

# Aerodynamic Analysis of Generative AI Supersonic Aircraft Design

Parker T. Blenk<sup>1</sup>

*University of Georgia, Athens, GA, 30602, United States*

Jacob L. Pence<sup>2</sup>

*University of Georgia, Athens, GA, 30602, United States*

Ramana Pidaparti<sup>3</sup>

*University of Georgia, Athens, GA, 30602, United States*

The aerospace industry, motivated by the potential for next-generation travel, requires the exploration of supersonic vehicle designs and manufacturing. Despite this, the design processes for supersonic fighter jets like the F-15, F-22, and F-35 have remained largely unchanged, relying on established frameworks. As Industry 4.0 progresses across various sectors, including aerospace design, integrating AI into different stages of the design process holds the potential to revolutionize how new designs are conceived. With the increasing precision of large language models (LLMs) and other AI technologies, there is a significant opportunity to transform current methodologies for supersonic aircraft. The incorporation of LLMs and AI can redefine these starting points, altering the entire design process. This paper explores the application of LLMs and AI in the preliminary design of supersonic aircraft, focusing on their ability to analyze and optimize aerodynamic properties. By utilizing AI-driven tools and computational fluid dynamics (CFD) simulations within CAE software such as ANSYS Fluent, we aim to evaluate the performance of AI-generated designs compared to traditional, experimentally validated supersonic aircraft.

## Nomenclature

$C_L$	=	coefficient of lift
$C_D$	=	coefficient of drag
$L/D$	=	Lift to Drag Ratio
$Mach$	=	speed of sound
$t/c$	=	thickness to chord ratio

## I. Introduction

The focus of the aviation industry in recent years has been shifting towards supersonic aircraft as technology in the industry continues to increase the potential for next generation travel. Despite the first supersonic flight happening in 1947 and the Concorde, a supersonic passenger plane, having been developed and successfully flown in 1969, the area of supersonic aircraft design/analysis has not undergone much change since then. Part of this stagnation is due to the FAA placing limits and bans on areas for supersonic flight. Recently NASA and Lockheed Martin have been part of the renewal in supersonic innovation with the creation of Boom, designed to limit the noise from sonic booms. Boom (<https://boomsupersonic.com/xb-1>) has its first successful flight in January 2025, demonstrating the future of supersonic flight travel.

However, despite the innovation in new supersonic designs, the design philosophy for fighter jets capable of supersonic flight has been the same for years. Comparing the designs of the F-15, F-22, and F-35 shows that the same base design has been used with only slight modifications based on mission needs for the plane. This process of using the same design tree for every iteration has worked, but it limits innovation. With the increase of industry 4.0 in many

---

<sup>1</sup> Graduate Student, College of Engineering, and Student Member

<sup>2</sup> Graduate Student, College of Engineering, and Student Member

<sup>3</sup> Professor, College of Engineering, 712B Boyd Research Center, and Associate Fellow

fields, the opportunity to change processes and increase innovation by introducing industry 4.0 into the aerospace field has potential.

Recent studies have demonstrated the potential of generative AI in aerospace design. For instance, a review on generative design methods and performance analysis of aircraft highlights how these techniques can optimize aircraft structures and improve performance [8]. The study discusses various case studies from aerospace research, showcasing the capabilities of generative methods and algorithms in providing multiple potential solutions to structural design challenges. Another study focuses on the use of deep learning for the inverse design of low-boom supersonic configurations [4]. This research explores how AI can be used to predict and optimize the far-field signals of supersonic aircraft, thereby reducing the sonic boom and improving overall performance. Generative AI along with LLMs (Large Language Model) can explore a wide range of supersonic design configurations to identify those that offer the best aerodynamic performance, leading to more efficient and faster aircraft and can allow for the creation of new designs efficiently.

The aim of this study is to determine if the use of LLMs and generative AI can result in aerodynamically viable supersonic aircraft designs. After a brief review of methodologies and ChatGPT prompts, a design model was developed and a CFD (Computational Fluid Dynamics) analysis was performed. Several simulation results are obtained and presented and compared to the existing analytical solutions. The results further demonstrate that various parameters affect the performance and hence needs to be further studied. The use of these new industry 4.0 technologies in aerospace design could revolutionize the field by allowing multiple designs to quickly be generated without relying on previous designs. The findings of this study contribute to an evolving discussion on how AI can reshape the aerospace design landscape, offering insights into its potential to enhance efficiency, innovation, and performance in the development of future supersonic vehicles.

## II. Methodologies

The supersonic aircraft designs were generated using ChatGPT o1 with the goal of determining the ability of generative AI to design supersonic aircraft. Two different starting prompts were created to give to ChatGPT to see what designs are created. ChatGPT o1 was chosen as the version that was used because o1 is the most advanced version of ChatGPT that is available to the public. The first of the prompts was a generic prompt that gave no details about mission criteria or design criteria, just that the design was supposed to be a non-commercial supersonic jet. The goal of this prompt was to see if the AI can recognize and include details in the aircraft design that are necessary for supersonic but not subsonic aircraft. The second prompt that was created gave design criteria and mission criteria for the theoretical design for ChatGPT to design around. The design criteria that were given to ChatGPT were based on the publicly available data on typical supersonic jets. This is the more realistic approach for real world aircraft design because aircraft are made for a specific mission, so if AI is incorporated into aircraft design in the future, the use case would be more similar to this prompt. The goal of the aerodynamic analysis is to determine if based on the flight characteristics of each design, if the design is viable for flight, but also, to determine if giving the AI more details for the design of the plane created a better design from an aerodynamic standpoint.

ChatGPT and other LLMs are capable of creating simple shape CAD (Computer Aided Design) models. However, the shape of a supersonic aircraft does not fit that description and is much too complex for the LLMs to create. This meant that the models that were going to be used in simulation needed to be created in another program based on the design characteristics that were provided by ChatGPT. The program chosen for the creation of the models is OpenVSP, which is a program made for model creation and low fidelity simulations of aircraft. The simulations in the program were not enough for the goals of this paper, but the model creation aspect of the program was perfect due to the ease of creation for complex geometries that are often seen in supersonic aircraft. The models for the wings, vertical, and horizontal stabilizers were made separately for each of the plane designs and then imported and combined in Fusion360. The fuselage models were publicly available models that closely matched the description of the fuselage (<https://airshow.openvsp.org/vsp/uKwiBfqZl5vXNPbrVDN9>) and then modified in order to fix the errors or inaccuracies based on the given fuselage characteristics.

The simulations to determine the aerodynamic characteristics of the designs were run in ANSYS Fluent and Fluent Aero. The aerodynamic performance of each aircraft was evaluated initially at an altitude of 55,000 ft at a Mach of 2 with an AoA (Angle of Attack) of 3.5 degrees, which aligns to the standard cruise conditions of the Concorde [5]. Along with the simulation at supersonic cruise conditions, a Mach sweep was performed for both aircraft over a range of Mach 0.95 to 1.7 in intervals of 0.15 at an AoA of 7 degrees. Based on Concorde flight data, at around 27,000 ft, the Concorde was just under the speed of sound. The assumption of a linear climb rate was made from Mach 0.95 to standard cruising conditions. This gives rough estimations of the altitude at each Mach value, which will ultimately provide an approximation of the L/D at each flight condition. The Mach 2 standard cruise simulations were run in

ANSYS Fluent, while the Mach sweep was run in Fluent Aero. Fluent Aero was used for the Mach sweep simulations because the program is tailored for aerospace simulations, like the ones in this paper, as well as it streamlines the process of simulating airflow over a range of flight conditions. This ease of setting up simulations, such as a Mach sweep, made Fluent Aero the obvious choice over ANSYS Fluent for this set of simulations. In order to simplify the simulations, the focus was made to just aerodynamic properties, so propulsion is not included in the simulations. For both supersonic plane designs, the simulations were run with the same initial conditions in order to allow for the best comparison between the designs. The altitude and speed of the simulations was based on the flight characteristics of the Concorde, which was chosen because of performance characteristics that were publicly available for it.

For the high-fidelity simulations that are required to accurately predict performance characteristics of supersonic flight, a fine mesh is a necessity. To minimize the total cell count, and to maximize the accuracy of the solution, a mesh about the plane of symmetry was considered. This will allow for decreased local cell sizings around key points of the aircraft, which was one aspect of the mesh that was heavily focused on. A body of influence was implemented surrounding the aircraft for further mesh refinement, as well as to capture the flow characteristics in the wake of the aircraft. Additionally, sizing refinements were added to the nose and body of the aircraft, where the flow initially contacts both models. Specific detail was given to the cell sizings around the edges of the aircraft where flow may be disrupted, such as leading and trailing edges, fuselage and wing connections, and wing tip edges. Finally, due to the limited computing power and cell numbers provided by the university, a  $y^+ = 30$  was chosen, providing a balance between computational time and cost to total cell count. The mesh featured 10 inflation layers and a first layer height of  $8.1 \times 10^{-04}$  m, which is dependent on the freestream density, viscosity, velocity, and reference length. This would be sufficient enough to capture the intricate flow behavior throughout the entire viscous sublayer. The volume mesh incorporated polyhedral cells, with both meshes having over  $6 \times 10^6$  cells.

### III. Generative Design Details

#### A. Generic Prompt

The first supersonic aircraft that was created and simulated was from a generic prompt that gave the AI little direction. The prompt that was given to ChatGPT was to design a typical supersonic jet and provide design characteristics, and no extra details about design criteria were given to the AI. Clarifying questions were asked in order to get major details that were not listed as first, such as wing root and tip chord length and wing location, but there were still some assumptions that were made, including smaller details on the fuselage. These assumptions were focused on details that were needed to make the model but would not have a large impact on aerodynamic performance. The design characteristics in table 1 are the results of the generic prompt that was given to ChatGPT o1.

**Table 1. Aircraft Design Characteristics from Generic Prompt**

Design Variable	Design Value
Length	105 ft
Fuselage Diameter (max)	7.55 ft
Wingspan, Area	50 ft, 753.5 ft <sup>2</sup>
Wing Leading Edge Sweep	60°
Chord Length (root, tip)	39.4, 4 ft
t/c (root, tip)	3.5 %, 2.5%
Airfoil	NACA 0004
Vertical Stabilizer Height, Area	13.3 ft, 118.4 ft <sup>2</sup>
Vertical Stabilizer Airfoil	Double Wedge (4% t/c)
Horizontal Stabilizer Span, Area	16.5 ft, 129 ft <sup>2</sup>
Horizontal Stabilizer Airfoil	Double Wedge (4% t/c)

Along with the base design characteristics that were given, ChatGPT gave other important design characteristics that are important for supersonic designs. The response had an entire section going through the internal structures of the wings and fuselage as well as a section going over avionics, flight controls, and environmental systems. Even though these results were not included in the simulations due to simplifications in the process, the AI recognizing and adding these design features shows promise for the ability to use AI in aircraft design. One goal when creating

the design was to only have the input of the LLM in the design, so if a detail that would normally be included in a supersonic design was not explicitly said, it was not included in the model. One example of this is in the fuselage shape. The fuselage for a supersonic aircraft should have a “coke-bottle” shape, but since the response from ChatGPT did not include or list that shape in the fuselage details, it was not added to the final model.

**B. Detailed Prompt**

The second model was created based on a prompt with specific design characteristics based on a typical supersonic jet. The conditions that were given to the LLM were takeoff, flight, and mission criteria. The prompt did not give exact values, but rather, a value range for each characteristic in order to allow there to still be design decisions for the LLM to make. The following prompt was given to ChatGPT to produce the second plane design:

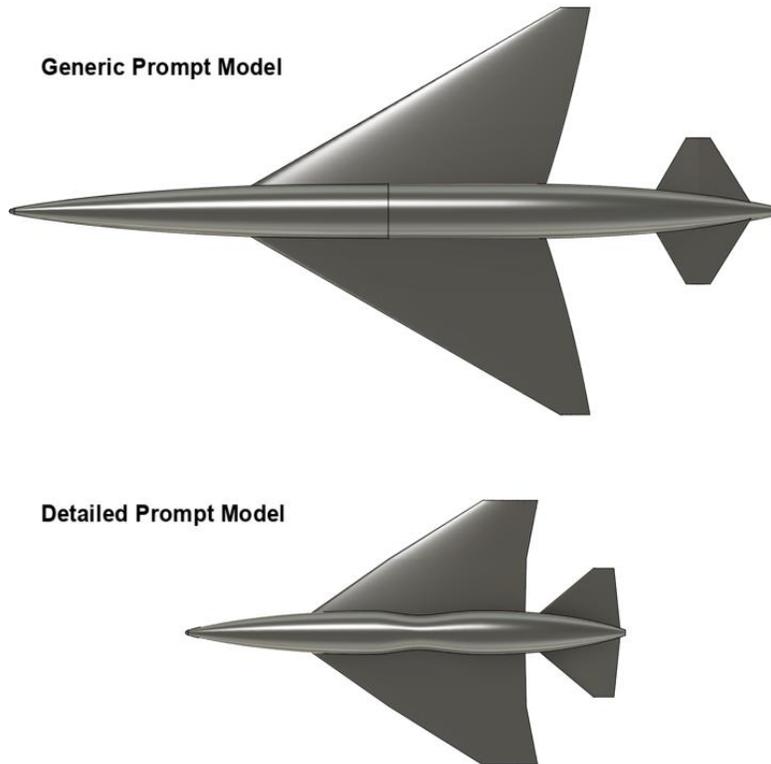
**AI Prompt:** *“Design a supersonic jet that meets the takeoff, flight, and mission criteria listed. For takeoff conditions, the takeoff speed is Mach 0.3, and the maximum takeoff weight (MTOW) is between 69,000 and 75,000 pounds. For the cruise conditions, the maximum speed of this aircraft is Mach 2.0 with a cruising speed between Mach 0.8-0.85, the cruising altitude is roughly 55,000 feet, and the cruise weight is between 54,000 and 60,000 pounds. There are no radar considerations for this aircraft, and the length of the aircraft should be between the range of 50-65 feet. One focus of the aircraft is the high-performance level at a large range of angles of attack, not just level flight. Lastly, provide an airfoil for this aircraft. Please take all of these flight and mission criteria and give exact aircraft design characteristics that will perform best for these criteria.”*

Similar to the generic plane design, additional clarifying questions were needed in order to accurately make the plane design because important information for making the model was not initially given. Some of the information that was needed but not given includes root and tip chords of the wings, wing location on the fuselage, and details about the horizontal stabilizer. The design characteristics that were generated by the AI in response are listed in table 2.

**Table 2. Aircraft Design Characteristics from Detailed Prompt**

Design Variable	Design Value
Length	60 ft
Fuselage Diameter (max)	6 ft
Wingspan, Area	32 ft, 600 ft <sup>2</sup>
Wing Leading Edge Sweep	58° outboard, 55° near root
Chord Length (root, tip)	30, 7.5 ft
t/c (root, tip)	4%, 4%
Airfoil	NACA 65A004
Vertical Stabilizer Height, Area	10 ft, 120 ft <sup>2</sup>
Vertical Stabilizer Airfoil	NACA 65A004
Horizontal Stabilizer Span, Area	13 ft, 120 ft <sup>2</sup>
Horizontal Stabilizer Airfoil	NACA 64A004

With this prompt, the LLM did not include any structural details in the creation of the plane design. However, the response did include more details for the aerodynamic designs of the plane, matching the emphasis in the prompt that the main goal of the design was aerodynamic focused. The response did include details about the propulsion system that would be used, but there was no discussion over the structural designs like there was in generic prompt. The airfoils and fuselage shape that was given in the response is more typical for supersonic designs, indicating that a more detailed prompt might result in better performance characteristics.



**Fig. 1 CAD Models of Both Plane Designs**

#### IV. Results

##### A. Simulation Results

Initially, both simulations were run at standard cruising conditions in ANSYS Fluent, which were described earlier. For simulation setup, the steady-state RANS equations were used along with the  $k-\omega$  SST (shear-stress transport) model. In addition, due to the rapid density changes experienced at supersonic flight, the density-based solver was considered with ideal gas for air. The viscosity of the fluid was characterized by Sutherland's Law, where the reference temperature and Sutherland temperature were 273.15 K and 110.4 K, respectively. For boundary conditions, the inlet condition was modelled as a pressure farfield in order to properly input the Mach number, gauge pressure, and AoA at 55,000 ft, with the turbulence intensity and turbulent viscosity ratio being set to 10% and 10, respectively. The aircraft itself assumed to be a stationary wall with a no-slip boundary condition, while the symmetry plane was set as symmetry. For output parameters, the total  $C_L$  and  $C_D$  were monitored for the wing and entire aircraft, which can be seen in Table 3. Each simulation was run for over 300 iterations, allowing the residuals and outputs to fully converge for the most accurate results.

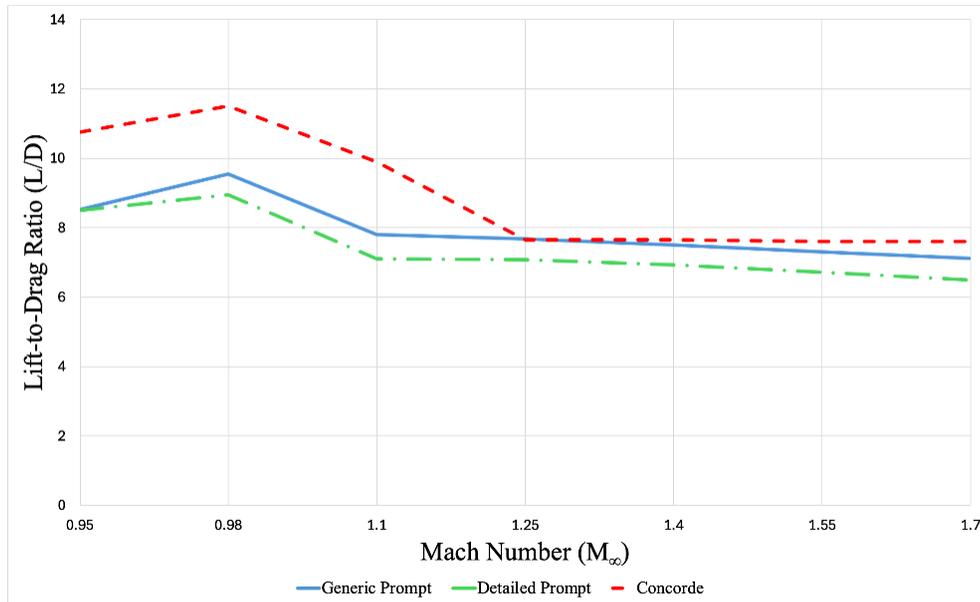
**Table 3. Comparison of Coefficients of Lift and Drag at Mach 2**

Variables	GM	DM
$C_L$ (Wing)	0.0453	0.0427
$C_L$ (Entire Plane)	0.0505	0.0446
$C_D$ (Wing)	0.0049	0.0057
$C_D$ (Entire Plane)	0.0078	0.0115
L/D (Wing)	9.2449	7.4912
L/D (Entire Plane)	6.4744	3.8783

Looking at the results provided in Table 3, it can be seen that when isolating the values for the wing in both models, the values closely align. Meanwhile, for the entire aircraft, the  $C_D$  significantly increases for the DM when comparing that of the GM. In addition, the value of  $C_L$  also decreases, ultimately almost halving the L/D for the DM. These values provided

a rough idea of how each model would perform in flight, but to further assess its performance in supersonic flight, a Mach sweep of each model was performed in Fluent Aero and compared to data provided by the Concorde.

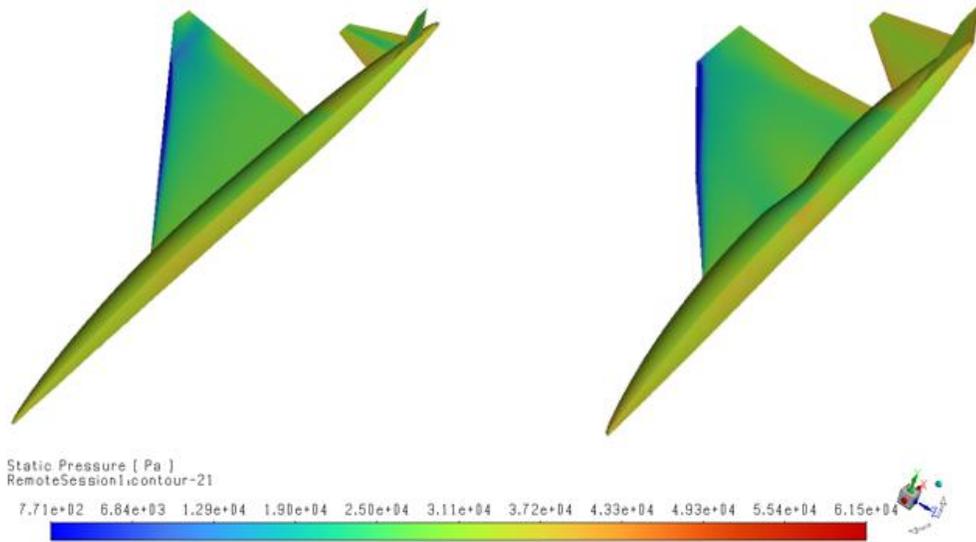
The CFD simulations in Fluent Aero were set up similarly to that of the simulations in ANSYS Fluent. The GM and DM were performed with the  $k-\omega$  SST model with a density-based solver. The Mach numbers were set to a range between 0.95 and 1.7 with evenly spaced intervals, and in conjunction the altitude was calculated at each Mach number based on the linear increase assumption stated earlier. One aspect of Fluent Aero that makes it user friendly is its ability to automatically populate the pressure and temperature at each altitude based on the Ideal-gas equations. The boundary condition parameters were set to be equivalent to those set in ANSYS Fluent. Due to an assumed increase in turbulent flow at a higher AoA, the simulations were run for 1000 iterations, monitoring  $C_L$  and  $C_D$  at each flight condition.



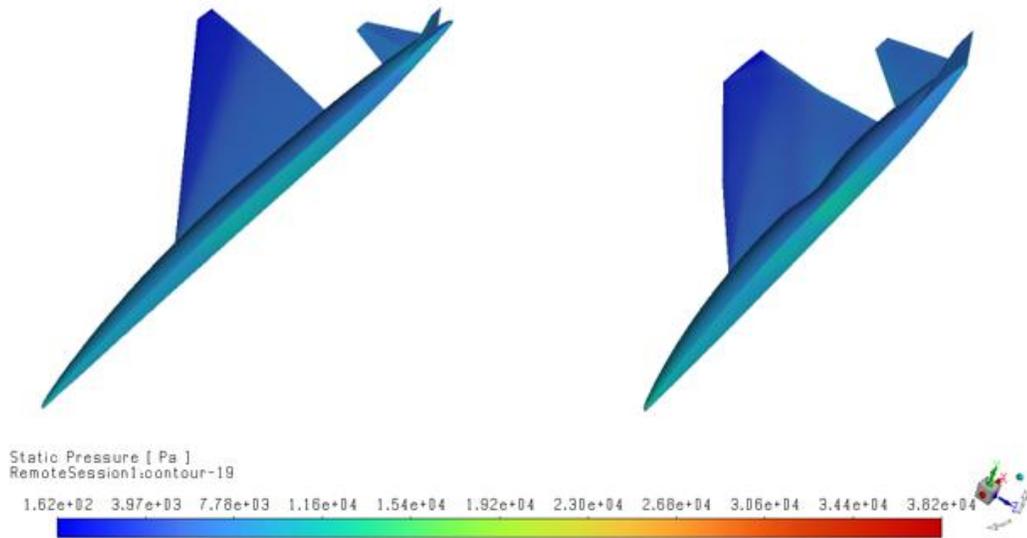
**Fig. 2 Comparison of L/D Between the Concorde, GM, and DM Over the Range of the Mach Sweep**

The L/D ratio was plotted as a curve at Mach number, which can be seen in Fig. 2. The values associated between each simulated Mach number are an approximation set by the simulated L/D's, which ultimately provide a rough accuracy to how the L/D would vary if it were simulated at those Mach numbers. When comparing the three sets of data provided, it can be seen that the Concorde outperformed both the GM and DM at low Mach numbers, as well as high Mach numbers. However, it should be noted that at Mach 1.25, the GM had a slightly higher L/D ratio than the Concorde before slowly decreasing as the Mach number increased. On the other hand, the DM performed worse at all Mach numbers from 0.97 to 1.7 when comparing it to the GM and Concorde. This aligns with what was shown in Table 3, that at higher Mach numbers the GM has marginally better aerodynamic characteristics than the DM. Although this is just a range of Mach numbers at one specific AoA, it does provide some insight to the aerodynamic performance of both aircrafts at supersonic flight conditions. Continuing this comparison, Figs. 3 & 4 depict the static pressure distribution over the half-body aircraft for both the GM (left) and DM (right) at Mach 0.95 and 1.7, respectively. For both Mach numbers, the scale for static pressure was the same for each model, providing a more accurate comparison. At Mach 0.95, for both models it can be seen that since they are in the transonic regime, there is a shock wave formation near the leading edge of each wing. This leads to an abrupt increase in static pressure directly after the shock wave, as well as more flow separation towards the trailing edge where the pressure increases again. When looking at each horizontal stabilizer, the double wedge airfoil provided a sharper decrease in static pressure, as opposed to the NACA 64A004 airfoil for the DM. Similar trends can be seen in Fig. 4, however since the aircraft

is now at supersonic speeds, there is no shock wave formation over the surface of the wing. Close to the leading edge there is a low region of static pressure, but flow separation past this point causes it to increase for both models.



**Fig 3 Comparison of the Static Pressure Contours of the GM and DM at Mach 0.95**



**Fig 4 Comparison of the Static Pressure Contours of the GM and DM at Mach 1.7**

These contours highlight the key differences in pressure distribution over the half-body aircraft for transonic speeds and near Mach 2, supersonic speeds. It provides detail to how each airfoil for the wing and horizontal stabilizer contribute to the  $C_L$  and  $C_D$  values, and ultimately the  $L/D$  for each Mach number shown in Fig. 2.

## B. Numerical Results for Validation

After the simulations were completed, the next goal was to verify the results to ensure that simulation values were accurate to what should be expected. The equations that were used for the verification were found in *Introduction to Aeronautics: A Design Process*. In order to verify the simulations, the  $C_L$  for the wing was determined using standard calculations given from [2]. Traditionally, the standard equation for calculating the lift-curve slope is characterized by Eq. (1), however that equation only works if the condition described is met. Since the generic prompt supersonic aircraft has a larger leading-edge sweep when comparing it to the detailed prompt wing leading edge sweep detailed in Table [here], this rendered the criteria mentioned above invalid. As a result, Eqs. (2) - (5) were utilized to calculate the lift-curve slope from the 2-D airfoil chart, in order to determine  $C_L$  for the wing in the generic prompt simulation. Additionally, when looking at the detailed prompt's design variables, it also does not meet the criteria, since the freestream Mach number is equal to the fraction on the right side of the inequality shown in Eq. (1). The equations used to calculate  $C_L$  for the wing in the generic prompt could not be used for the wing in the detailed prompt as no requisite 2-D airfoil data was found for the NACA 65A004 airfoil. Even though the  $C_L$  could only be calculated for one simulation, the verification of one of the results is beneficial because both simulations were run with the same settings.

$$C_{L\alpha} = \frac{4}{\sqrt{M_\infty^2 - 1}}; \text{ If } M_\infty > \frac{1}{\cos(\Lambda_{LE})} \quad (1)$$

$$e = \frac{2}{2 - AR + \sqrt{4 + AR^2(1 + \tan^2(\Lambda_{tmax}))}} \quad (2)$$

$$C_{l\alpha} = \frac{c_l}{\alpha - \alpha_{L=0}} \quad (3)$$

$$C_{L\alpha} = \frac{C_{l\alpha}}{1 + \frac{57.3 C_{l\alpha}}{\pi e AR}} \quad (4)$$

$$C_L = C_{L\alpha}(\alpha - \alpha_{L=0}) \quad (5)$$

The result from the calculations demonstrated a  $C_L$  of roughly 0.05058 for the wing of the GM. Compared to the simulation result in table 1, that yields a 10.5 percent error. The cause of the error is likely due to estimations that were made about values from the airfoil. The estimations had to be made because there was not the  $C_L$  vs AoA graphs for the airfoil that the model used. In order to get the value that was used in the calculation, the closest airfoil that had data was used to get values. Additionally, the values pulled from the graph could only be accurate to two decimal places. The combination of inexact data for an airfoil that was only close to the correct airfoil created the error seen between the calculations and the simulations.

## V. Discussion

When determining the aerodynamic viability of a plane design, there are many factors that can be used. For this paper, the approach that was chosen to analyze the plane design was to look at the lift-to-drag ratio. This was the chosen method because other methods, such as analyzing pressure or velocity changes over the wing or plane, have an effect on the lift to drag ratio, so lift to drag ratio is a good metric to use for incorporating multiple aspects. In order to determine if the designs are aerodynamically viable, each design is being compared to the lift-to-drag ratio of the Concorde. The Concorde was chosen as the comparison vehicle because it has a similar flight profile to what the designs were made for as well as the Concorde has publicly available data on L/D ratios that a lot of aircraft do not.

Comparing the two AI generated designs shows that the GM performed better than the DM in every simulation. This is likely due to the GM being closer in design to the Concorde, so the GM was better suited to the flight profile of the Concorde than the DM. However, the design being better in every simulation could also mean that the GM is a better design regardless of flight conditions. The GM being a better design is likely due to the design and placement of the vertical and horizontal stabilizers. The GM has double wedge airfoils for both the vertical and horizontal stabilizers, and the double wedge airfoil is an efficient shape for supersonic flight. The DM had NACA 65 series airfoil which is good for supersonic conditions, but the horizontal stabilizers had 5 degrees of dihedral tilt. The dihedral

tilt along with the raised position of the horizontal stabilizer that was forced by the short fuselage and long root chord of the wing likely caused an increase in drag from the stabilizers in the DM that was not present in the GM.

Based on the simulations at level cruise conditions, the generic prompt plane is a better design than the detailed prompt plane. The L/D of 3.8783 provided by the DM is worse than most aircraft regardless of their use, and it is about half of what the Concorde is reported as having at the same conditions. However, this one simulation alone does not determine that a design is not viable, especially because of the nature of cruising flight, a design can be viable with a low L/D. After the Mach 2 simulation, the GM looks promising because the L/D of 6.4744 is only slightly less than the report value of 7 for the Concorde at the same conditions. Based on the cruise condition simulations, the GM appears to be viable while the DM is borderline if it has good enough aerodynamic performance.

The values from the Mach sweep help provide another angle to determine aerodynamic viability because the performance of an aircraft during climb is more important than cruise for most aircraft. Similar to the cruise conditions simulations, the AI generated designs performed worse than the Concorde over the Mach sweep. However, the L/D value for the Concorde over the Mach sweep is L/D max, which means that it might not have occurred at the AoA of 7 degrees that the GM and DM simulations used. These L/D max values for the Concorde were used for comparison even though it is not a direct comparison because it still provides a real baseline value. Fig 2 shows that neither design performed better than the L/D max of the Concorde over the entire Mach sweep. Over Mach 1.25, none of the differences between the L/D of the GM or DM and the Concorde are over 12 percent. This is close enough to feel confident that the designs are aerodynamically viable. The simulations did not analyze takeoff and landing conditions, but the aerodynamic performance in the other flight conditions give confidence that both designs will perform well throughout the flight regime, further research and analysis is needed in order to confirm however. Also, since a lot of supersonic designs rely more on propulsion to generate lift at takeoff since the wings are built for the high-top speeds seen by these aircraft, the GM and DM can be viable designs even with potential lower L/D at takeoff and landing conditions.

## VI. Conclusion

As industry 4.0 becomes more prevalent in every field, the incorporation of AI into the design process will be seen in many industries, including aerospace. However, there are doubts over whether LLMs are able to produce quality results in more complicated fields. This paper explored the application of LLMs and AI in the preliminary design of supersonic aircraft, focusing on their ability to analyze and optimize aerodynamic properties. By utilizing AI-driven tools and computational fluid dynamics (CFD) simulations within CAE software such as ANSYS Fluent, we conducted analysis to evaluate the performance of AI-generated designs compared to traditional, experimentally validated supersonic aircraft. The results further demonstrate that various parameters affect the performance. For the two designs considered through LLM prompts, it was found that the two designs did not produce aerodynamic characteristics that were on the same level as the Concorde, but the designs were still reasonable to be deemed aerodynamically viable designs for an actual aircraft. Further analysis is needed to see if AI can produce every aspect of a supersonic aircraft design, including propulsion and structures, and to see if newer models of LLMs can produce better designs as well as performance.

## References

- [1] Arovitola A, Di Nuzzo PE, Pezzella G, Viviani A. "Aerodynamic Analysis of a Supersonic Transport Aircraft at Landing Speed Conditions", *Energies*, 2021; 14(20):6615. <https://doi.org/10.3390/en14206615>
- [2] Brandt, Steven A., *Introduction to Aeronautics: A Design Perspective*, American Institute of Aeronautics and Astronautics, March 2015
- [3] ChatGPT, OpenAI, Ver. o1, San Francisco, CA, 2015
- [4] Chen, S., Qiu, J., Yang, H. *et al.* Deep learning for inverse design of low-boom supersonic configurations. *Adv. Aerodyn.* **5**, 13 (2023). <https://doi.org/10.1186/s42774-023-00145-1>
- [5] Leishman, J. Gordon, *Introduction to Aerospace Flight Vehicles*, Embry-Riddle Aeronautical University, Jan 2023, Chap. 13
- [6] Mair, W. Austyn, *Aircraft Performance*, Cambridge University Press, 1992, Chap. 3, 10. <https://doi.org/10.1017/CBO9780511607134>
- [7] Mason, W.H. "Some Supersonic Aerodynamics", Virginia Tech University Configuration Aerodynamics Class, 2016. [https://archive.aoe.vt.edu/mason/Mason\\_f/SupersonicPres.pdf](https://archive.aoe.vt.edu/mason/Mason_f/SupersonicPres.pdf)
- [8] Mathew, B. C; Kumar, A., Pal, D., Verma, D.K, and R. K. Saini, Brandt, *Review on Generative Design Methods and Performance Analysis of Aircraft*, *AIP Conf. Proc.* 2962, 020001 (2024).
- [9] Ordaz, Irian and Rallabhandi, Sriram K. "Boom Minimization Framework for Supersonic Aircraft Using CFD Analysis", NASA, 2010. <https://ntrs.nasa.gov/api/citations/20100002817/downloads/20100002817.pdf>
- [10] Starr, Fred, "The Supersonic Conundrum: The Faster You Go, The Less Fuel is Used" August 2020. <https://fredstarr.com/wp-content/uploads/The-Supersonic-Conundrum-pdf.pdf>