**	0,004263	0,004303	**0,004504**	0,004433	0,004262
Correlation	**0,690379**	0,303462	0,333927	**0,455012**	0,387353	0,332715

Table 1. The Haralick features were calculated from sample no.6 in Figure 3. The bold values indicate the dominant angle in the grain.

Figure 4. (Left) Spindles formed by the medullary rays run mostly parallel to the annual growth ring. (Right) Spindles formed by the medullary rays running mostly at an angle of 315° to the annual growth ring.

Left			Right		
0°	45°	315°	0°	45°	315°
5178,516	8084,819	8464,274	8776,126	8683,538	**8148,223**
Std. Deviation: **1797,534**			Std. Deviation: **443,994**		

Table 2. The contrast from different angles and the data deviation from images in Figure 4.

Our benchmark using six-fold cross-validation shows that two algorithms (DT and ET) give very good R^2 for the training set. ET with energy features as the inputs performs as the best model with the highest R^2 of 0.902 (Figure 5). The results indicate that choosing an appropriate model and input features is important to capture the natural variations in wood grains that affect the curvatures. Figure 6 shows the distribution of predicted curvatures from the best model (ET with energy features as inputs) versus real curvatures measured from physical samples and curvatures calculated using a Timoshenko model. Using only visual input for the L grain directions, the data-driven model can predict the curvature of bilayers with a thickness ratio $h_1 : h_2$ of 1 : 1 with higher accuracy than the Timoshenko model and such expands the range of thickness ratios that can be accurately predicted as the Timoshenko model usually over-predicts curvatures in this range (Grönquist et al., 2018).

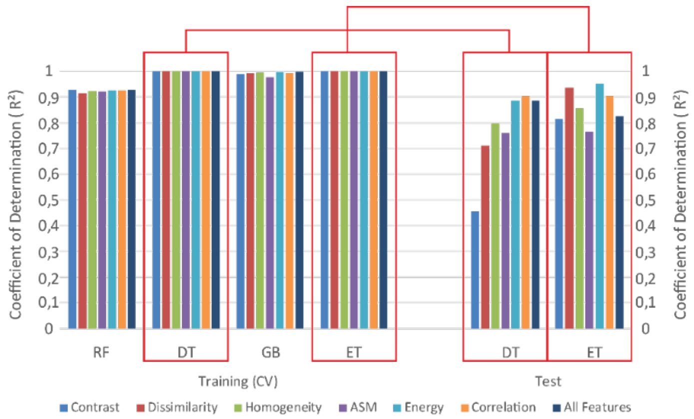

Figure 5. Coefficient of determination (R^2) of various ML algorithms using a different set of features for both training set (evaluated using -fold cross-validation) and the test set R^2 of the best models out of the cross-validation. Algorithms: Random Forest (RF), Decision Tree (DT), Gradient Boost (GB), and Extra Tree (ET).

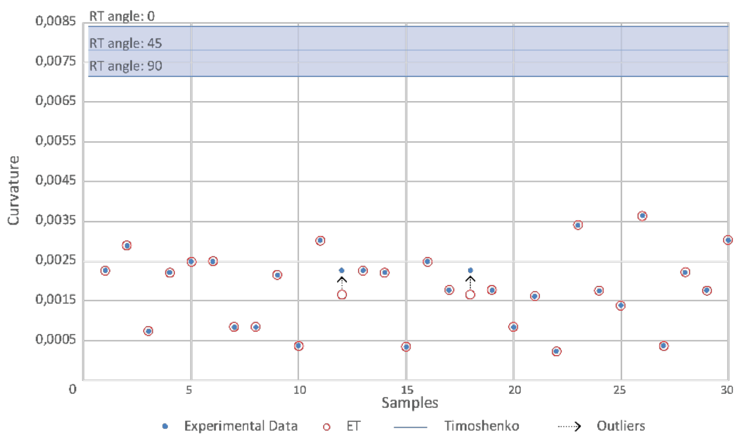

Figure 6. Distribution of predicted curvatures from the best model (ET with energy features as inputs) vs. the real curvatures vs. Timoshenko in three different RT angles.

4. Limitations

We recognize some limitations in our current research that we would like to develop in the future. There is a limitation in material properties and scale as material behaviour changes when the scale changes. The effect of features might also be different across different scales. To work on this issue, we plan to test several techniques such as hybrid modelling that uses a data-driven model based on experimental data (high fidelity) to correct parameters in simulated models (low fidelity) or transfer learning.

Our current models are now limited to a narrow range of curvatures due to the constant bilayer configuration. We want to extend the curvature range in the dataset by adding more variations in thickness and aspect ratios. We also aim to develop models that can read, process, and return spatial information. We will test and implement various analysis techniques that can represent local variations in grain as 2D or 3D vector fields by processing images or computerized tomography scan data as inputs and return 3D information as the prediction. Such models will be more sufficient to be implemented as design tools for free-form wood structures, yet require bigger data set as the complexity of the models also expands. In this case, we will compare our future models with 3D numerical models to evaluate their performance.

5. Conclusion

In conclusion, our paper reports a proof-of-concept for employing ML algorithms, a small dataset from physical samples, and machine vision techniques to model the hygroscopic behaviour of self-shaping wood bilayers in a way that incorporates the naturally inhomogeneous characteristics of wood. Despite focusing only on one wood bilayer setup, our models can work on a thickness ratio setup that was impossible for a Timoshenko model and establish a reliable relationship between the local grain variations and the curvature of self-shaping wood bilayers. The modelling of such relationships is difficult with state-of-the-art models, yet it is essential to produce more realistic predictions.

Using machine-vision-based features generation techniques such as a GLCM and tree-based regression models opens a new research horizon in the development of explainable Artificial Intelligence (AI)-based predictive models for designing self-shaping wood bilayer structures. Even though it is not yet further explored in this paper, tree-based regression models can provide decision paths that can help to explain how specific combinations of variable grains in wood boards produce certain curvatures.

We also envision technology-driven innovations in wood construction that promote more material resourcefulness and responsible material consumption by minimizing material loss due to the wood sorting process that only considers idealized wood variations. We plan to combine the techniques in this paper with combinatorial optimization algorithms to build a tool for designing a self-shaping wood structure that not only accounts for material feature variations but also material resource availability.

Finally, our research should be integral with the United Nation's Sustainable Development Goal 12 to ensure sustainable consumption and production patterns and complement previous research in ML for material behaviour-driven design within the CAADRIA community, specifically in data generation technique and ML model explorations.

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References

Fragkia, V., Foged, I. W., & Pasold, A. (2021). Predictive Information Modeling: Machine Learning Strategies for Material Uncertainty. *Technology|Architecture + Design*, 5(2), 163–176. https://doi.org/10.1080/24751448.2021.1967057

Grönquist, P., Wittel, F. K., & Rüggeberg, M. (2018). Modeling and design of thin bending wooden bilayers. *PLOS ONE*, 13(10), e0205607. https://doi.org/10.1371/journal.pone.0205607

Grönquist, P., Wood, D., Hassani, M. M., Wittel, F. K., Menges, A., & Rüggeberg, M. (2019). Analysis of hygroscopic self-shaping wood at large scale for curved mass timber structures. *Science Advances*, 5(9), eaax1311. https://doi.org/10.1126/sciadv.aax1311

Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). Textural Features for Image Classification. *IEEE Transactions on Systems, Man, and Cybernetics*, 3(6), 610–621. https://doi.org/10.1109/TSMC.1973.4309314

Haryanto, T., Pratama, A., Suhartanto, H., Murni, A., Kusmardi, K., & Pidanic, J. (2020). Multipatch-GLCM for Texture Feature Extraction on Classification of the Colon Histopathology Images using Deep Neural Network with GPU Acceleration. *Journal of Computer Science*, 16(3), 280–294. https://doi.org/10.3844/jcssp.2020.280.294

Hassani, M. M., Wittel, F. K., Hering, S., & Herrmann, H. J. (2015). Rheological model for wood. *Computer Methods in Applied Mechanics and Engineering*, 283, 1032–1060. https://doi.org/10.1016/j.cma.2014.10.031

He, X., Grassi, G., & Paoletti, I. (2021). Geometric Deep Learning: Prediction of Shape-Shifting Textiles. In *The 12th Annual Symposium on Simulation for Architecture and Urban Design (SimAUD): Human+*, SimAUD 2021. The Symposium on Simulation for Architecture and Urban Design (SimAUD).

Hering, S., Keunecke, D., & Niemz, P. (2012). Moisture-dependent orthotropic elasticity of beech wood. *Wood Science and Technology*, 46(5), 927–938. https://doi.org/10.1007/s00226-011-0449-4

Lundberg, S., & Lee, S.-I. (2017, November 24). A Unified Approach to Interpreting Model Predictions. In *The 31st Conference on Neural Information Processing Systems 2017*. The Conference on Neural Information Processing Systems (NeurIPS).

Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., & Lee, S.-I. (2019). Explainable AI for Trees: From Local Explanations to Global Understanding. *ArXiv:1905.04610 [Cs, Stat]*. Retrieved January 10, 2022, from http://arxiv.org/abs/1905.04610

Menges, A., & Reichert, S. (2012). Material Capacity: Embedded Responsiveness. *Architectural Design*, 82(2), 52–59. https://doi.org/10.1002/ad.1379

Olsson, A., & Oscarsson, J. (2017). Strength grading on the basis of high resolution laser scanning and dynamic excitation: A full scale investigation of performance. *European Journal of Wood and Wood Products*, 75(1), 17–31. https://doi.org/10.1007/s00107-016-1102-6

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research,* 12(85), 2825–2830.

Ramage, M. H., Burridge, H., Busse-Wicher, M., Fereday, G., Reynolds, T., Shah, D. U., Wu, G., Yu, L., Fleming, P., Densley-Tingley, D., Allwood, J., Dupree, P., Linden, P. F., & Scherman, O. (2017). The wood from the trees: The use of timber in construction. *Renewable and Sustainable Energy Reviews*, 68, 333–359. https://doi.org/10.1016/j.rser.2016.09.107

Rossi, G., & Nicholas, P. (2018). Re/Learning the Wheel. Methods to Utilize Neural Networks as Design Tools for Doubly Curved Metal Surfaces. In *ACADIA 2018: Recalibration. On Imprecision and Infidelity*, (pp. 146–155). The Association for Computer Aided Design in Architecture (ACADIA).

Rowell, R. M. (Ed.). (2012). *Handbook of Wood Chemistry and Wood Composites (2nd ed.)*. CRC Press. https://doi.org/10.1201/b12487

Rüggeberg, M., & Burgert, I. (2015). Bio-Inspired Wooden Actuators for Large Scale Applications. *PLOS ONE,* 10(4), e0120718. https://doi.org/10.1371/journal.pone.0120718

van der Walt, S., Schönberger, J. L., Nunez-Iglesias, J., Boulogne, F., Warner, J. D., Yager, N., Gouillart, E., & Yu, T. (2014). scikit-image: Image processing in Python. *The PeerJ Bioinformatics Software Tools Collection*, 2, e453. https://doi.org/10.7717/peerj.453

Vasques, A. N. (2021). Utilizing U-Net shaped networks as simulation tools in form-finding processes for fabric. In *The 12th Annual Symposium on Simulation for Architecture and Urban Design (SimAUD): Human+, SimAUD 2021. The Symposium on Simulation for Architecture and Urban Design (SimAUD).*

Wimmer, G., Schraml, R., Hofbauer, H., Petutschnigg, A., & Uhl, A. (2021). Two-Stage CNN-Based Wood Log Recognition. In O. Gervasi, B. Murgante, S. Misra, C. Garau, I. Blečić, D. Taniar, B. O. Apduhan, A. M. A. C. Rocha, E. Tarantino, & C. M. Torre (Eds.), *Computational Science and Its Applications – ICCSA 2021* (Vol. 12955, pp. 115–125). Springer International Publishing.

Wood, D., Brütting, J., & Menges, A. (2018). Self-Forming Curved Timber Plates: Initial Design Modeling for Shape-Changing Material Buildups. In *The Annual Symposium of the International Association for Shell and Spatial Structures, IASS 2018*. The International Association for Shell and Spatial Structures (IASS).

Wood, D. M., Correa, D., Krieg, O. D., & Menges, A. (2016). Material computation—4D timber construction: Towards building-scale hygroscopic actuated, self-constructing timber surfaces. *International Journal of Architectural Computing*, 14(1), 49–62. https://doi.org/10.1177/1478077115625522

Wood, D., Grönquist, P., Bechert, S., Aldinger, L., Riggenbach, D., Lehmann, K., Rüggeberg, M., Burgert, I., Knippers, J., Menges, A. (2020). From Machine Control to Material Programming: Self-Shaping Wood Manufacturing of A High Performance Curved Clt Structure – Urbach Tower. In Burry, J., Sabin, J., Sheil, B., & Skavara, M. (Eds.), *Fabricate 2020* (pp. 50–57). UCL Press

Wood, D., Vailati, C., Menges, A., & Rüggeberg, M. (2018). Hygroscopically actuated wood elements for weather responsive and self-forming building parts – Facilitating upscaling and complex shape changes. *Construction and Building Materials*, 165, 782–791. https://doi.org/10.1016/j.conbuildmat.2017.12.134

Zwierzycki, M., Nicholas, P., & Ramsgaard Thomsen, M. (2018). Localised and Learnt Applications of Machine Learning for Robotic Incremental Sheet Forming. In K. De Rycke, C. Gengnagel, O. Baverel, J. Burry, C. Mueller, M. M. Nguyen, P. Rahm, & M. R. Thomsen (Eds.), *Humanizing Digital Reality* (pp. 373–382). Springer Singapore. https://doi.org/10.1007/978-981-10-6611-5_32