Texas Tech University

Final Project:

Aerodynamic Design of an SUV

Sergio Hernandez-Acosta

Computational Fluid Dynamics ME 3165

Dr. Haiwen Ge

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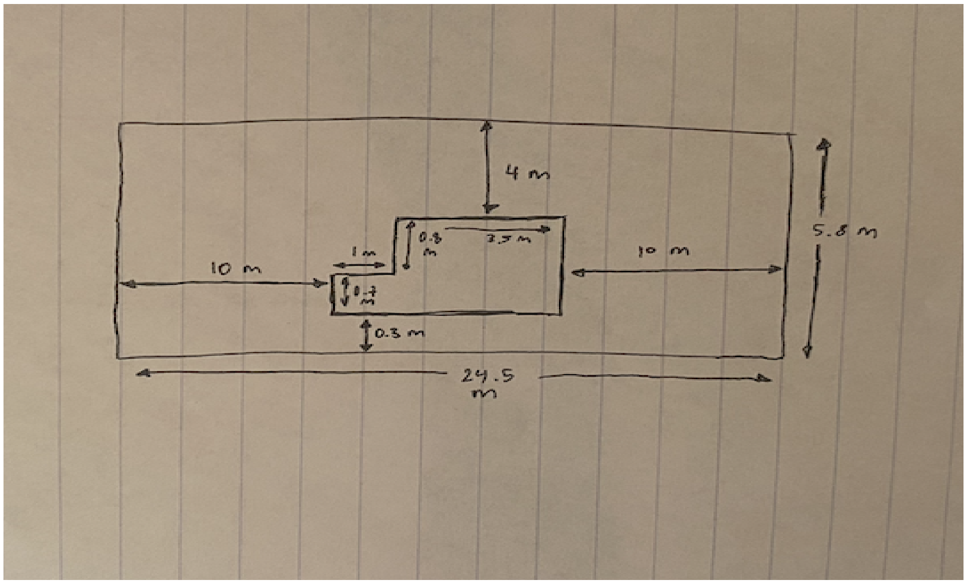
Setup

Design Before Ansys Drawing:



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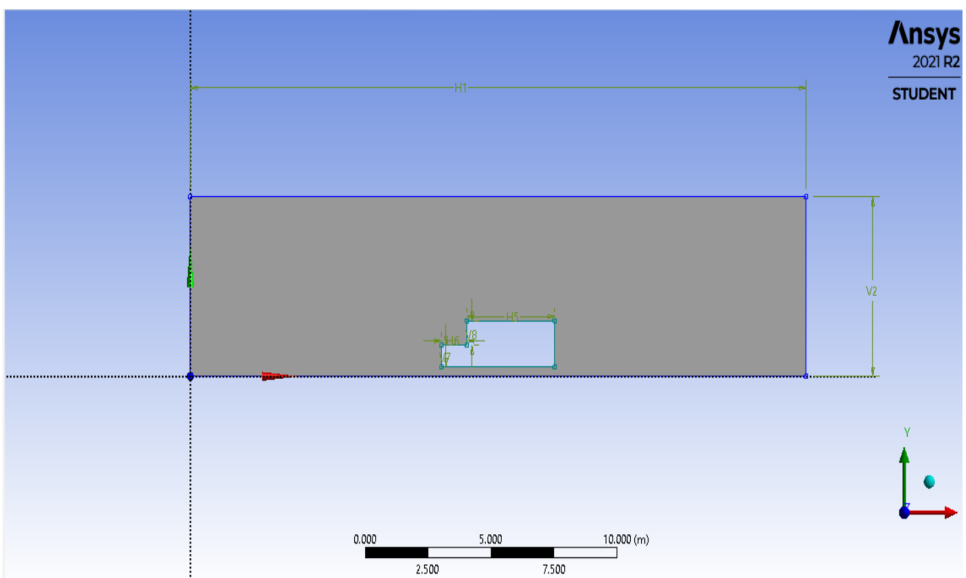
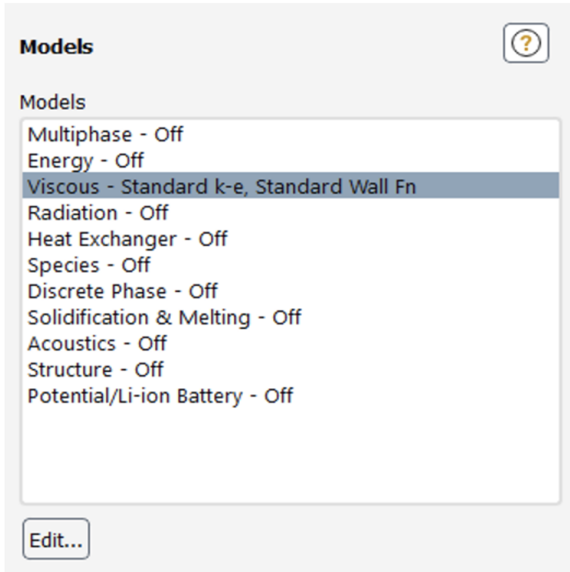
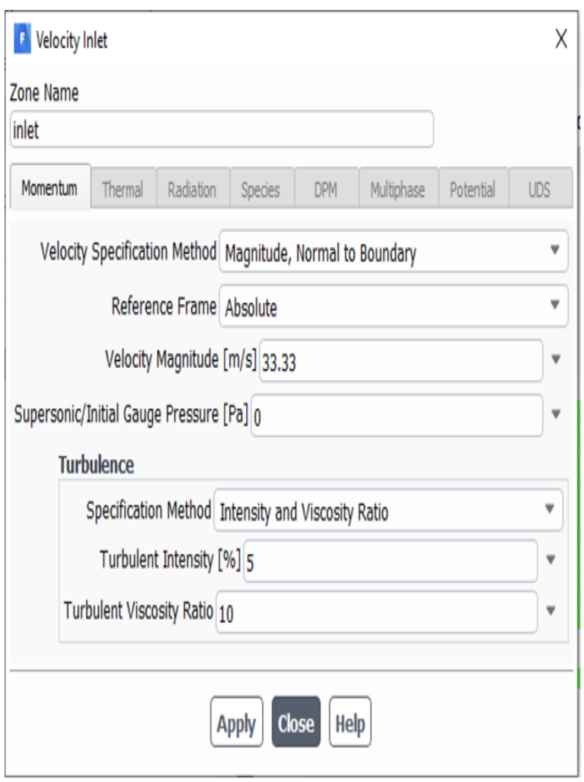


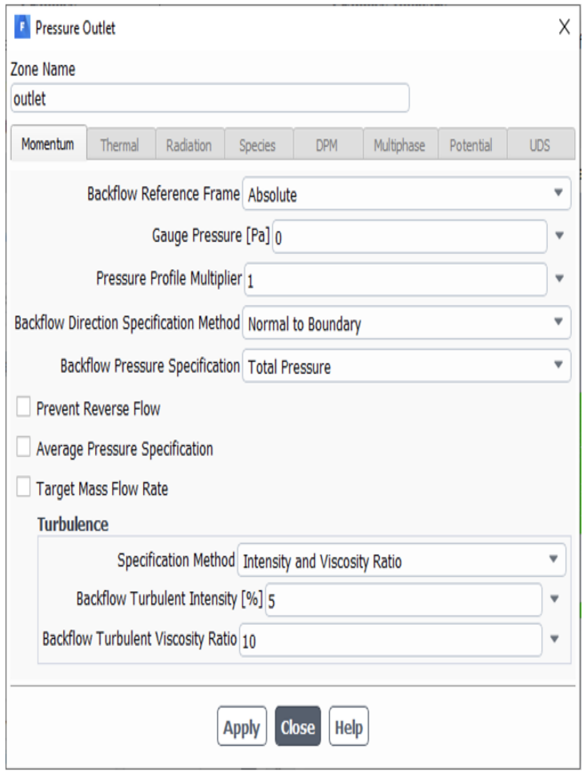
Models:



Boundary Conditions:

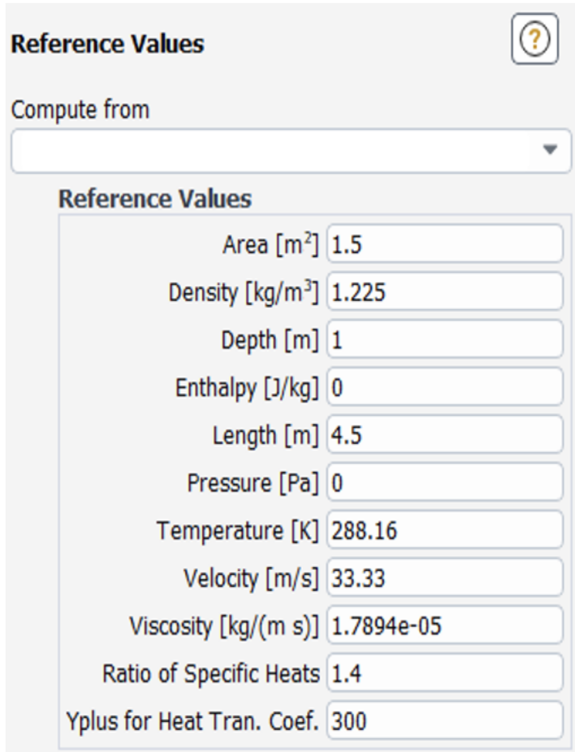


Inlet Conditions

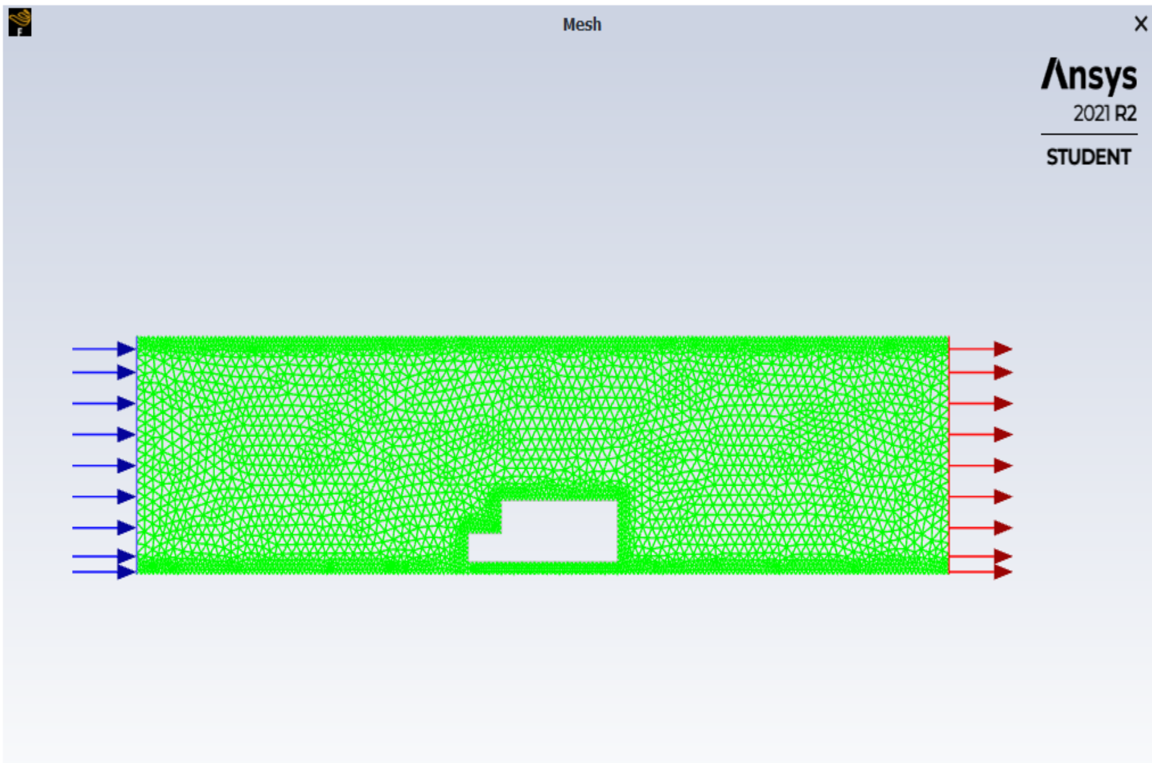


Outlet Conditions

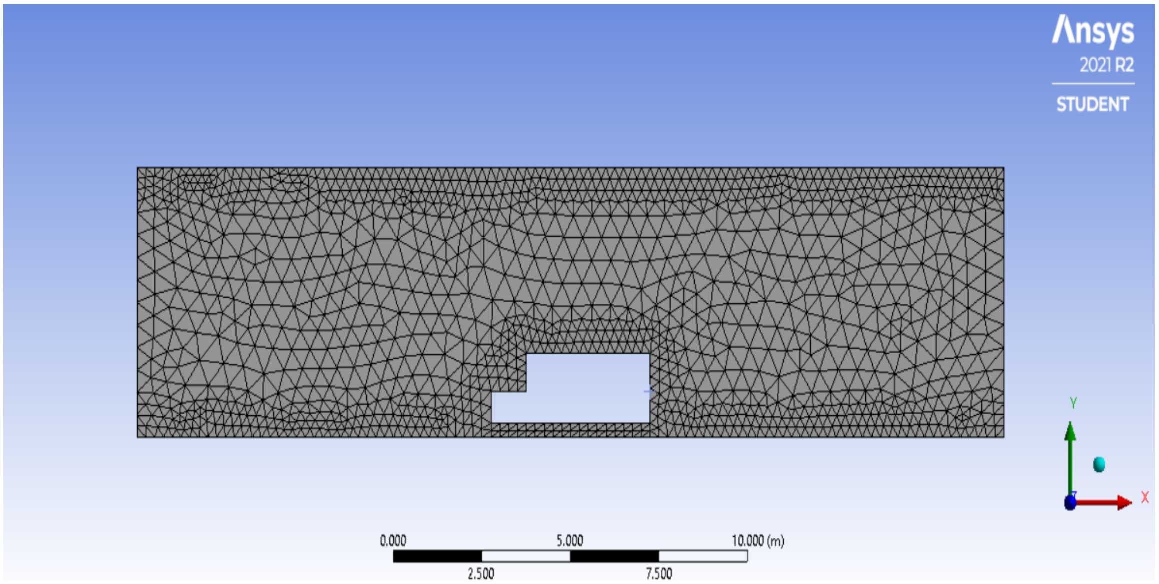
Reference Values:



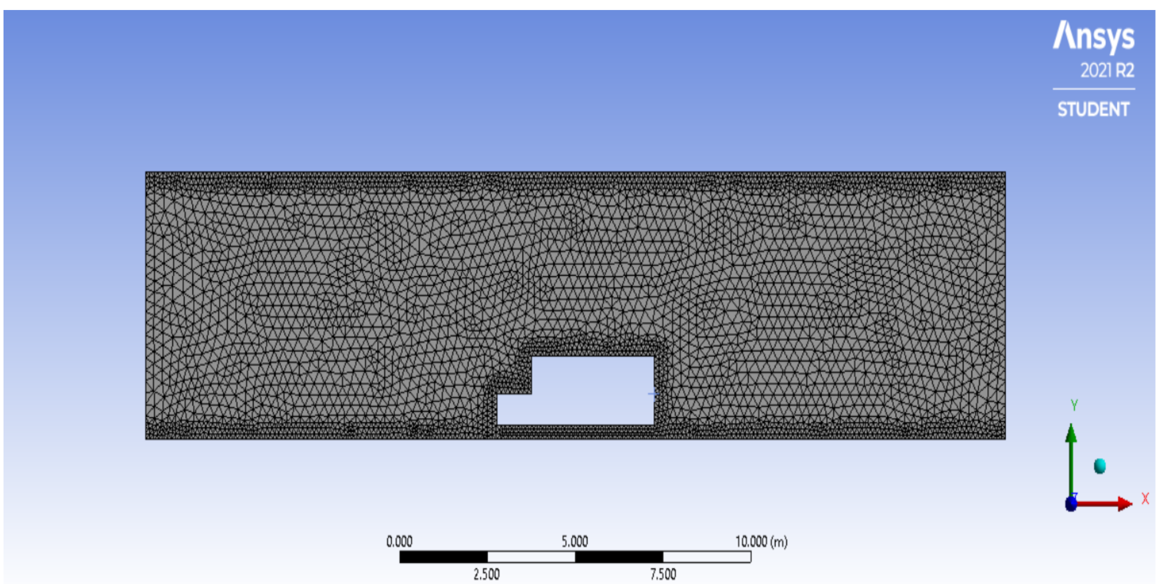
Geometry of Computational Domain



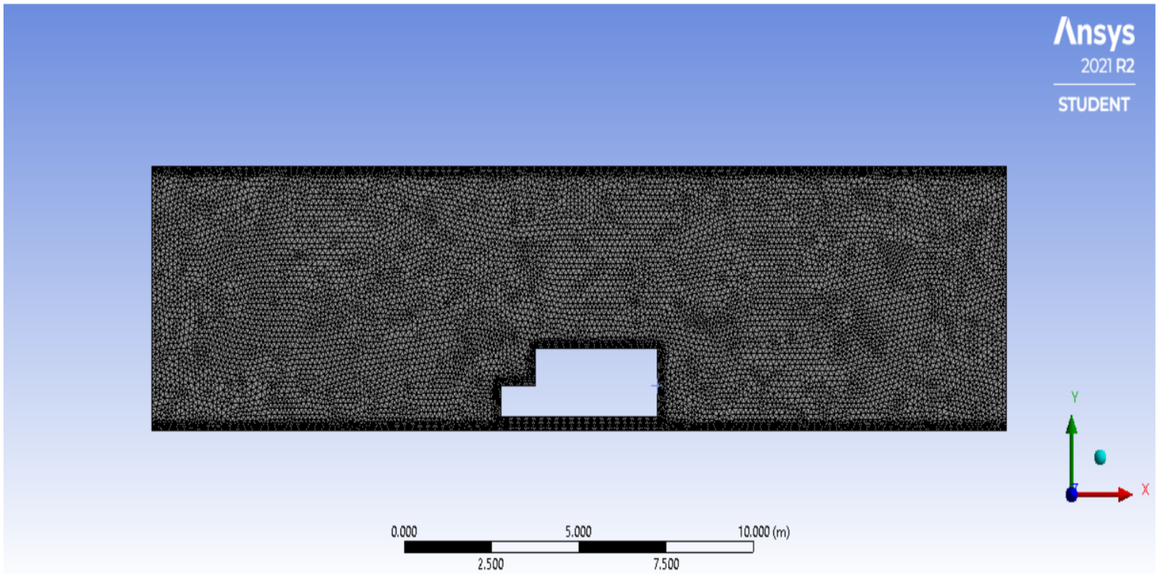
Grid Size Effect on Drag Coefficient



Mesh = 0.5m
C_D = 1.9369



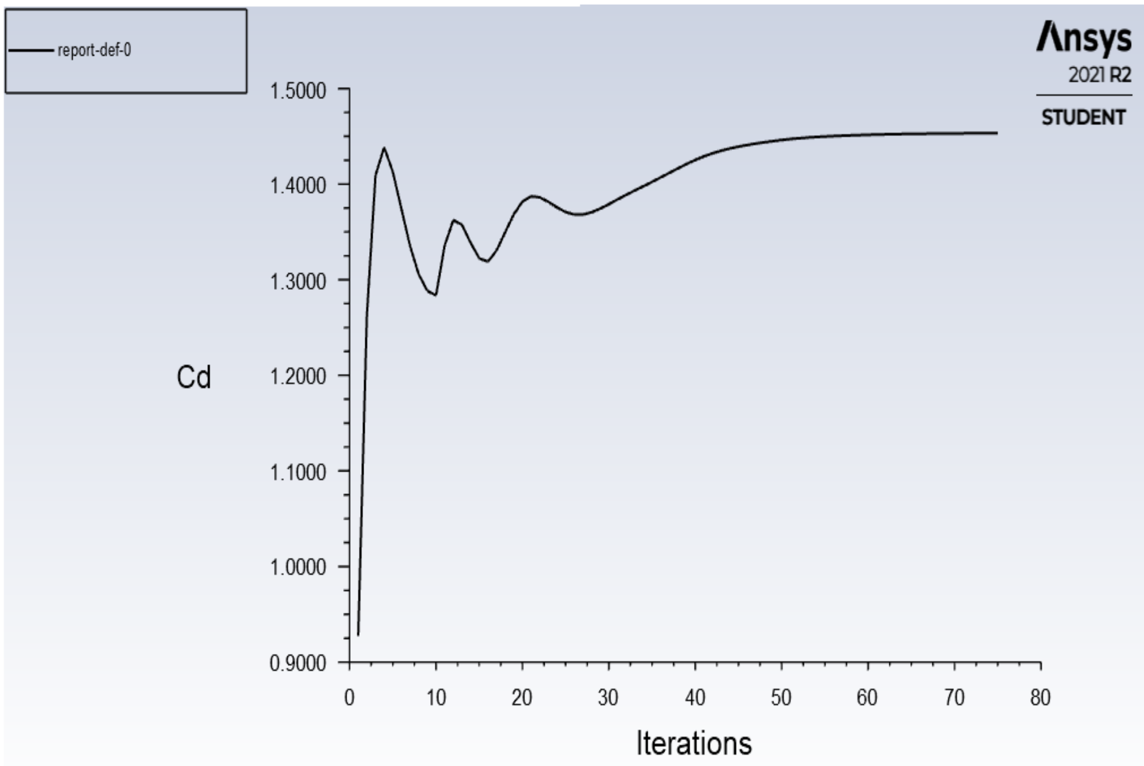
Mesh = 0.25m
C_D = 1.6760



Mesh = 0.125m
C_D = 1.4533

For this section of the experiment, three separate mesh renderings were used. The very first step was to change the default size that Ansys provided for the body, at approximately 1m. Next, however, the reference point was reduced in half to 0.5m. Starting at that rather large and inefficient 0.5m, the increments reduce the mesh sizes in half for three iterations until a mesh size of 0.125m. It can be observed that lowering the grid size from 0.5m in element size down to 0.25m, or in the first iteration, the drag coefficient decreases.

In the second iteration, when the element size is further decreased to 0.125m, one can observe that the drag coefficient also decreases. Therefore, when comparing the results, it is noted that the 0.125m element size seems to be the most sound choice for grid sizing on the body. This decision can be further supported by the fact that this mesh size of 0.125m seems the most fit to achieve the best result in aerodynamic efficiency due to the drag coefficient, C_D. Thus, a size of 0.125m shall be utilized as the final, accepted mesh size to run the experiment on. In conclusion, as mesh sizes decrease, so does the the drag coefficient.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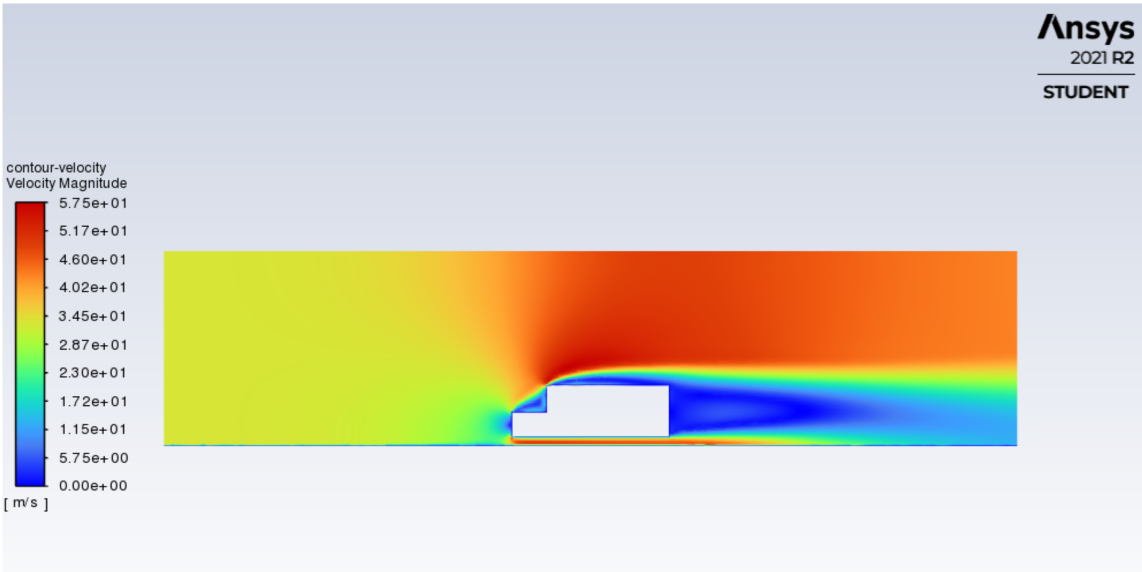
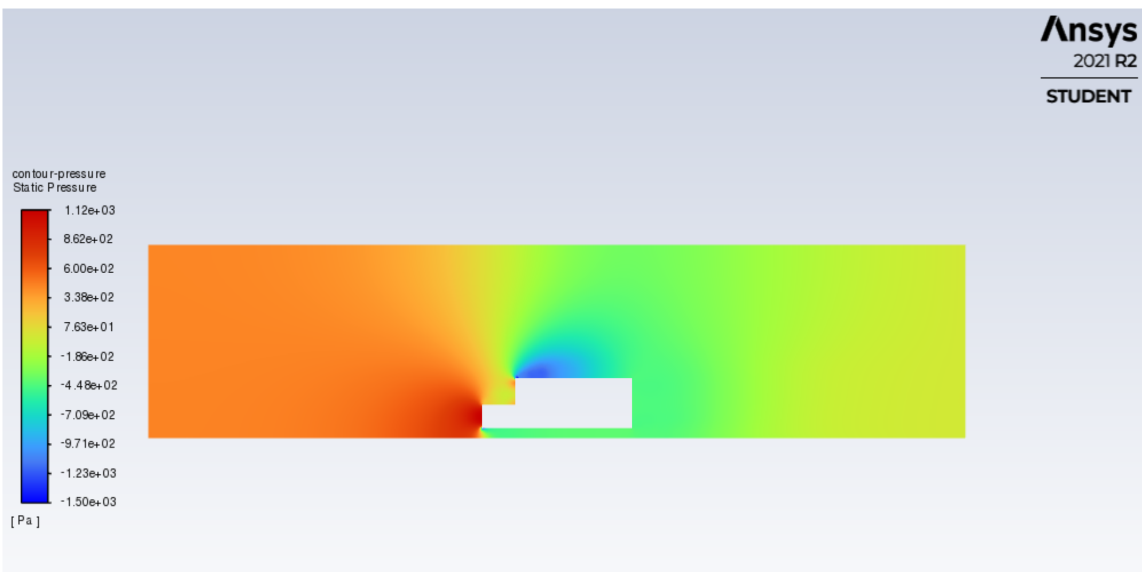
Iterations

C_D Plot

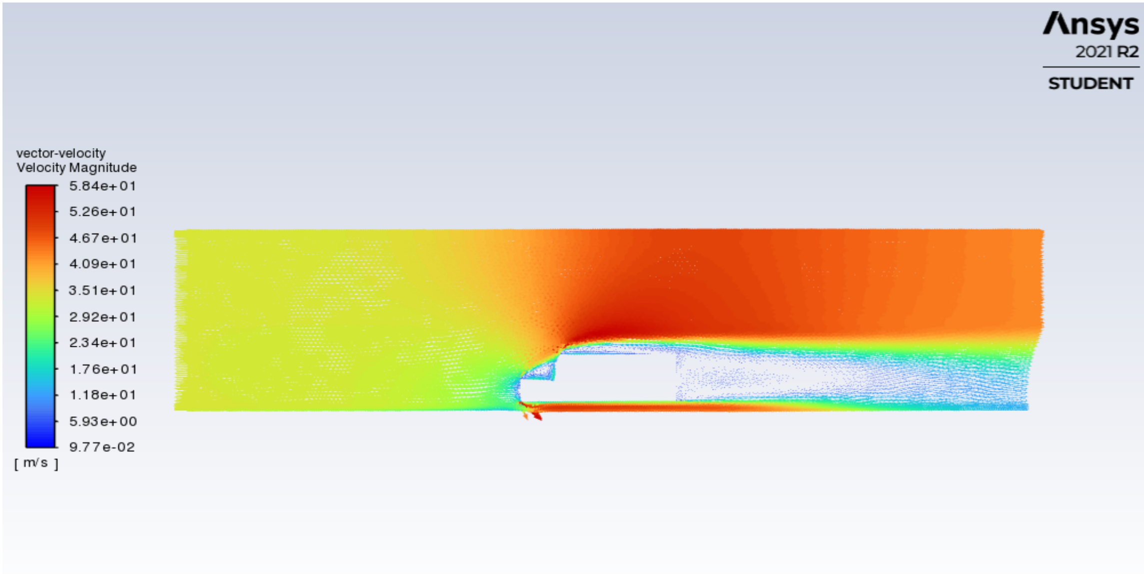
Flow Field Analysis of Default Design



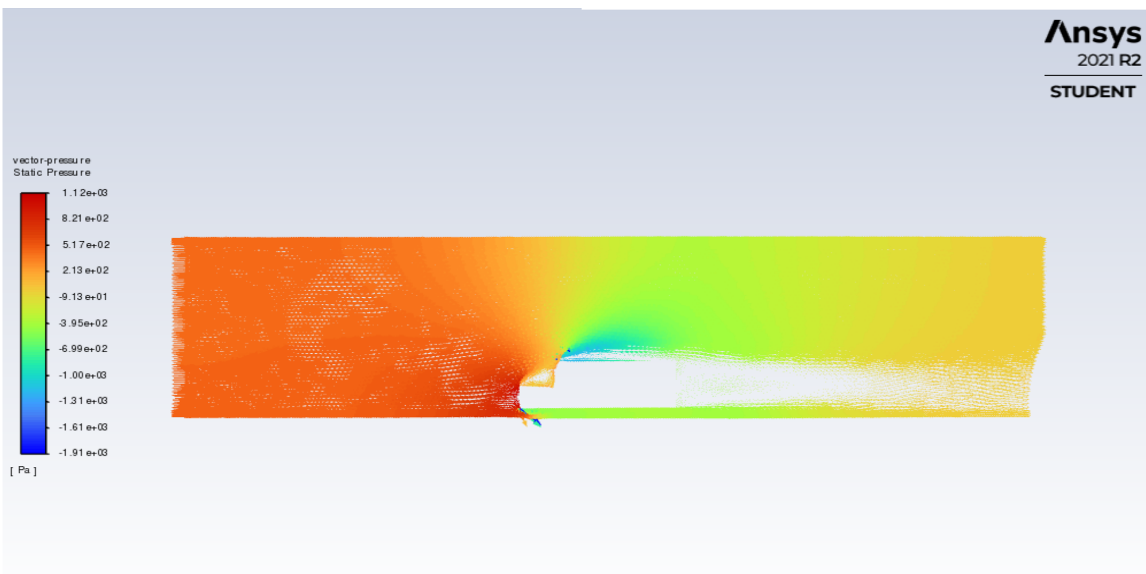
Velocity Contour Plot



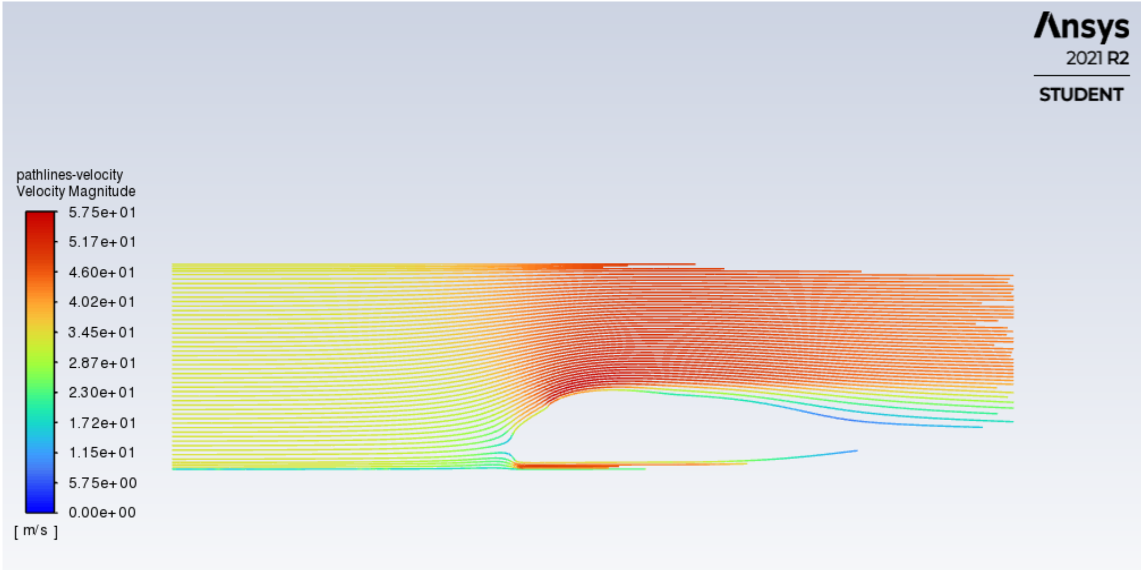
Pressure Contour Plot



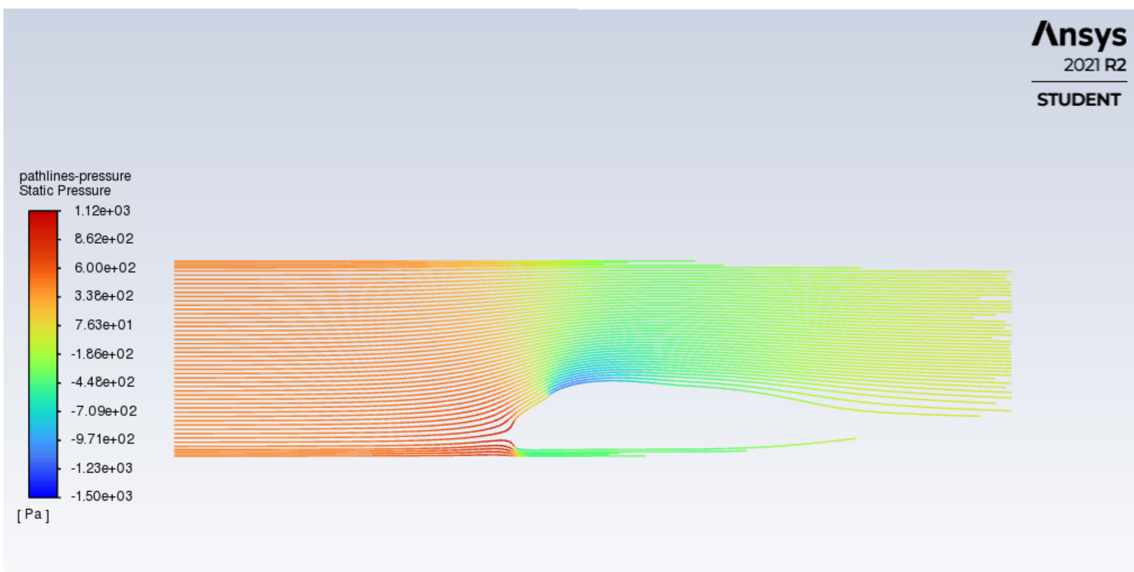
Velocity Vector Plot



Pressure Vector Plot



Velocity Pathline Plot



Pressure Pathline Plot

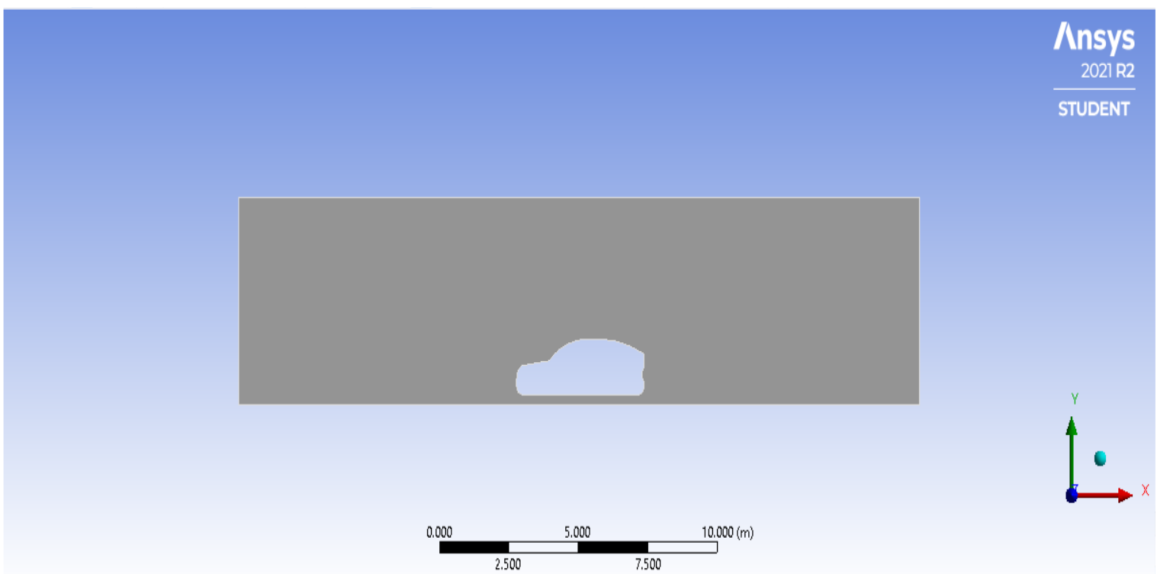
In this stage of post-processing, or flow analysis, the experiment renders a substantial amount of pertinent data. For example, it can be concluded that this body shape for the SUV, or rather the cross-sectional geometry, is largely unsuitable. It is noted that a force of a high magnitude must be present in order to generate the entrapped air pocket that the SUV is traveling through (this is inferred from the pressure graphs).

The velocity of the displaced, free-air essentially duplicates when it reaches the peak of the geometry, or the roof of the vehicle. Subsequently, the air decreases back to half of its original velocity in the space that has been created right behind the SUV. Another concerning detail exists at the front of the body. The front of the SUV is geometrically square and sharp. From an aerodynamic standpoint, this geometrical build causes the SUV to be rather boxy and bulky. Nevertheless, the pressure contours, pathlines, and vector plots confirm this disadvantage. The most high-stress region in this entire model exists solely at the front of the body.

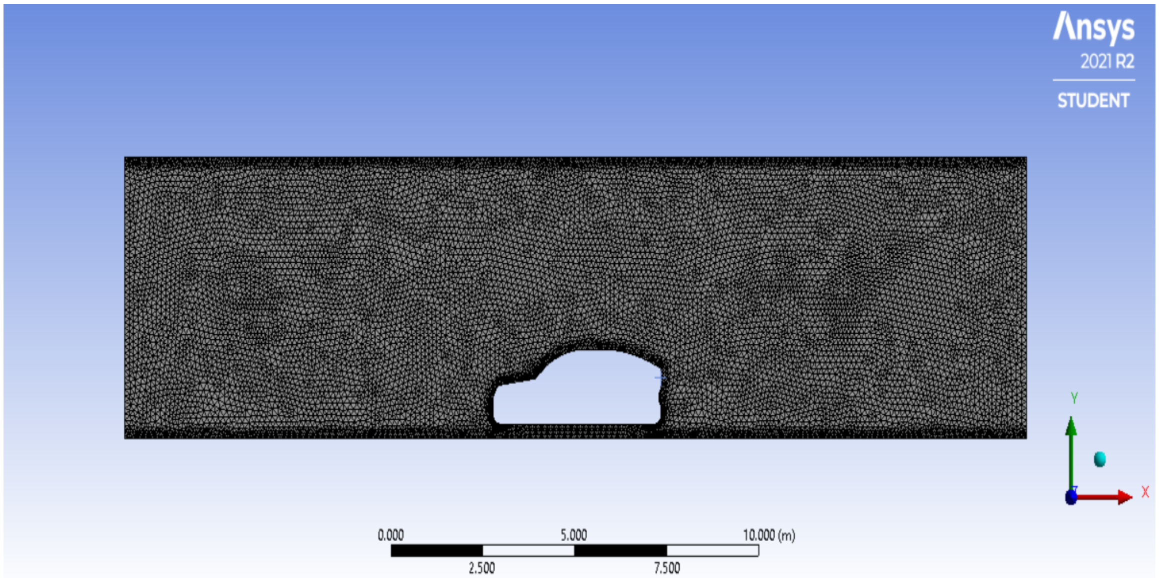
All in all, there is much to gather from the quantitative representation of the velocity and pressure flows, and what it signifies qualitatively. Ultimately, the flow field analysis demonstrates how aerodynamically inefficient the two-dimensional SUV geometry is. There are a substantial amount of changes to the model that can be done to optimize the vehicle. Some of the most critical issues to address include equally distributing the pressure, increasing the velocity behind the vehicle, and also minimizing high-stress regions.

Optimized Design and Reasoning

In order to optimize the aerodynamics of the SUV vehicle, the most predominant factor of concern is drag. Drag is defined as the force that opposes a body's motion in whatever medium of fluid (air, for example). Theoretically, the cross-sectional geometry best capable of creating a strong aerodynamic force resembles a teardrop, also known as an airfoil, as it generates a stronger force of lift. Therefore, I attempted to implement such a design in order to reduce the front-hitting drag force. Moreover, I also looked at SUVs online that purported to have relatively low drag coefficients and attempted to emulate the shape.



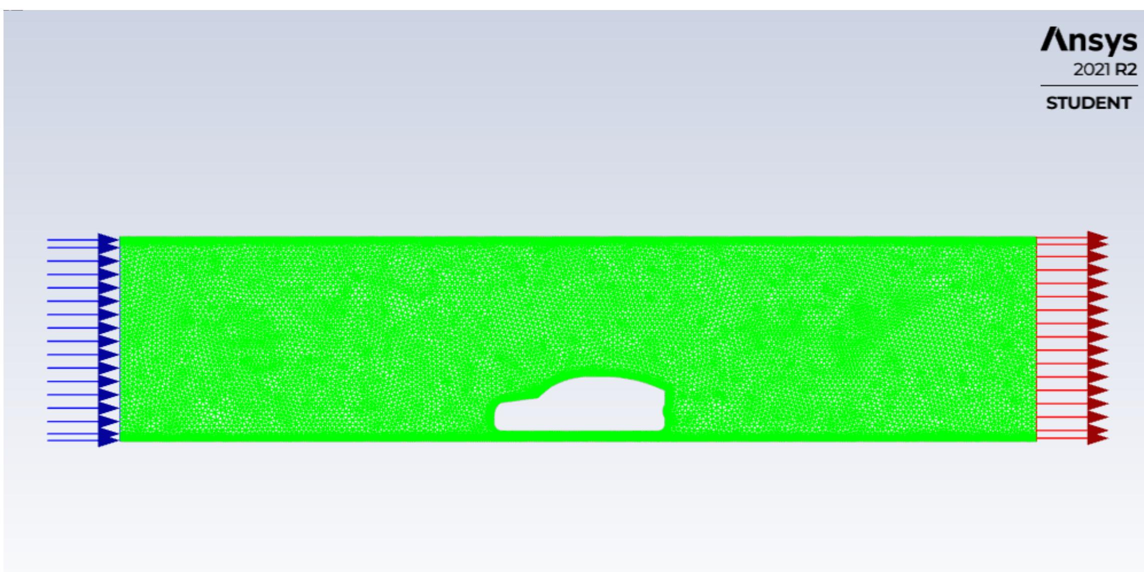
Geometry of Optimized Design



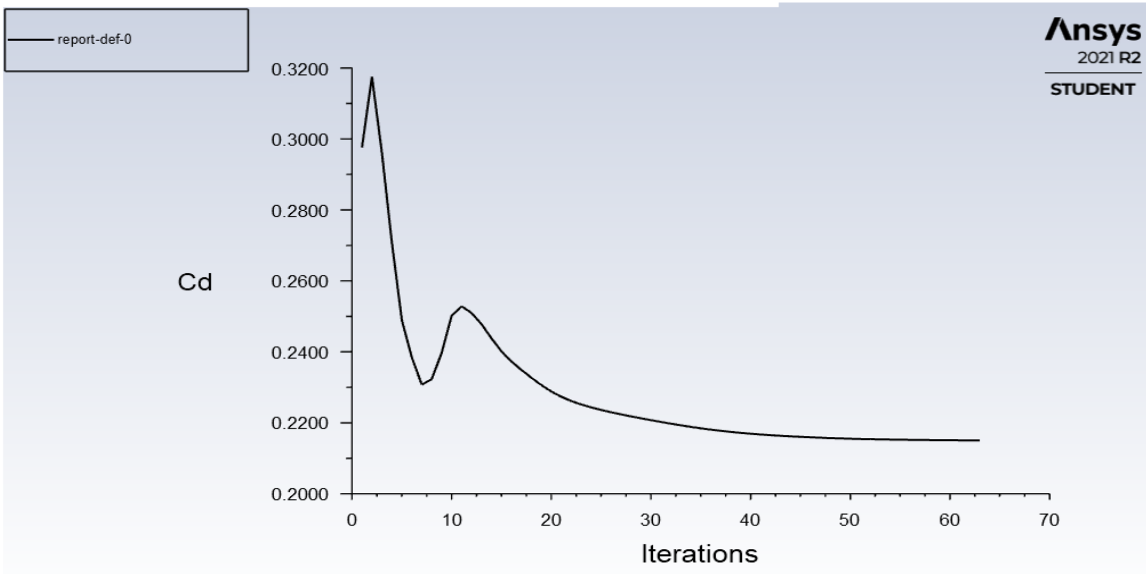
Mesh of Optimized Design

Mesh Size = 0.125m

C_D = 0.21503



Computational Domain



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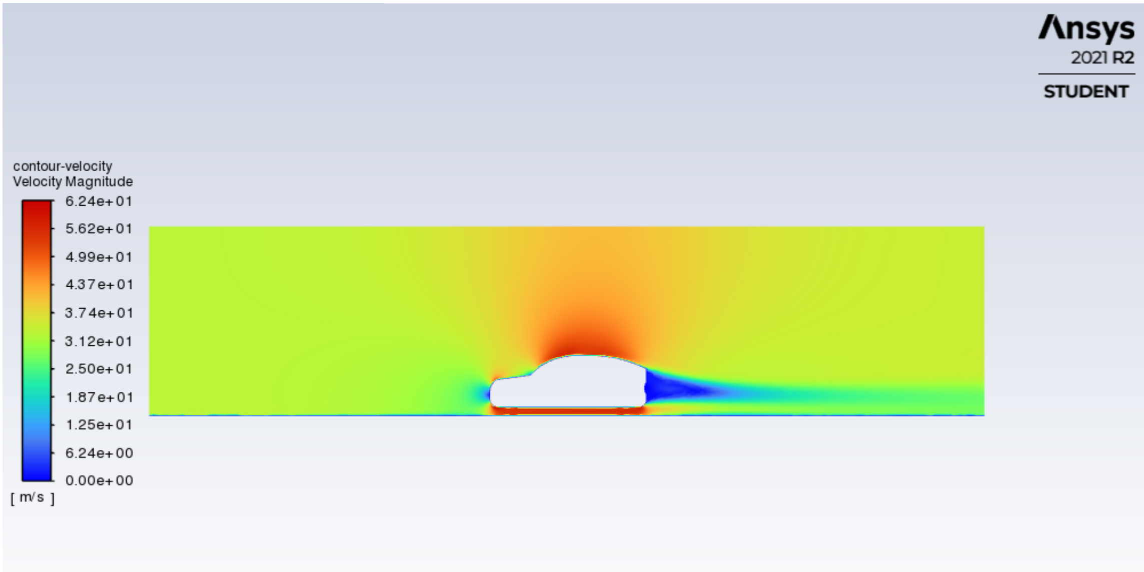
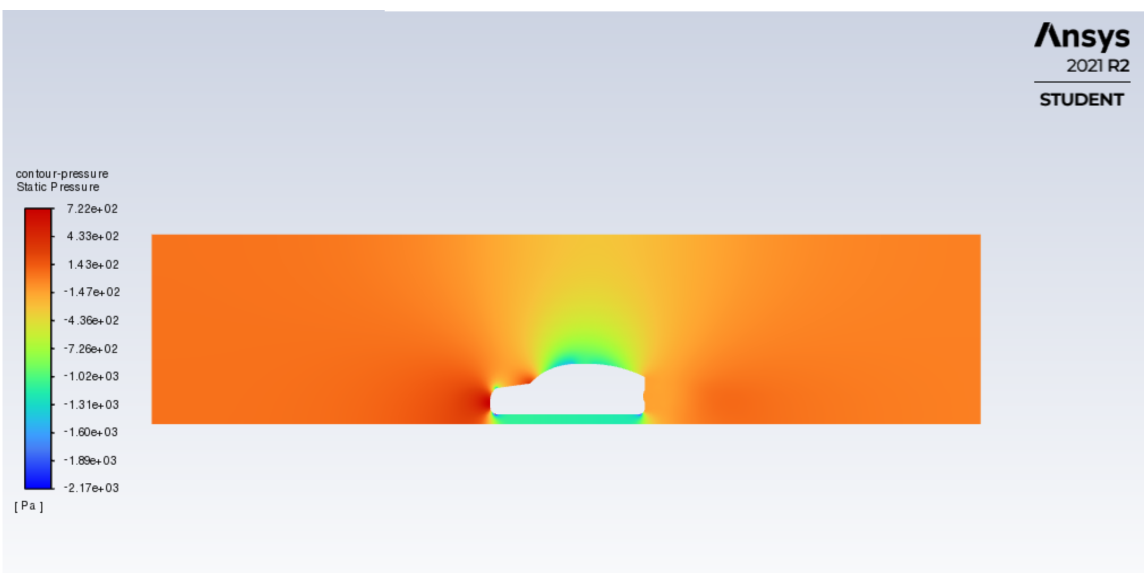
20
30
40
50
60
70
Iterations

C_D Plot

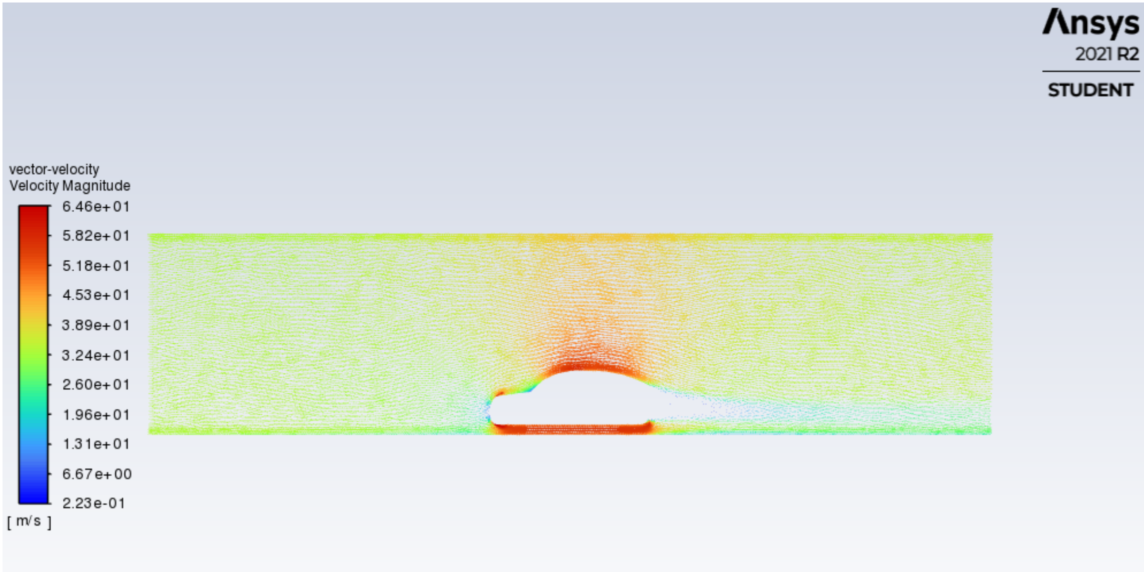
Flow Field Analysis of the Optimized Design



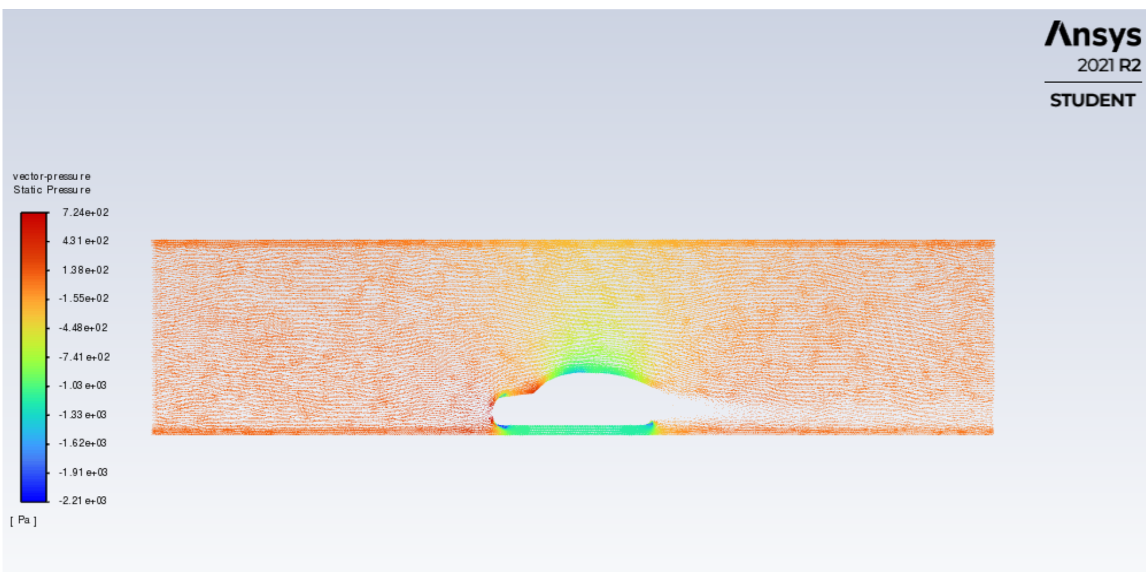
Velocity Contour Plot



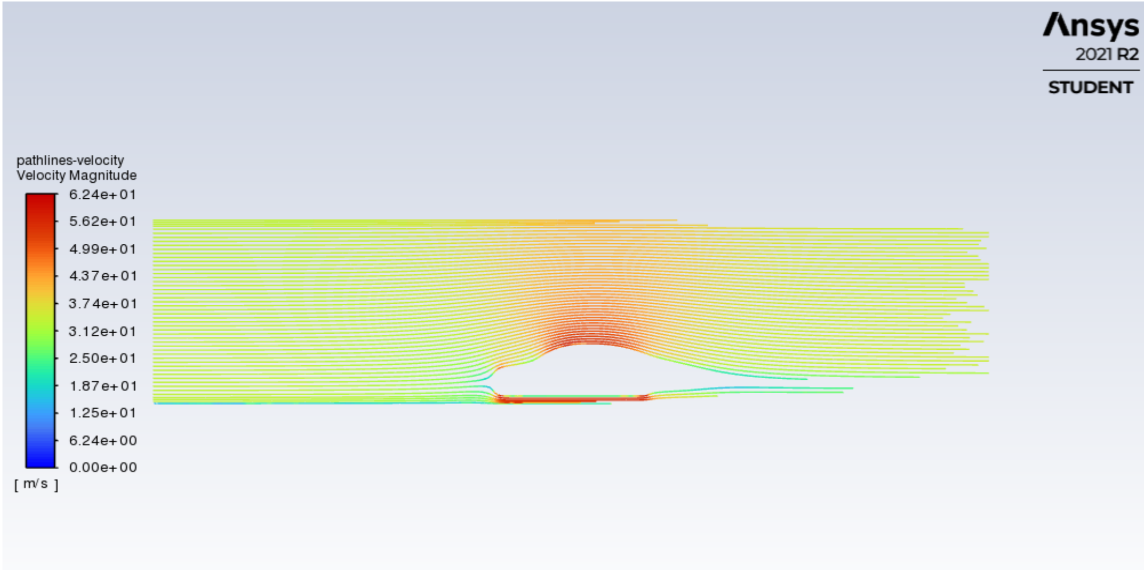
Pressure Contour Plot



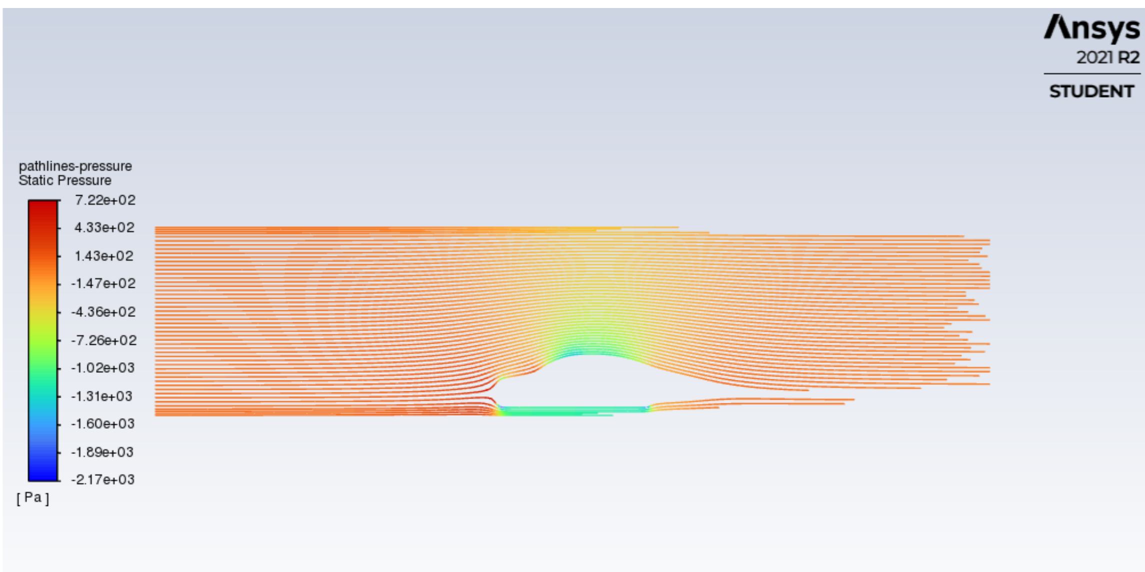
Velocity Vector Plot



Pressure Vector Plot



Velocity Pathline Plot



Pressure Pathline Plot

The flow field analysis demonstrates certain pertinent results. After optimizing the geometry based on the default case, the resulting C_D, or drag coefficient, is 0.21503. Using three significant figures to observe the first case and this optimized case, the two values of the drag coefficient are 1.45 and 0.22, respectively. This can be categorized as a successful and perhaps an even impressive optimization as the drag coefficient was reduced by approximately 85%.

Comparison of Drag Coefficient of Vehicle Design vs. an SUV in the Market.

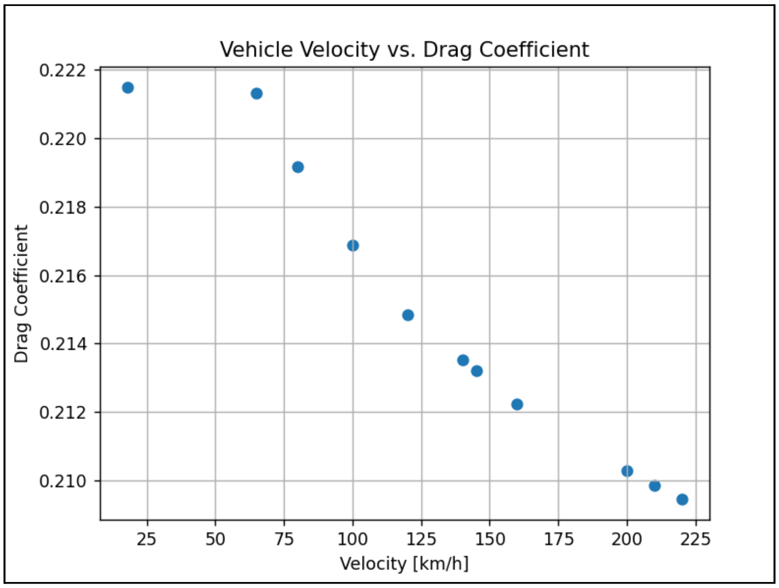
For this section of the report, the candidate SUV that is on the market and will be used in comparison is the Toyota RAV4 Crossover SUV. The drag coefficient, C_D, of the RAV4 is 0.31.[2] According to a source, the average drag coefficient for an SUV ranges between 0.35 and 0.45.[3] The drag coefficient of the RAV4 is marginally lower than that of the mean of most SUVs.

Picture of a white, 2016 Toyota RAV4.[1]

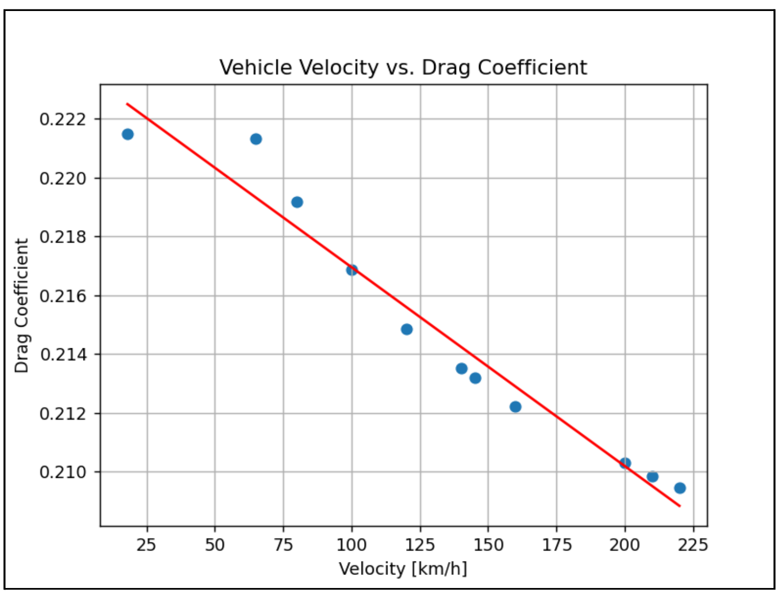
Since the drag coefficient of the RAV4 is lower than an average SUV, the RAV4 can be considered quite aerodynamically efficient. Thus, this selected vehicle from the market is a rather competitive selection to compare the candidate experimental SUV.

Nevertheless, the drag coefficient of the experimental sample was 0.22 and can also be described as aerodynamically efficient. In fact, not only does the optimized design have a better drag coefficient than the RAV4, but it is also substantially lower than the average SUV.

Plot of Vehicle Velocity & Drag Coefficient



Here is the plot of vehicle velocity and drag coefficient. Vehicle velocity is on the Y axis, denoted in kilometers per hour [km/h]. Conversely, the X axis demonstrates the drag coefficient. Moreover, the plot has a line of best fit, which outputs a formula of $y = (-6.76 \cdot 10^{-5})x + 2.24 \cdot 10^{-1}$.



Similarly, I took the liberty of computing the coefficient of determination as well, or the R^2, which comes out to 0.95753. It can be observed from the graph that there is a negative, directly proportional relationship between vehicular velocity and the drag coefficient. However, the R^2 of 0.95753 expresses that there is, in fact, an incredibly strong correlation between the two variables.

```python
import matplotlib.pyplot as plt
import numpy as np


dt = np.array([
         [18 , 0.22148609],
         [65 , 0.22131121],
         [80 , 0.21917301],
         [100 , 0.21686321],
         [120 , 0.21484317],
         [140 , 0.21353279],
         [145 , 0.21320634],
         [160 , 0.21223401],
         [200 , 0.21028894],
         [210 , 0.20984355],
         [220 , 0.20945567],
])

velocity = dt[:, 0]
dragcoefficient = dt[:, 1]


# Calculating parameter
theta = np.polyfit(velocity, dragcoefficient, 1)
print(f'The parameters of the line: {theta}')

# Now, calculating the y-axis values against x-values according to
# the parameters theta0, theta1 and theta2
y_line = theta[1] + theta[0] * velocity


correlation_matrix = np.corrcoef(velocity, dragcoefficient)
correlation_xy = correlation_matrix[0,1]
r_squared = correlation_xy**2
print(r_squared)

# Plotting the data points and the best fit line
plt.scatter(velocity, dragcoefficient)
plt.plot(velocity, y_line, 'r')
plt.title('Vehicle Velocity vs. Drag Coefficient')
plt.ylabel('Drag Coefficient')
plt.xlabel('Velocity [km/h]')
plt.grid(True)

plt.show()
```

Python code

References

[1] "2016 Toyota RAV4 Buyer's Guide: Reviews, Specs, Comparisons." *MotorTrend*, MotorTrend, https://www.motortrend.com/cars/toyota/rav4/2016/.

[2] Roper, David L. *Toyota RAV4 AWD-I Hybrid 2016*, 2008, http://roperld.com/science/ToyotaRAV4Hybrid.htm.

[3] Patrascu, Daniel. "What Is the Car Drag Coefficient?" *Autoevolution*, 21 Oct. 2018, https://www.autoevolution.com/news/what-is-the-car-drag-coefficient-129508.html.