Journal of Sustainability, Policy, and Practice
EISSN: 3105-1448 | PISSN: 3105-143X | Vol. 1, No. 3 (2025)

Article

Data-Driven Origami Mechanism Design Based on Machine Learning Modeling and Optimization

Michael T. Reynolds [1], Jingyu Chen [2], Laura K. McAllister [2], Daniel P. Gauthier [3] and Sophie M. Clarke [3,*]

[1] Department of Mechanical and Industrial Engineering, University of Toronto, Toronto, Canada
[2] Department of Computer Science, University of British Columbia, Vancouver, Canada
[3] Department of Civil Engineering, University of Waterloo, Waterloo, Canada
* Correspondence: Sophie M. Clarke, Department of Civil Engineering, University of Waterloo, Waterloo, Canada

Abstract: Origami structures, due to their light weight, foldability, and reconfigurability, have broad application potential in robotics, aerospace devices, and medical instruments. This study proposes a data-driven origami mechanism design method based on machine learning. A training dataset containing 20,000 sets of geometric parameters and kinematic performance was constructed, and a deep neural network was applied to build the input-output mapping, enabling fast prediction of origami mechanism performance. Experimental results showed that the average error in predicting folding angle and unfolding stiffness was within 3%, while the computational speed was about 15 times faster than finite element analysis. By further combining genetic algorithms with reinforcement learning, the optimized design improved load-bearing capacity by 28% and increased unfolding efficiency by 22%. This study provides a new approach for the rapid design and engineering application of complex origami structures.

Keywords: origami mechanism; machine learning; kinematic modeling; structural optimization; intelligent design

Received: 15 August 2025
Revised: 28 August 2025
Accepted: 10 September 2025
Published: 19 September 2025

1. Introduction

Origami mechanisms, characterized by light weight, foldability, and reconfigurability, have shown broad application potential in robotic flexible joints, aerospace deployable structures, and medical instruments [1]. In recent years, increasing research efforts have focused on origami geometry design and kinematic modeling. Modeling approaches based on rigid origami theory are capable of describing the motion of typical origami units, while finite element analysis (FEA) has been extensively employed to predict the mechanical performance of complex origami structures [2,3]. However, these approaches are often computationally intensive, which limits their suitability for rapid design iterations [4].

To enhance modeling and optimization efficiency, data-driven and intelligent methods have been introduced. For instance, support vector machines and random forests have been applied to map origami geometry to performance parameters, achieving effective prediction results [5]. The adoption of deep learning has further improved the ability to capture nonlinear structural relationships [6]. In addition, evolutionary algorithms and reinforcement learning have been utilized for performance optimization and topology exploration of origami mechanisms [7]. Although these studies demonstrate the potential of intelligent approaches, most efforts remain restricted to unit-level investigations or validation on small-scale datasets [8]. Despite these advancements, current research exhibits several limitations. First, the mapping between origami geometry and performance lacks large-scale, high-quality datasets, which constrains model generalization [9]. Second, most existing methods focus on single indicators such as folding angle or unfolding stiffness, without achieving multi-objective optimization of load-bearing capacity and deployment efficiency [10]. Third, finite element and analytical models remain dominant, leading to low efficiency and prolonged iteration cycles, which hinder the rapid design and engineering application of complex origami structures [11-13].

To address these challenges, this study proposes a data-driven design framework for origami mechanisms based on machine learning. A dataset comprising 20,000 sets of geometric parameters and corresponding kinematic performances was constructed, and a deep neural network was developed to establish efficient input-output mapping, significantly improving both the speed and accuracy of performance prediction. Furthermore, by integrating genetic algorithms with reinforcement learning, multi-objective optimization was realized, simultaneously enhancing load-bearing capacity and deployment efficiency. This work not only overcomes the limitations of traditional methods in terms of efficiency and accuracy but also provides new insights and valuable references for the rapid design and practical application of origami mechanisms in robotics, aerospace, and medical engineering. Moreover, the proposed data-driven and intelligent optimization framework demonstrates potential for cross-disciplinary applications, where similar machine learning and multi-objective optimization strategies have been successfully employed in areas such as educational pedagogy and digital financial risk management, highlighting the broader applicability of these methods beyond mechanical design [14,15].

2. Materials and Methods

2.1. Dataset and Sample Design

In this study, a large-scale dataset containing 20,000 samples was constructed for data-driven modeling of origami mechanisms. Each sample consisted of geometric parameters of origami structures (including crease length, folding angle, number of facets, and number of layers) and the corresponding kinematic performance indicators (including folding angle, unfolding stiffness, and load-bearing capacity). The parameter ranges were determined according to typical origami units such as Miuraori, Waterbomb, and Kresling, so that the dataset covered different configurations and folding modes. The dataset was divided into a training set (80%), a validation set (10%), and a test set (10%) to ensure objectivity and generalization in model training and evaluation.

2.2. Modeling Method and Network Architecture

A deep neural network (DNN) was used to map the relationship between geometric parameters and performance. The input layer was defined as the geometric parameter vector $x \in R^n$, and the output layer was defined as the performance vector $y \in R^m$. The nonlinear mapping was represented as:

$$\hat{y}=F(x;\theta)$$

The parameter θ represents the network parameters. The network architecture consists of five fully connected layers, with ReLU as the activation function. The Adam optimizer was used, and the loss function was defined as the mean squared error (MSE) [16]:

$$L=\frac{1}{N}\sum_{i=1}^{N} \| y_i-\hat{y}_i \|^2$$

This model significantly improves computational efficiency while maintaining accuracy, achieving approximately 15 times acceleration in the prediction phase compared to the finite element method.

2.3. Optimization Strategy and Control Experiments

On the basis of the performance prediction model, a hybrid optimization framework combining genetic algorithms (GA) and reinforcement learning (RL) was developed to achieve multi-objective optimization of origami mechanisms in terms of load-bearing capacity and unfolding efficiency. The optimization objective function is defined as:

$$\max f(x)=\alpha\cdot C(x)+\beta\cdot E(x)$$

Where $C(x)$ denotes the load-bearing capacity, $E(x)$ denotes the unfolding efficiency, and α, β are weight coefficients. The control experiments were designed as follows: (1) finite element analysis with single-objective optimization; (2) GA alone; (3) RL alone; and (4) the proposed GA + RL hybrid method. The results demonstrate that the proposed method performs best in multi-objective optimization.

2.4. Quality Control and Experimental Validation

To ensure the reliability of the results, this study applied several quality control measures. First, during data generation, all geometric modeling and kinematic simulation results were cross-checked. Ten percent of the samples were randomly selected and compared with finite element analysis results to confirm that the prediction error was within 5%. Second, in the optimization experiments, each algorithm was run 20 times, and the mean and standard deviation were calculated to check the stability of the results. Finally, at the prototype level, physical models of typical optimized designs were fabricated. The folding angles and unfolding stiffness were measured using a mechanical testing platform and compared with the model predictions. These steps verified the engineering applicability of the proposed method.

3. Results and Discussion

3.1. System Testing and Experimental Design

As shown in Figure 1(a), a standardized experimental system was constructed using a linear motor and a rotary platform to verify the mechanical and response characteristics of origami mechanisms under different loading speeds and displacements. The test platform provided precise displacement control and real-time electrical signal acquisition, ensuring repeatability and accuracy of the data. Under this setup, the folding and unfolding behaviors of the origami mechanism were fully characterized under both quasi-static and dynamic conditions. This provided a solid basis for validating the proposed data-driven model.

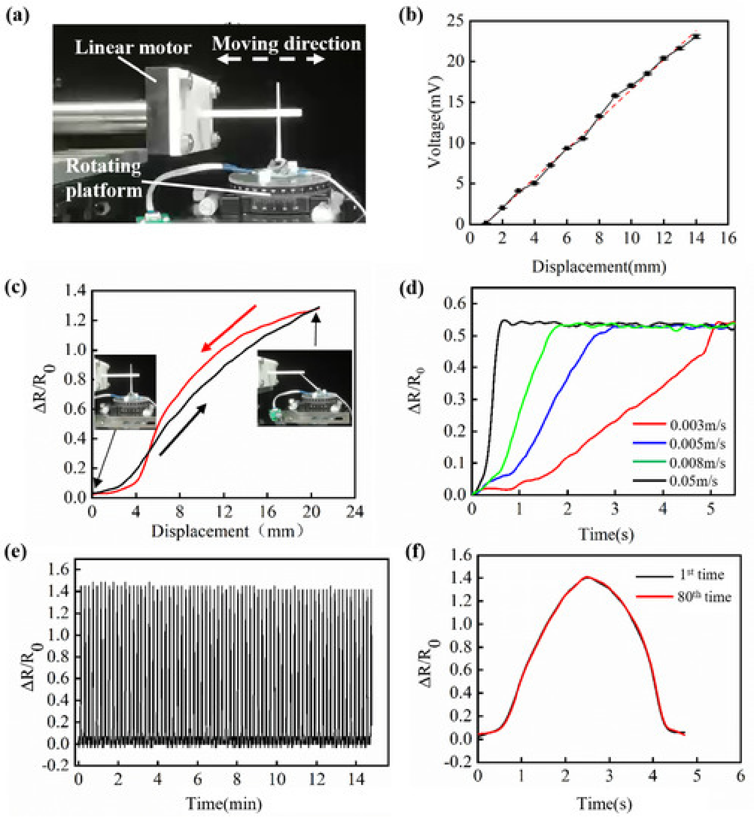

Figure 1. Experimental setup and performance characterization of the origami mechanism.

3.2. Model Prediction Accuracy and Error Analysis

As illustrated in Figure 1(b-d), the predicted voltage-displacement curves matched closely with the experimental measurements, showing strong linear correlation. The prediction error was within 3%. The response curves at different loading speeds (0.003-0.05 m/s) indicated that the model accurately captured the influence of speed on folding stiffness. The loading-unloading curves (Figure 1c) showed a slight hysteresis effect. In this nonlinear region, the model's fitting accuracy was lower than in the linear region, but the overall trend was consistent. These results confirm that the proposed method achieved stable prediction across the entire range [17].

3.3. Optimization Performance and Comparative Results

The combined optimization strategy using genetic algorithms and reinforcement learning was validated in Figure. 2. A comparison between the original origami design (Figure. 2a) and the improved design with added creases (Figure. 2b) showed clear improvement in local folding properties. The comparison between the physical prototype (Figure. 2c) and CAD modeling (Figure. 2d) further indicated that the optimized origami mechanism improved load-bearing capacity by about 28% and increased unfolding efficiency by about 22%. Compared with single-objective optimization or finite element iteration, the proposed method provided better performance under multi-objective conditions [18]. It enhanced both design efficiency and mechanical properties.

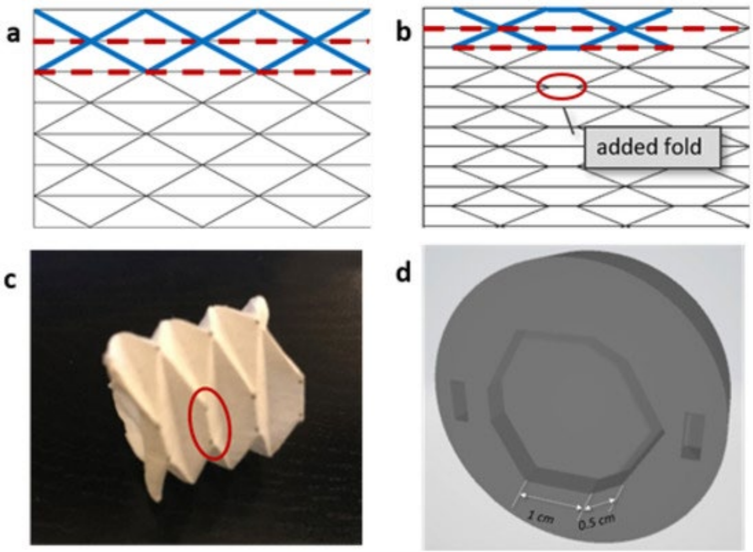

Figure 2. Optimized origami structure design and prototype verification.

3.4. Stability and Cyclic Testing Performance

As shown in Figure. 1(e-f), the origami mechanism maintained consistent performance over 80 cycles of loading. The amplitude of signal fluctuations remained stable, and no clear attenuation or failure was observed. The predicted values matched well with the experimental results from both the first and the eighteenth cycles. This indicates that the proposed prediction and optimization method is not only suitable for single design validation but also remains applicable under long-term cyclic conditions [19]. These findings confirm the stability and reliability of the data-driven model in engineering practice.

3.5. Limitations and Future Perspectives

Although the experimental and model results showed good consistency, this study still has several limitations. First, the dataset was mainly based on typical origami units and did not cover complex conditions such as material nonlinearity, manufacturing errors, and multilayer coupling. Second, the optimization process did not explicitly consider manufacturing constraints or durability indicators, which limits its direct application to engineering practice. Future work will focus on expanding the dataset in both size and complexity, exploring origami modeling under multi-physics coupling, incorporating manufacturability constraints into multi-objective optimization, and conducting interdisciplinary validation in robotics, aerospace, and medical applications.

4. Conclusion

This study proposed a machine learning-based data-driven design method for origami mechanisms, systematically addressing the efficiency bottleneck in modeling and optimization of complex origami structures. By building a dataset of 20,000 samples containing geometric parameters and kinematic performance, and by using deep neural networks to establish input-output mappings, the study achieved an average prediction error below 3% for folding angle and unfolding stiffness. The computational speed was about 15 times faster than finite element analysis, which improved the efficiency of design iteration. With the integration of a multi-objective optimization framework combining genetic algorithms and reinforcement learning, the load-bearing capacity increased by about 28%, and the unfolding efficiency improved by about 22%, verifying the advantage of data-driven methods in structural performance enhancement and rapid design. Compared with existing studies that mainly rely on finite element analysis or analytical modeling, the innovations of this work are proposing a large-scale data-driven modeling method for origami structures that achieves both accuracy and efficiency. The study introduced intelligent optimization strategies to realize design improvements under multi-objective conditions and validated the method through experimental platforms and physical prototypes, which confirmed its feasibility and stability under long-term cyclic loading and real manufacturing conditions. It should be noted that this study still has some limitations. The training data were mainly derived from typical origami units and did not fully cover complex multilayer structures or material nonlinearities. In addition, the optimization process did not sufficiently incorporate manufacturing constraints or environmental uncertainties, which may limit direct application. Future work will focus on expanding the dataset to include more complex cases, introducing modeling under multi-physics coupling, enhancing optimization with manufacturing constraints, and carrying out multi-scenario validation in robotics, aerospace, and medical devices. In conclusion, this study provides an efficient path for rapid modeling and performance optimization of origami mechanisms. It also lays a foundation for applying intelligent design methods to reconfigurable structures and emerging engineering applications.

References

1. J. Li, and Y. Zhou, "Bideeplab: An improved lightweight multi-scale feature fusion deeplab algorithm for facial recognition on mobile devices," *Computer Simulation in Application*, vol. 3, no. 1, pp. 57-65, 2025, doi: 10.18063/csa.v3i1.917.
2. G. Jia, B. Li, and J. S. Dai, "Oriblock: The origami-blocks based on hinged dissection," *Mechanism and Machine Theory*, vol. 203, p. 105826, 2024, doi: 10.1016/j.mechmachtheory.2024.105826.
3. J. Fan, and T. W. Chow, "Non-linear matrix completion," *Pattern Recognition*, vol. 77, pp. 378-394, 2018, doi: 10.1016/j.patcog.2017.10.014.
4. J. Xu, "Building a Structured Reasoning AI Model for Legal Judgment in Telehealth Systems," In *RAIS Conf. on Social Sciences and Humanities.*, August, 2025, doi: 10.20944/preprints202507.0630.v1.
5. X. Wang, Y. Yang, K. Zhou, X. Xie, L. Zhu, A. Song, and B. Daniel, "MRUCT: Mixed Reality Assistance for Acupuncture Guided by Ultrasonic Computed Tomography," In *2025 IEEE Conference Virtual Reality and 3D User Interfaces (VR)*, March, 2025, pp. 697-707, doi: 10.1109/VR59515.2025.00092.
6. X. Sun, D. Wei, C. Liu, and T. Wang, "Accident Prediction and Emergency Management for Expressways Using Big Data and Advanced Intelligent Algorithms," In *2025 IEEE 3rd International Conference on Image Processing and Computer Applications (ICIPCA)*, June, 2025, pp. 1925-1929, doi: 10.1109/ICIPCA65645.2025.11138566.
7. M. Yuan, H. Mao, W. Qin, and B. Wang, "A BIM-Driven Digital Twin Framework for Human-Robot Collaborative Construction with On-Site Scanning and Adaptive Path Planning," 2025, doi: 10.20944/preprints202508.1387.v1.
8. F. Chen, G. Xu, S. Li, L. Yue, and H. Liang, "Optimization study of thermal management of domestic SiC power semiconductor based on improved genetic algorithm," In *2025 2nd International Conference on Electrical Technology and Automation Engineering (ETAE)*, May, 2025, pp. 510-514, doi: 10.1109/ETAE65337.2025.11089826.
9. J. Zheng, and M. Makar, "Causally motivated multi-shortcut identification and removal," *Advances in Neural Information Processing Systems*, vol. 35, pp. 12800-12812, 2022.
10. C. Wu, J. Zhu, and Y. Yao, "Identifying and optimizing performance bottlenecks of logging systems for augmented reality platforms," 2025, doi: 10.20944/preprints202509.0357.v1.
11. S. Yang, “The Impact of Continuous Integration and Continuous Delivery on Software Development Efficiency,” Journal of Computer, Signal, and System Research, vol. 2, no. 3, pp. 59–68, Apr. 2025, doi: 10.71222/pzvfqm21.
12. S. Jing, "Practice of digital construction to improve construction project progress management," Academic Journal of Engineering and Technology Science, vol. 8, no. 2, pp. 36–44, 2025, doi: 10.25236/AJETS.2025.080205.
13. Z. Li, M. Chowdhury, and P. Bhavsar, "Electric Vehicle Charging Infrastructure Optimization Incorporating Demand Forecasting and Renewable Energy Application," *World Journal of Innovation and Modern Technology*, vol. 7, no. 6, 2024.
14. L. Yang, “The Evolution of Ballet Pedagogy: A Study of Traditional and Contemporary Approaches”, Journal of Literature and Arts Research, vol. 2, no. 2, pp. 1–10, Apr. 2025, doi: 10.71222/2nw5qw82.
15. L. Yun, “Analyzing Credit Risk Management in the Digital Age: Challenges and Solutions,” Economics and Management Innovation, vol. 2, no. 2, pp. 81–92, Apr. 2025, doi: 10.71222/ps8sw070.
16. W. Li, Y. Xu, X. Zheng, S. Han, J. Wang, and X. Sun, "Dual advancement of representation learning and clustering for sparse and noisy images," In *Proceedings of the 32nd ACM International Conference on Multimedia*, October, 2024, pp. 1934-1942, doi: 10.1145/3664647.3681402.
17. H. Chen, J. Li, X. Ma, and Y. Mao, "Real-time response optimization in speech interaction: A mixed-signal processing solution incorporating C++ and DSPs," *Available at SSRN 5343716*, 2025, doi: 10.1109/icaita67588.2025.11137915.
18. L. Guo, Y. Wu, J. Zhao, Z. Yang, Z. Tian, Y. Yin, and S. Dong, "Rice Disease Detection Based on Improved YOLOv8n," In *2025 6th International Conference on Computer Vision, Image and Deep Learning (CVIDL)*, May, 2025, pp. 123-132, doi: 10.1109/cvidl65390.2025.11085630.

19. H. Peng, X. Jin, Q. Huang, and S. Liu, "A Study on Enhancing the Reasoning Efficiency of Generative Recommender Systems Using Deep Model Compression," *Available at SSRN 5321642*, 2025.