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SKETCH-TO-BIM: ENHANCING THE DYNAMO BASED AUTOMATED TRUSS DESIGN OPTIMIZATION WORKFLOW

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Abstract

Although digital technologies have enhanced structural designers' capabilities for optimal designs, reliance on manual workflows still poses obstacles in modeling, analysis, and optimization. This raises the question of feasibility for a combined framework, focusing on an adaptive, automated workflow to transform hand-sketched truss designs into optimized structural models in a Visual Programming (VP) environment while employing Building Information Modeling (BIM) tools. Thus, the research unfolds: (i) training a deep-learning model for feature extraction; (ii) developing a sketch application to connect Dynamo to any touchscreen device to streamline the draft generation process; (iii) converting optimized sketches from Dynamo to validated structural models in Robot Structural Analysis (RSA); (iv) validating the proposed method with a benchmark problem sourced from the open literature. Results of this unified Sketch-to-BIM workflow demonstrate valuable improvements in design accuracy, weight reduction, and structural performance, along with significant time savings as the entire cycle completes in approximately 13 minutes, reducing the duration of typical manual workflows by an order of magnitude.

Keywords: dynamo, metaheuristic algorithms, optimization, robot structural analysis, sketch-to-bim.

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1. Introduction

The Architecture, Engineering, Construction, and Operations (AECO) industry is increasingly adopting digital solutions with Building Information Modeling (BIM) to enhance efficiency, accuracy, optimization, and positive environmental impact. Generative Deep-Learning (DL) models for automated design and visualization topics are becoming increasingly evident [1], yet these designs are usually limited to image form, and transforming them into conceptual and optimized digital engineering models is challenging [2], [3], [4]. In this context, the referenced study [5] aimed to convert architectural sketches into BIM models by employing a DL-based framework along with processes such as preprocessing, thinning, and line segmentation, to enhance client-architect communication. In [6], the authors attempted to convert 2D structural sketches, such as beams and columns, into Finite-Element Analysis (FEA) models to offer a sketch-based modelling alternative. This aimed to simplify and expedite the conversion of engineering sketches into FEA models while improving user interaction with simulation tools through a sketch-based interface rather than traditional, complex command-line or menu-driven interfaces. The scholars of [7] used YOLO-based object detection approaches to detect elements such as hand-drawn beam diagrams, loads, boundary conditions, and numerical values and perform analyses based on this data with limitations, such as recognizing only orthogonal loads, integer values without units, and uniformly distributed loads, along with constraints requiring sketches to be neatly drawn. For further details on this topic, readers can refer to the survey study [8], which examined multiple methodologies, explained sketch-based image retrieval topics, and outlined core challenges, such as ambiguity in sketch recognition and variations in sketch styles. Furthermore, the study details primary technologies and benchmark datasets crucial for evaluating various methods. The literature also emphasizes the growing importance of sustainability and the circular economy, since just buildings consume approximately 40% of the total energy generated globally, and structural optimization is one aspect of decreasing these values and serving sustainability purposes [1]. Moreover, Artificial Intelligence (AI) technologies have

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enabled more efficient utilization of optimization algorithms at reduced computational costs, making structural optimization more accessible and practical for the AECO sector [1]. AI-based metaheuristic algorithms (MAs), which are necessary in structural optimization because of the relationship between objective functions and decision variables, which often cannot be represented in closed form due to the complexity of the problem, effectively solve large-scale and complex problems [9], yet their practical implementation requires further research and integration with commercial software, as stated in [10], [11], [12]. The review article [13] underscores the potential of MAs to improve the AECO field while highlighting the need to bridge the gap between academic research and industry applications.

Based on the literature review, a significant challenge and contribution lie in translating designers' sketches and imaginations into analyzable formats, a process whose importance is evidenced by benefits such as improved communication and the convenience of integrated Sketch-to-BIM (StB) workflows within a single interface, avoiding the need for separate analysis programs. Consequently, this study focuses on generating BIM models from images—even hand-sketched ones—by employing tools such as Dynamo and Robot Structural Analysis (RSA) in a structurally optimized format to provide a streamlined design and optimization framework that unlocks the full potential of designers. This opens doors for futuristic speech-to-structure approaches and provides a foundation for generative modeling and modification in the AECO field. Transforming hand-sketched models to optimized structural models is significantly faster than manual or parametric techniques and is easy to implement since it does not require programming, technical knowledge, or expertise. However, significant work remains for these digital technologies to develop practical, industry-ready solutions that can seamlessly integrate with existing workflows while addressing real-world constraints and requirements [1], [14], [15], [16]. The primary objective is to train a DL model to extract features from hand-sketched images. Subsequently, the overall workflow is enhanced by developing a sketching application for Dynamo that adaptively connects Dynamo to any tablet, phone, or Kindle, enabling users to create initial sketches. This application also includes a sketch refinement feature using the trained DL model, giving additional features such as adding, removing, scaling, and aligning elements, etc., to modify the refined line model. Furthermore, the system's adaptability is assessed, its performance is benchmarked against conventional workflows, and its efficiency in optimizing both size and shape variables is validated. The results indicate significant time savings, enhanced design exploration, and improved structural performance, making a strong case for the system's practical application in the AECO industry. With the present study, the integration of optimization on the design gap is addressed, as the optimization step is considered a vital part of the design processes by the authors and addresses the mentioned practical aspects, with the provided combined workflow. The optimization process incorporates MAs with RSA to perform structural optimization, which involves optimizing member cross-sections for sizing, adjusting node positions for shaping, and combining these aspects for overall topology optimization, as described by [13]. There are a vast number of MAs in the open literature; major ones include Genetic Algorithms (GAs), which dominate due to their flexibility and being one of the first examples of MAs, together with Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) [13]. The decision on which MA to use depends on the designer, and since MAs employ trial-and-error methods, their success mostly depends on problem specifics and algorithm parameters [17]. The MA for the present research was selected based on the study, which states that DE is the most utilized and successful MA among scholars and its parameter-free approach saves valuable time for the designer by preventing manual effort on fine-tuning the parameters which have a high impact on the result [17], [18]. As an alternative to DE, GA, because of its deep roots, was employed along with an adaptive epsilon constraint handling technique to provide methodological variety even though identifying and employing the single best MA is beyond this study's scope since the provided workflow allows users to select and easily switch the MA within Dynamo [11], [19]. As a final objective, the optimized model is generated automatically from a hand-drawn sketch in Dynamo and industry-standard commercial RSA software with the real-world section properties. For this, direct integration through Application Programming Interface (API), along with automated section selection for optimized models from standard profiles, was implemented with parametric handling of boundary conditions and loads. The scope of the study is limited to 2D truss structures. Implementing the definition of loads, supports, and forces with the sketched image, along with 3D structures, is a topic of future studies. The significance of this study lies in unifying image processing, structural analysis, and optimization into one streamlined workflow, addressing a critical gap in the AECO field. By integrating computer vision and ML into Revit-Dynamo, the proposed workflow automates the design process and introduces new, interactive optimization routines, which result in enhanced exploration of design alternatives for BIM.

2. Methodology

The methodology consists of the following steps: (i) generating a synthetic line intersection dataset using Python and computer vision techniques; (ii) training a YOLOv8 DL model for node detection; (iii) designing an application for Dynamo, which seamlessly transfers data between computer and touchscreen device, to provide initial sketches; (iv) employing the RSA API to demonstrate the adaptability of the provided workflow with BIM; (v) testing the methodology on a benchmark problem to provide detailed outcomes of the proposed methodology.

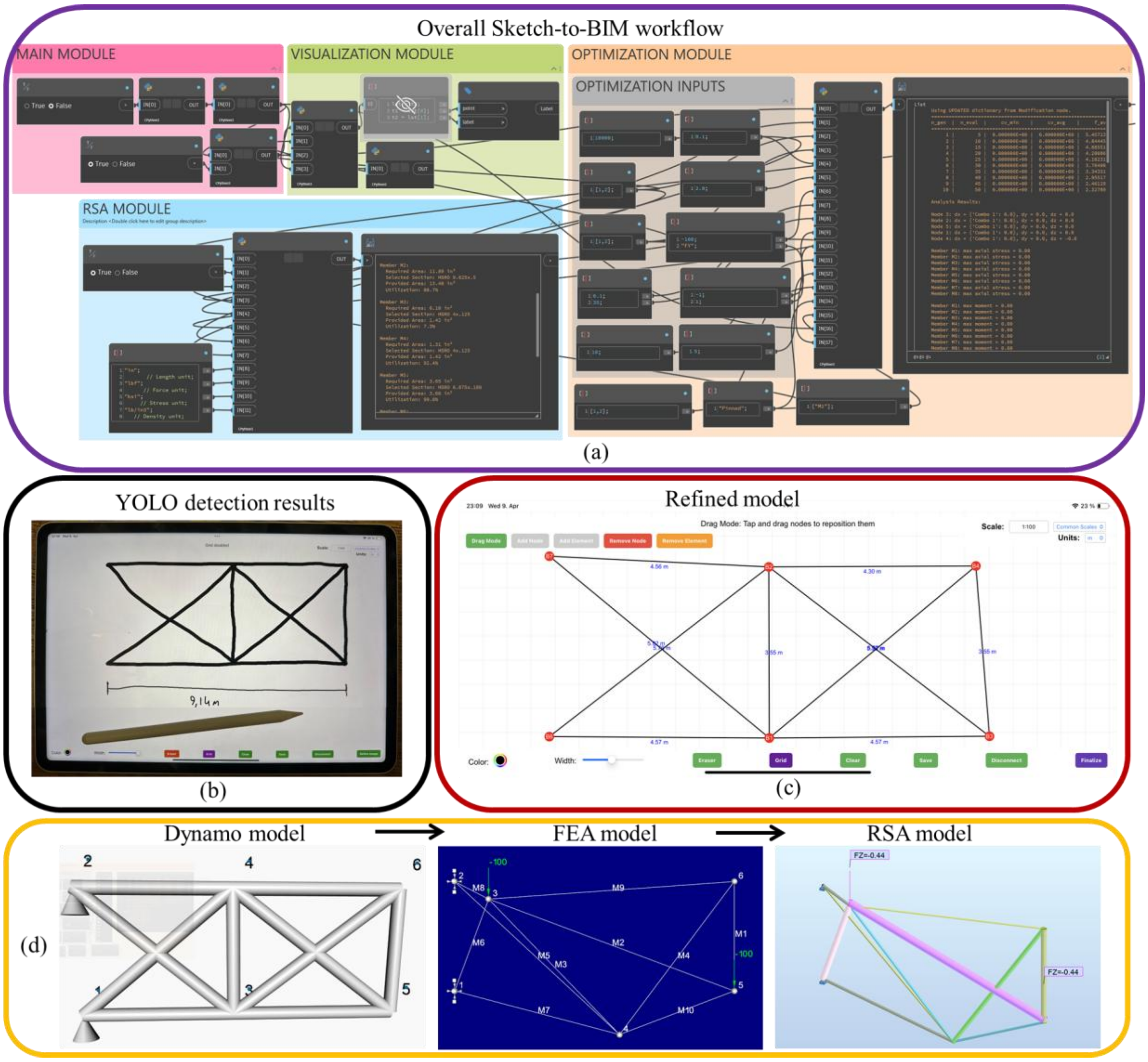

Figure 1. An overall presentation of the methods described in the present study

The initial step of the StB workflow is to generate an initial sketch, which was significantly enhanced by integrating an intuitive sketch-generation and refinement application developed for Dynamo that leveraged HTML and Python-based technologies. The HTML frontend (Figure 1b–c) provides a canvas for intuitive drawing, enabling users to create sketches directly via touchscreen devices or a computer. The web application employs WebSockets to maintain real-time communication with the Python backend, which was created with Python's Tkinter, allowing the reception and real-time visualization of sketches on both computer screens and touchscreen devices. The drawing app provides interactive functionality for sketch refinement using DL-based techniques. Upon receiving the refined model from the frontend, the application visualizes and provides tools for further editing, including drag-and-drop nodes, adding or removing elements or nodes, and alignment and repositioning functionalities. The integrated real-time scale feature ensures accurate dimensional representation of sketches, which was critical for subsequent stages. To extract features from 2D sketched images, a comprehensive synthetic dataset was generated, comprising 35,000 labeled synthetic images, and a YOLOv8 DL model, specifically utilizing the yolov8x variant known for its robust feature extraction capabilities, was trained on this synthetic dataset. This extensive dataset was created using a specialized Python script developed explicitly for this research. The script employed stochastic methods to simulate a diverse range of structural node intersections, including X-shaped, T-shaped, V-shaped, star-shaped intersections as well as significant imperfect intersections. These imperfect intersections intentionally introduced realistic anomalies, such as varying degrees of curvature, gaps, and misalignments, to better emulate practical conditions encountered in real-world sketches. Following dataset preparation, the training procedure was performed with hyperparameters such as the AdamW optimizer, image resolution of 416×416 pixels, and an enhanced selection of image augmentation methods including rotation, shear transformations, mosaic, and mix-up techniques. These augmentations were purposefully applied to enhance the model's ability to generalize and accurately detect structural nodes under various visual distortions and transformations. Moreover, the trained YOLOv8 model incorporated image-preprocessing steps such as grayscale conversion and normalization to standardize the input data, and can annotate detected nodes and elements to refine the model. Once refined, the digital sketch data was seamlessly transferred to Dynamo using custom nodes leveraging Dynamo's Python scripting capability, forming an analyzable structural model ready for optimization, which undergoes an optimization process using AI-based MAs, notably DE and GA. If the user-specified option shown in Figure 1a is active in Dynamo, by leveraging Python for .NET, the code dynamically loads the Interop.RobotOM.dll assembly to tap into Robot's COM-based API. Given user inputs, it systematically builds a structural model by creating nodes and bars, assigning supports, applying loads, and defining essential material properties like Young's modulus and density from Dynamo inputs on the optimized structural model obtained in the optimization module presented in Figure1a. The code also provided a section selection strategy for optimized cross-sections from real-world sections available in RSA, as shown in Figure1d. Finally, the script invokes Robot's calculation engine to run an FEA on the optimized structure, provided results depicted in Figure1d, and saved the project at the designated file location. All code and scripts were provided in a GitHub account to increase the effectiveness of research and support reproducibility [20]. This integrated and adaptive methodology thus provided a streamlined and user-friendly framework, bridging conceptual hand sketches and optimized, validated structural models within the BIM environment, significantly advancing the capabilities of the AECO industry.

3. Preliminary Results

The results section provides a comprehensive overview of the analysis and optimization outcomes of the well-known 10-bar truss structure, which was employed by many scholars [10], [11], [12], [21], [22]. The structure was generated and optimized from a hand-sketched drawing using the proposed workflow presented in Figure 1 and then compared with the literature, with the results shared in Table 1 and Figure 2 which demonstrate notable findings, reflecting the effectiveness of the proposed technique and its adaptability. The structural configurations were sourced from the [21], and the problem was solved by considering only displacement constraints. The coordinates of nodes 3, 4, and 6 (Figure 1d) were chosen as design parameters; in those terms, this is a size and shape optimization problem with 13 design variables. The execution time from start to end took approximately 800 seconds, including the drawing time, and the presented result in the Table 1 were obtained using DE.

Table 1. 10-bar truss comparison results

	[21]	[22]	[23]	This Study
Objective (kg)	2549.2	2490.6	2302.4	1850.6
Analysis Num.	400	10000	15100	4000
Runs & Algorithm	- & GA	24 & ACO	30 & PSOC	6 & DE, GA

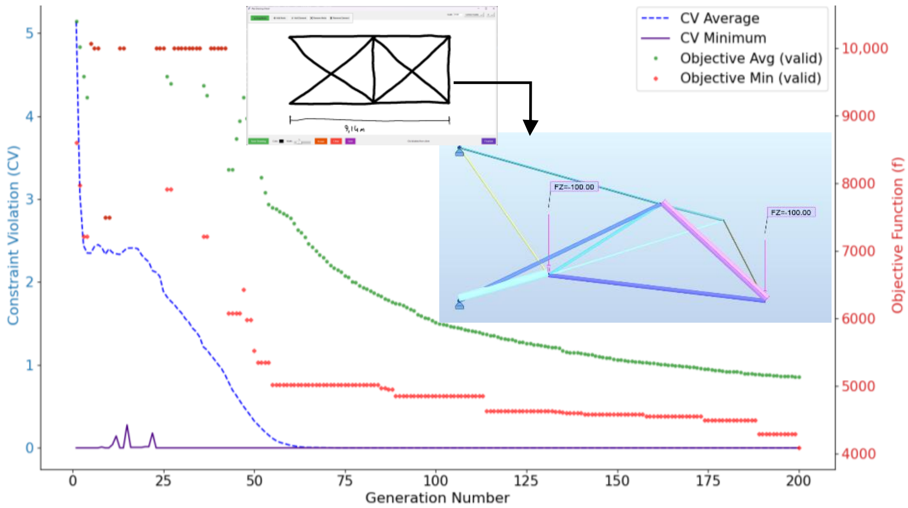

Figure 2. The optimization history along with the final result

4. Conclusions and Discussion

The present study focuses on enhancing the workflow from hand-drawn structural models to optimized digital models in a BIM environment. The results demonstrate the significance and success of the proposed sketch-to-BIM methodology using visual programming with Dynamo. In future studies, a hybrid node extraction method could be introduced as an alternative to the DL approach, allowing users to choose the method best suited to their needs. This could leverage the strengths of the presented approaches while mitigating their weaknesses. Alternatively, more advanced DL-based feature detection tools could be developed to identify forces, supports, and their types from sketches. The framework could also be expanded to generate building plans and benefit from more extensive error and bug detection, as well as a broader range of test examples, including frame structures. Overall, this method enhances the design and optimization process by combining both aspects and simplifying the use of advanced technologies compared to traditional approaches. The automated workflow offers advantages, such as time savings, increased accuracy, the ability to explore more design options, and seamless integration. However, limitations related to varying drawing styles among individuals, inconsistent image quality, and the handling of 3D structures are yet to be investigated.

References

[1] S. K. Baduge et al., “Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications,” Automation in Construction, vol. 141, p. 104440, Sep. 2022, doi: 10.1016/j.autcon.2022.104440.

[2] W. Huang and H. Zheng, “Architectural Drawings Recognition and Generation through Machine Learning,” Proceedings of the 38th Annual Conference of the Association for Computer Aided Design in Architecture (ACADIA), 2018, doi: 10.52842/conf.acadia.2018.156.

[3] P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, “Image-to-Image Translation with Conditional Adversarial Networks,” 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 5967–5976, Jul. 2017, doi: 10.1109/cvpr.2017.632.

[4] N. Nauata, K.-H. Chang, C.-Y. Cheng, G. Mori, and Y. Furukawa, “House-GAN: Relational Generative Adversarial Networks for Graph-Constrained House Layout Generation,” Computer Vision – ECCV 2020, pp. 162–177, 2020, doi: 10.1007/978-3-030-58452-8_10.

[5] W. Jeong, B. Kong, M. D. Adhikari, and S.-G. Yum, “The Development of a Framework for the Automated Translation of Sketch-Based Data into BIM Models,” Buildings, vol. 14, no. 4, p. 916, Mar. 2024, doi: 10.3390/buildings14040916.

[6] T. C. Hutchinson, F. Kuester, and M. E. Phair, “Sketching Finite-Element Models within a Unified Two-Dimensional Framework,” Journal of Computing in Civil Engineering, vol. 21, no. 3, pp. 175–186, May 2007, doi: 10.1061/(asce)0887-3801(2007)21:3(175).

[7] I. Joffe, Y. Qian, M. Talebi-Kalaleh, and Q. Mei, “A Computer Vision Framework for Structural Analysis of Hand-Drawn Engineering Sketches,” Sensors, vol. 24, no. 9, p. 2923, May 2024, doi: 10.3390/s24092923.

[8] X. Zhang, X. Li, Y. Liu, and F. Feng, “A survey on freehand sketch recognition and retrieval,” Image and Vision Computing, vol. 89, pp. 67–87, Sep. 2019, doi: 10.1016/j.imavis.2019.06.010.

[9] M. Stolpe, “Truss optimization with discrete design variables: a critical review,” Structural and Multidisciplinary Optimization, vol. 53, no. 2, pp. 349–374, Sep. 2015, doi: 10.1007/s00158-015-1333-x.

[10] F. Yavan and R. Maalek, “Reliability-Constrained Structural Design Optimization Using Visual Programming in Building Information Modeling (BIM) Projects,” Applied Sciences, vol. 15, no. 3, p. 1025, Jan. 2025, doi: 10.3390/app15031025.

[11] F. Yavan, R. Maalek, and S. Maalek, “Enhancing Spatial Truss Designs by Integrating Metaheuristic Optimization Techniques via Visual Programming in BIM-based Projects,” Proceedings of International Association for Shell and Spatial Structures (IASS) Annual Symposia, Aug. 2024.
[12] F. Yavan, R. Maalek, and V. Toğan, “Structural Optimization of Trusses in Building Information Modeling (BIM) Projects Using Visual Programming, Evolutionary Algorithms, and Life Cycle Assessment (LCA) Tools,” Buildings, vol. 14, no. 6, p. 1532, May 2024, doi: 10.3390/buildings14061532.
[13] T. W. Liao, P. J. Egbelu, B. R. Sarker, and S. S. Leu, “Metaheuristics for project and construction management – A state-of-the-art review,” Automation in Construction, vol. 20, no. 5, pp. 491–505, Aug. 2011, doi: 10.1016/j.autcon.2010.12.006.
[14] D. M. Silitonga and O. F. Jin, “Application of Artificial Intelligence (AI) in Construction Management: A Systematic Literature Review,” INVOTEK: Jurnal Inovasi Vokasional dan Teknologi, vol. 23, no. 3, pp. 155–166, Apr. 2024, doi: 10.24036/invotek.v23i3.1153.
[15] F. Jiang, J. Ma, C. J. Webster, X. Li, and V. J. L. Gan, “Building layout generation using site-embedded GAN model,” Automation in Construction, vol. 151, p. 104888, Jul. 2023, doi: 10.1016/j.autcon.2023.104888.
[16] S. Kazemzadeh Azad and S. Kazemzadeh Azad, “A standard benchmarking suite for structural optimization algorithms: ISCSO 2016–2022,” Structures, vol. 58, p. 105409, Dec. 2023, doi: 10.1016/j.istruc.2023.105409.
[17] A. H. Halim, I. Ismail, and S. Das, “Performance assessment of the metaheuristic optimization algorithms: an exhaustive review,” Artificial Intelligence Review, vol. 54, no. 3, pp. 2323–2409, Oct. 2020, doi: 10.1007/s10462-020-09906-6.
[18] Z. Ma, G. Wu, P. N. Suganthan, A. Song, and Q. Luo, “Performance assessment and exhaustive listing of 500+ nature-inspired metaheuristic algorithms,” Swarm and Evolutionary Computation, vol. 77, p. 101248, Mar. 2023, doi: 10.1016/j.swevo.2023.101248.
[19] J. Blank and K. Deb, “Pymoo: Multi-Objective Optimization in Python,” IEEE Access, vol. 8, pp. 89497–89509, 2020, doi: 10.1109/access.2020.2990567.
[20] F. Yavan, Accessed: Jan. 23, 2025, “Sketch-to-BIM,” GitHub. [Online]. Available: https://github.com/ugurfeyzullah/Sketch-to-BIM.
[21] S. Rajeev and C. S. Krishnamoorthy, “Discrete Optimization of Structures Using Genetic Algorithms,” Journal of Structural Engineering, vol. 118, no. 5, pp. 1233–1250, May 1992, doi: 10.1061/(asce)0733-9445(1992)118:5(1233).
[22] C. V. Camp and B. J. Bichon, “Design of Space Trusses Using Ant Colony Optimization,” Journal of Structural Engineering, vol. 130, no. 5, pp. 741–751, May 2004, doi: 10.1061/(asce)0733-9445(2004)130:5(741).
[23] M. Jafari, E. Salajegheh, and J. Salajegheh, “Optimal design of truss structures using a hybrid method based on particle swarm optimizer and cultural algorithm,” Structures, vol. 32, pp. 391–405, Aug. 2021, doi: 10.1016/j.istruc.2021.03.017.