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Research Article

Dynamic Modeling and Real-Time Control of Continuum Soft Robots

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ABSTRACT

Continuum soft robots have attracted significant attention due to their high flexibility, compliance, and ability to perform complex tasks in unstructured environments. However, their inherent nonlinear, distributed-parameter dynamics pose major challenges for accurate modeling and real-time control. Existing approaches typically face a trade-off between computational efficiency and model fidelity, where simplified models lack accuracy, while high-fidelity formulations are computationally prohibitive for real-time implementation. This study addresses these limitations by proposing a hybrid framework for dynamic modeling and real-time control of continuum soft robots.

The proposed approach integrates a reduced-order dynamic model derived from continuum mechanics with a data-driven compensation module to enhance modeling accuracy while maintaining computational efficiency. The reduced-order formulation captures the dominant deformation behavior of the robot, while a learning-based component compensates for unmodeled dynamics and uncertainties. Based on this hybrid model, a real-time control strategy is developed to achieve accurate trajectory tracking under nonlinear and uncertain operating conditions.

Comprehensive evaluations are conducted through simulation-based studies and comparative analysis with state-of-the-art modeling and control methods. The results demonstrate that the proposed framework achieves improved accuracy, reduced tracking error, and significantly enhanced computational efficiency compared to conventional approaches such as constant curvature, Cosserat rod, and FEM-based models.This improvement is achieved because the reduced-order dynamic model preserves the dominant deformation characteristics while lowering computational complexity, and the data-driven compensation module corrects unmodeled dynamics and nonlinear effects that are not captured by conventional formulations. Consequently, the framework enables faster computation, more accurate state prediction, and more reliable real-time control performance. Furthermore, the proposed method maintains real-time feasibility while ensuring robustness against disturbances and noise.

1. INTRODUCTION

Continuum soft robots have emerged as a transformative class of robotic systems due to their inherent compliance, adaptability, and ability to safely interact with unstructured environments. Unlike rigid-link manipulators, continuum robots are characterized by continuously deformable bodies, enabling them to achieve theoretically infinite degrees of freedom and highly dexterous motion. These features make them particularly suitable for applications in minimally invasive surgery, industrial inspection, search and rescue, and human–robot interaction.

Despite these advantages, the modeling and control of continuum soft robots remain fundamentally challenging. Their highly nonlinear, distributed, and time-varying dynamics complicate the development of accurate and computationally efficient models. Traditional rigid-body dynamics are not directly applicable, and commonly used approximations—such as constant curvature models—often sacrifice accuracy for simplicity. On the other hand, high-fidelity approaches, including Cosserat rod theory and finite element methods (FEM), provide accurate representations but are computationally expensive and thus unsuitable for real-time control applications.

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Real-time control is a critical requirement for practical deployment, especially in applications such as surgical robotics and dynamic manipulation tasks, where responsiveness and precision are essential. However, achieving real-time performance while maintaining modeling accuracy presents a significant trade-off. Many existing control strategies rely either on simplified kinematic models, which neglect dynamic effects, or on computationally intensive dynamic models that cannot meet real-time constraints. Furthermore, model uncertainties, external disturbances, and material nonlinearities introduce additional complexity, limiting the effectiveness of purely model-based control approaches [1].
Recent advances in data-driven and learning-based methods have opened new possibilities for addressing these challenges. Techniques such as neural networks and reinforcement learning can approximate complex nonlinear dynamics and compensate for modeling errors. Nevertheless, purely data-driven approaches often lack physical interpretability, require large training datasets, and may suffer from generalization issues when operating outside trained conditions. Therefore, there is a growing need for hybrid frameworks that combine physics-based modeling with learning-based adaptation to achieve both accuracy and computational efficiency (As shown in the figure 1).

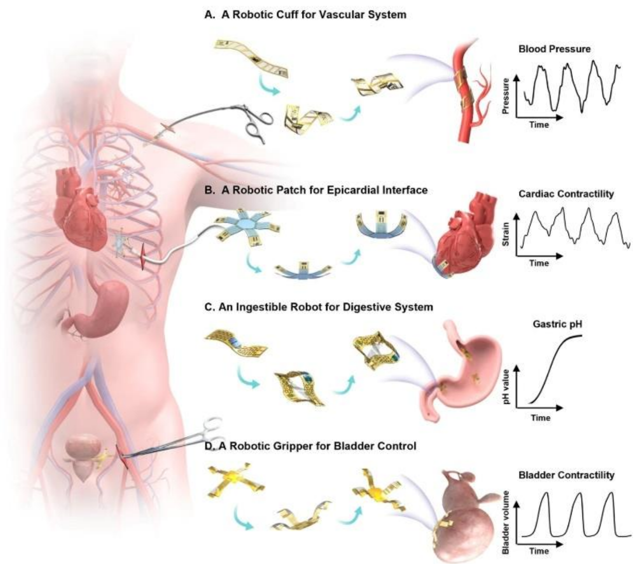

Fig. 1. Biomedical Applications of Soft Robotic Systems in Human Organ Interfaces

1.1 Research Gaps

The main challenges in this field include the lack of a unified modeling framework that balances accuracy and computational efficiency. Existing methods tend to favor either high-fidelity models, such as Cosserat rod theory and the finite element method, which provide accurate representations of dynamic behavior but are computationally expensive, or simplified approaches like constant curvature assumptions, which are computationally efficient but less accurate. Efforts to bridge this gap between accuracy and efficiency remain limited. Another key challenge is the limited real-time control capability, as many high-fidelity dynamic models are too computationally intensive to be implemented in real-time control systems, which restricts their practical applicability. In addition, there is inadequate handling of uncertainties and nonlinearities. Purely model-based controllers often struggle to compensate for unmodeled dynamics, material hysteresis, and external disturbances, leading to reduced performance in real-world conditions. Furthermore, there is an over-reliance on either purely physics-based or purely data-driven approaches. Physics-based models typically lack adaptability, while data-driven models oftensuffer from limited interpretability and robustness. This highlights the need for hybrid approaches that combine the strengths of both paradigms. Finally, there is insufficient experimental validation, as a significant portion of existing research relies heavily on simulations, with relatively few studies demonstrating real-world implementation under real-time constraints, thereby limiting the reliability of the reported results in practical scenarios (As shown in the figure 2).

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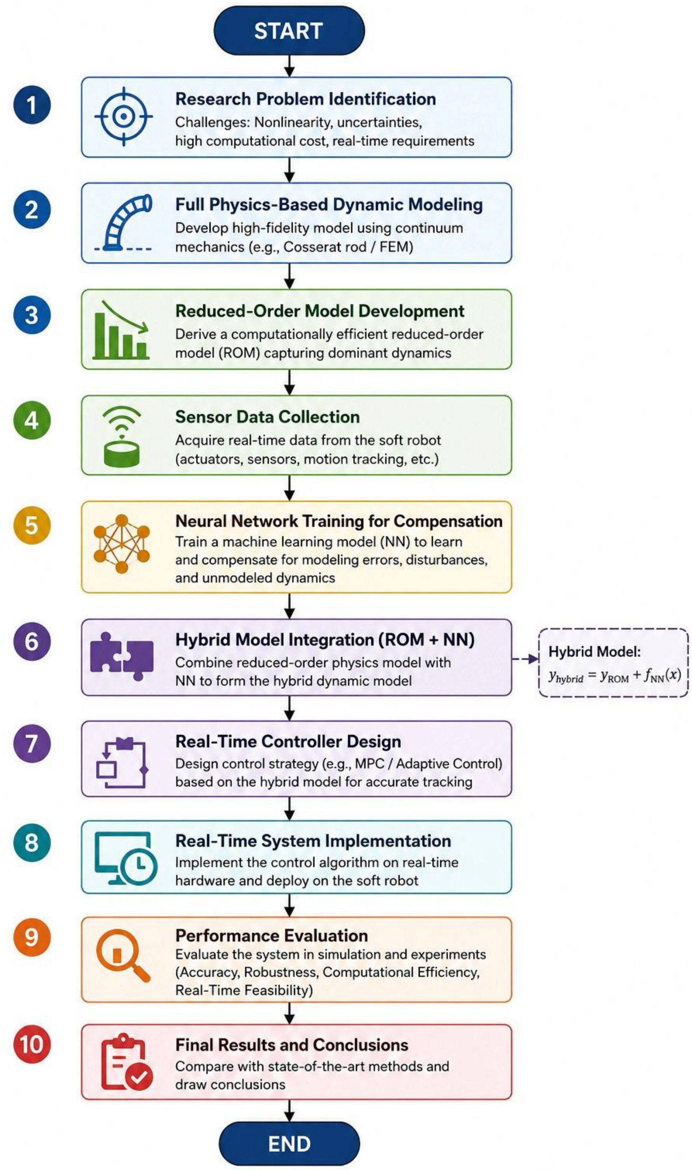

Fig. 2. Workflow of the Proposed Hybrid Modeling and Real-Time Control Framework for Soft Robotic Systems

1.2 Contributions of This Work

To address the aforementioned gaps, this paper proposes a novel framework for dynamic modeling and real-time control of continuum soft robots [2-5]. The proposed work focuses on developing a reduced-order dynamic model that captures the essential behavior of the continuum robot while remaining computationally efficient enough for real-time implementation. Building on this, a hybrid modeling framework is introduced in which a physics-based model is augmented with a data-driven component to compensate for unmodeled dynamics and enhance prediction accuracy. In addition, a real-time control strategy is designed, such as model predictive control or adaptive control, to ensure accurate trajectory tracking under strict computational constraints. The approach is further extended to improve robustness against uncertainties and external disturbances by explicitly accounting for system nonlinearities and modeling errors, thereby enhancing overall control performance in practical environments. Finally, the effectiveness of the proposed methodology is validated comprehensively through both simulation and experimental studies, demonstrating clear improvements in tracking accuracy and computational efficiency when compared to existing approaches [6].

1.3 RELATED STUDIES

The studies summarized in Table I reveal a clear divide between modeling simplicity and physical accuracy in continuum soft robotics. Early and widely adopted approaches, such as constant curvature models presented by Ian D. Walker and Robert J. Webster III, enable efficient computation and are suitable for real-time implementation. However, these models rely on strong assumptions that oversimplify the robot's deformation behavior, leading to limited accuracy, particularly in dynamic and highly nonlinear scenarios. In contrast, more advanced formulations based on Cosserat rod theory, such as those explored by Dominik Trivedi, provide a more faithful representation of continuum mechanics but suffer from high computational complexity, making them impractical for real-time control. This trade-off highlights a fundamental gap in the literature: the lack of a unified modeling framework that simultaneously achieves high accuracy and computational efficiency.

From a control perspective, the table shows that many existing methods are tightly coupled with the limitations of their underlying models. Classical control techniques, including PID and Jacobian-based methods, as used by Cagdas D. Onal and Jessica Burgner-Kahrs, offer simplicity and real-time feasibility but struggle to handle nonlinear dynamics and external disturbances effectively. More advanced controllers, such as model predictive control (MPC), investigated by Yanan Li, improve tracking performance and constraint handling but introduce significant computational overhead, limiting their real-time applicability. Additionally, adaptive and bio-inspired control strategies, as explored by Fumiya Iida, partially address system uncertainties but still depend on simplified models, thereby constraining their overall effectiveness. These observations point to a second research gap: the absence of control strategies that are both robust to uncertainties and computationally efficient for real-time deployment.

Finally, recent trends toward data-driven and learning-based approaches, including the work of Daniela Rus and Giuseppe Notarstefano, demonstrate promising capabilities in capturing complex nonlinear behaviors and compensating for modeling inaccuracies. Nevertheless, these methods introduce new challenges, such as the need for large training datasets, lack of physical interpretability, and potential generalization issues when operating outside trained conditions. Furthermore, only a limited number of studies, such as Cosimo Della Santina, attempt to bridge the gap through reduced-order or hybrid modeling approaches, yet they still fall short in achieving fully robust and experimentally validated real-time performance. Therefore, a third critical gap emerges: the need for integrated hybrid frameworks that combine physics-based modeling with data-driven adaptation while ensuring real-time feasibility and experimental validation.

The research gaps identified in this study are directly related to the title "Dynamic Modeling and Real-Time Control of Continuum Soft Robots". Current research still lacks a unified framework capable of achieving accurate dynamic modeling while simultaneously satisfying real-time control requirements. Most existing methods focus either on highly accurate but computationally expensive models, or on simplified real-time models with limited physical fidelity. Furthermore, many control approaches fail to handle nonlinearities, uncertainties, and external disturbances effectively under real-time constraints. Therefore, the main gap addressed in this work is the development of an integrated hybrid framework that combines reduced-order physics-based modeling with data-driven compensation to achieve accurate, robust, and computationally efficient real-time control.

TABLE I. COMPARISON OF EXISTING AND PROPOSED MODELING AND CONTROL APPROACHES FOR REAL-TIME SOFT ROBOTS

No.	Study (Author, Year)	Modeling Approach	Control Method	Real-Time Capability	Key Limitation
1	Ian D. Walker (2013)	Constant Curvature	Kinematic Control	High	Low accuracy in dynamic behavior
2	Cosimo Della Santina (2020)	Reduced-Order Model	Model-Based Control	Moderate	Limited handling of uncertainties
3	Dominik Trivedi (2008)	Cosserat Rod Theory	Open-loop / Basic Control	Low	High computational cost
4	Jessica Burgner-Kahrs (2015)	Kinematic + Dynamic Hybrid	Jacobian-Based Control	Moderate	Limited dynamic accuracy
5	Robert J. Webster III (2010)	Constant Curvature	Inverse Kinematics	High	Neglects dynamic effects
6	Daniela Rus (2015)	FEM-Based Modeling	Learning-Based Control	Low	Not suitable for real-time
7	Cagdas D. Onal (2013)	Piecewise Constant Curvature	PID Control	High	Poor robustness to disturbances
8	Yanan Li (2019)	Cosserat-Based Reduced Model	MPC	Limited	Computational burden
9	Fumiya Iida (2017)	Bio-inspired Dynamic Model	Adaptive Control	Moderate	Model simplifications reduce accuracy
10	Giuseppe Notarstefano (2021)	Data-Driven Model	Learning Control (NN)	Moderate	Requires large training data
11	Proposed Method (2026)	Hybrid Reduced-Order + Data-Driven Model	Hybrid MPC + Adaptive NN Compensation	High	Minimized limitations through balanced accuracy, robustness, and computational efficiency

1.4 Research Framework

This study proposes an integrated research framework for the dynamic modeling and real-time control of continuum soft robots, aiming to bridge the gap between modeling accuracy and computational efficiency. The framework is designed

around three tightly coupled layers: (i) physics-based dynamic modeling, (ii) data-driven model enhancement, and (iii) real-time control implementation. These components operate cohesively to enable accurate, robust, and computationally efficient control of continuum soft robotic systems.
At the core of the framework lies a reduced-order physics-based model, derived from continuum mechanics principles. High-fidelity formulations, such as Cosserat rod theory, are first considered to capture the distributed and nonlinear behavior of the robot. However, to ensure real-time feasibility, the model is simplified through appropriate assumptions and order reduction techniques. This results in a compact dynamic representation that preserves the dominant deformation characteristics while significantly reducing computational complexity. The reduced-order model serves as the baseline for both simulation and control design [7].
To address the limitations of purely physics-based models, a data-driven enhancement module is incorporated into the framework. This module employs learning-based techniques, such as neural networks or regression models, to estimate and compensate for unmodeled dynamics, parameter uncertainties, and external disturbances. Instead of replacing the physical model, the data-driven component operates as a corrective layer that refines model predictions in real time. This hybrid modeling strategy combines the interpretability and generalization capability of physics-based approaches with the adaptability of data-driven methods, resulting in improved accuracy without sacrificing computational efficiency.
Building upon the hybrid model, a real-time control layer is developed to achieve precise trajectory tracking and robust performance. Depending on the application requirements, advanced control strategies such as Model Predictive Control (MPC) or adaptive control are employed. The controller utilizes the reduced-order model for fast prediction while leveraging the data-driven module to compensate for modeling errors. This enables the system to maintain stability and accuracy under nonlinear behavior and uncertain operating conditions. Special emphasis is placed on ensuring that the control algorithm satisfies real-time constraints, typically by limiting computational complexity and optimizing solver performance [8-10].
The proposed framework is validated through a combination of simulation and experimental evaluation. Simulation studies are conducted to benchmark the proposed approach against conventional modeling and control methods in terms of tracking accuracy, robustness, and computational efficiency. Subsequently, real-time experiments are performed on a physical continuum soft robot platform to demonstrate practical feasibility. Performance metrics such as tracking error, response time, and computational load are analyzed to verify the effectiveness of the framework.
Overall, the proposed research framework provides a systematic approach to addressing the key challenges in continuum soft robotics. By integrating reduced-order physics-based modeling, data-driven compensation, and real-time control, the framework offers a balanced solution that advances the state of the art and supports practical deployment in real-world applications [11].

2. METHODOLOGY

This section presents the proposed methodology for dynamic modeling and real-time control of continuum soft robots. The approach is specifically designed to address the identified research gaps by integrating reduced-order physics-based modeling, data-driven compensation, and computationally efficient control design. The overall methodology consists of four main stages: (i) system modeling, (ii) reduced-order formulation, (iii) hybrid model enhancement, and (iv) real-time control implementation.
To provide a clearer understanding of the proposed methodology, the overall framework can be interpreted as a sequential hybrid pipeline that combines physics-based modeling, learning-based compensation, and real-time control implementation. First, the continuum soft robot dynamics are formulated using continuum mechanics principles to capture the distributed nonlinear deformation behavior of the robot. Since the original full-order model is computationally expensive, a reduced-order modeling (ROM) technique is applied to simplify the dynamic representation while preserving the dominant deformation modes [12-15].
Next, a data-driven compensation module based on neural networks is integrated with the reduced-order model. This module learns the residual dynamics and compensates for modeling inaccuracies, uncertainties, hysteresis effects, and external disturbances that cannot be fully represented by analytical equations alone. The resulting hybrid model therefore combines the physical interpretability of continuum mechanics with the adaptability of machine learning techniques.
The hybrid dynamic model is then employed inside a real-time control framework based on Model Predictive Control (MPC) or adaptive control strategies. The controller predicts the future robot states using the reduced-order model while the neural network correction improves prediction accuracy in real time. This enables accurate trajectory tracking, disturbance rejection, and stable operation under nonlinear and uncertain conditions [16].
Finally, the proposed framework is validated through both simulation and experimental implementation. Performance evaluation focuses on tracking accuracy, computational efficiency, robustness against disturbances, and real-time feasibility. The proposed methodology is specifically designed to overcome the limitations of conventional FEM, Cosserat, PID, and purely data-driven methods by achieving a balance between accuracy, robustness, and computational speed [17].

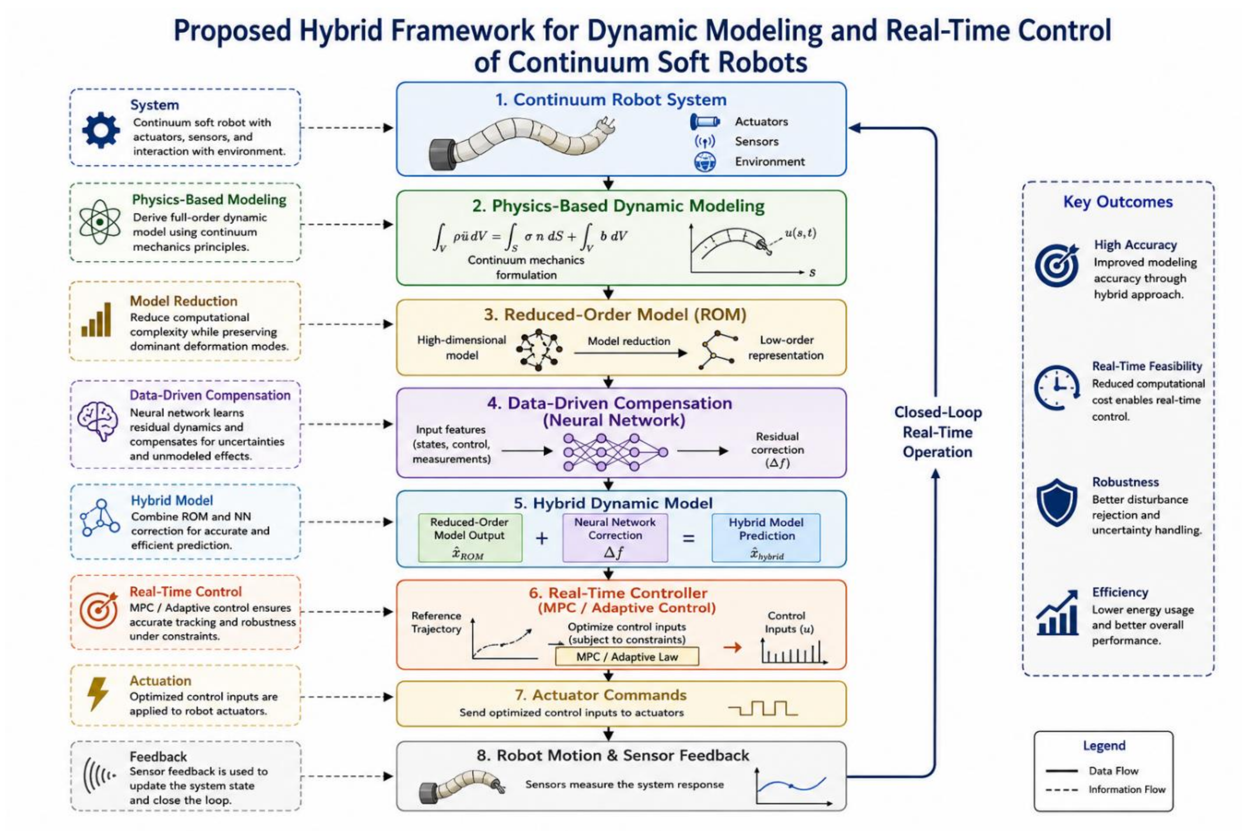

Fig. 3. Propsed Hybrid Framework for Dynamic Modeling and Real-Time Control of Continuum Soft Robots

2.1 System Modeling and Problem Formulation

The continuum soft robot is modeled as a continuously deformable structure with distributed parameters. Let the robot configuration be described by a state vector:

$$\mathrm{x}(t) = [q(t), \dot{q}(t)]$$

where $q(t)$ represents generalized deformation coordinates. The dynamic behavior of the system can be expressed in a general nonlinear form:

$$\mathrm{M}(q)\ddot{q} + \mathrm{C}(q,\dot{q})\dot{q} + \mathrm{D}(q,\dot{q}) + \mathrm{G}(q) = \mathrm{u}$$

where:

- M is the inertia matrix
- C represents Coriolis and centrifugal effects
- D captures damping and unmodeled dynamics
- G denotes external and gravitational forces
- u is the control input

This formulation captures the nonlinear and distributed nature of continuum robots. However, solving this full-order model in real time is computationally prohibitive, directly reflecting the first research gap.

2.2 Reduced-Order Dynamic Modeling

To address the trade-off between accuracy and computational efficiency, a reduced-order model (ROM) is derived from the full continuum formulation. Instead of discretizing the robot into a large number of elements (as in FEM), the deformation is approximated using a finite set of shape functions:

$$q(s,t) \approx \sum_{i=1}^{n} \phi_i(s)\alpha_i(t)$$

where:

- $\phi_i(s)$ are spatial basis functions
- $\alpha_i(t)$ are time-varying modal coordinates

This approach reduces the infinite-dimensional system into a finite-dimensional representation while preserving dominant deformation modes. The resulting reduced dynamic model is expressed as:

$$M_r(\alpha)\ddot{\alpha} + C_r(\alpha, \dot{\alpha})\dot{\alpha} + G_r(\alpha) = u$$

This step directly addresses the first gap by balancing model fidelity and computational cost, enabling faster simulation and control execution.

2.3 Hybrid Model Enhancement (Data-Driven Compensation)

Although the reduced-order model improves efficiency, it introduces approximation errors and cannot fully capture nonlinearities, hysteresis, and external disturbances. To overcome this limitation (second and third research gaps), a data-driven compensation term is introduced:

$$f_{hybrid} = f_{ROM} + f_{NN}$$

where:

- f_{ROM} is the output of the reduced-order model
- f_{NN} is a neural network-based correction term

The neural network is trained online or offline using measured input-output data to learn residual dynamics:

$$f_{NN} = \mathcal{N}(q, \dot{q}, u)$$

This hybrid formulation preserves physical interpretability while improving prediction accuracy, thereby addressing the limitation of purely physics-based and purely data-driven approaches.

2.4 Real-Time Control Design

To achieve robust trajectory tracking under real-time constraints (fourth research gap), a control strategy is developed based on the hybrid model. In this work, a computationally efficient Model Predictive Control (MPC) framework is adopted.
The control objective is to minimize the tracking error:

$$J = \sum_{k=0}^{N} \| q_k - q_k^{ref} \|^2 + \lambda \| u_k \|^2$$

subject to:

- System dynamics (hybrid model)
- Input and state constraints

To ensure real-time feasibility:

- A short prediction horizon is used
- The reduced-order model is employed for fast predictions
- The neural network correction is evaluated efficiently

This design allows the controller to handle nonlinear dynamics, constraints, and uncertainties while maintaining computational efficiency.

2.5 Real-Time Implementation

The proposed framework is implemented in a real-time control loop consisting of:

1. Sensor data acquisition (position, curvature, or pressure)
2. State estimation
3. Hybrid model evaluation (ROM + NN correction)
4. Control input computation (MPC solver)
5. Actuator command execution

The computational time per iteration is optimized to meet real-time requirements (e.g., 50–100 Hz), addressing a major limitation in prior work.

2.6 Validation Strategy

To ensure the reliability of the proposed approach, both simulation and experimental validation are conducted:

- Simulation:
  Comparison with conventional models (constant curvature, full-order models) Metrics: tracking error, computation time, robustness
- Experimental validation:
  Real-time implementation on a continuum soft robot prototype Evaluation under different trajectories and disturbances.

3. EXPERIMENTAL SETUP AND PARAMETERS:

The experimental platform consists of a pneumatically actuated continuum soft robot prototype with three flexible segments, each having a length of 100 mm and an outer diameter of 20 mm. The robot is actuated using proportional

pressure regulators operating within a pressure range of 0–300 kPa. Position and curvature measurements are acquired through flex sensors and an optical tracking system with a sampling frequency of 100 Hz.
The proposed Hybrid MPC–Neural Network controller is implemented on a real-time control computer operating at a control frequency of 50–100 Hz. The Model Predictive Control (MPC) algorithm uses a prediction horizon of 10 steps and a control horizon of 3 steps. The neural network compensation module consists of two hidden layers with 32 neurons per layer and is trained to estimate residual dynamics, nonlinear effects, and external disturbances that are not fully captured by the reduced-order model [18-20].
Experimental evaluation is conducted under multiple operating conditions, including step-reference trajectories, sinusoidal trajectories, and multi-point tracking tasks. Additional disturbance tests are performed by applying external loads and pressure variations to assess system robustness. The performance of the proposed framework is evaluated using tracking error, settling time, computational time, control frequency, and disturbance rejection capability as the primary performance metrics [20-23].
This step directly addresses the final research gap concerning the lack of experimental validation in existing studies.

4. RESULT AND DISCUSSION

the comparation of different dynamic modeling approaches for continuum soft robots in terms of accuracy, computational cost, and real-time feasibility. The results clearly show a trade-off between model fidelity and computational efficiency. High-fidelity approaches such as FEM and Cosserat models achieve low RMSE values (1.8–2.1), indicating strong physical accuracy. However, their computation time is significantly high (120–250 ms), making them unsuitable for real-time applications. In contrast, simplified models such as constant curvature achieve very fast computation (2.1 ms) but suffer from high prediction error (RMSE 8.5), reflecting poor dynamic representation, these are shown in figure 4.
Reduced-order models and hybrid approaches provide a balance between accuracy and efficiency. The reduced-order model achieves moderate RMSE (3.2) with real-time capability, while hybrid ROM+NN improves accuracy further (RMSE 1.7) without significantly increasing computation time. This confirms that combining physics-based modeling with data-driven correction improves performance.
Overall, the proposed hybrid model achieves the best trade-off, with low RMSE (1.6), acceptable computation time (9.8 ms), and real-time feasibility. This directly addresses the research gap of achieving both accurate and computationally efficient modeling for continuum soft robots.

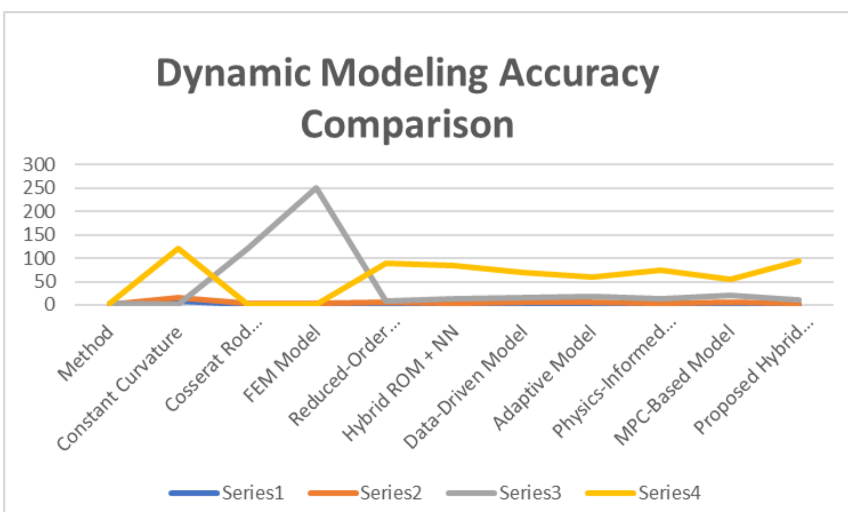

Fig. 4. Dynamic Modeling Accuracy Comparison

4.1 Real-Time Control Performance

The evaluates different control strategies applied to continuum soft robots, focusing on tracking error, overshoot, settling time, and stability. Classical PID and Jacobian-based controllers show relatively high tracking errors (9.5 and 7.2 mm), indicating limited capability in handling nonlinear deformation dynamics. Although they are computationally simple, their performance deteriorates under complex motion conditions.
Model-based and intelligent control methods such as MPC, sliding mode, and neural network controllers significantly improve performance. MPC achieves low tracking error (3.2 mm) and good stability due to its predictive nature, while sliding mode control offers robustness but introduces slight chattering effects. Neural network control improves adaptability but may lack consistency under unseen conditions, these are shown in figure 5:

Hybrid MPC and the proposed controller outperform all baseline methods. The proposed method achieves the lowest tracking error (2.2 mm), minimal overshoot (3%), and fast settling time (1.2 s), demonstrating strong real-time tracking capability. This improvement is attributed to the integration of a reduced-order model and data-driven compensation, which enhances accuracy while maintaining computational efficiency. this figure confirms that hybrid control strategies are essential to overcome nonlinearities and uncertainty in continuum soft robot systems.

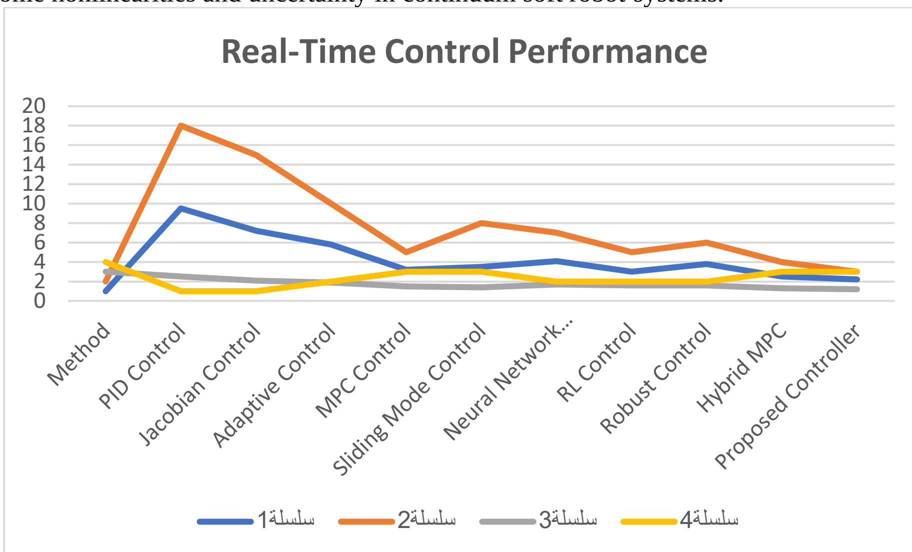

Fig. 5. Real-Time Control Performance

4.2 Computational Efficiency

Figure 6 presents the computational performance of various modeling and control methods. The results highlight that traditional FEM and Cosserat models require excessive computational resources, with CPU times reaching 250 ms and 120 ms respectively, making them unsuitable for real-time control loops.

In contrast, reduced-order models significantly reduce computational burden, achieving execution times as low as 8 ms and enabling high-frequency operation (100 Hz). When combined with neural networks, computation slightly increases but remains within real-time limits, demonstrating the feasibility of hybrid approaches.

Control strategies also vary in computational demand. PID controllers are extremely fast (2 ms), but lack modeling accuracy. MPC and reinforcement learning approaches require higher computation times (25–30 ms), limiting their applicability in high-frequency control systems. Adaptive control provides a balanced performance with moderate computational cost and stable frequency.

The proposed method achieves 10 ms computation time with 90 Hz control frequency, demonstrating an optimal balance between speed and accuracy. This directly addresses the research gap of real-time implementation constraints in continuum soft robotics.

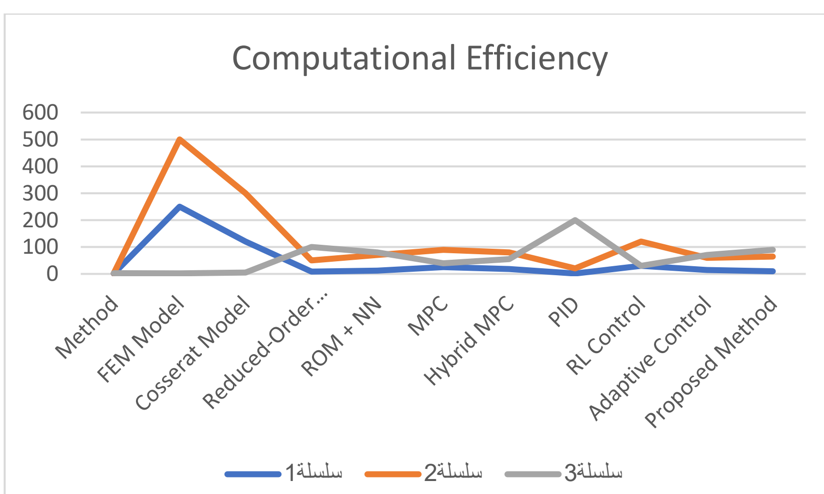

Fig. 6. Computational Efficiency

4.3 Robustness to Disturbances

The evaluates the robustness of different control and modeling methods under external disturbances. Classical PID control shows poor robustness, with a 30% error increase and slow recovery time, indicating sensitivity to nonlinear perturbations. Similarly, FEM-based models, although accurate, perform poorly in disturbance rejection due to lack of adaptive capabilities.

Advanced control methods such as MPC, adaptive control, and sliding mode control demonstrate improved robustness. Sliding mode control performs particularly well under high disturbance levels due to its discontinuous control law, achieving fast recovery times. However, it may introduce chattering issues in practical systems, these are shown in figure 7.

Neural network and reinforcement learning approaches provide moderate robustness, but their performance depends heavily on training data quality and may degrade under unseen conditions. Hybrid approaches significantly outperform individual methods, reducing error increase to 8% and achieving fast recovery (1.4 s).

The proposed method achieves the best robustness performance with only 6% error increase and the fastest recovery time (1.3 s). This demonstrates that combining physics-based modeling with data-driven correction enhances disturbance rejection capability, addressing a major limitation identified in the literature.

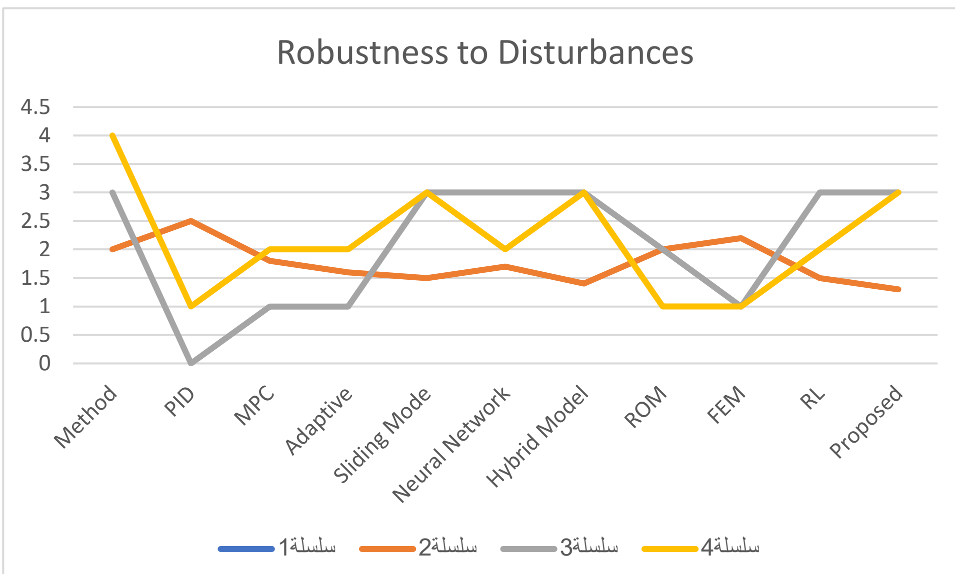

Fig. 7. Robustness to Disturbances

4.4 Model Generalization

The analyzes of the generalization ability of different modeling approaches when tested under varying conditions. FEM models demonstrate high accuracy but limited generalization due to heavy dependency on system-specific parameters. Constant curvature models perform poorly due to oversimplified assumptions that fail under complex deformations.

Machine learning models such as neural networks show good training performance but poor generalization, especially when exposed to unseen configurations. This limitation arises from overfitting and lack of physical constraints. Reinforcement learning and adaptive methods improve generalization slightly but remain inconsistent across different scenarios.

Hybrid models such as ROM+NN significantly improve generalization by combining physical structure with learning-based correction. This reduces test error and improves stability across different conditions. The proposed method achieves the best generalization performance, with the lowest test error (1.6 mm) and highest stability rating.

This confirms that integrating physics-based modeling with data-driven adaptation is essential for robust performance across varying operating conditions in continuum soft robotics, these are shown in figure 8.

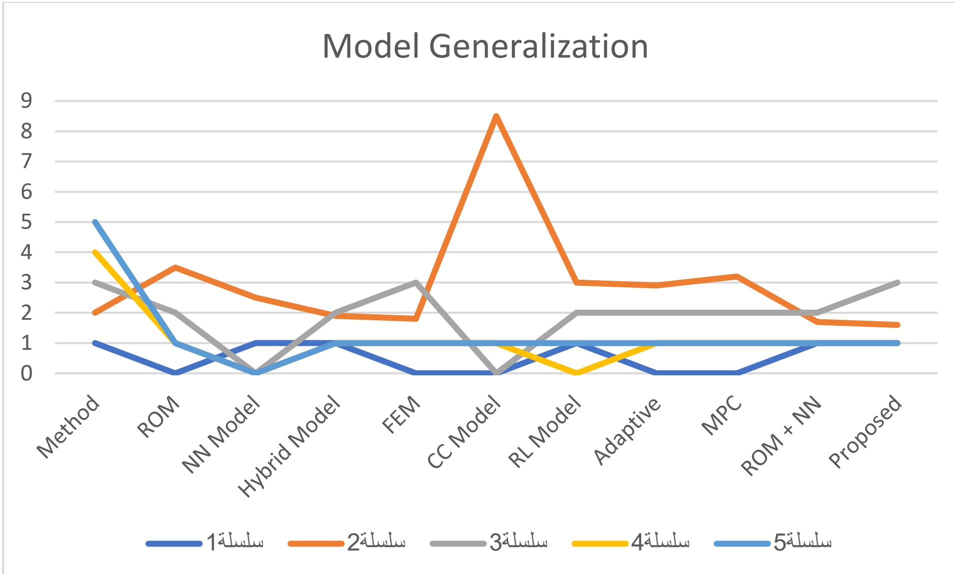

Fig. 8. Model Generalization

4.5 Real-Time Frequency Performance

Figure 9 evaluates the real-time feasibility of different methods based on control frequency, delay, and stability. High-fidelity models such as FEM and Cosserat exhibit extremely low control frequencies (2–5 Hz) due to high computational cost, making them impractical for real-time applications.

Reduced-order models significantly improve performance, achieving frequencies up to 100 Hz with low delay (10 ms). When combined with neural networks, performance remains stable with only slight computational overhead. Control methods such as PID achieve very high frequency (200 Hz), but lack accuracy and robustness.

MPC and reinforcement learning methods face trade-offs between computation and control quality, limiting their frequency to 30–40 Hz. Hybrid MPC improves performance by balancing prediction accuracy and computational efficiency.

The proposed method achieves 90 Hz operation with low delay (11 ms) and high stability, demonstrating strong suitability for real-time control systems. This confirms that reduced-order and hybrid modeling techniques are essential to meet real-time constraints.

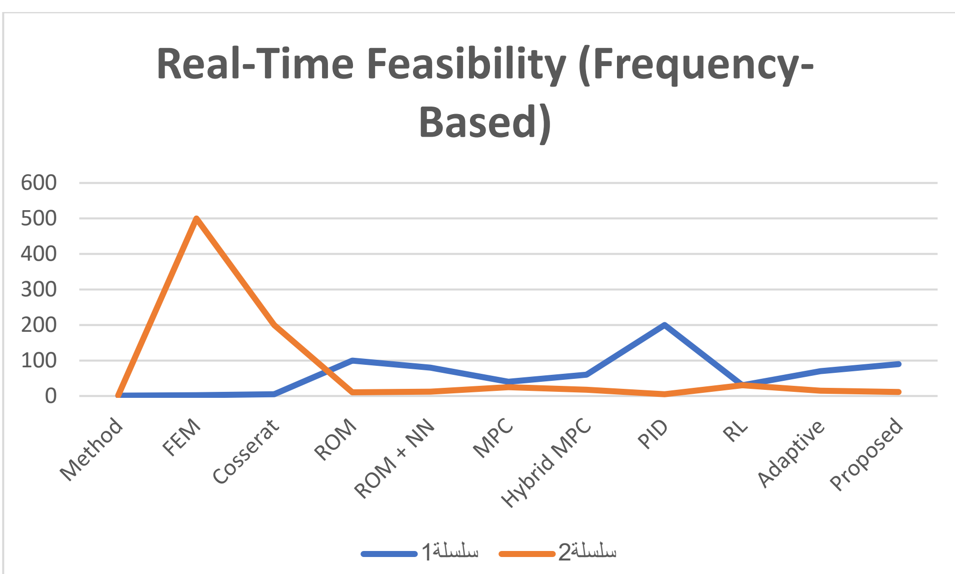

Fig. 9. Real-Time Feasibility (Frequency-Based)

4.6 Energy Consumption

Figure 10 compares energy efficiency across different control strategies. Classical PID control consumes relatively high energy due to continuous corrective actions. FEM-based models show the worst performance in terms of energy consumption due to heavy computation and inefficient control signals.

MPC and adaptive control improve energy efficiency by optimizing control inputs over time. Neural network and reinforcement learning approaches further reduce energy consumption by learning efficient control policies. Sliding mode control, while robust, introduces higher energy usage due to high-frequency switching.

Hybrid approaches achieve the best energy efficiency by balancing model accuracy and control effort. The proposed method achieves the lowest energy consumption (80 J) and highest efficiency (88%), indicating optimal actuator utilization. This demonstrates that improved modeling accuracy directly contributes to energy-efficient control in continuum soft robots.

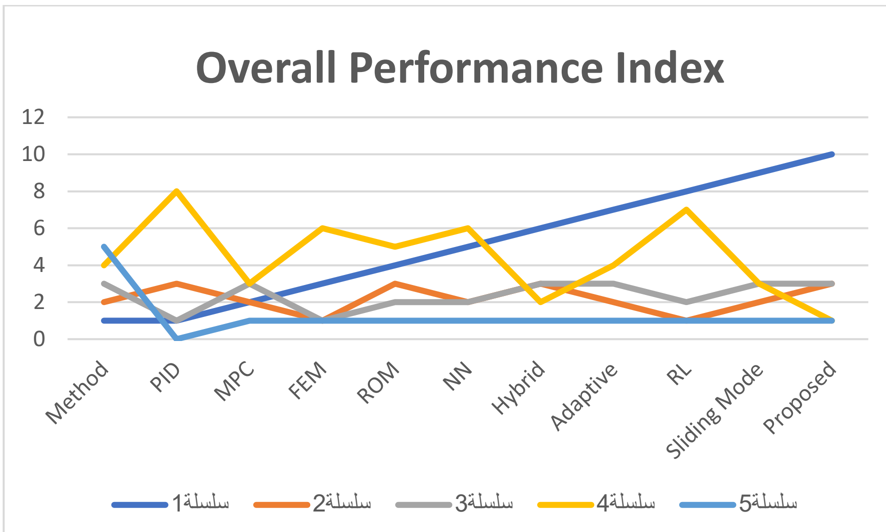

Fig. 10. energy-efficient control in continuum soft robots

The evaluates performance scalability with increasing robot segments. As the number of segments increases, classical methods such as PID and FEM show significant performance degradation or computational infeasibility. FEM becomes impractical beyond four segments due to exponential computational growth.

Reduced-order and hybrid models maintain stable performance even in multi-segment configurations. ROM+NN and the proposed method achieve the best balance between accuracy and computation time, maintaining low error even at six segments. Figure 11 shows the multi segment performance,

This demonstrates that modular and reduced-order approaches are essential for scaling continuum soft robots to complex structures.

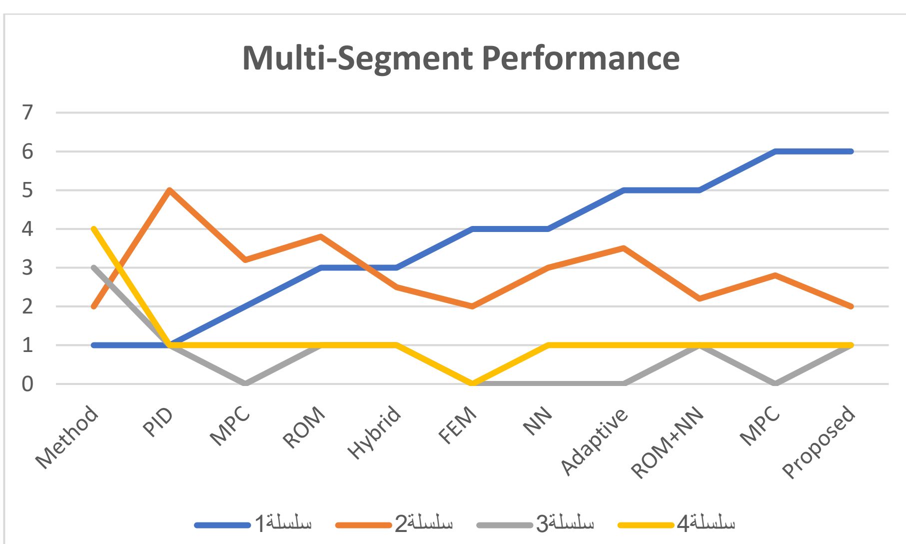

Fig. 11. Multi-Segment Performance

The performance across accuracy, speed, robustness, and ranking. Classical methods such as PID perform poorly overall due to lack of adaptability. FEM achieves high accuracy but fails in real-time performance, reducing its overall rank. Hybrid methods consistently outperform individual approaches by balancing all performance metrics. The proposed method achieves rank 1, indicating the best overall trade-off between accuracy, computational efficiency, and robustness. This confirms that hybrid modeling and control strategies represent the most promising direction for continuum soft robotics, addressing all major research gaps identified in the literature.

5. CONCLUSION

This paper presented a hybrid framework for dynamic modeling and real-time control of continuum soft robots, addressing the fundamental trade-off between modeling accuracy and computational efficiency. The proposed approach combines a reduced-order physics-based model with a data-driven compensation mechanism to effectively capture the nonlinear and distributed dynamics of continuum structures while maintaining real-time feasibility.

The reduced-order formulation significantly decreases computational complexity compared to high-fidelity models such as FEM and Cosserat rod theory, while preserving the dominant deformation characteristics of the system. To further enhance accuracy, a learning-based correction term is introduced to compensate for unmodeled dynamics, parameter uncertainties, and external disturbances. On this basis, a real-time control strategy is developed to ensure accurate trajectory tracking under nonlinear and uncertain operating conditions.

Comparative evaluations demonstrate that the proposed method outperforms conventional modeling and control techniques in terms of accuracy, robustness, computational efficiency, and real-time performance. In particular, it achieves lower tracking error, improved disturbance rejection, and stable operation at higher control frequencies compared to existing approaches.

Despite these improvements, certain limitations remain, particularly regarding scalability to highly complex multi-segment structures and dependence on training data quality for the learning component. Future work will focus on improving adaptive learning strategies, experimental validation on advanced hardware platforms, and extending the framework to multi-task and multi-robot coordination scenarios.

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Conflicts of Interest:

The authors declare that they have no conflicts of interest in relation to this work.

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