AI-Enhanced Control and Aerodynamic Optimization for Hypersonic Flight

Ethan A. Wiseman[1] and Brian N. Lopez[2]

University of Florida, Gainesville, FL, 32603, USA

Abstract

Hypersonic flight is a uniquely challenging frontier in aerospace engineering. Hypersonic vehicles travel at speeds exceeding Mach 5, encountering nonlinear aerodynamic behaviors, extremely high temperatures, material degradation, and shock interactions. Classic control systems and computational fluid dynamics (CFD) are effective at lower speeds but become very limited when applied to nonlinear flight variables. This can lead to elevated degrees of uncertainty as well as high computational cost. This paper explores how artificial intelligence (AI) and reinforcement learning (RL) can be applied to hypersonic control systems and provide adaptive solutions to optimize aerodynamics. A MATLAB and Simulink surrogate was created to illustrate such ideas. The surrogate simulated aerodynamic coefficients and resulting loads in real time to emulate changing flight conditions. AI-enabled control systems can learn from prior data to update vehicle dynamics, improving aerodynamic efficiency and enhancing stability. Integration of AI and hybrid approaches may enable safer and more maneuverable hypersonic vehicles in the future and have the potential to play a large role in aerospace and defense.

I. Nomenclature

AoA, (α)	=Angle of Attack (deg)
DNN	= Deep Neural Network
HFV	= Hypersonic Flying Vehicle
FEA	= Finite Element Analysis
MATLAB	= Matrix Laboratory
DoF	= Degrees of Freedom
M	= Mach Number (-)
q	= Pitch Rate (rad/s)
q_p	= Dynamic pressure (Pa)
k	= Scaling factor
V	= Freestream velocity (m/s)
a	= Speed of Sound(m/s)
S	= Reference area (m²)
c	= Mean aerodynamic chord (m)
L	= Lift force (N)
D	= Drag force (N)
M_{pitch}	= Pitching moment (N·m)
RMSE	= Root-mean-square error
p	= Air Density (kg/m^3)

[1] Undergraduate, Aerospace Engineering, Student Member 1923027

[2] Undergraduate, Aerospace Engineering, Student Member 1923400

II. Introduction

Flying at hypersonic speeds has been explored since the Cold War, but its reliability has remained limited. The potential of hypersonic flight and its applications to military, missiles, space access, and numerous other aerospace applications have driven constant interest in vehicles capable of operating in such environments. It is one of the most challenging yet strategically important feats of the modern world. Hypersonics are defined as speeds at Mach 5 or above, approximately 4,000 miles per hour. The civil and military applications of hypersonics have led to major interest in developing vehicles and weapons systems.

While these hypersonic missiles date back to the mid-1900s, the nonlinear dynamics and vehicle responses were largely misunderstood. During the late 1950's, the U.S. Air Force and NASA combined to set a speed record of 4,520 miles per hour or Mach 6.7. The development of the air-breathing engine, scramjet (supersonic combustion ramjet), led to further advancement, and in the 2000's, Mach 5.1 was sustained for 200 seconds [1]. The advances sparked research across defense, future transport, and other applications.

Classical control systems are viable for supersonic speeds; however, when approaching or exceeding Mach 5, the systems become unpredictable. This contributes to the slow progression and higher funding of hypersonics. Recently, AI, machine learning (ML), and RL have been applied to such systems to make aerodynamic loads more manageable to predict. AI-based approaches have the potential to significantly improve flight control performance.

III. Background of Hypersonic Flight

A. Definition and Flight Regime

When an aircraft or spacecraft is in flight below Mach 5 (subsonic or supersonic), it experiences significant stress, but the flow physics are not as strongly interdependent. Above Mach 5, typical of many modern-day rockets, the aerodynamics become more complex with added heat, shock waves, and deformation. Fluid mechanics, thermodynamics, and chemical composition are bound tightly together, needing to be considered when predicting aerodynamic behavior [1]. Many innovations have been developed to address these technical challenges and enable safe operation at these high speeds.

B. Dangers of Hypersonic Flight

As speeds increase, the Mach angle decreases, making shock waves imminent in hypersonic flight and introducing a new danger [2]. The shock layer, or the layer between the surface of the ship and the waves, becomes smaller as a result of the shock angle being smaller. The compressed shock layer creates a region of waves constantly striking the body of the aircraft, leading to material degradation and aerothermal heating. This can create a very dangerous and hard-to-manage environment that cannot be tolerated for an extensive period of time [1]. This makes the aircraft difficult to maneuver effectively.

With shock waves come high thermal heating and structural deformation. As the aircraft body inevitably deforms during flight, it can cause uncertainty in the aerodynamic shape [3]. This uncertainty in the drag, lift, and pitch-moment coefficients can shift the equilibrium, reducing stability and requiring quick adjustments. While this range of uncertainty can be small due to the small amount of time in hypersonic flight, it can still be significant enough to cause problems [3]. Without addressing these problems, flying at hypersonic speeds for more than a few minutes is unlikely.

C. Classical Controls versus Hypersonic Controls

Classical Controls can be evaluated using CFD. These computer simulations enable scientists to predict coefficients and improve aerodynamics quickly. By quickly predicting gas and liquid flow, accurate predictions can be made, making classical controls understandable. When it comes to hypersonic, nonlinear control systems, the simulation methods become increasingly complex. Many alternative methods are used to model hypersonic flow; however, they take tremendous amounts of time and money [4]. Aerodynamic coefficients change so rapidly that accurately modeling flow is challenging, as models are often accurate but not precise enough.

However, with the increasing understanding of hypersonic flow, it is possible to instead use AI. Adaptive hypersonic control systems, utilizing AI, could be a promising approach, eliminating human error from the equation. AI offers a potential path to a more robust hypersonic control system.

IV. Role of Artificial Intelligence in Hypersonic Flight

A. Why are Artificial Intelligence and Neural Networks Useful?

AI is advantageous when combating the high degree of unpredictability that comes with hypersonics. While experienced pilots can make quick decisions and be reliable in some high-speed flight cases, it is not quick enough when a vehicle has reached hypersonic speeds. Autonomous or mainly autonomous flying is safer for the pilot and allows hypersonic flight vehicles (HFV) to fly longer and with more stability [5]. AIs are trained to create the most optimal trajectories for the HFV to fly while handling many different constraints compared to classical flight. However, making these optimal trajectories is extremely difficult, requiring vast amounts of time, money, and other resources [5]. This makes AI vital in the role of hypersonic flight.

A Neural Network (NN) is a subsection of AI that can learn patterns through layers of neurons that make decisions from given data [6]. This section of AI proves extremely useful when learning nonlinear flight dynamics from HFV data. Many studies have been done on different types of NN's to learn things like flow fields and aerodynamic coefficients at different angles of attack, as previously stated, grow lower and lower, causing shock waves [7]. With the ability to rapidly output results based on changing conditions, NN will be a vital step to create a hybrid and autonomous AI-enhanced control system.

B. AI for Real-Time Aerodynamic Prediction

The rapidly shifting aerodynamic coefficients due to nonlinear effects make predictions challenging, specifically methods such as CFD. CFD provides valuable data, but it is too computationally expensive and time-intensive when running thousands of flight variations to satisfy the needs of HFVs. However, NNs can serve as a practical alternative that can learn the relationship between the flight conditions and aerodynamics when trained well [8]. With quick prediction comes better optimization. Rapid predictions will allow for the testing of many more design solutions, increasing the chances of success dramatically [8]. Applying NN in real-time as well as in simulation can lower the uncertainty of HFV travel, making it vital to see a higher use rate in the future.

A major issue facing hypersonic vehicles is the ability to maneuver effectively. The coupling of degrees of freedom and not simply lateral and longitudinal directional changes is much more complex. Many NN's that are implemented in HFVs imply simple lateral and longitudinal directional change. Some maneuvers using 6 degrees of freedom, like spirals, are much harder to pull off in HFVs. This is highly unlikely without AI or NNs; however, there has been an effort to improve maneuverability [9].

Through advanced simulations in finite element analysis (FEA) and CFD, researchers have been able to create high-fidelity plots and data that create a way to incorporate 6 DoF in hypersonic flying vehicles with highly trained DNN's. One of the main problems with hypersonic speeds is the lack of time that is available when going so extremely fast. Using trained DNNs can bridge this gap, allowing for efficient predictions and navigation. Solving these problems so quickly can lead to faster updates, making time a non-factor. This study was done with unpowered gliding HFVs, making the results meaningful but leaving out some important factors [9]. Technology needs to advance to make engineers' designs and ideas come true, and a way to assist in this problem is by using hybrid HFVs.

C. Hybrid Control Systems

Solely AI-driven control systems for HFVs have the capabilities to adapt very quickly; however, technology must also be capable of supporting certain logistics. This is why hybrid methods can guarantee stability and grant assurance by combining both AI and classical control systems. Classical controls are well understood and predictable, but cannot react quickly in harsh environments. Putting these ideas together can create a control system that has both reliability and adaptability [10].

Methods that use robust means have been developed to handle such difficult constraints in a way that minimizes uncertainty. In the robust model, predictive control has been established using the sum of squares that keeps a bounded, invariant. Essentially, the controller cannot exceed the known stability boundaries [11]. This is similar to a classical controller, just in a hypersonic setting. The classical part of the system guarantees the reliability of controllers that are known to be safe. This type of control system could benefit greatly from AI because of the "boxed-in" nature of the controller. The constraints in the system prevent commands that would happen to destabilize the vehicle because of the "state-dependent limits" that are clearly defined [11]. The AI that would be utilized within this system would not be able to run on its own accord, having certain limitations and preventing bad decisions because it is run through a stability-guaranteeing controller.

Using hybrid controllers like the one laid out above can make AI less formidable. Stability can be achieved in the controller by enforcing high constraints and a high degree of robustness. AI can simply be an add-on to increase efficiency and not hinder safety. As AI and NN become better tested and trusted, constraints can be relaxed, and AI can have a greater effect on control systems.

V. Control-Oriented Surrogate Modeling and Simulink Demonstration

To bypass CFD calculations and to reduce complexity, a stand-alone surrogate model was created to demonstrate fast aerodynamic components. A MATLAB script was used to generate a simplified nonlinear aerodynamic dataset and a fast surrogate model that can be run through Simulink [19]. The goal of this endeavor is not to recreate hypersonic conditions or get CFD-level accuracy, but to prove general statements and develop a model that gives hypersonic-like results with minimal computational load.

A. Surrogate Model

To attain fast aerodynamic results, the MATLAB script maps the state vectors (α, M, q) to the aerodynamic coefficients (Cl, Cd, Cm). AoA, Mach number (M), and pitch rate (q) are used to create a dataset range. A set of equations was made that forces the behavior to be nonlinear with additions of α in the lift, drag, and moment equations. Furthermore, Mach coupling was implemented to scale the aerodynamic coefficients with a multiplicative factor depending on the Mach number, where k is a scaling factor:

$$1 + k(M - 3)$$

Figure 1 shows the lift trend of $Cl(\alpha)$ at Mach 6 and $q = 0$. The plot shows the nonlinear relationship and motivates why a surrogate is helpful when predicting coefficients.

Using the dataset that was previously generated, an NN surrogate was implemented in the script using MATLAB Deep Learning Toolbox functions [20]. A NN can learn complicated geometry, higher dimensional input, and can produce more accurate results. This method is important when handling complex inputs such as altitude, density, and anything that is varying by time. This route was embedded to provide a high capability option and remained a MATLAB-only comparison method and was not deployed in Simulink due to implementation constraints [21].

In addition, the same dataset was used to fit a second-order polynomial regression surrogate. This surrogate is a good fit for the data set and is computationally quick. It is easy to implement in Simulink without needing the NN objects or functions. For this study, polynomial regression was used to produce the figures below and used in the Simulink demonstrations.

The accuracy of the (Cl, Cd, Cm) is checked in Figure 2 as a scatter plot with the true results being the reference values gathered from the nonlinear formulas used in the MATLAB script. The predicted polynomial values are what the polynomial surrogate outputs. The RMSE shown on each plot is the average prediction error magnitude for the coefficient being graphed and all of them are very low, meaning a good fit. The Cl plot shows more nonlinearity than the other two meaning that the polynomial regression cannot match it as tightly. This results in the largest RMSE value. The perfect line in a true vs. predicted scatter plot is a 45-degree straight line that is linear, in which all the plots in figure two are close too.

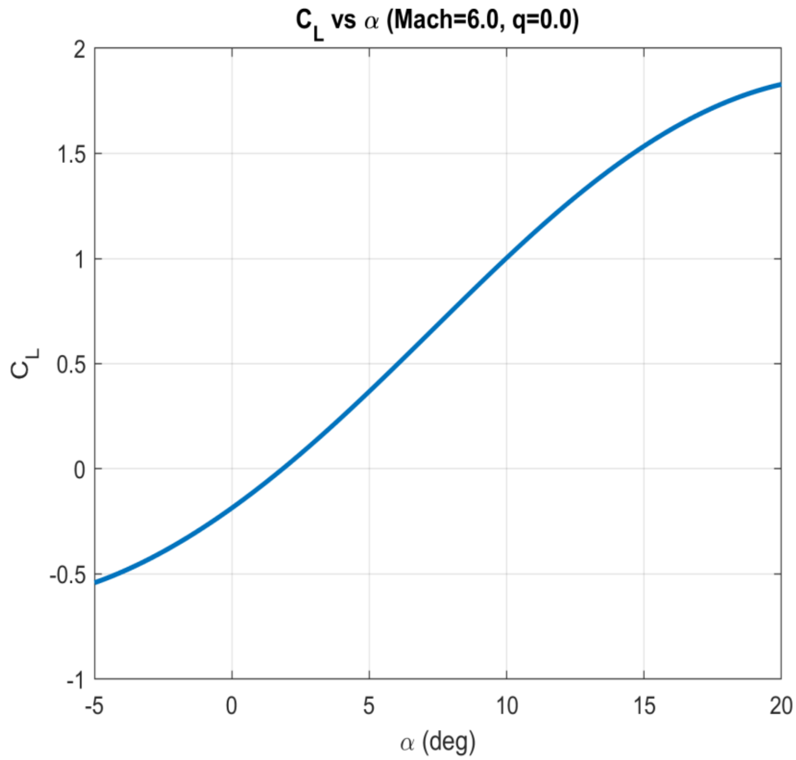

Fig. 1 The $Cl\ vs\ \alpha$ (Mach 6 and $q\ =\ 0$) shows a nonlinear line as both variables increase.

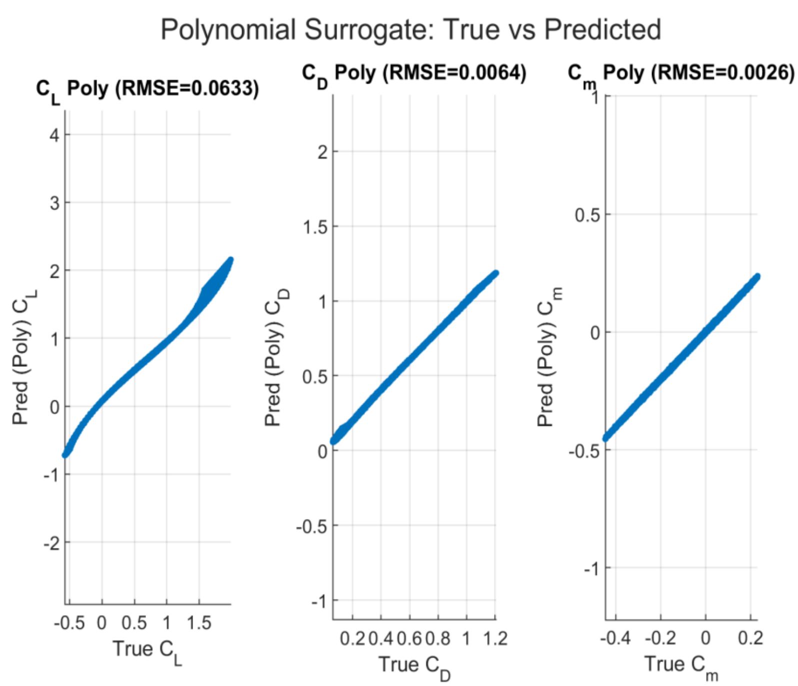

Fig. 2 True vs. Predicted Scatter Plot of Cl, Cd, Cm with RSME values

B. Simulink Real-Time Coefficients and Loads

Simulink is a block-based environment that allows models to be expressed and displayed with different signal inputs and time steps [21]. In the model previously laid out, there is an embedded polynomial regression that will be used as the MATLAB function block in Simulink to take input values given through constants and step changing blocks and outputs like Cl, Cd, Cm shown through sink blocks. Figure 3 shows the coefficient response to the AoA step block being changed as the input condition, demonstrating immediate updates. This instantaneous jump represents the exact challenges that CFD has.

Coefficients are then turned into loads using aerodynamic relationships:

$$q_p = \frac{1}{2}\rho V^2 \quad V \approx Ma \quad L = qS(Cl) \quad D = qS(Cd) \quad M_{pitch} = qSc(Cm)$$

The loads (lift, drag, and pitching moment signals) are shown in Figure 4, illustrating how rapid coefficient changes translate directly into shifts in moments and loads, which is one of the main reasons for AI/surrogate methods at hypersonic speeds.

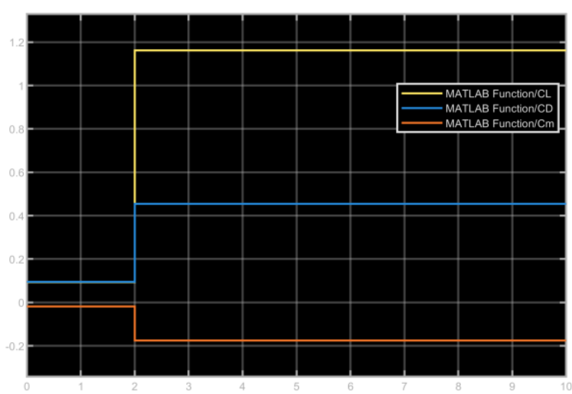

Fig. 3 Simulink Coefficient Step Response.

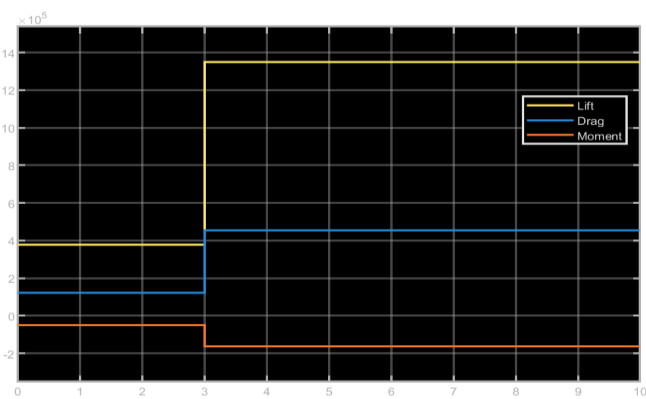

Fig. 4 Simulink Load Step Response.

C. Relevance to Hypersonic Control and Limitations

Hypersonic control systems rely on aerodynamic estimates to be done quickly and with a high degree of accuracy. While the NN and polynomial regression above are highly simplified, they create a good model and demonstrate how quick and concise calculations in hypersonics are important. Rather than relying on computationally expensive and time-consuming simulations in CFD, a surrogate-type model can provide instantaneous results coefficient estimates and resulting loads and moments. This allows for logic to be updated in real time. Both figures 3 and 4 are good representations of the immediate response times for the coefficient and loads when step changes are made quickly.

This demonstration has clear limitations, such as the dataset that is used. This is a synthetic representation and not of CFD hypersonic data standards. This model only takes into account coupling and scaling Mach numbers to simulate nonlinear patterns. However, at hypersonic speeds, aerothermal heating, shock waves, and deformations all need to be considered to produce accurate results. This is one of the key limitations of surrogate modeling. Its training on a fixed dataset may need serious adjusting and fixing when given no limitations for real-world environmental challenges. Overall, this model was not meant to mimic exact hypersonic flight, but to stress the importance and benefits of how NN and AI can lead to better results.

VI. Current Work by Government & Industry

A. Air Force Research Laboratory

The Air Force Research Laboratory (AFRL) conducts extensive research into the applications of AI and ML learning techniques for advanced flight control and aerodynamic modeling. AFRL's platforms, Autonomous Aircraft Experimentation (AAx) and programs such as X-62A Variable In-Flight Simulator Test Aircraft (VISTA) are focused on developing and evaluating autonomous flight control systems employing learning-enabled algorithms under dynamic and uncertain aerodynamic conditions [12]. Utilizing a modified F-16, the AFRL can emulate different flight characteristics and host advanced autonomy software to investigate algorithms in unpredictable environments. Through cooperation with the Defense Advanced Research Projects Agency (DARPA) Air Combat Evolution program, the team conducted 21 test flights of the X-62A, including challenging defensive and offensive maneuvers for autonomous flights. As the test flights continued, many members of the team could edit and add software, making the AI better [13].

While demonstrated at sub-hypersonic speeds, AFRL's research addresses challenges of nonlinear flight regimes and demonstrates the groundwork of reinforcement learning that is applicable to hypersonic flight stability. AFRL aims to accelerate ML operations and transition AI into operational use, highlighting the focus and role of adaptive and autonomous control systems when handling nonlinear and uncertain flight conditions. Through continued flight testing by the AFRL and DARPA, AI will continue to become better. AFRL is building a framework for the future use of AI to enhance autonomous flight control in HFVs.

B. Lockheed Martin and Northrop Grumman

Corporations like Lockheed Martin and Northrop Grumman have both shown great interest in the AI/ML field relating to HFVs. Lockheed has integrated AI and ML across aerospace autonomy and mission systems, including participation in DARPA’s artificial intelligence reinforcements (AIR) initiative [14]. These efforts emphasize ML techniques capable of approximating complex system behavior in real time. For hypersonic flight controls, ML based models accelerate aerodynamic estimation. Lockheed Martin's AI programs and control development indicate a shift toward AI-assisted control systems capable of nonlinear and hypersonic flight regimes [14].

Northrop Grumman’s Glide Phase Interceptor (GPI) program applies advanced digital engineering and adaptive systems in high-speed environments [15]. The GPI is designed to detect, track, and intercept hypersonic glide vehicles while in their atmospheric glide phase, a phase of rapid state changes and limited reaction time [15]. While the algorithms are not publicly available, modern interceptor systems increasingly use AI for both targeting and trajectory. These developments align with the broad industry trend toward AI-enhanced systems and real-time modeling applicable to hypersonic states.

C. Defense Advanced Research Projects Agency (DARPA)

The Defense Advanced Research Projects Agency (DARPA) also emphasizes the integration AI into advanced aerospace systems through programs such as Artificial Intelligence Reinforcements (AIR) [16]. AIR focuses on applying ML to improve prediction and decision-making in dynamic airspace environments. Like other research, it is not limited exclusively to hypersonic vehicles, but the program’s objectives directly align with challenges found in hypersonic flight control. Rapid aerodynamic variation and nonlinear vehicle response are some of the obstacles DARPA’s AIR initiative explores, relating to hypersonic flight.

Supporting development of AI-driven modeling tools capable of handling complex system behavior in real time, DARPA promotes systems that enhance control and performance under conditions of uncertainty [16]. For hypersonic systems, this translates to a variety of improved systematic aspects, including faster response and dynamic control adaptation during high-speed maneuvering. These efforts from DARPA continue to reflect the trend toward hybrid AI-classical control systems, where ML supports traditional control systems in extreme regimes

D. NASA

In conjunction with other organizations, NASA supports the development of AI systems through programs such as the Flight Opportunities for Advanced Space Technologies (FAST) initiative [17]. The FAST program promotes testing of emerging systems, including data-driven modeling and adaptive control architectures in high-speed flight. The program provides a pathway for validating AI guidance systems under realistic conditions.

In relation to hypersonic flight control, the ability to test predictive models in flight is especially important. Estimation and model learning support the need for quick state predictions as shock interactions and thermal loads increase. Programs like FAST can help bridge the gap between simulation-based ML development and real-world aerospace applications, helping to support long-term use of AI in HFVs.

VII. Limitations and Future Directions

A. Current Challenges

While the progress made with AI integration in aviation is extensive, hypersonic flight with AI optimization still has many barriers to cross. Although many simulations have been made with success, the implementation of hypersonics with AI in real life is still in its early stages. The testing done so far has been with jets that are not even at hypersonic speed, like AFRL's X-62, and is still in very early stages [12]. AI is being slowly implemented in stages to make piloting adaptive and efficient. Testing at hypersonic speeds have been done with unpowered, gliding HFVs [9]. This has given a good blueprint for 6 DoF at hypersonic speeds, but it still has a long way to go. Going from simulations to real-world implementations is extremely difficult, so safety must be proven.

Safety is a huge factor when considering the testing of HFVs. AI and NNs can be unpredictable if not exposed to certain flight conditions. The NNs must be trained and run through many simulations to be safe to move over to real-world testing. NN requires a huge amount of trial and error to learn a complex environment. It must be able to make its own decisions and reliably produce consistent results [17]. With the long training times, this can be a grueling and frustrating process.

B. Near-Term Paths

An effective way to combat such challenges is through hybrid approaches. In the case of missile penetration, mitigating DNNs' long training times and trial-and-error by combining traditional penetration techniques with RL has been fruitful. Like the hybrid system outlined earlier, this hybrid approach can reduce training time and improve safety [17]. Through systems, including classical controls, it can increase stability and help with consistency. These types of systems are much more realistic in the near future and will be accessible. As engineers and developers become more familiar with hypersonics and AI, fully autonomous and AI-controlled systems will begin to appear and take over control systems.

Learning based control systems have shown strong results in non-hypersonic vehicles with large amounts of real-world testing and promising results [12]. Significant resources and money have been invested in ML systems, with companies like Lockheed Martin, DARPA, AFRL, and NASA at the forefront of innovation. The starting methods have laid a good foundation to slowly implement AI into hypersonic control systems. Once these methods have been proven, they will bleed into other aspects of aviation.

C. Long-term Opportunities

Looking forward, getting AI into real-world onboarding decision-making is the ultimate goal. With hybrid systems, parameters are set, constraining DNNs significantly, and pairing them with previously proven systems. These constraints limit control authority by AI and rely on simulation behavior. During the design process, surrogate models have shown promise when allowing engineers to study different shapes and unconventional methods. Surrogate models are in the shape of ML models and can replace CFD and FEA while being cheaper and faster [18]. This modelling can improve efficiency and allow creativity to flourish due to time constraints being less pertinent. With steady progress in this field, it is still impossible to give a real time frame on when hypersonic vehicles will be manned by AI-enhanced controls. Near-term progress will continue to develop and provide frameworks for future endeavors of AI adaptation.

VIII. Conclusion

Through the exploration of AI and RL in hypersonics, it is clear this method will shape the future of aerospace. Not just in purely hypersonics, but to any control system. AI, RL, and NNs all have places in classical and hypersonic control systems, creating an adaptive and efficient environment that can optimize aerodynamics and improve the nonlinear and unpredictability issues that lie deep in hypersonic flight. The payoff of implementing AI in control systems will be substantial, allowing for more autonomous flight with adaptive systems. Already, most large aerospace corporations around the world have invested largely in AI and ML systems, to learn and create systems for the future. Because of the long path that AI inevitably has, practical applications in the short-term need to keep improving. Hybrid applications that combine AI and proven methods are a great way to continue to advance aerodynamic optimization and learn more about AI-enhancing controls. With continued advances in high-fidelity innovation in ML, onboarding should become possible, ultimately leading to higher maneuverability and safety. AI-enhancing hypersonic flight will have an unbelievable payoff in the future and lead the aerospace industry into the future.

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