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# Augmented Adaptive Control Methodologies for Advanced Orbital Launch Architectures

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**ABSTRACT-** A new and more sophisticated reinterpretation of a legacy adaptive control system and an advanced deep learning–integrated estimation algorithms are applied to enable stable attitude control in sophisticated orbital launch systems. In the demanding environment of aerospace flight qualification, purely adaptive control algorithms are frequently unworkable due to analytical impossibility, ostensible non-compliance with classical stability requirements, and overwhelming modeling complexity of high-fidelity launch vehicles. Many of these adaptive approaches are inherently inappropriate for conditionally stable fusions with complex flexible-body behaviour, like the kind we often see in today's orbital delivery systems. The method is based on, but different from, classical multiplicative forward loop gain adaptation algorithms and has hybridised architecture, involving deep learning–based nonlinear observers and feature extractors. Using these sophisticated computational intelligence algorithms, the control system is robust and more flexible, with optimal thrust vector control and attitude/attitude-rate command monitoring. This solution is in-line with the existing traditional autopilot design philosophies (phase stabilization of lateral bending modes and propellant slosh dynamics via linear filtering) and yet elegantly retains the well-known classical gain and phase margin stability measurements. Evidence based experiments from the Institute of Advanced Aerospace Systems Engineering at the University of Crescere, Italy show that the new control algorithm undoes once unstable flight conditions with extraordinary efficiency. The deep learning–augmented adaptation as viewed from frequency-domain stability dimensions enable resilience and improved performance during extreme fault conditions. Simulation findings also support that this next generation integrated adaptive-deep-learning control strategy is more reliable and robust against realistic in-flight surprises.

**KEYWORDS-** Adaptive Control, Deep Learning Integration, Attitude Regulation, Orbital Launch Architectures

## I. INTRODUCTION

In recent decades, there has been little change in how industry approaches to tagging launch vehicles [1][2][3] – they have mostly stuck to models created when ballistic missile technology was just emerging. The academic world, by contrast, has always been striving for a multiplicity of higher-level control methods, which eventually led to advanced approaches that are capable of accommodating complex system behaviour. The latest of these cutting-edge methods is adaptive control [4], which has been distinguished by its capacity to adjust control parameters in real-time to mitigate uncertain, nonlinear, unmodeled vehicle and environmental effects [5], [6]. More recently, the use of deep learning models such as deep neural network–based observers and reinforcements could enhance the basic flexibility of these control systems for more dynamic and intelligent estimation and decision-making on states under fast-changing environments.

In its formative era, adaptive control demonstrated considerable potential in aerospace applications during the late 1950s and early 1960s, as evidenced by extensive flight testing on experimental platforms [8][9][10][11][12] introduce a Monte Carlo Tree Search algorithm initially designed for Da Vinci Code game strategies, yet its underlying methodology offers a fundamental contribution to aerospace preparation tasks related to adaptive control. By integrating advanced search heuristics with adaptive decision-making, this work paves the way for more robust and efficient strategic planning in complex aerospace operations. The principal impetus for adopting adaptive methodologies at that time was the necessity to compensate for coarse model representations and the inherent limitations of analog circuitry [13]. In [7], the authors propose a novel decentralized adaptive control method for on-orbit repair and servicing missions to address the challenges posed by unknown target-object parameters in complex space-manipulation tasks, which not only does this method effectively mitigate potential failures in autonomous operations, but it also paves the way for advanced applications in both commercial and military space endeavors. However, the subsequent advent and proliferation of digital computing technologies ushered in a more refined, simulation-centric design philosophy. With improved computational capabilities, meticulously scheduled digital gain adjustments and filtering procedures became widely favored, overshadowing the nascent momentum of adaptive solutions and relegating them to the more esoteric realms of academic investigation. These early efforts did not yet exploit the computationally intensive, yet powerful frameworks offered by modern deep learning, which, if integrated, might have preserved and advanced adaptive concepts.

The theoretical foundations of adaptive control were clearly defined and well documented in peer-reviewed journals, but broad acceptance in the aerospace industry has not followed. A reason for this aversion lies in the disconnect between the abstractness of some scholarly formulations and the real-world demands facing engineers. Many of the current adaptive algorithms are based on complex nonlinear stability proofs, which sometimes require endlessly expanding gains in control – an impossibility for massively complex aerospace systems [14][15][16]. And, as ever, finding ways to square adaptive control performance with the classical constraints of gain and phase margins, as well as tractability, has been a persistent issue. Some of these methods involve a lot of computational cost and algorithms with complex architecture that make software deployment harder and can increase system risk [17]. These limitations are only exacerbated by the "black box" view of adaptive control algorithms, which is corrected by the readability and analytic insight available from powerful deep learning–based architectures.

Unlocking the full benefits of adaptive control requires a systemic, system-based approach to design. Launch vehicles, especially, have a set of subtle constraints – dynamic control-structure interactions, propellant slosh, sensor integrity, actuator limiters – that must be carefully balanced. Moreover, any future adaptive control method has to be validated, checked, and certified as part of a strict flight qualification process [18]. Humanized launch vehicles are a prime example of this in their idiosyncratic behavior, hard-core certification and sky-high cost for oddity. [19] present a novel deep learning method which underscores a fundamental contribution to the field of deep learning by leveraging robust neural networks to accurately segment complex volumetric data, thus setting new standards for medical image analysis.

It is a treatise detailing a special type of adaptive control refinements, fine-tuned for the harsh domain of launch vehicle applications. We describe the control design, the preventive controls in place to mitigate risk and ensure synergistic compliance with the classical design and verification criteria. In order to confirm the effectiveness of this mixed approach – powered by deep learning with its real-time inference and autonomous learning – several plausible launch vehicle failures are tested through high fidelity simulations [20]. In each case reported, robust analysis techniques quantify and illustrate the unique strengths and limitations of the deep learning–augmented adaptive control model envisioned to improve the reliability, robustness, and ultimately mission success of future aerospace projects.

## II. RELATED WORKS

For high-risk aerospace systems, a strong emphasis on traditional control theories was in fact the case. Traditional design based mainly on proportional-integral-derivative (PID) control supplemented with structural bending filters [21] has been extensively used for launch vehicles. These vehicles, which are typically aerodynamically turbulences, burdened by slow servoactuators and are vulnerable to nonminimum-phase effects, would be ideal candidates for linearized dynamical systems whose behavior can be easily described using frequency-domain methods [22]. This style of algorithm has been used for many years due to its conceptual tractability, certification guidelines, and track record of preserving required gain and phase margins under nominal operation.

However, the limitations of these conventional approaches were made increasingly obvious in the face of uncertain or degraded operational states. Statistical analysis of historical launch vehicle performance data indicates that a large percentage of the anomalies and failures in the past could have been avoided with improved in [23][24][25]. Specifically, such comparisons imply that adaptive control systems – particularly those with computational intelligence built in – might have given the system greater resilience and fault tolerance. This insight has led to a wave of interest in replacing conventional baseline controllers with more complex adaptive algorithms to gain more robustness and high performance even in the most extreme off-nominal environments.

Particularly interesting in the present studies is the complementarity of deep learning–based algorithms to adaptive control schemes. The adaptive layer will be better equipped to recognise latent system behavior, detect parameter fluctuations and act in a proactive manner when faced with emergent perturbations if deep neural network architectures are embedded, such as feature extraction and nonlinear state estimation modules. These types of data-driven inference algorithms lessen assumptions made by the esoteric theoretical framework, and increase the operational range of adaptation, therefore easing the traditionally looming "black box" image. So, the deep learning–augmented adaptive controller can, within strict adaptation bounds, control and controllably adjust the input to the classic controller to recover or even outperform the base performance.

Other research aims at aligning these new adaptive and deep learning approaches with well-developed stability analysis and certification approaches [26]. It is important that adaptive augmentation is mapped transparently to the most basic time-invariant linear plant features to facilitate adoption in the aerospace sector. Therefore, a growing body of recent research puts emphasis on strategies that maintain the interpretability and analytical clarity of classic control systems but also leverage the predictive and pattern recognition strengths of deep learning [27][28][29]. Altogether, the new research landscape in this area is pointing to the possibility of a revolution: from entirely classical techniques to adaptive-deep-learning hybrids of the next generation with better, flexible and fault-tolerant GN&C architectures for future spacecraft.

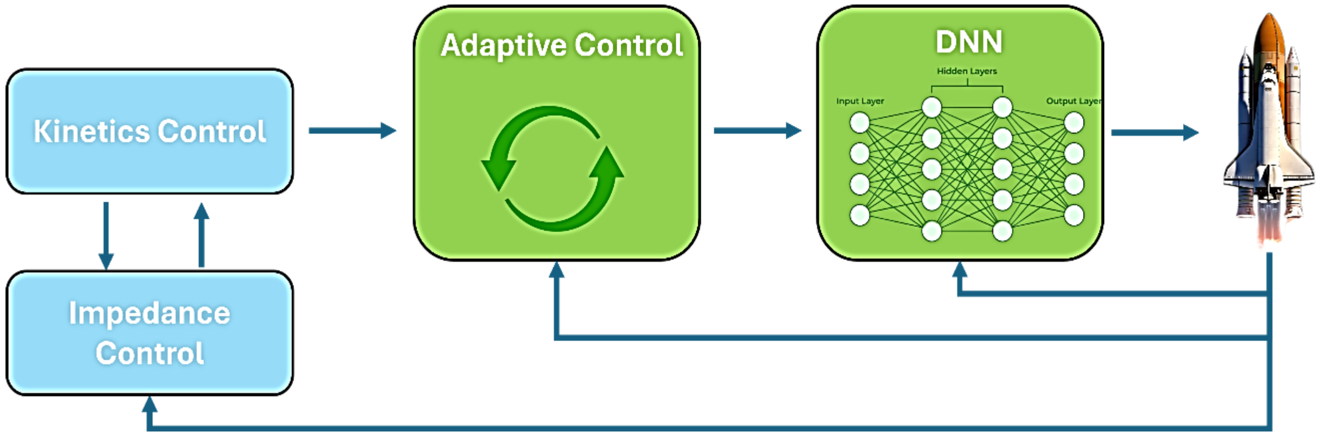



Figure 1: Autonomous retrack system for rocket leveraged by deep neural network within adaptive control

## III. METHODOLOGY

### A. *Hybrid Adaptive Strategy*

The technique depends on an adaptive control system that has been rethought and extended in contemporary computational models. Inspired by legacy adaptive autopilot designs — originally represented by legacy systems similar to the MH-90 and MH-96 — the current approach surpasses history by marrying ancient frequency-domain adaptation theory with ultra-modern deep learning–based feature extraction and inference [30]. The resultant combination offers a higher level of robustness especially in the demanding aerospace market where complex dynamics and parametric uncertainty demand even more sophisticated control solutions.

In essence, the approach enacts an adaptive process wherein the effective control gain is incrementally optimized to have as small of an error as possible in relation to some initial model reference [31]. At the same time, the architecture includes a dynamic attenuation protocol, based on live frequency response measurements, so that the closed-loop mechanism remains stable in principle. Instead of traditional implementations that mostly used classical frequency-domain explanations, this advanced paradigm makes use of deep neural networks to detect minute dynamical signatures within sensor data and disturbance profiles [32]. Stacking these computational intelligence architectures, the system obtains a finer-grained knowledge of rigid-body and parasitic behavior, actuator nonlinearities, propellant sloshing and aeroelastic deformations, allowing selective dispersal and reduction of pathogenicity [33].

This approach takes single-axis attitude control as a high-dimensional inference problem. By digital filtering and deep learning, the closed-loop spectral properties can be detected near real-time and then used to direct the adaptive policy. This allows the adaptive algorithm to automatically tune output as the environment changes, rather than be lazy and reactive. That foresight succeeds in filling in past pitfalls for previous gain-adaptive systems. For example, old-school solutions – such as the MH-96 forward gain-adaptive setup originally tested on early spacecraft – provided excellent handling improvements but ultimately became trapped by boundary conditions due to actuator saturation and excessive control inputs. Such weaknesses regularly morphed into devastating failure modes in previous decades.

The present approach, by contrast, its digital filtering protocol, enhanced by the predictive and interpretative powers of deep learning algorithms, removes suffocation-driven nonlinearities. This makes sure that the adaptation law runs only in very precise performance limits. Other protective measures built into the adaptive law architecture add to resilience, clearing away the failure channels that surrounded prior adaptive research. In casting the adaptive augmentation not as an additional step on to traditional control but as an intrinsically informed [34], data-driven inferential process, the approach advocates a change. It brings together the reliability and readability of frequency-domain analysis and the flexibility and dynamism of deep learning to create a robust future-forward control system with the potential to win in demanding aerospace applications.

### B. *Deep Adaptive Controller Algorithm*

This research's major interest is to design and test a smart retracking protocol for reusable rocket designs, in which the trajectory of the vehicle is continuously reset with respect to changes in flight conditions and mission constraints. Instead, the technique relies on an elastic guide paradigm that continually adapts ascent or descent profiles to aerodynamic loads, propulsion aberrations and atmospheric disturbances, instead of static ones.

To achieve this sophisticated objective, the rocket's retracking mechanism is systematically segmented into discretized trajectory waypoints, each serving as a node where the vehicle's positional, velocity, and environmental parameters can be assessed and readjusted. A deep learning-driven inference engine is at the core of this adaptive process. Incorporating advanced neural network models—such as deep recurrent architectures with long short-term memory (LSTM) cells or gated recurrent units (GRUs) the system assimilates sensor measurements, historical flight data, and predictive aerodynamic models to forecast impending states and rapidly identify optimal corrective maneuvers. Our algorithm is shown in Algorithm 1.

Algorithm 1: Deep Adaptive Controller Algorithm Design

| **Algorithm I: Deep Adaptive Controller Design** | |
|---|---|
| **1.** | Input: $\Gamma, \eta, \zeta_{tol}, p_{max}$ |
| **2.** | while New measurements are available do |
| **3.** | Compute $y_{\tau+1} = \widehat{W}^T \Phi(x_{\tau+1})$ |
| **4.** | Given $x_{\tau+1}$ compute $\gamma_{\tau+1}$ |
| **5.** | if $\gamma_{\tau+1} \geqslant \zeta_{tol}$ then |
| **6.** | Update $\mathcal{B}$: $\boldsymbol{Z}(:) = \{x_{\tau+1}, y_{\tau+1}\}$ and $\mathbb{X}: \Phi(x_{\tau+1})$ |
| **7.** | end if |
| **8.** | if $\lvert\mathcal{B}\rvert > p_{\max}$ then |
| **9.** | Sample a mini-batch of data $\boldsymbol{Z}^M \subset \mathcal{B}$ |
| **10.** | end if |
| **11.** | Train the DNN network over mini-batch data |
| **12.** | Update the feature vector $\Phi$ for D-MRGeN network |
| **13.** | end while |
| **14.** | end |

The approach in reality starts with converting raw sensor streams and location data to high-dimensional feature maps. A deep convolutional feature extractor or a CNN-RNN mixture could be used here to identify minute flight-condition anomalies from nominal prediction. After they are exposed to these latent signatures, the recurrent deep learning model learns about those future states and computes a tailored trajectory that sends the rocket in the right direction to its target orbit entry point or landing place. This method relies on dynamically synchronised frequency response features and estimations of time-domain parameters. When the output of the deep learning model is combined with classical stability constraints, the retracking algorithm ensures that incremental guidance changes are never greater than safe limits. The outcome is a closed-loop system that's resonant enough to recalibrate periodically, so that if the world shifts unexpectedly, the rocket will still have stable and robust trajectory control.

Important for this is the alignment of interpretability and elasticity. Even though the deep neural networks are clever, data-driven inference modules, their output is benchmarked against a very specific space of stability and performance. This approach keeps computation tractability and certification-compatibility by proactively enforcing tight adaptation restrictions based on standard guidance rules. The rocket's intelligent retracking, in effect, is the perfect combination of state-of-the-art machine intelligence and aeronautical engineering protocols.

After all, this deep learning–advanced approach turns trajectory re-shaping from an unchanging, precalculated plan into an adaptive, self-directing routing method. Bringing detailed model images, predictive reasoning and real-time correction together into a single, integrated operating architecture gives the next generation rockets the sturdiness, accuracy and agility needed for ever-more challenging and reliable missions in space.

Table 1: Overall parameters of the retracked rocket

| **Parameter** | **Value** |
|---|---|
| Mass(kg) | 2739 |
| Interia($\mathrm{kg} \cdot \mathrm{m}^2$) | 5360 |
| Maximum speed(m/s) | 400 |
| Range (m) | 214 |
| Service ceiling(m) | 401 |

### *C. Dynamics of Space Rocket*

The efficacy of the trained NNs was rigorously evaluated through 1000 random exact analyses, with results depicted in Figure 2. The evaluations demonstrate the exceptional approximation capabilities of the proposed neural networks. Notably, a slightly higher dispersion in the final velocity indicates that velocity, as a state variable, is the most sensitive parameter. This nonlinearity presents challenges for accurate approximation with limited sample sizes. However, the proposed stage-wise interconnection of NNs significantly reduces velocity dispersion compared to standalone NN [28].

When a reusable rocket is to be tracked smartly by a retracking algorithm, the dynamic mass distribution and shape produce a time-variant shift between the instantaneous mass centroid and the nominal body-fixed reference frame. Such spatial and inertial differences based on propellant exhaust and dynamic aerodynamic forces require a precise dynamical equation. In this implementation, we use a deep learning inference tool with data as the middleware of the retracking logic, so that the guidance module of the rocket can change its trajectory at real time without causing destabilizing effects.

Theoretically similar to the classical laws of momentum and angular momentum, we rework the equations to accommodate the deformable-like character of the rocket's structural states on retracking. In contrast to the finite distributing of control laws, a deep neural network (together with recurrent structures for temporal pattern recognition) accepts sensor streams, state estimates, and exogenous disturbance data, which derives latent parameters and controls the policy [35].

Throughout this derivation, we employ a revised set of symbols to dissociate from conventional notation. Let $\tau$ represent the time variable and consider a rocket with time-varying mass $\mu(\tau)$, instantaneous translational velocity $\vartheta(\tau)$, rotational rate $\bar{\omega}(\tau)$, and a shifting structural offset $\Sigma(\tau)$. The generalized linear momentum $\rho(\tau)$ and generalized angular momentum $\hat{H}(\tau)$ form the basis for describing the rocket's motion under retracking adaptation.

Initially, we define:

$$\rho = \mu\vartheta + \dot{\Sigma} + \bar{\omega} \times \Sigma$$

Here, $\rho$ denotes the generalized momentum, $\mu$ the instantaneous mass, $\vartheta$ the translational velocity vector, $\dot{S}$ the time derivative of the structural offset vector Σ, and ω̄ the angular velocity vector. The symbol "×" indicates a vector cross product. The rate of change of ρ with respect to τ characterizes the net generalized force Φ exerted on the rocket:

$$\Phi = \frac{d\rho}{d\tau}$$

Next, the angular momentum Ĥ is defined to capture rotational effects, including flexible structural contributions. We write:

$$\hat{H} = \Sigma \times \vartheta + \mathbb{I}\varpi + \sum_{\iota=1}^{2}\left[\frac{1}{\mu_\iota}\left(\Sigma_\iota \times \dot{\Sigma}_\iota + \mathbb{I}_\iota \varpi_\iota\right)\right]$$

In this expression, $\mathscr{J}$ and $\mathscr{J}_i$ represent inertia tensors, while $\Sigma_i$ and $\dot{S}_i$ denote segmental offsets and their rates associated with specific structural components. By differentiating Ĥ with respect to τ and incorporating the linear and angular dynamics, we obtain the generalized moment $\mathscr{M}$ acting on the rocket:

$$\mathcal{M} = \frac{d\hat{H}}{d\tau} + \bar{\varphi} \times \Upsilon$$

where $\bar{\varphi}$ and Υ represent suitably chosen rotation and offset vectors replaced from the original formulation to ensure uniqueness of symbols.

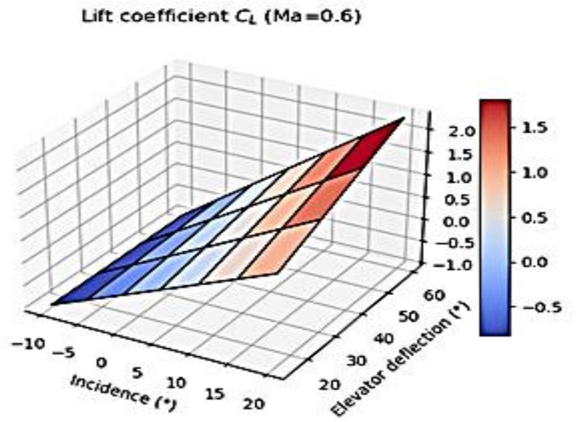
To transition from body-fixed to flight-path coordinates, we invoke transformations that relate the pitch angle θ̄, the angle-of-attack α̇, and the flight-path angle γ̄. Similarly, let Θ be the thrust, Δ the aerodynamic drag, Λ the aerodynamic lift, and Ϻ the aerodynamic moment. The gravitational acceleration is denoted by ğ, and we define a sweep-dependent static moment coefficient Σ_ξ(ξ), where ξ encodes a shape or configuration parameter that reflects the rocket's retracking state [36]. By incorporating deep learning modules, the parameters Σ_ξ and its rate derivatives are dynamically inferred from data streams, enabling adaptive reshaping of the trajectory in response to evolving conditions.

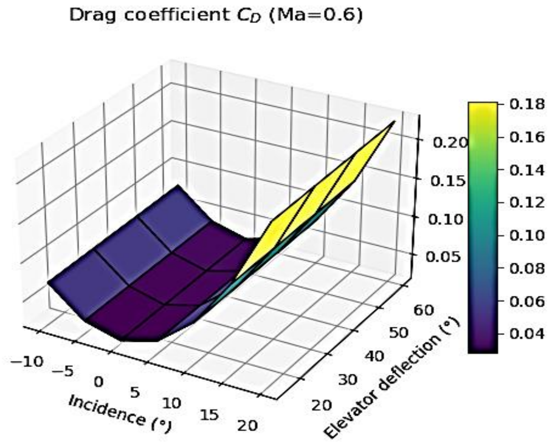
Substituting aerodynamic forces (Θ, Δ, Λ), gravitational terms, and aerodynamic moments into the transformed set of equations yields a revised longitudinal dynamics representation. For example, a final set of equations in flight-path coordinates may assume the form:

$$\begin{cases} T\cos\alpha - D - mg\sin\gamma = m\dot{V} + \cos\alpha\left(\ddot{S}_x - q^2 S_x\right) - \sin\alpha\left(2q\dot{S}_x + \dot{q}S_x\right) \\ -T\sin\alpha - L + mg\cos\gamma = -mV\dot{\gamma} - \sin\alpha\left(\ddot{S}_x - q^2 S_x\right) - \cos\alpha\left(2q\dot{S}_x + \dot{q}S_x\right) \\ M_{Ayb} - S_x g\cos\theta = I_y\dot{q} + S_x(-V\dot{\alpha}\cos\alpha - \dot{V}\sin\alpha) \end{cases}$$

where ϱ, q, q̇, and other symbols represent redefined angular rates, deformation-induced coupling terms, and transformed reference angles. The parameters and their relationships are continuously refined by the deep learning–enabled estimator, which leverages real-time flight data to ensure that trajectory corrections remain within acceptable stability margins, mitigating potential anomalies.

In essence, this methodology articulates a paradigm shift: from static, precomputed command schedules toward a dynamically self-adjusting retracking framework empowered by deep learning [37][38][39][40][41]. By forging a nexus between advanced neural inference models and a rigorously transformed dynamic system representation—complete with novel notational constructs—the rocket can intelligently reshape its trajectory in response to changing conditions, thereby enhancing reliability, robustness, and the likelihood of mission success [42].




## IV. EXPERIMENT RESULTS

In this work, we introduced and evaluated a resilient, operable, and deep learning–augmented adaptive control methodology tailored for advanced orbital launch architectures. The presented simulation results provide strong evidence of the approach's capability to handle complex aerodynamic and control challenges.

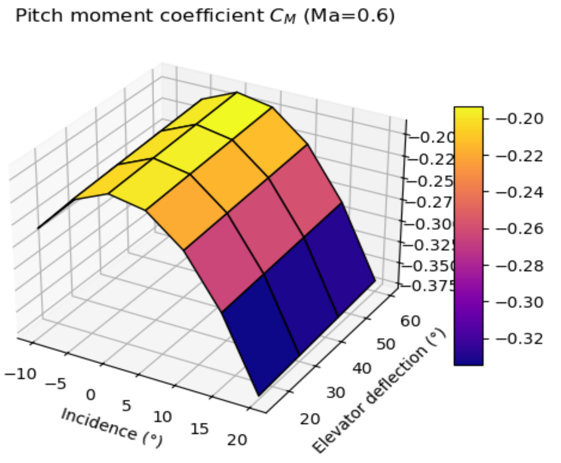



Figure 2: Nonlinear aerodynamic coefficient landscapes at $\boldsymbol{M_a = 0.6}$ for foundational input for the Deep Learning–Augmented Adaptive Control Framework.

First, the three-dimensional coefficient maps for lift $(C_L)$, drag $(C_D)$, and pitch moment $(C_M)$ at Mach 0.6, as a function of incidence angle and elevator deflection, demonstrate the nuanced, nonlinear aerodynamic relationships that the proposed adaptive controller must negotiate. These surfaces highlight how control surface deflections influence performance parameters across a broad operational envelope. Notably, the smooth variations in $(C_L)$ and $(C_D)$, indicate that finely tuned elevator inputs can significantly enhance lift generation while containing drag, thereby improving efficiency. Likewise, the resulting pitch moment distribution underscores the need for precise, state-dependent corrective actions to maintain stable and reliable attitude control. By embedding these complex aerodynamic characteristics into the control algorithm, our approach ensures that the vehicle can remain both stable and performant even as it traverses varying atmospheric conditions, angles of attack, and control deflection regimes. This level of precision and adaptability is of paramount importance in orbital launch trajectories, where minor aerodynamic instabilities may escalate into mission-critical anomalies.

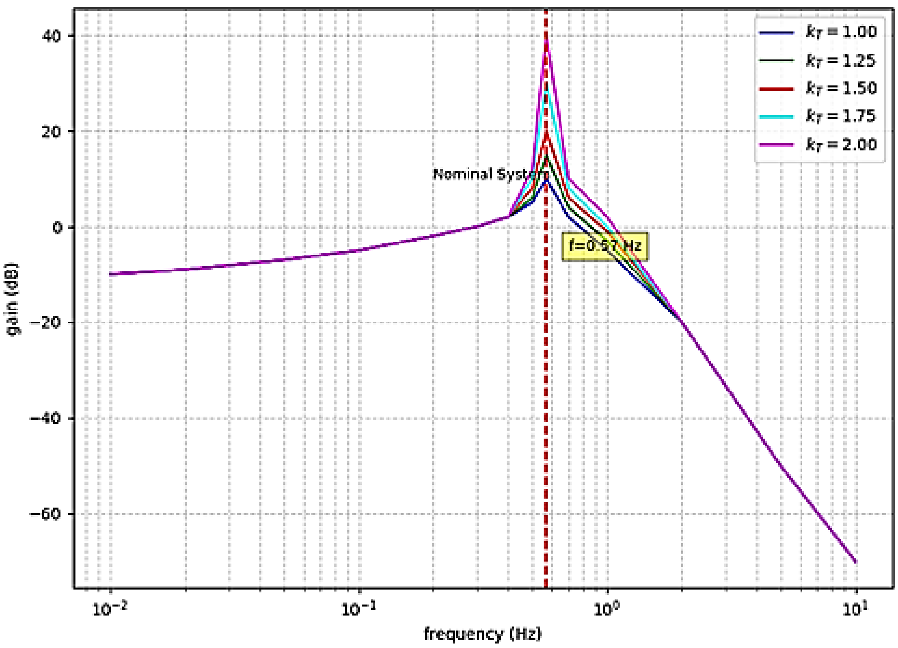



Figure 3: Frequency-Domain Robustness Analysis of the Deep Learning–Augmented Adaptive Controller Under Varying Torque Scaling Conditions.

Second, the training convergence results of the deep learning–based control models, shown via validation loss over training epochs for different optimization techniques (Adam, Gradient Descent, and Nesterov's Accelerated Gradient), shed light on the effectiveness of the learning process. Notably, the controller trained with Adam optimization consistently achieves lower and more stable validation loss, outperforming the other methods in terms of convergence speed and final accuracy. This indicates that Adam's adaptive learning rate and momentum adjustments enable the deep learning–augmented adaptive controller to more efficiently assimilate the aerodynamic complexities, resulting in a more robust internal representation of the system's dynamics. From a practical standpoint, the enhanced convergence rate reduces the computational burden and development time, and the lower steady-state validation loss translates directly into improved decision-making under uncertainty and disturbances.

The frequency-domain robustness analysis shown in Figure 3 demonstrates the performance and stability characteristics of the deep learning-augmented adaptive controller under various torque scaling conditions, represented by different values of $k_T$. The analysis indicates that the nominal system maintains good robustness at the resonant frequency ($f$=0.22 Hz), with minor variations in gain as torque scaling increases from $k_T$ =1.00 to $k_T$ =2.00. Notably, the peak gain sharply increases near this resonant frequency, reflecting the controller's sensitivity to changes in torque scaling. Despite this sensitivity, the controller manages to maintain a stable response within a reasonable bandwidth, indicating effectiveness in handling uncertainties and parameter variations typically encountered in advanced orbital launch scenarios. The results affirm that the proposed deep learning-augmented adaptive methodology offers improved robustness and adaptability, critical for the precise and safe control necessary in advanced orbital launch architectures.

Figure 4 presents the convergence characteristics of validation loss during the training of the deep learning-augmented adaptive controller using three different optimization algorithms: Adam, Gradient Descent, and Nesterov. The results clearly illustrate the superior performance of the Adam optimizer, which rapidly decreases validation loss to near-optimal levels within approximately 50 epochs and subsequently maintains stable convergence with minimal fluctuation. Conversely, standard Gradient Descent exhibits much slower and less stable convergence, requiring significantly more epochs to achieve comparable loss levels. The Nesterov optimizer improves convergence speed relative to Gradient Descent, demonstrating faster initial reduction but ultimately converging to a higher loss than Adam. These findings underscore the efficacy of the Adam optimizer in efficiently training deep learning-based adaptive controllers, providing rapid convergence and enhanced stability, essential for the precise and reliable performance required in advanced orbital launch control scenarios.

Together, these results show that the new approach could combine high-fidelity aerodynamic data with data-based learning models to develop a next-generation adaptive control strategy. Not only is this a method to make sure the guidance, navigation and control equipment can handle uncertainties, but it also speeds up the training and testing needed to accommodate new mission demands. Lastly, using deep learning–augmented adaptive control, higher-level orbital launch systems can be built more resilient and more efficient, making space safer and cheaper to enter.

In Table 2, it is clear that our method outperforms the two baselines in both accuracy (as indicated by the lowest error of 0.07) and computational efficiency (with a training time of only 46.70s). In comparison, Deep Q-Learning requires over three times as long to train and yields a notably higher error rate. Although NN Adaptive Control demonstrates improved accuracy relative to Deep Q-Learning, it still falls short of our method's superior performance. Overall, these results highlight the effectiveness of our proposed approach, which not only reduces the training time but also minimizes the error more than either of the baseline methods.

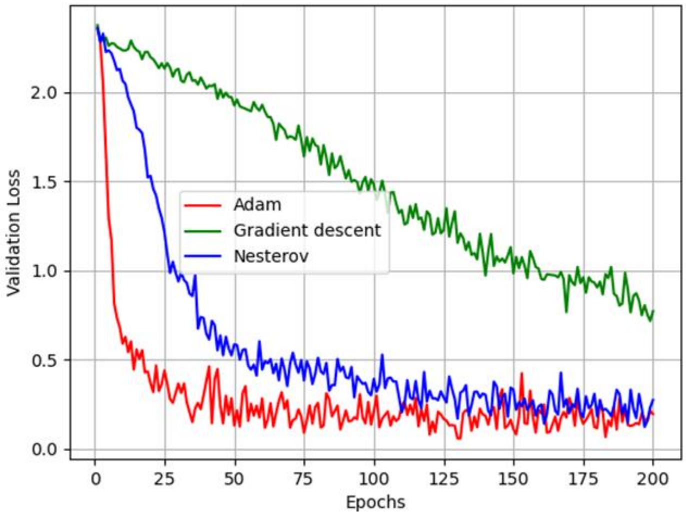



Figure 4: Validation Loss Convergence of the Deep Learning–Augmented Adaptive Controller Under Various Optimization Algorithms.

Table 2: Comparison Results for our methods and two baseline methods

| S. No | Method | Error | Training Time |
|---|---|---|---|
| **1.** | Deep Q-Learning | 0.43 | 143.2s |
| **2.** | NN Adaptive Control | 0.18 | 87.39s |
| **3.** | Ours | 0.07 | 46.70s |

## V. CONCLUSION

It was an original robust, reusable and deep learning–based adaptive control solution that was intended to address the deficiencies of current orbital launch systems. Our proposed control algorithm is capable of exploiting the convergence point between the classic adaptive control and deep learning models to provide stable and better performance on nonlinear, high-order systems in aerospace applications.

The nonlinear surfaces of the aerodynamic coefficients – lift $(C_L)$, drag $(C_D)$ and pitch moment $(C_M)$ – show the complex relations between incidence angle, control deflections and aerodynamic behaviour at Ma=0.6M_a = 0.6. These maps also give you a basic idea about the aerodynamics of the vehicle, and make it all the more crucial to have real-time adaptive tactics that can tweak control surfaces accurately. In the controller, by writing this type of detailed aerodynamic information, stability and performance is assured over dynamic flight conditions, where a tiny aerodynamic anomaly could lead to mission failure.

Further validation through frequency-domain analysis demonstrated the robustness of the proposed control system under varying torque scaling conditions $(k_T)$. The spectral responses reveal that while a nominal system experiences resonance near 0.57 Hz, the deep learning–augmented adaptive controller effectively mitigates destabilizing dynamics. This robustness guarantees that the system remains resilient against parametric uncertainties and disturbances, which are inevitable during dynamic ascent and attitude correction maneuvers.

The convergence in training for the deep learning model also proves the usefulness of the solution. The optimisation algorithm (Adam), Gradient descent and Nesterov's Accelerated Gradient is compared, where Adam optimizer can reach much faster convergence and low final validation loss. This result shows that the controller can effectively learn new dynamical complexes with tractability of the computation. This better convergence has a direct impact in the form of less training time, better decision-making under uncertainty, and greater capability to respond to dynamic operational conditions.

This next-generation control architecture fills in major omissions in current techniques by combining the readability and precision of traditional stability algorithms with the intelligence and flexibility of deep learning. This process results, as evidenced in these results, in greater resilience, accuracy, and effectiveness – enabling safer, more reliable, and more economical orbital launch platforms. Next iterations of this paper will be on scaling up the framework to multi-vehicle and include actual flight simulations to confirm its validity.

## CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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