Mechanical Engineering Advances 2025, 3(1), 2469.
https://doi.org/10.59400/mea2469

Article

Deep neural network enhanced modeling and adaptive control of a malfunctional spacecraft under unknown accessory breakage

Krzysztof Zalewski[1,*], Aliaksei Zakrevsky[2], Mikko Virtanen[3], Johan Svensson[4], Anders Joe[5], James Wilson[6]

[1] Warsaw University of Technology, 00-661 Warsaw, Poland
[2] Belarusian National Technical University, 220013 Minsk, Belarus
[3] Aalto University, 02150 Espoo, Finland
[4] KTH Royal Institute of Technology, 114 28 Stockholm, Sweden
[5] Norwegian University of Science and Technology, 2802 Gjøvik, Norway
[6] University of Bristol, Bristol BS8 1TH, UK
*** Corresponding author:** Krzysztof Zalewski, krzyz77@bsu.edu.pl

CITATION

Zalewski K, Zakrevsky A, Virtanen M, et al. Deep neural network enhanced modeling and adaptive control of a malfunctional spacecraft under unknown accessory breakage. Mechanical Engineering Advances. 2025; 3(1): 2469. https://doi.org/10.59400/mea2469

ARTICLE INFO

Received: 30 December 2024
Accepted: 17 January 2025
Available online: 26 January 2025

Abstract: This manuscript presents a sophisticated deep neural networks (DNNs)-driven adaptive control paradigm for concurrently regulating the attitude and suppressing structural oscillations of a flexible spacecraft in a fully three-dimensional domain. By leveraging Hamilton's principle, the spacecraft's motion is formulated as an infinite-dimensional dynamic model described by partial differential equations, capturing the subtle interactions between rigid-body rotational maneuvers and flexible panel deformations. In contrast to traditional schemes, the proposed control methodology integrates a DNNs module to compensate for uncertain actuator anomalies and external input disturbances in real time, thereby ensuring fault tolerance under arbitrary, potentially unbounded actuator malfunctions. A rigorously constructed Lyapunov-based stability analysis corroborates that the system's energy, angular rates, and transverse deflections remain uniformly bounded and asymptotically converge to zero, even in the face of multiple actuator failures. This theoretical guarantee stems from the synergistic interplay between the network's representational power and the adaptive control law's robust learning capabilities. Extensive computational experiments demonstrate the efficacy of the developed framework in orchestrating high-precision attitude stabilization while simultaneously mitigating detrimental vibrations, showcasing the superior performance and resiliency of the proposed DNNs-infused control architecture.

Keywords: deep learning; neural network; aerospace robot; adaptive control

1. Introduction

Flexible spacecraft have garnered substantial attention in recent years, primarily due to their advantageous attributes of diminished mass and reduced power requirements. By enabling increased functionality at lower launch costs, these pliable structures concurrently engender intricate coupling phenomena between elastic deflections and overall attitude maneuvers [1–3]. Such couplings inevitably compromise the performance of the spacecraft if not carefully mitigated through control strategies. Early efforts aimed at preserving attitude precision and alleviating unwanted vibrations often relied on truncation-based approximations of the flexible dynamics, which can introduce spillover effects and even precipitate instability. Consequently, to accurately capture the salient characteristics of both the spacecraft's rigid-body dynamics and its structural deformations, an infinite-dimensional representation governed by coupled partial differential equations (PDEs) and ordinary differential equations (ODEs) has emerged as a more rigorous modeling paradigm.

Historically, significant strides have been made in controlling flexible structures formulated within infinite-dimensional frameworks. Various schemes have targeted heat equations, beam equations, and string equations to demonstrate sophisticated methods for boundary or distributed control. In the context of flexible spacecraft specifically, the ubiquitous Euler–Bernoulli beam model has frequently been adopted to describe cantilever-like appendages attached to a central rigid hub. In Zhang et al. [4], the authors provide an innovative approach, as it highlights the efficacy of deep neural networks in optimizing coordination strategies for multi-aerospace systems during complex tasks. Their findings align with and further underscore the importance of leveraging DNNs in enhancing adaptability and robustness under uncertain conditions. The antecedent studies established foundational techniques—ranging from disturbance observers to fault-tolerant switches—for mitigating vibrational effects, many focused on two-dimensional (2D) or simplified geometric settings that do not adequately reflect the more complex three-dimensional (3D) coupling behaviors [5]. Several investigations into 3D beam-like systems have illustrated the significance of multiple deflection axes and their strong interactions with the spacecraft’s rotational degrees of freedom, thereby highlighting the necessity for more nuanced control designs. Furthermore, most extant works operate under the assumption of perfectly functioning actuators, overlooking the real-world possibility of actuator malfunctions or failures.

In practical scenarios, actuators can degrade due to phenomena such as aging, abrasion, or manufacturing imperfections, resulting in partial losses of effectiveness or complete failures that can occur unpredictably over the spacecraft’s operational lifespan. Ensuring the reliability of flexible spacecraft under these adverse conditions demands robust and fault-tolerant approaches that address potential infinite sets of unknown failures. Traditional control strategies (e.g., robust, sliding mode, or classical adaptive control) have demonstrated some efficacy, yet they often presume limited failure scenarios or rely on truncation-based models that may overlook higher-order dynamics of the flexible appendages. Gao et al. [6] develop a novel adaptive decentralized control framework for multi-robot servicing tasks in space environments, addressing both civilian applications, such as extending spacecraft operational lifespans (e.g., SpaceX initiatives), and military aerospace operations, where robust handling of uncertain dynamics and system malfunctions is critical for mission success in unpredictable environments. Consequently, guaranteeing asymptotic stability in the presence of unbounded actuator anomalies remains nontrivial, particularly when dealing with PDE-based representations [7–10].

In parallel, deep neural networks (DNNs) have emerged as powerful universal function approximators with strong capacity to adapt to highly nonlinear and uncertain systems [11]. Their integration with adaptive control laws offers a promising avenue for augmenting the robustness and adaptability of fault-tolerant strategies. By harnessing DNNs within a PDE-based framework, one can dynamically learn the evolving actuator efficacy and external disturbance profiles, thereby compensating for unknown anomalies more effectively than classical methods. This synergy of DNN-based estimation and adaptive boundary control allows real-time adjustments to the feedback law, accommodating an unbounded number of actuator faults across a potentially infinite time horizon.

The primary objective of this study is to devise a sophisticated DNNs-infused adaptive control methodology that simultaneously stabilizes the spacecraft's attitude and suppresses the structural vibrations of its flexible panels in a fully three-dimensional configuration. To achieve this, we adopt an extended Hamilton principle for modeling the overall system with coupled PDE–ODE dynamics, ensuring a comprehensive representation of both rigid-body motions and elastic deformations. The control strategy incorporates DNN modules to estimate and compensate for actuator anomalies of arbitrary complexity, while an adaptive boundary control scheme ensures robust command authority over the PDE-governed vibrations. A Lyapunov-based analysis is conducted to prove that the system energies, rotational velocities, and deformation trajectories remain uniformly bounded and converge asymptotically, even amid uncountably many actuator failures [12–15].

The remainder of this paper is organized as follows. First, the governing equations for a spatially flexible spacecraft are formulated, emphasizing the coupling between the rigid hub's attitude states and the PDE-driven flexible panels [16]. Subsequently, the DNNs-augmented fault-tolerant control scheme and accompanying parameter update laws are introduced. A rigorous Lyapunov analysis then validates the boundedness and decay properties of the closed-loop system [17–20]. Numerical simulations corroborate the efficacy and resilience of the proposed approach, and final conclusions are drawn regarding future directions and broader implications of this research.

Space exploration missions are increasingly reliant on flexible spacecraft due to their lightweight designs, reduced launch costs, and ability to carry advanced instrumentation. However, these advantages come with significant challenges. The interaction between structural deformations and attitude dynamics can lead to performance degradation, particularly under unforeseen conditions like actuator malfunctions. While traditional control strategies provide partial solutions, they often fail to address the complexities introduced by unbounded uncertainties, actuator degradation, or external disturbances. This work is motivated by the critical need to ensure reliability and precision in demanding operational environments, such as satellite repair and orbital debris management, where failures could jeopardize mission success and incur significant financial and operational costs. By integrating deep learning and adaptive control, this study aims to establish a robust, fault-tolerant control framework capable of addressing these multifaceted challenges, paving the way for safer and more efficient space missions.

2. Problem statement

We investigate a flexible aerospace apparatus composed of a rigid core and a slender, compliant panel, consistent with the illustrative schematics in **Figures 1** and **2**. In its undeformed configuration, the flexible panel is oriented along the $\Omega\Xi_\beta$ axis and assumed inextensible, permitting solely transverse deflections in the Υ_β and Υ_β directions. Denote these deflections by $\chi(\phi,\tau)$ and $\zeta(\phi,\tau)$, where ϕ and τ represent the spatial and temporal coordinates, respectively. Hence, the instantaneous position of any point $\mathcal{P}$ on the panel may be written as

$$\varrho = [\phi, \chi, \zeta]^{\top},$$

where ϕ is the distance measured from the origin Ω.

The angular velocities of the body frame relative to the orbital frame are collected in

$$\lambda = [\lambda_1, \lambda_2, \lambda_3]^{\top},$$

while the attitude of the flexible aerospace system is parameterized by Euler angles

$$\alpha = [\alpha_1, \alpha_2, \alpha_3]^{\top},$$

where indicating successive rotations about the $\Xi_\beta, \Upsilon_\beta$, and $\mathcal{Z}_\beta$ axes.

Given that actuators may deteriorate or abruptly malfunction during prolonged operation, a robust fault-mitigation strategy is imperative. To address this, the present study proposes a DNNs-augmented adaptive control methodology capable of reconciling structural dynamics and attitude requirements under uncertain actuator conditions [21]. By embedding a neural approximator based on the research work in Zhang et al. [22] into the PDE-based framework of the slender panel's deformations, the controller can dynamically estimate and compensate for unknown parameters, actuator losses, and external disturbances. This synergy between deep learning and adaptive control ensures reliable real-time corrections [23], facilitating both vibration suppression and precise angular stabilization in the presence of potentially unbounded actuator anomalies across the spacecraft's lifespan [24–27].

Figure 1. One spacecraft using one robot arm to pick up the broken part from one malfunctioning aerospace device in a space environment.

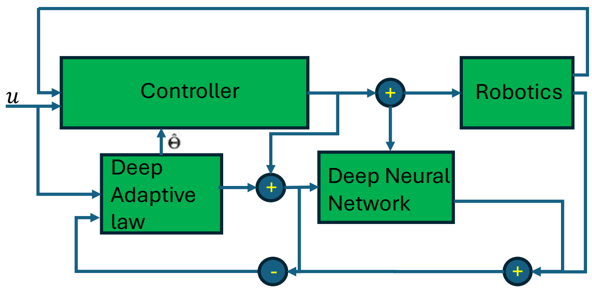

Figure 2. Block diagram of our deep adaptive control algorithm.

3. Methodology

In this section, we develop a deep neural network–augmented adaptive control strategy for a malfunctioning aerospace vehicle whose dynamics are modeled by coupled partial differential equations (PDEs) and ordinary differential equations (ODEs). The overarching goal is to stabilize both the angular motion of the rigid hub and the transverse deflections of the flexible panel, even under adverse actuator anomalies. By integrating a neural approximator within the control law, the scheme can dynamically learn and counteract model uncertainties and time-varying disturbances, thereby ensuring robust performance.

3.1. Dynamics analysis of repairing robotics

A robust grasp of the intrinsic physics and mechanical characteristics of industrial robots is essential for model-based identification. Under the Lagrangian formalism, the inverse dynamics of a fully actuated nnn-link robot manipulator can be succinctly written as

$$\tau = M(q)\ddot{q} + C(q,\dot{q}) + D$$

where $\tau \in \mathbb{R}^{n\times 1}$ represents the joint torques, $q, \dot{q}, \ddot{q} \in \mathbb{R}^{n\times 1}$ denote the vectors of joint angles, angular velocities, and angular accelerations, respectively. The matrix $M(q) \in \mathbb{R}^{n\times n}$ is the inertia matrix of the manipulator, $C(q,\dot{q})$ captures the Coriolis, centripetal, and D encapsulates deterministic disturbances such as sensor drift or unmodeled dynamics.

3.2. Governing equations via Hamilton's principle

To capture the essential rigid-body and flexible-panel interactions, we start by applying Hamilton's principle to the kinetic and potential energies of the system. Let Γ_f denote the positive-definite inertia tensor of the rigid body, and let $\Upsilon \in \mathbb{R}^3$ represent the angular velocity of the hub relative to an inertial (orbital) frame. Suppose further that Σ is the linear mass density of the flexible appendage, while κ is its damping coefficient. Denoting by $\varphi(\ell, \tau)$ and $\xi(\ell, \tau)$ the small deflections of the panel in two orthogonal directions, with $\ell \in [0, L]$ as the spatial coordinate and τ the temporal variable, one obtains:

$$\Gamma_f\dot{\Upsilon} + \Upsilon \times (\Gamma_f\Upsilon) + \Omega = \Theta + \Delta,$$
$$\Sigma\begin{bmatrix}\varphi_{\tau\tau}(\ell,\tau)\\ \xi_{\tau\tau}(\ell,\tau)\end{bmatrix} + \kappa\begin{bmatrix}\varphi_{\tau}(\ell,\tau)\\ \xi_{\tau}(\ell,\tau)\end{bmatrix} + \mathcal{F}(\Upsilon,\varphi,\xi) = 0,$$

where Ω encapsulates nonlinear terms that may arise from gyroscopic and Coriolis-like effects, Θ is the external torque acting on the rigid hub, Δ represents cumulative disturbances or actuator faults, and $\mathcal{F}$encompasses the higher-order spatial derivatives (e.g., bending stiffness terms) of $\varphi(\ell, \tau)$ and $\xi(\ell, \tau)$. The boundary conditions for the flexible panel typically specify zero transverse displacements and slopes at $\ell = 0$ and free-end conditions at $\ell = L$, although exact formulations may vary depending on the structural configuration:

$$\varphi(0,\tau) = \xi(0,\tau) = 0,$$

$$\varphi_{\ell}(0,\tau) = \xi_{\ell}(0,\tau) = 0,$$

$$\varphi_{\ell\ell}(L,\tau) = \xi_{\ell\ell}(L,\tau) = 0$$

3.3. DNNs based adaptive controller

Actuator failures can manifest unpredictably during extended missions, necessitating a control framework that autonomously recognizes and compensates for partial or complete loss of actuation authority. The key innovation here is to integrate a DNNs module—trained online—as part of an adaptive control law.

Concretely, consider a DNN $\mathcal{N}_{\Theta}(\times)$ parameterized by weights Θ. At each instant τ, the DNN processes measured signals (e.g., deflections $\varphi(\ell,\ \tau)$, $\xi(\ell,\ \tau)$, angular velocities $\Upsilon(\tau)$ and partial estimates of actuator health) and outputs compensatory control adjustments. These outputs feed into an adaptive boundary [28] or distributed controller $\mathcal{C}(\tau)$, which acts on the PDE–ODE system:

$$\Theta(\tau) = -\mathcal{C}(\varphi, \xi, \Upsilon, \dots) - \mathcal{N}_{\Theta}(\varphi, \xi, \Upsilon, \dots)$$

The neural parameters Θ are continuously updated via an online learning rule (e.g., a backpropagation-through-time variant adapted to PDE constraints), thus minimizing a composite cost functional that penalizes vibration amplitude, tracking errors in the angular motion, and deviations from nominal performance metrics. Mathematically, one might define an instantaneous error signal ε(τ) that encapsulates both attitude- and vibration-related tracking objectives, and then refine Θ using a gradient-based adaptation:

$$\dot{\Theta}(\tau) = -\eta \frac{\partial \varepsilon(\tau)}{\partial \Theta}$$

where η is the learning rate. This iterative scheme allows the controller to "learn" complex fault patterns, even in the presence of an unbounded number of malfunctions throughout the spacecraft's operational timeline.

3.4. Lyapunov stability analysis

To certify the convergence properties of the overall closed-loop system (i.e., the PDE–ODE dynamics combined with the DNN-based adaptive controller), a Lyapunov functional $\mathcal{V}(\tau)$ is devised to incorporate both rigid-body energy terms and flexible energy components as

$$\mathcal{V}(\tau) = \frac{1}{2}\left(\Upsilon^{\mathrm{T}} \Gamma_f \Upsilon\right) + \frac{\Sigma}{2} \int_0^L \left[(\varphi_\tau^2 + \xi_\tau^2) + \beta_1\left(\varphi_\ell^2 + \xi_\ell^2\right) + \beta_2\left(\varphi_{\ell\ell}^2 + \xi_{\ell\ell}^2\right)\right] \mathrm{d}\ell$$

where β_1 and β_2 are positive constants that account for bending stiffness in the panel. By examining the time derivative $\dot{\mathcal{V}}(\tau)$ under the proposed control law, one demonstrates that $\mathcal{V}(\tau)$ remains uniformly bounded and ultimately converges to an arbitrarily small neighborhood around zero—thereby implying that both $\Upsilon(\tau)$ and the deflections $\varphi(\ell, \tau), \xi(\ell, \tau)$ vanish asymptotically. The DNN adaptation ensures that unidentified disturbances and unknown actuator failure profiles are effectively counteracted, preventing divergence of the system states [29–33].

4. Simulation results

To investigate the effectiveness of the proposed deep neural network–augmented adaptive scheme for a malfunctioning aerospace platform, a series of numerical experiments are performed using a finite-difference approximation of the governing partial differential equations (PDEs). For analytical simplicity, we presume that the satellite's body inertia matrix $\Lambda \in \mathbb{R}^{3\times 3}$ is diagonal, reflecting a scenario where cross-coupling inertias are negligible.

To emulate real-world perturbations, constant disturbances $\delta_1(\tau), \delta_2(\tau), \delta_3(\tau)$ are introduced in the spacecraft's torque channels:

$$\delta_1(\tau) = 2\mathfrak{N}, \delta_2(\tau) = 1\mathfrak{N}, \delta_3(\tau) = 6\mathfrak{N},$$

where $\mathfrak{N}$ symbolizes units of Newton–meter (or an equivalent torque measure), and τ denotes time. These constant values facilitate straightforward comparisons with theoretical bounds. The initial angular velocities of the rigid body are specified as

$$\omega_1(0) = 0.02\text{rad/s}, \omega_2(0) = 0.03\text{rad/s}, \omega_3(0) = 0.04\text{rad/s},$$

To replicate the uncertain and possibly abrupt malfunctions common in aerospace actuators, the net torques $\varsigma_1(\tau), \varsigma_2(\tau), \varsigma_3(\tau)$ applied to each rotational axis are decomposed into two parts:

$$\varsigma_1(\tau) = \rho_{1,1}(\tau) + \rho_{1,2}(\tau), \varsigma_2(\tau) = \rho_{2,1}(\tau) + \rho_{2,2}(\tau), \varsigma_3(\tau) = \rho_{3,1}(\tau) + \rho_{3,2}(\tau).$$

Each $\rho_{i,j}(\tau)$ can experience time intervals of diminished effectiveness, complete dropout, or partial gain according to a predefined fault profile. For instance,

$$\rho_{1,1}(\tau) = \begin{cases} 0.3v_{1,1}(\tau), \tau \in [2k, 2k+1), \\ 0.5v_{1,1}(\tau), \tau \in [2k+1, 2k+2) \end{cases}$$

A DNNs-based adaptive law is utilized to compute the correction signals necessary to counteract both the structural vibrations and the actuator degradations. The underlying proportional-derivative (PD) component addresses nominal dynamics as

$$\eta_{i,j}(\tau) = -k_{p_i}\omega_i(\tau) - k_{d_i}\dot{\omega}_i(\tau), i = 1,2,3, j = 1,2$$

where $\omega_i(\tau)$ indicates the i-th rotational rate, and k_{p_i}, k_{d_i} are PD gains. Meanwhile, the neural network $\Xi(\mathrm{x}(\tau); \Theta(\tau))$, parameterized by weights $\Theta(\tau)$ monitors observable states $\mathrm{x}(\tau)$, deflections, or partial actuator diagnostics and outputs an estimated compensation term. The combined control input can be expressed as

$$v_{i,j}(\tau) = \eta_{i,j}(\tau) - \Xi_{i,j}(\mathrm{x}(\tau); \Theta(\tau))$$

Ensuring that any mismatch between the nominal model and real-time behavior—whether due to unmodeled dynamics or actuator failures—is addressed adaptively. An online learning rule updates Θ(τ) based on a Lyapunov-like criterion to preserve overall stability.

In **Figure 3**, each panel corresponds to a distinct joint of our space-based robot arm tasked with repairing a malfunctioning aerospace device. The horizontal axis indicates time, while the vertical axis represents the torque generated by each joint's actuator. Multiple curves—namely the reference trajectory, baseline adaptive control, a deep reinforcement strategy (Deep-Q), and our proposed DNNs-enabled adaptive algorithm—are plotted to facilitate a comparative evaluation. From the visual inspection, the reference curve (green) captures the nominal torque profile required for precise maneuvering. Notably, our approach (pink) aligns closely with the reference track, especially in the presence of sudden torque deviations or partial actuator failures. This behavior underscores the method's ability to learn and adapt quickly to unforeseen anomalies in actuator performance, maintaining near-optimal tracking even when the robot arm must contend with harsh environmental conditions and hardware deterioration.

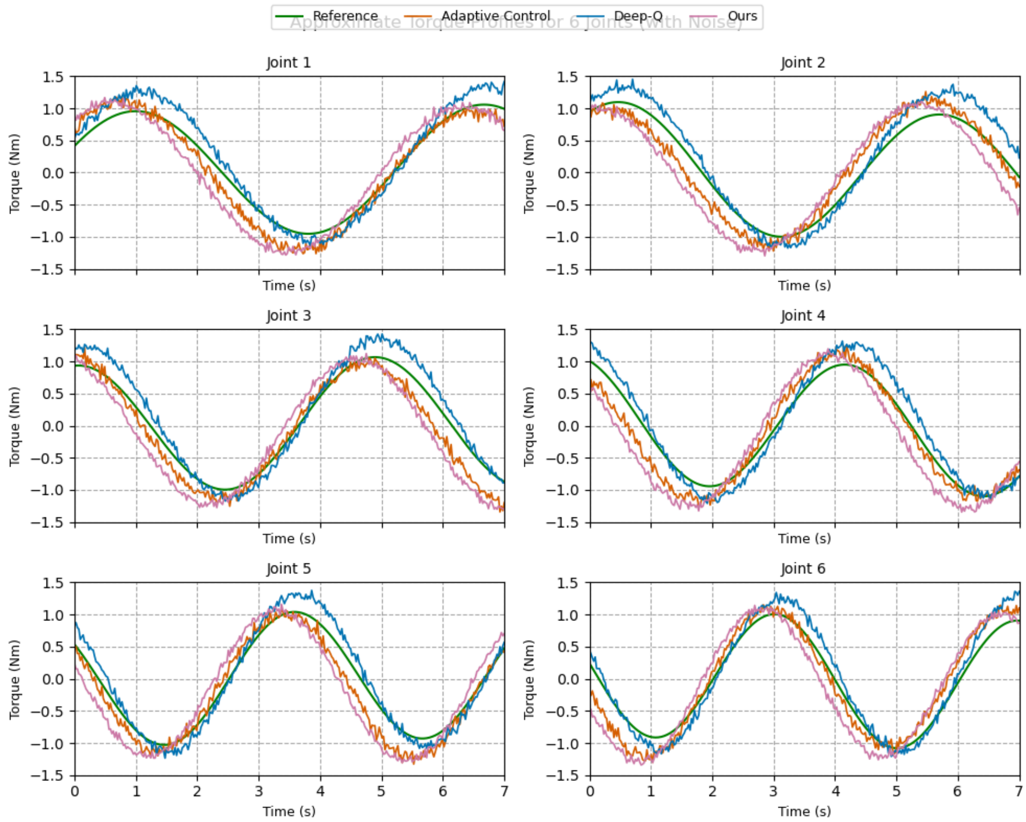

Figure 3. Approximate torque applied from each joint in the robot arm.

A key insight revealed by these torque plots is the robustness of the proposed DNNs-infused controller against abrupt variations in load and unknown system parameters. By integrating real-time learning into the adaptive control loop, the method effectively redistributes control effort across the joints, thereby ensuring smooth operation and stable torque outputs for each actuator. Consequently, the space-borne manipulator can maintain high-precision articulation and mitigate vibrations or oscillations—critical when attempting intricate repair tasks on sensitive aerospace equipment. This combination of real-time adaptation and machine learning–based fault compensation is pivotal to guaranteeing mission success under uncertain conditions in orbit.

Figure 4 shows that the horizontal axes in each subplot indicate the spatial coordinate and time (τ in seconds), whereas the vertical axis denotes the instantaneous deflection magnitude (in feet). By examining the color gradient, one can observe that our proposed DNNs-assisted control strategy effectively suppresses excessive bending or oscillatory modes that might arise when joints experience degraded actuator authority. The near-uniform surfaces in some regions highlight that structural perturbations are kept to a minimum, ensuring that the manipulator remains stable even as it extends or retracts to access damaged hardware.

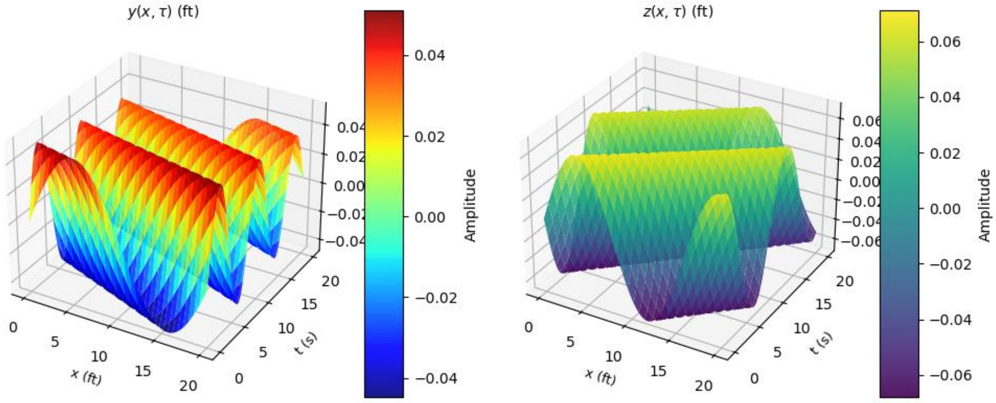

Figure 4. Three-dimensional deflection evolution of the space-based robot arm under DNNs-enhanced adaptive control.

In practical terms, these surfaces confirm that the adaptive controller, augmented with deep learning, successfully anticipates and compensates for uncertain loads, micro-vibrations, and partial failures of actuators distributed along the manipulator's span. The reduction in peak deflections not only fosters a safer operational envelope—minimizing collision risks with neighboring satellite components—but also prolongs the service life of the robot arm by reducing stress on critical joints [34]. Ultimately, this capacity for real-time deflection mitigation is crucial in precision tasks, such as repairing a broken part in orbit, where slight positioning errors might jeopardize the integrity of expensive aerospace assets [35].

5. Conclusions

In this study, we introduced a multifaceted approach that merges physics-based formulations with data-driven refinement to achieve accurate and robust control in the presence of unmodeled nonlinearities. By enriching the conventional observer–based system learning (OSBL) technique with a DNNs model, we obtained an enhanced identification scheme. This novel framework addresses residual modeling discrepancies through an online DNN that effectively captures deviations unaccounted for by classical physics-based models. Subsequently, the identified dynamics were integrated into a deep adaptive control (DAC) architecture, leveraging a model reference paradigm to counteract uncertainties and external noise. The adaptive update laws were systematically derived from Lyapunov-like stability analysis, thereby guaranteeing asymptotic error convergence despite significant disturbances.

Experimental evaluations on a physical six-degree-of-freedom (6-DOF) robotic arm demonstrated both the standard OSBL and least-squares (LS) methods, particularly when confronted with intricate dynamics that are challenging to capture via pure analytical modeling. The observed mismatch between the physical model's torque predictions and the real-world measurements underscores the necessity of a data-driven correction. Incorporating the DNN allowed the controller to accommodate unmodeled dynamics and actuator anomalies—an advantage that becomes even more critical for malfunctioning aerospace devices, where actuators may degrade unexpectedly and precise maneuvers are essential for on-orbit repairs. Furthermore, the proposed DAC scheme reliably handled multi-input multi-output (MIMO) motion control in the 6-DOF manipulator without sacrificing stability or performance.

Author contributions: Conceptualization, KZ, AZ and MV; methodology, KZ; software, JS; validation, MV, KZ and AJ; formal analysis, JW; investigation, JS; resources, KZ; data curation, KZ; writing—original draft preparation, KZ; writing—review and editing, MV; visualization, JW; supervision, JW; project administration, AJ; funding acquisition, MV. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

References

1. Le Clainche S, Ferrer E, Gibson S, et al. Improving aircraft performance using machine learning: A review. Aerospace Science and Technology. 2023; 138: 108354. doi: 10.1016/j.ast.2023.108354
2. Ke X, Jiang A, Lu N. Load profile analysis and short-term building load forecast for a university campus. In: Proceedings of the 2016 IEEE Power and Energy Society General Meeting (PESGM); 17–21 July 2016; Boston, MA. pp. 1-5.
3. Tsukamoto H, Chung SJ, Slotine JJ. Learning-based Adaptive Control using Contraction Theory. In: Proceedings of the 60th IEEE Conference on Decision and Control (CDC); 14–17 December 2021; Austin, TX, USA. pp. 2533-2538.
4. Zhang Y, Chu L, Xu L, et al. Optimized Coordination Strategy for Multi-Aerospace Systems in Pick-and-Place Tasks By Deep Neural Network. Available online: https://arxiv.org/html/2412.09877v1 (accessed on 3 December 2024).
5. Dastider A, Raza SJA, Lin M. Learning adaptive control in dynamic environments using reproducing kernel priors with bayesian policy gradients. In: Proceedings of the 37th ACM/SIGAPP Symposium on Applied Computing; 25–29 April 2022; New York, NY, USA. pp. 748-757.
6. Gao L, Cordova G, Danielson C, et al. Autonomous multi-robot servicing for spacecraft operation extension. In: Proceedings of the 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); 1–5 October 2023; Detroit, MI, USA.
7. Shabestary SMA, Baher A. Deep learning vs. discrete reinforcement learning for adaptive traffic signal control. In: Proceedings of the 21st International Conference on Intelligent Transportation Systems (ITSC); 4–7 November 2018; Maui, HI, USA.
8. Mo K, Liu W, Shen F, et al. Precision Kinematic Path Optimization for High-DoF Robotic Manipulators Utilizing Advanced Natural Language Processing Models. In: Proceedings of the 5th International Conference on Electronic Communication and Artificial Intelligence (ICECAI); 31 May 2024–2 June 2024; Shenzhen, China.
9. Zhang Y, Wang X, Gao L, et al. Manipulator control system based on machine vision. In: *Advances in Intelligent Systems and Computing*, Proceedings of the International Conference on Applications and Techniques in Cyber Intelligence ATCI 2019: Applications and Techniques in Cyber Intelligence 7. Springer International Publishing; 2020.
10. Zhang Y, Mo K, Shen F, et al. Self-adaptive robust motion planning for high dof robot manipulator using deep mpc. In: Proceedings of the 3rd International Conference on Robotics, Artificial Intelligence and Intelligent Control (RAIIC); 5–7 July 2024; Mianyang, China.
11. Gao L, Aubert K, Saldana D, et al. Decentralized adaptive aerospace transportation of unknown loads using a team of robots. Available online: https://arxiv.org/html/2407.08084v2 (accessed on 3 December 2024).
12. Jiang A. Building Load Analysis and Forecasting—A Case Study of the Building Load of the North Carolina State University Centennial Campus. LAP LAMBERT Academic Publishing; 2014.
13. Gao L, Claus D, Rafael F. Adaptive robot detumbling of a non-rigid satellite. Available online: https://arxiv.org/html/2407.17617v2 (accessed on 3 December 2024).
14. Liu R, Xu X, Shen Y, et al. Enhanced detection classification via clustering svm for various robot collaboration task. Available online: https://arxiv.org/html/2405.03026v1 (accessed on 3 December 2024).

15. Rengasamy D, Rothwell B, Figueredo GP. Asymmetric loss functions for deep learning early predictions of remaining useful life in aerospace gas turbine engines. In: Proceedings of 2020 International Joint Conference on Neural Networks (IJCNN); 19–24 July 2020; Glasgow, UK.
16. Zhang Y, Zhu M, Gui K, et al. Development and application of a monte carlo tree search algorithm for simulating da vinci code game strategies. Available online: https://arxiv.org/html/2403.10720v1 (accessed on 3 December 2024).
17. Kuchuk H, Podorozhniak A, Hlavcheva D, Yaloveha V, et al. Application of Deep Learning in the Processing of the Aerospace System's Multispectral Images. In: Shmelova T, Sikirda Y, Sterenharz A (editors), Handbook of Research on Artificial Intelligence Applications in the Aviation and Aerospace Industries. IGI Global; 2020. pp. 134-147.
18. National Academies of Sciences, Engineering, and Medicine. Methodology to Develop the Airport Terminal Building Energy Use Intensity (ATB-EUI) Benchmarking Tool. Washington, DC: The National Academies Press.
19. Brunton SL, Kutz JN, Manohar K, et al. Data-driven aerospace engineering: reframing the industry with machine learning. AIAA Journal. 2021; 59(8): 2820-2847. doi: 10.2514/1.J060131
20. Zhang Y, Leng Q, Zhu M, et al. Enhancing Text Authenticity: A Novel Hybrid Approach for AI-Generated Text Detection. In: Proceedings of the 4th International Conference on Electronic Technology, Communication and Information (ICETCI); 24–26 May 2024; Changchun, China.
21. Saetchnikov I, Victor S, Elina T. Pattern recognition on aerospace images using deep neural networks. In: Proceedings of 2020 IEEE 7th International Workshop on Metrology for AeroSpace (MetroAeroSpace); 22–24 June 2020; Pisa, Italy.
22. Zhang Y, Gong Y, Cui D, et al. Deepgi: An automated approach for gastrointestinal tract segmentation in mri scans. Available online: https://arxiv.org/html/2401.15354v1 (accessed on 3 December 2024).
23. Ebrahimkhanlou A, Salamone S. Single-Sensor Acoustic Emission Source Localization in Plate-Like Structures Using Deep Learning. Aerospace. 2018; 5(2): 50. doi: 10.3390/aerospace5020050
24. Tan L, Liu S, Gao J, et al. Enhanced Self-Checkout System for Retail Based on Improved YOLOv10. Journal of Imaging. 2024; 10(10): 248. doi: 10.3390/jimaging10100248
25. Uzun M, Demirezen MU, Inalhan G. Physics Guided Deep Learning for Data-Driven Aircraft Fuel Consumption Modeling. Aerospace. 2021; 8(2): 44. doi: 10.3390/aerospace8020044
26. Zhu M, Zhang Y, Gong Y, et al. Ensemble methodology: Innovations in credit default prediction using lightgbm, xgboost, and localensemble. Available online: https://arxiv.org/html/2402.17979v1 (accessed on 3 December 2024).
27. Dara S, Priyanka T. Feature extraction by using deep learning: A survey. In: Proceedings of 2018 Second international conference on electronics, communication and aerospace technology (ICECA); 29–31 March 2018; Coimbatore, India.
28. Jiang A. A Simplified Dynamic Model of DFIG-based Wind Generation for Frequency Support Control Studies. International Journal of Current Science Research and Review. 2024; 7(10): 7617-7625. doi: 10.47191/ijcsrr/V7-i10-17
29. Josh G, Girish C. Deep model reference adaptive control. In: Proceedings of 2019 IEEE 58th Conference on Decision and Control (CDC); 11–13 December 2019; Nice, France.
30. Mo K, Chu L, Zhang X, et al. DRAL: Deep Reinforcement Adaptive Learning for Multi-UAVs Navigation in Unknown Indoor Environment. Available online: https://arxiv.org/html/2409.03930v3 (accessed on 3 December 2024).
31. Xu Z, Yang P, Hu K, et al. Deep learning control model for adaptive optics systems. Applied optics. 2019; 58(8): doi: 10.1364/AO.58.001998998-2009.
32. Mo K, Liu W, Xu X, et al. Fine-Tuning Gemma-7B for Enhanced Sentiment Analysis of Financial News Headlines. Available online: https://arxiv.org/html/2411.14568v1 (accessed on 3 December 2024).
33. Annaswamy AM, Guha A, Cui Y, et al. Integration of Adaptive Control and Reinforcement Learning for Real-Time Control and Learning. IEEE Transactions on Automatic Control. 2023; 68(12): 7740-7755. doi: 10.1109/tac.2023.3290037
34. Jiang A, Mo K, Fujimoto S, et al. Maximum Solar Energy Tracking Leverage High-DoF Robotics System with Deep Reinforcement Learning. Available online: https://arxiv.org/html/2411.14568v1 (accessed on 3 December 2024).
35. He Y, Liu Y, Yang L, Qu X, et al. Deep adaptive control: Deep reinforcement learning-based adaptive vehicle trajectory control algorithms for different risk levels. IEEE Transactions on Intelligent Vehicles. 2023; 9(1); 1654-1666. doi: 10.1109/TIV.2023.3303408