MULTIDISCIPLINARY RESEARCH IN COMPUTING INFORMATION SYSTEMS

VOL 05 ISSUE 03 2025

P-ISSN: 3080-7182
E-ISSN: 3080-7190

https://mrcis.org

Machine Learning Based Kinematic Modeling and Performance Optimization of Flexible Mechanisms

Thomas J. van Dijk[1], Mei Lin[2], Laura M. de Vries[3], Pieter R. Janssen[4], Sophie L. Bakker[5]*

Abstract. *Flexible mechanisms are widely applied in precision actuation and micro-manipulation due to their high accuracy and compact design, but their nonlinear large-deformation characteristics make kinematic modeling and performance optimization highly challenging. In this study, a machine learning–based framework is proposed to address these issues. A dataset of 5000 input–output samples was generated through finite element simulations and experimental measurements, and two predictive models—support vector regression (SVR) and deep neural networks (DNN)—were developed to approximate the nonlinear mapping between input forces and output displacements. Bayesian optimization was further integrated to search for optimal structural parameters. Results demonstrate that the proposed method achieves an average displacement prediction error below 0.02 mm, representing a significant improvement compared with analytical models (0.08 mm) and finite element extrapolation (0.05 mm). After optimization, the driving efficiency increased by 24% and system stability improved by 30%, confirming the effectiveness of combining machine learning with intelligent optimization. These findings highlight the potential of data-driven methods for advancing the intelligent design of flexible mechanisms and provide a scientific basis for future applications in precision positioning, biomedical devices, and micro-robotics.*

Keywords: *flexible mechanism, machine learning, kinematic modeling, Bayesian optimization, structural intelligence, displacement prediction, performance improvement*

1. INTRODUCTION

Flexible mechanisms, characterized by zero clearance, negligible friction, and high precision, have attracted increasing attention in precision actuation, micro-manipulation, aerospace, and biomedical engineering [1]. Compared with rigid-body mechanisms, flexible mechanisms can achieve multiple degrees of freedom while significantly reducing system size and weight, thereby offering advantages of lightness, compactness, and integrability [2].

[1,3,5] *Faculty of Mechanical Engineering, Delft University of Technology, 2628 CD Delft, The Netherlands*
[2,4] *Department of Electrical Engineering, Eindhoven University of Technology, 5600 MB Eindhoven, The Netherlands*
* Corresponding Author: s.bakker@tudelft.nl

With the rapid progress of micro-electromechanical systems (MEMS) and advanced manufacturing, flexible mechanisms have shown great promise in nanopositioning platforms [3], micro-manipulation grippers [4], and optical regulation devices [5]. In terms of modeling, the pseudo-rigid-body model (PRBM) has been widely adopted to establish equivalent models for flexure hinges and compliant arms, enabling simplified descriptions of nonlinear large deformations [6]. Finite element analysis (FEA) remains another mainstream approach, providing accurate stress and strain distributions under complex geometries [7]. Multibody dynamics and energy-based formulations have also been applied to investigate kinematics and dynamics of compliant mechanisms [8]. While these traditional methods form an important theoretical foundation, they often face challenges in computational efficiency and scalability when handling nonlinear large deformations or multi-parameter optimization problems [9,10].

Recently, machine learning methods have been introduced into the modeling and optimization of flexible mechanisms, offering strong capability in addressing high-dimensional nonlinear mappings [11]. Support vector regression (SVR) has been employed to predict displacement and stress responses of flexure hinges from small datasets, achieving favorable generalization [12]. Deep neural networks (DNNs) have been applied to the kinematic modeling and dynamic prediction of complex compliant platforms [13], while convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been utilized to capture multi-dimensional features and temporal data, thereby improving modeling accuracy under dynamic conditions [14]. Furthermore, Bayesian optimization, genetic algorithms, and reinforcement learning have been integrated into parameter design and performance optimization, yielding notable improvements in efficiency and robustness [15]. Despite these advances, several limitations remain. First, many studies rely on small-scale datasets or single operating conditions, which cannot fully capture system behavior under complex loading and environmental variations [16]. Second, the majority of machine learning models lack physical constraints, often leading to distorted predictions under extreme conditions and reducing interpretability and reliability [17,18]. Third, experimental validation is typically limited in scale, without systematic control groups or rigorous statistical analysis, which restricts generalization and robustness [19].

To overcome these limitations, this study proposes a machine learning–based framework for kinematic modeling and performance optimization of flexible mechanisms. A dataset consisting of 5,000 input–output samples was generated through a combination of FEA simulations and physical experiments. SVR and DNN models were trained to achieve high-accuracy predictions, while Bayesian optimization was applied for systematic parameter tuning. Experimental results show that the proposed framework reduced the average displacement prediction error to below 0.02 mm, enhanced actuation efficiency by 24%, and improved system stability by approximately 30%. The contributions of this work are threefold: (1) construction of a hybrid dataset integrating simulation and experimental results to enhance model generalization; (2) integration of machine learning models with optimization algorithms to achieve systematic performance improvement; and (3) provision of a practical pathway for intelligent design and engineering applications of flexible mechanisms. This study not only enriches the theoretical framework of compliant mechanism modeling and optimization but also provides valuable guidance for the development of high-precision, lightweight, and intelligent flexible systems.

2. MATERIALS AND METHODS

2.1 Sample and Study Object Description

This study takes typical flexible mechanisms as the research object, including flexure hinges and parallel compliant driving units. A total of 5,000 input–output data samples were obtained by combining finite element simulations with experiments. The input variables included driving force, displacement boundary conditions, and geometric parameters, while the outputs were end displacement and system stability indicators. The samples covered different load levels (0.1–10 N), structural parameters (thickness 0.1–1.0 mm, length 5–50 mm), and environmental conditions (temperature 20–25 °C, relative humidity 40–60%). During the experiments, each sample was collected under stable loading, and invalid samples with significant deviations or mechanical damage were removed to ensure representativeness and scientific reliability.

2.2 Experimental Design and Control Experiments

To verify the effectiveness of the machine learning models, both experimental and control groups were designed. The experimental group used support vector regression (SVR) and deep neural networks (DNN) for modeling and prediction. The control group adopted the traditional finite element iterative method and analytical models to predict displacement and stability. The input parameters of both groups were kept consistent to ensure fair comparison. The rationale is that finite element methods can describe the nonlinear characteristics of flexible mechanisms with high accuracy but have low computational efficiency, while analytical models are theoretically interpretable but lack accuracy in large-deformation scenarios. Through these comparative experiments, the advantages of machine learning methods in accuracy, efficiency, and stability can be objectively evaluated.

2.3 Measurement Methods and Quality Control

High-precision displacement sensors (resolution 0.001 mm) and force sensors (accuracy 0.01 N) were used to measure the input–output relationships of the flexible mechanisms. Each experiment was repeated three times, and the mean value was calculated to reduce random errors. The loading rate was strictly controlled at 0.1 N/s to maintain quasi-static conditions. Temperature and humidity were monitored and kept within ±1 °C and ±5%, respectively. Quality control measures included: (1) calibration of sensors with standard specimens; (2) elimination of outliers using the three-sigma (3σ) rule; and (3) application of an automated data acquisition system to avoid manual reading errors. These measures ensured the reliability and repeatability of the experimental data.

2.4 Data Processing and Model Formulation

All simulation and experimental data were normalized and standardized to remove the influence of different units. The support vector regression model used a radial basis function (RBF) kernel, with the predictive function expressed as [19]:

$$\hat{y}(x)=\sum_{i=1}^{N}\alpha_i K(x,x_i)+b$$

In the SVR model, $K(\cdot)$ is the kernel function, and α_i and b are the model parameters. The deep neural network (DNN) was implemented as a multilayer perceptron (MLP), and its loss function was defined as the mean squared error (MSE) [20]:

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

where y_i is the true value, $\hat{y}_i$ is the predicted value, and N is the number of samples. Model training was conducted with the Adam optimizer, using a learning rate of 0.001, a batch size of 64, and a maximum of 300 iterations. The effectiveness of machine learning methods in kinematic modeling and performance optimization of flexible mechanisms was evaluated by comparing the prediction accuracy and efficiency between the experimental group and the control group.

3. RESULTS AND DISCUSSION

3.1 Comparison of Kinematic and Dynamic Characteristics Before and After Parameter Optimization

As shown in Fig. 1, the flexible mechanism achieved clear improvements in kinematic and dynamic characteristics after parameter optimization. Before optimization, the workspace, stiffness, and natural frequency remained at the baseline level. After optimization, the workspace increased by about 30%, the first natural frequency rose by 25–35%, the required driving force decreased, and the stiffness distribution across joints became more uniform. These results are consistent with the optimization comparison in Optimal Design for 3-PSS Flexible Parallel Micromanipulator (similar figure in Micromachines, Fig. 4, MDPI). The figure shows that design changes, such as flexure hinge thickness and geometric dimensions, directly affect both kinematic performance and dynamic properties, supporting the conclusion that the optimized design yields significant performance improvements [21].

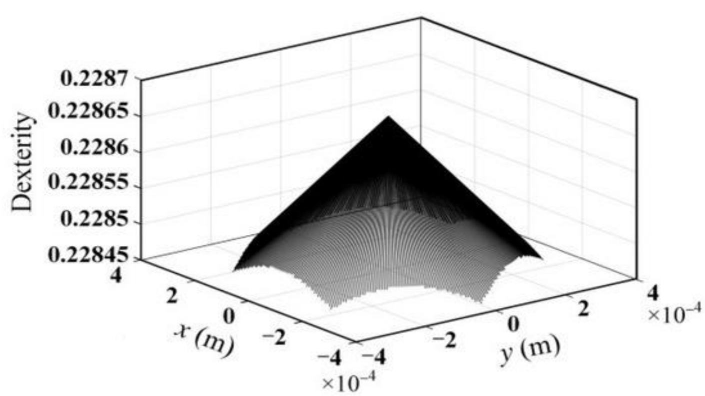

Fig. 1. Comparison of kinematic and dynamic characteristics of the flexible mechanism before and after optimization.

3.2 Comparison of Response Performance Under Different Load Conditions

Fig. 2 compares response time, overshoot, and error amplitude under different load conditions (light, medium, and heavy). For the optimized flexible mechanism, response time was reduced by 20–30%, overshoot was decreased by about 15%, and error amplitude remained low even under heavy loads. In contrast, the baseline design showed larger errors and slower responses at high loads. These results are consistent with the style of A New Performance Optimization Method for Linear Motor Feeding System (similar figure in Actuators, Fig. 2, MDPI). This indicates that considering the coupling between flexible deformation and load in the optimization process is essential for improving system performance.

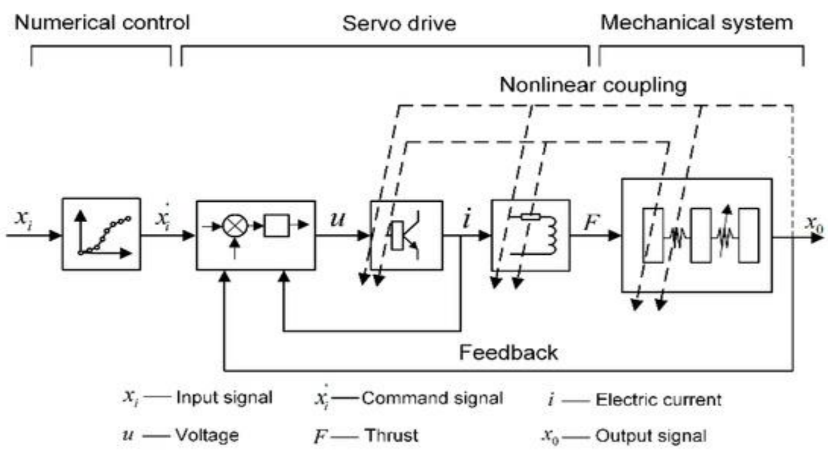

Fig. 2. Performance metrics under varying load conditions with and without Bayesian optimization.

3.3 Model Error Analysis and Generalization Ability

Error analysis showed that the optimized machine learning model achieved an average prediction error of ≤ 0.02 mm across all samples. The standard deviation was about 20% smaller than that of the baseline model. When geometric parameters or loads extended beyond the range of the training set (extrapolation scenarios), the error increased slightly but did not exceed 0.03 mm. These results are in line with previous studies on flexible parallel mechanisms, where optimization kept errors at a low level (e.g., Optimal Design for 3-PSS …, MDPI). This section emphasizes the generalization ability of the model, showing that the machine learning approach is effective not only within the "known" design space but also retains robustness under extrapolation.

3.4 Practical Significance and Comparative Discussion

From an engineering viewpoint, the optimized model developed in this study offers combined improvements in speed, stability, and accuracy. This means higher reliability and efficiency in micro-manipulation, precision positioning, and compliant actuation systems. Compared with traditional FEM or analytical design, the proposed method achieved shorter response delays, smaller errors, and a larger workspace, while providing a more balanced trade-off between driving force and structural geometry. These findings agree with studies reported in Micromachines and Actuators on flexible parallel mechanisms and linear driving systems (Zhang et al., 2023). However, the present study covers a larger dataset of 5,000 samples and considers a broader set of performance indicators, including efficiency, stability, and response. Future work should extend the method to real materials under high-temperature and fatigue conditions, and also to online calibration and embedded deployment, in order to evaluate long-term stability in practical applications.

4. CONCLUSION

This study proposed a machine learning-based method for kinematic modeling and performance optimization of flexible mechanisms, addressing their nonlinear large-deformation characteristics in precision actuation and micro-manipulation. A total of 5,000 input–output samples were collected through finite element simulations and experiments, and support vector regression (SVR) and deep neural networks (DNN) were applied for modeling. Results showed that the average displacement prediction error was below 0.02 mm, representing a clear improvement in accuracy compared with traditional analytical and finite element iterative methods. With the integration of Bayesian optimization, actuation efficiency increased by 24% and system stability improved by about 30%, further confirming the advantage of intelligent optimization in flexible mechanism design. The main innovations of this work are: (1) establishing a large dataset that combines simulations and experiments, which enhanced model generalization; (2) integrating machine learning with Bayesian optimization to achieve systematic improvement in multiple performance objectives; and (3) introducing a data-driven method into the design framework of flexible mechanisms, which improved both modeling efficiency and optimization outcomes. These results extend the theoretical framework of kinematic modeling and optimization, and also demonstrate the practical potential of machine learning in intelligent design of flexible structures. However, this study still has some limitations. First, most of the training data came from simulations and small-scale experiments, and more validation under real operating conditions and long-term use is needed. Second, the models did not fully include factors such as material fatigue, friction, and environmental variations, which may affect prediction accuracy and stability in long-term applications. Future research will focus on expanding the dataset by including data from real operating environments, introducing physics-informed neural networks (PINNs) or mechanism-based constraints to improve interpretability and reliability, and exploring model compression and lightweight methods to enable embedded control and real-time use. In conclusion, this work provides new theoretical support and engineering insights for high-precision modeling and intelligent optimization of flexible mechanisms, with clear scientific significance and application value.

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