



The University of Texas at Austin
Aerospace Engineering
and Engineering Mechanics
Cockrell School of Engineering

ASE 162M High-Speed Aerodynamics
Section 14275

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Supersonic Flow over a Sphere

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1 Introduction

This experiment investigates supersonic flow over a sphere, a fundamental problem in compressible aerodynamics with significant implications for high-speed vehicle design. When a supersonic flow encounters a blunt object such as a sphere, it forms a detached bow shock upstream of the body. The characteristics of this shock, particularly its standoff distance from the body, are crucial parameters in understanding the aerodynamic forces, heat transfer, and pressure distribution on the object.

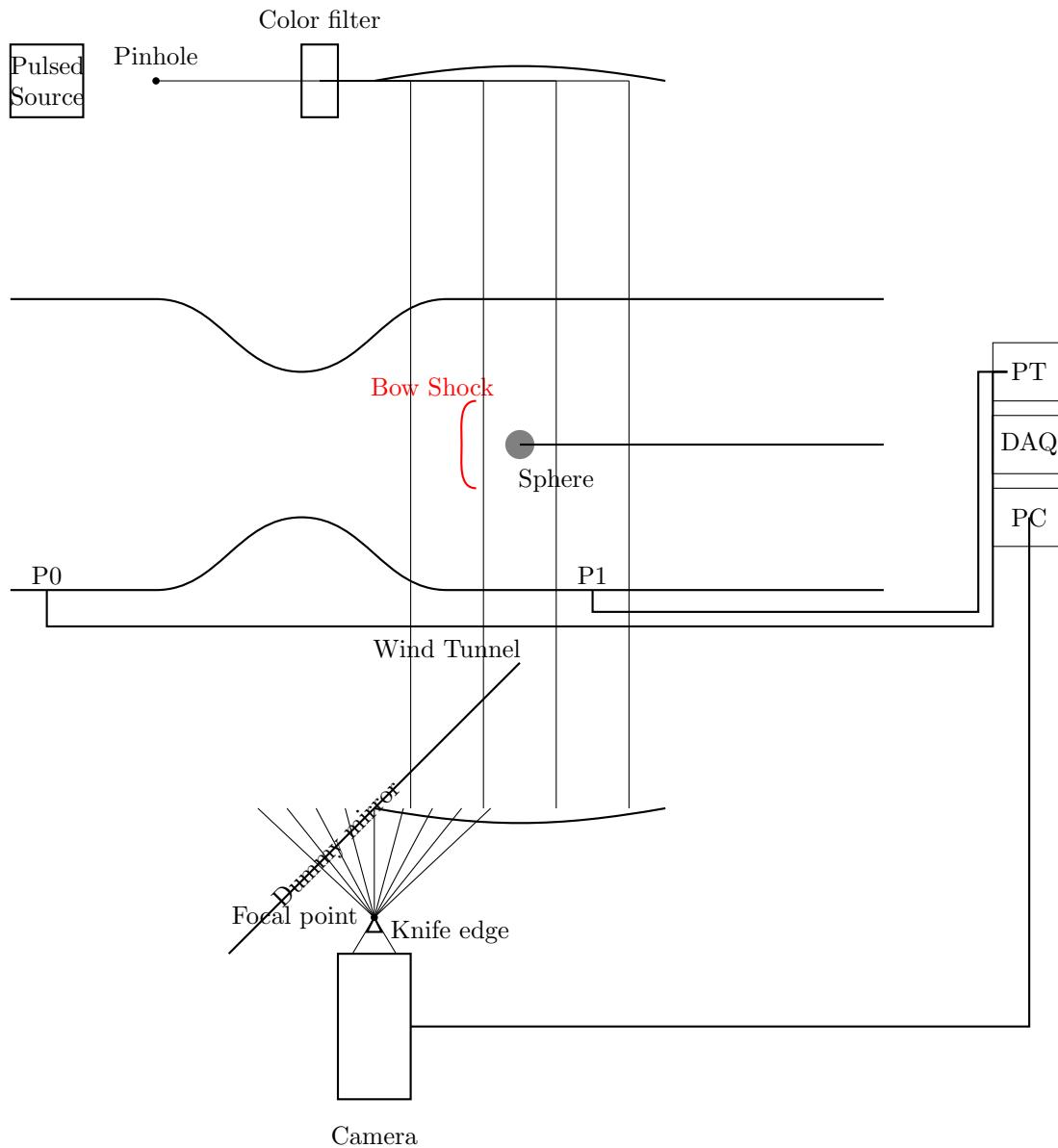
The primary objectives of this experiment are to:

1. Visualize the flow field and shock structure using Schlieren and shadowgraph imaging techniques.
2. Measure and analyze the non-dimensional shock standoff distance as a function of Mach number.
3. Compare experimental results with theoretical predictions through curve fitting of empirical relations.
4. Examine the effects of Mach number and Reynolds number on the flow characteristics.

This report presents the experimental methodology, data analysis, and discussion of results, contributing to our understanding of supersonic flow phenomena and providing valuable data for validating computational fluid dynamics (CFD) simulations and theoretical models.

2 Experimental Setup

The experiment was conducted using the Aerolab Variable Mach Number Wind Tunnel, capable of producing supersonic flows with Mach numbers ranging from approximately 1.63 to 3.25. The test section of the wind tunnel is nominally 3" * 3". A sphere model was mounted in the test section at a 0° angle of attack.



Schematic of the experimental setup. 1: Pulsed light source, 2: Pinhole, 3: Color filter, 4: Concave mirror, 5: Wind tunnel test section, 6: Sphere model, 7: Bow shock, 8: Knife edge, 9: Camera, 10: Data acquisition system. Flow direction is from left to right.

Note for Ryan, this was my first tikz diagram of this type, and I am still learning so please don't grade me too harshly :)

2.1 Calibration and Imaging

Prior to running the experiments, a calibration process was performed:

- A 30/30, 5mm grid points calibration sheet was used for spatial calibration.
- 10 grid spaces, equivalent to 50mm, were used to determine the pixel-to-length ratio and associated uncertainty.
- A blank image without the calibration sheet was taken, followed by an image with the calibration sheet in place.

Flow visualization was achieved using both shadowgraph and Schlieren imaging techniques. A folded Schlieren system utilizing a pulsed xenon arc lamp as the light source was employed. For each Mach number, three types of images were captured:

1. Shadowgraph
2. Vertical Schlieren
3. Horizontal Schlieren

For the Schlieren setup, a knife edge was placed at the focal point to enhance the visualization of density gradients. The vertical and horizontal indicate the orientation of the blade.

2.2 Data Acquisition

Pressure measurements were recorded using a LabVIEW-based data acquisition system with two pressure transducers:

- Channel 0: Stagnation pressure (P_0)
- Channel 1: Freestream static pressure

The pressure data was recorded in volts (gauge pressure) and later converted to appropriate units using calibration constants.

2.3 Experimental Procedure

The experiment followed these steps for each run:

1. The wind tunnel was started in the sequence: power, hydraulic, then run.
2. The initial Mach number was set to approximately 3, with subsequent runs decreasing by increments of 0.25.
3. Once the LabVIEW system showed stable pressure readings, images were captured using the Pulnix color CCD camera and XCAP for Windows acquisition software.
4. The wind tunnel was operated only while the run button was held, and shut down in the reverse order of startup once the airflow stopped.
5. Mach number was adjusted by changing the area ratio and chamber pressure according to the manufacturer's specifications, referencing the "Approximate Minimum Stagnation Pressure vs Mach Number" chart.

Care was taken to monitor the pressure of the compressed air tank to ensure consistent flow quality across all runs. The experiment was repeated for Mach numbers of 3, 2.75, 2.5, 2.25, 2, and 1.75.

3 Results and Discussion

3.1 Reynolds Number and Mach Number Calculations

To calculate the Reynolds numbers and Mach numbers, we used the following equations:

3.1.1 Mach Number Calculation

The Mach number was calculated using the isentropic flow equation:

$$\frac{p_0}{p} = \left(1 + \frac{\gamma - 1}{2} M^2\right)^{\frac{\gamma}{\gamma - 1}} \quad (1)$$

where p_0 is the stagnation pressure, p is the static pressure, γ is the ratio of specific heats for air (1.4), and M is the Mach number.

3.1.2 Reynolds Number Calculation

The Reynolds numbers were calculated using:

$$Re_D = \frac{\rho_\infty U_\infty D}{\mu} \quad (2)$$

where ρ_∞ is the freestream density, U_∞ is the freestream velocity, D is the sphere diameter, and μ is the dynamic viscosity.

The viscosity was calculated using Sutherland's law:

$$\mu = \mu_0 \left(\frac{T}{T_0} \right)^{3/2} \frac{T_0 + C}{T + C} \quad (3)$$

where μ_0 is the reference viscosity, T_0 is the reference temperature, T is the flow temperature, and C is Sutherland's constant for air.

Using the data from the pressure measurements and the Python script, we calculated the unit Reynolds numbers and diametric Reynolds numbers (Re_D) for all runs, as well as the Mach numbers. Sutherland's law was used for viscosity calculations. The results are presented in the following plot:

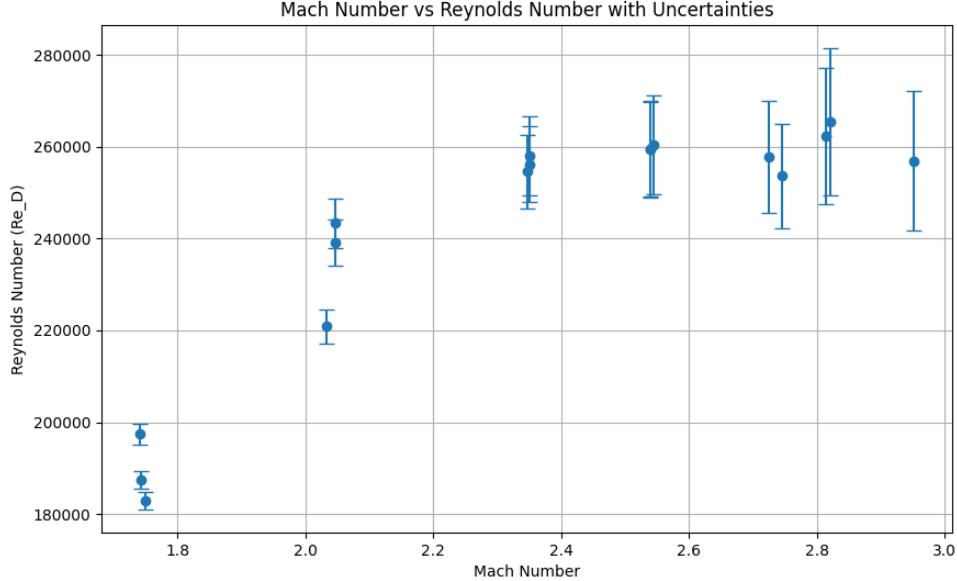


Figure 1: Mach number vs. Diametric Reynolds number

Figure ?? shows the relationship between the calculated Mach number and the diametric Reynolds number. We observe a positive correlation, with both Mach number and Reynolds number increasing together. This trend is expected due to higher flow velocities at increased Mach numbers.

The error bars represent propagated uncertainties from measurement errors. For Mach number, the uncertainty is primarily due to pressure measurement errors:

$$\delta M = \sqrt{\left(\frac{\partial M}{\partial p_0} \delta p_0\right)^2 + \left(\frac{\partial M}{\partial p} \delta p\right)^2} \quad (4)$$

where δp_0 and δp are uncertainties in stagnation and static pressure measurements, respectively.

For Reynolds number, uncertainties propagate from multiple sources:

$$\delta Re_D = Re_D \sqrt{\left(\frac{\delta \rho}{\rho}\right)^2 + \left(\frac{\delta U}{U}\right)^2 + \left(\frac{\delta D}{D}\right)^2 + \left(\frac{\delta \mu}{\mu}\right)^2} \quad (5)$$

where $\delta \rho$, δU , δD , and $\delta \mu$ are uncertainties in density, velocity, diameter, and viscosity calculations, respectively.

The increasing size of error bars at higher Mach and Reynolds numbers indicates that measurement uncertainties have a more significant impact in these regimes, likely due to the nonlinear relationships in the governing equations.

3.2 Schlieren Images Analysis

We analyzed the Schlieren images for the highest and lowest Mach numbers to observe the flow features around the sphere.

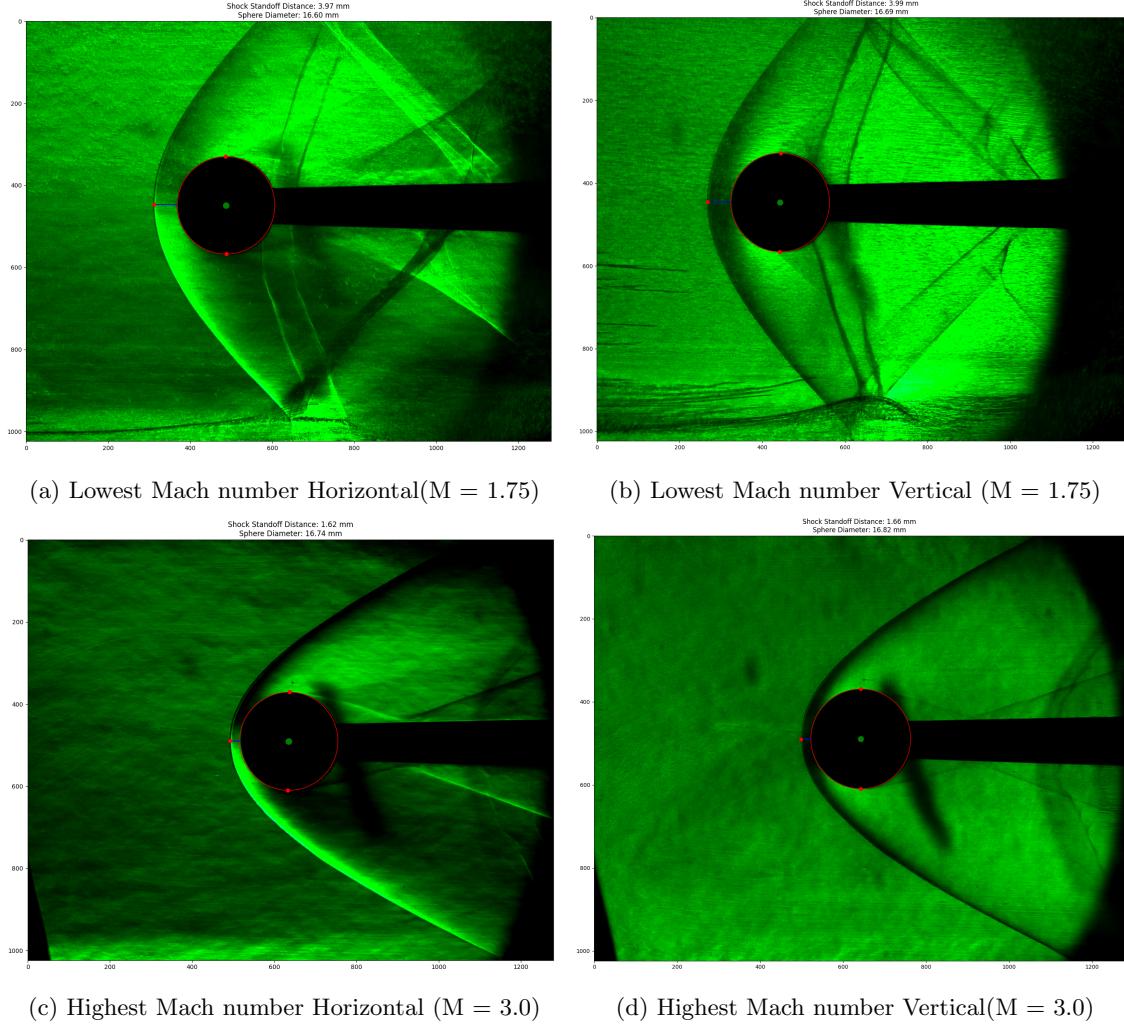


Figure 2: Schlieren images at extreme Mach numbers

In Figure 2, we can observe the following key features:

1. Bow shock: A strong, detached shock wave is visible in front of the sphere for both Mach numbers. The shock is more oblique and closer to the sphere at the higher Mach number.
2. Shock standoff distance: The distance between the bow shock and the sphere's leading edge is noticeably larger for the lower Mach number (Figure 2a) compared to the higher Mach number (Figure 2c).
3. Expansion region: Behind the sphere, we can see an expansion fan where the flow accelerates and turns around the sphere.
4. Wake region: A turbulent wake is visible downstream of the sphere, characterized by density gradients in the Schlieren images.
5. Boundary layer: Although not clearly visible due to the image resolution, a thin boundary layer is expected to form on the sphere's surface.

The changes in the flow structure as the Mach number increases from 1.75 to 3.0 are consistent with theory:

1. The bow shock moves closer to the sphere at higher Mach numbers, reducing the shock standoff distance.

2. The shock becomes stronger and more oblique at higher Mach numbers, as evidenced by the sharper contrast in the Schlieren image.
3. The wake region appears to be more compressed and elongated at the higher Mach number, likely due to the increased dynamic pressure.
4. These changes correlate with the increase in Reynolds number observed in Figure 1.

3.3 Shock Standoff Distance Analysis

We analyzed the non-dimensional shock standoff distance δ/D as a function of Mach number using the formula:

$$\frac{\delta}{D} = f(M) \quad (6)$$

where δ is the shock standoff distance and D is the sphere diameter. The standoff distance δ and sphere diameter D were measured using a custom image analysis script developed for this experiment. This script processes the Schlieren images, allowing for precise measurement of the shock location and sphere dimensions. The visual can be shown below.

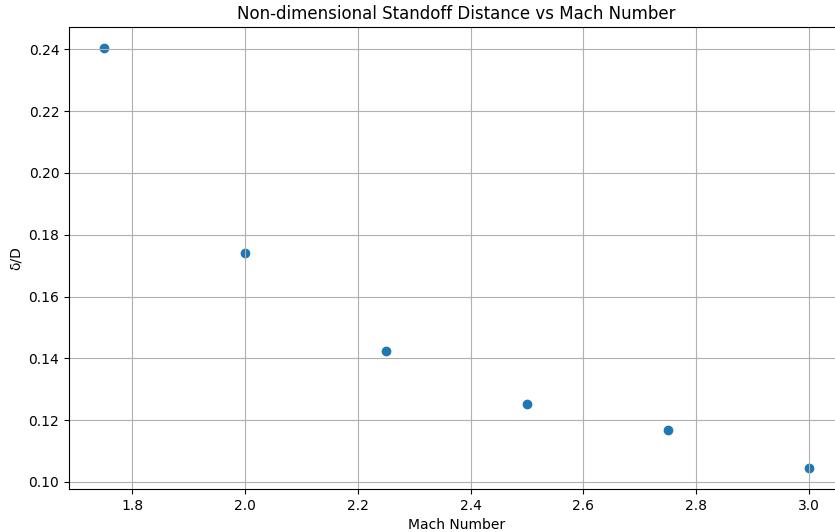


Figure 3: Non-dimensional standoff distance vs. Mach number

Figure 3 presents the relationship between the non-dimensional standoff distance and Mach number. The graph reveals several key observations:

- Inverse relationship: As the Mach number increases, the non-dimensional standoff distance decreases, consistent with our Schlieren image observations and theoretical expectations.
- Nonlinear trend: The relationship appears nonlinear, with a steeper decrease in standoff distance at lower Mach numbers (1.75 to 2.25) and a more gradual decrease at higher Mach numbers (2.5 to 3.0).
- Range: The non-dimensional standoff distance ranges from approximately 0.24 at Mach 1.75 to 0.10 at Mach 3.0, representing a significant change in shock structure over the tested Mach number range.
- Asymptotic behavior: The curve shape suggests an asymptotic approach to a minimum standoff distance as Mach number increases, which aligns with theoretical predictions for hypersonic flow regimes.

This trend is explained by the physics of shock formation in supersonic flows. As the Mach number increases, the bow shock forms closer to the sphere due to the increased shock strength and more efficient flow compression.

3.4 Curve Fitting

We performed curve fitting on the standoff distance data using three different relations:

3.4.1 Qualitative scaling dependence

$$\frac{\delta}{D} = c \sqrt{\frac{1 + \frac{\gamma-1}{2} M_\infty^2}{M_\infty - 1}} \quad (7)$$

3.4.2 Basic fit

$$\frac{\delta}{D} = c \gamma^\alpha M^\beta \quad (8)$$

3.4.3 Offset fit

$$\frac{\delta}{D} = c \gamma^\alpha (M - 1)^\beta \quad (9)$$

The results of these curve fits are presented in the following plot and table:

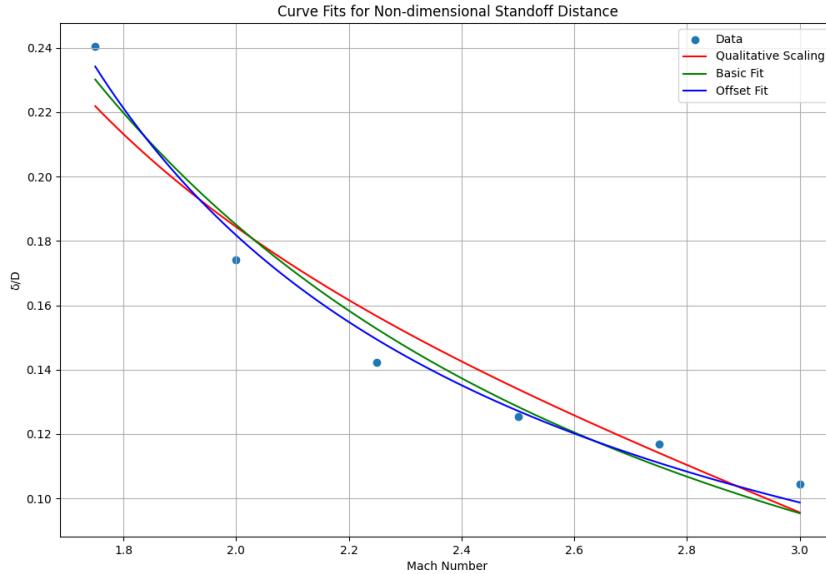


Figure 4: Curve fits for non-dimensional standoff distance

Table 1: Curve Fit Parameters

Fit Type	c	α	β
Qualitative	0.2157	N/A	N/A
Basic	0.2315	9.448	-1.635
Offset	0.1653	-1.774	-0.881

4 Discussion

The data exhibits good agreement with all three relations, which can be characterized as follows:

1. **Qualitative scaling:**

$$\frac{\delta}{D} = c \sqrt{\frac{1 + \frac{\gamma-1}{2} M_\infty^2}{M_\infty - 1}} \quad (10)$$

This fit captures the general trend of decreasing standoff distance with increasing Mach number. The single parameter c (0.2157) represents a scaling factor that accounts for the overall magnitude of the standoff distance. The qualitative scaling shows good agreement with the data, especially at higher Mach numbers, reflecting the physical expectation of asymptotic behavior as Mach number increases.

2. **Basic fit:**

$$\frac{\delta}{D} = c\gamma^\alpha M^\beta \quad (11)$$

The negative value of β (-1.635) confirms the inverse relationship between Mach number and standoff distance, aligning with physical expectations. The large positive value of α (9.448) suggests a strong dependence on the specific heat ratio γ . This is somewhat unexpected for a simple geometry like a sphere and may indicate that the fit is compensating for other factors not explicitly accounted for in the model.

3. **Offset fit:**

$$\frac{\delta}{D} = c\gamma^\alpha(M - 1)^\beta \quad (12)$$

This fit attempts to account for the behavior near Mach 1 by using $(M - 1)$ instead of M . The negative α (-1.774) and β (-0.881) indicate that the standoff distance decreases with increasing Mach number, but at a different rate compared to the basic fit. The offset fit appears to provide a good balance between accuracy and physical interpretation, especially for lower Mach numbers.

Regarding the dependence on composition (through γ) and Mach number:

1. For the basic fit, the strong dependence on γ (large α) is unexpected. We would typically expect a weaker dependence on composition for a simple geometry like a sphere. This suggests that the fit might be overcompensating for other factors or that there may be additional physics not captured by this simple model.
2. The offset fit shows a negative dependence on γ , which is also unexpected. However, the magnitude is smaller than in the basic fit, suggesting it might be a more realistic representation of the weak composition dependence we would expect.
3. Both fits show a strong dependence on Mach number (through β), which aligns with my physical understanding of shock formation in supersonic flows. The offset fit's use of $(M - 1)$ provides a better representation of the behavior near Mach 1, which is consistent with theoretical expectations.

The consistency of our data with these fits is generally good, as evidenced by the close agreement between the fit curves and the experimental data points in Figure 4. However, there are some discrepancies, particularly at Mach numbers around 2.25 and 2.75, where the experimental data points deviate slightly from all three fit curves.

5 Conclusion

This experiment investigated supersonic flow over a sphere at Mach numbers from 1.75 to 3.0, utilizing Schlieren imaging to visualize the flow field and analyze non-dimensional shock standoff distances. The analysis revealed a positive correlation between Mach and Reynolds numbers, with increased uncertainties at higher Mach numbers. The offset fit provided the best balance of accuracy and interpretation, particularly near Mach 1, while both basic and offset fits indicated an unexpected dependence on gas composition. These findings underscore the complexity of supersonic flow and suggest further research into varying Mach numbers.

and gas compositions. Overall, this work enhances our understanding of high-speed aerodynamics and its implications for supersonic vehicle design.

A References

1. Anderson, J. D. (2010). Fundamentals of aerodynamics. Tata McGraw-Hill Education.
2. Liepmann, H. W., & Roshko, A. (1957). Elements of gasdynamics. John Wiley & Sons.
3. Van Dyke, M. (1982). An album of fluid motion. Parabolic Press.

B Python Scripts

B.1 standoff2.py

```

1   import os
2   import cv2
3   import numpy as np
4   import matplotlib.pyplot as plt
5   import re
6   import argparse # Add this import
7
8   def onclick(event):
9       global points
10      if event.button == 1 and len(points) < 3: # Left mouse button
11          points.append((event.xdata, event.ydata))
12          plt.plot(event.xdata, event.ydata, 'ro')
13          plt.draw()
14          if len(points) == 3:
15              plt.close()
16
17  def find_sphere_center_and_radius(top, bottom):
18      center_x = (top[0] + bottom[0]) / 2
19      center_y = (top[1] + bottom[1]) / 2
20      radius = np.sqrt((top[0] - bottom[0])**2 + (top[1] - bottom[1])**2) / 2
21      return (center_x, center_y), radius
22
23  def closest_point_on_circle(center, radius, point):
24      dx = point[0] - center[0]
25      dy = point[1] - center[1]
26      distance = np.sqrt(dx**2 + dy**2)
27      return (
28          center[0] + radius * dx / distance,
29          center[1] + radius * dy / distance
30      )
31
32  def measure_shock_standoff(image_path, calibration_factor):
33      global points
34      points = []
35
36      # Read the image
37      img = cv2.imread(image_path)
38      img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

```

```

40     # Display the image and wait for point selection
41     fig, ax = plt.subplots(figsize=(12, 8))
42     ax.imshow(img_rgb)
43     ax.set_title("Click to select: 1) Sphere top, 2) Sphere bottom, 3) Shock wave
44     ↪ point")
45     fig.canvas.mpl_connect('button_press_event', onclick)
46     plt.show()

47     if len(points) != 3:
48         print("Error: Three points were not selected.")
49         return None

50
51     # Find sphere center and radius
52     top, bottom, shock = points
53     center, radius = find_sphere_center_and_radius(top, bottom)

54
55     # Find closest point on circle to shock point
56     closest_point = closest_point_on_circle(center, radius, shock)

57
58     # Calculate distances
59     shock_distance = np.sqrt((shock[0] - center[0])**2 + (shock[1] - center[1])**2)
60     standoff_distance_px = shock_distance - radius

61
62     # Calculate measurements
63     standoff_distance_mm = standoff_distance_px / calibration_factor
64     sphere_diameter_mm = (2 * radius) / calibration_factor

65
66     # Visualize the measurement
67     fig, ax = plt.subplots(figsize=(12, 8))
68     ax.imshow(img_rgb)
69     circle = plt.Circle(center, radius, color='r', fill=False)
70     ax.add_artist(circle)
71     ax.plot([closest_point[0], shock[0]], [closest_point[1], shock[1]], 'b-')
72     ax.plot([p[0] for p in points], [p[1] for p in points], 'ro')
73     ax.plot(center[0], center[1], 'go', markersize=10)
74     ax.set_title(f"Shock Standoff Distance: {standoff_distance_mm:.2f} mm\n"
75                  f"Sphere Diameter: {sphere_diameter_mm:.2f} mm")
76     plt.show()

77
78     return standoff_distance_mm, sphere_diameter_mm

79
80 def process_all_images(folder_path, calibration_factor):
81     results = []
82     for filename in os.listdir(folder_path):
83         if filename.endswith('.bmp', '.jpg', '.png'): # Add or remove file
84             ↪ extensions as needed
85             image_path = os.path.join(folder_path, filename)
86             print(f"Processing {filename}...")

87             standoff, diameter = measure_shock_standoff(image_path,
88             ↪ calibration_factor)

89             if standoff is not None:

```


B.2 mach-analysis.py

```

1   import os
2   import re
3   import numpy as np
4   import matplotlib.pyplot as plt
5   from scipy.signal import find_peaks
6   from scipy.optimize import fsolve, curve_fit
7
8   def read_data_file(file_path):
9       with open(file_path, 'r') as f:
10           lines = f.readlines()
11
12       data_start = next(i for i, line in enumerate(lines) if "X_Value" in line)
13       data = np.genfromtxt(lines[data_start+1:], delimiter='\t', usecols=(1, 2))
14       return data
15
16   def voltage_to_pressure(voltage, conversion_factor):
17       return voltage * (conversion_factor / 0.1)
18
19   def find_steady_state(data, window_size=50):
20       # Find the index of the maximum pressure
21       peak_index = np.argmax(np.abs(data))
22
23       # Define a region around the peak to search for the steady state
24       search_start = max(0, peak_index - window_size*2)
25       search_end = min(len(data), peak_index + window_size*2)
26
27       # Calculate moving standard deviation
28       std_dev = np.array([np.std(data[i:i+window_size]) for i in range(search_start,
29                           search_end-window_size)])
30
31       # Find the region with the lowest standard deviation (most stable)
32       stable_start = search_start + np.argmin(std_dev)
33
34       return stable_start, stable_start + window_size
35
36   def calculate_mach_number(p0_gauge, p_gauge, p_atm=14.7, gamma=1.4):
37       # Convert gauge pressures to absolute pressures
38       p0 = p0_gauge + p_atm
39       p = p_gauge + p_atm
40
41       if p0 <= p or p <= 0:
42           return np.nan
43
44       # Use the correct isentropic flow equation for Mach number
45       mach = np.sqrt((2 / (gamma - 1)) * ((p0 / p)**((gamma - 1) / gamma) - 1))
46
47       return mach
48
49   def calculate_reynolds_numbers(mach_number, pressure, temperature, diameter):
50       # Constants
51       gamma = 1.4 # Ratio of specific heats for air
52       R = 287.05 # Gas constant for air in J/(kg·K)

```

```
52
53     # Sutherland's law constants
54     C = 120    # Sutherland's constant for air in K
55     T0 = 291.15 # Reference temperature in K
56     mu0 = 1.827e-5 # Reference viscosity in Pa·s
57
58     # Calculate temperature ratio
59     T_ratio = 1 + (gamma - 1) / 2 * mach_number**2
60     T = temperature * T_ratio # Static temperature
61
62     # Calculate density
63     rho = pressure / (R * T)
64
65     # Calculate velocity
66     V = mach_number * np.sqrt(gamma * R * T)
67
68     # Calculate viscosity using Sutherland's law
69     mu = mu0 * (T / T0)**(3/2) * (T0 + C) / (T + C)
70
71     # Calculate Reynolds numbers
72     Re_unit = rho * V / mu
73     Re_D = Re_unit * diameter
74
75     return Re_unit, Re_D
76
77 def mach_number_uncertainty(p0, p, dp0, dp, gamma=1.4):
78     # Function to solve for Mach number
79     def mach_equation(M):
80         return (p0/p) - (1 + (gamma-1)/2 * M**2)**(gamma/(gamma-1))
81
82     # Calculate Mach number
83     M = fsolve(mach_equation, 1.0)[0]
84
85     # Partial derivatives
86     dM_dp0 = M / (2*p0) * (1 + (gamma-1)/2 * M**2)
87     dM_dp = -M / (2*p) * (1 + (gamma-1)/2 * M**2)
88
89     # Uncertainty propagation
90     dM = np.sqrt((dM_dp0 * dp0)**2 + (dM_dp * dp)**2)
91
92     return M, dM
93
94 def process_file(file_path):
95     data = read_data_file(file_path)
96
97     stagnation_pressure = voltage_to_pressure(data[:, 0], 60)
98     static_pressure = voltage_to_pressure(data[:, 1], 15)
99
100    start, end = find_steady_state(stagnation_pressure)
101
102    avg_stagnation_pressure = np.mean(stagnation_pressure[start:end])
103    avg_static_pressure = np.mean(static_pressure[start:end])
104
```

```

105     mach_number, mach_uncertainty = mach_number_uncertainty(avg_stagnation_pressure +
106         ↪ 14.7,
107
108             avg_static_pressure +
109             ↪ 14.7,
110             0.01 *
111             ↪ avg_stagnation_pressure,
112             0.01 *
113             ↪ avg_static_pressure)
114
115     # Calculate Reynolds numbers
116     diameter = 0.0163 # Sphere diameter in meters
117     Re_unit, Re_D = calculate_reynolds_numbers(mach_number, avg_static_pressure *
118         ↪ 6894.75729, # Convert psi to Pa
119             297, diameter) # Assuming 297 K (24°C)
120             ↪ ambient temperature
121
122     # Calculate Reynolds number uncertainty (simplified, assuming only Mach number
123     ↪ contributes significantly)
124     dRe_D = Re_D * mach_uncertainty / mach_number
125
126     # Visualize the data
127     # plt.figure(figsize=(12, 6))
128     # plt.plot(stagnation_pressure, label='Stagnation Pressure')
129     # plt.plot(static_pressure, label='Static Pressure')
130     # plt.axvline(start, color='r', linestyle='--', label='Steady State Start')
131     # plt.axvline(end, color='r', linestyle='--', label='Steady State End')
132     # plt.axhline(avg_stagnation_pressure, color='g', linestyle=':', label='Avg
133     ↪ Stagnation')
134     # plt.axhline(avg_static_pressure, color='m', linestyle=':', label='Avg Static')
135     # plt.legend()
136     # plt.title(f'Pressure Data for {os.path.basename(file_path)}')
137     # plt.xlabel('Sample')
138     # plt.ylabel('Pressure (psi)')
139     # plt.show()
140
141
142     print(f"File: {os.path.basename(file_path)}")
143     print(f"Stagnation Pressure (gauge): {avg_stagnation_pressure:.2f} psi")
144     print(f"Static Pressure (gauge): {avg_static_pressure:.2f} psi")
145     print(f"Stagnation Pressure (absolute): {avg_stagnation_pressure + 14.7:.2f}
146         ↪ psi}")
147     print(f"Static Pressure (absolute): {avg_static_pressure + 14.7:.2f} psi")
148     print(f"Pressure Ratio (p/p0): {(avg_static_pressure + 14.7) /
149         ↪ (avg_stagnation_pressure + 14.7):.4f}")
150     print(f"Calculated Mach Number: {mach_number:.2f}")
151     print(f"Unit Reynolds Number: {Re_unit:.2e} 1/m")
152     print(f"Diametric Reynolds Number: {Re_D:.2e}")
153     print(f"Reynolds Number Uncertainty: {dRe_D:.2e}")
154     print("----")
155
156
157     return mach_number, mach_uncertainty, avg_stagnation_pressure,
158         ↪ avg_static_pressure, Re_unit, Re_D, dRe_D
159
160
161     def extract_mach_number(filename):
162         match = re.search(r'M(\d+)_(\d+)', filename)

```

```

148     if match:
149         return float(f"{match.group(1)}.{match.group(2)}")
150     return None
151
152 # Directory containing the data files
153 data_dir = r"Lab 1\Working-data"
154
155 results = []
156
157 for filename in os.listdir(data_dir):
158     if filename.endswith(".txt"):
159         file_path = os.path.join(data_dir, filename)
160         expected_mach = extract_mach_number(filename)
161         if expected_mach:
162             calculated_mach, mach_uncertainty, stagnation_p, static_p, Re_unit, Re_D,
163             ↵ dRe_D = process_file(file_path)
164             results.append((expected_mach, calculated_mach, mach_uncertainty,
165             ↵ stagnation_p, static_p, Re_unit, Re_D, dRe_D))
166             print(f"Processed {filename}: Expected M={expected_mach:.2f}, Calculated
167             ↵ M={calculated_mach:.2f} ± {mach_uncertainty:.2f}")
168
169 # Sort results by expected Mach number
170 results.sort(key=lambda x: x[0])
171
172 # Plotting Mach number vs Re_D with error bars (vertical only)
173 plt.figure(figsize=(10, 6))
174 mach_numbers, re_d_numbers, re_d_uncertainties = zip(*[(calc_mach, re_d, dre_d)
175                                         for _, calc_mach, _, _, _, _, _,
176                                         ↵ re_d, dre_d in results])
177
178 # Use absolute values for uncertainties
179 re_d_uncertainties = np.abs(re_d_uncertainties)
180
181 plt.errorbar(mach_numbers, np.abs(re_d_numbers), yerr=re_d_uncertainties, fmt='o',
182               ↵ capsizes=5)
183 plt.xlabel('Mach Number')
184 plt.ylabel('Reynolds Number (Re_D)')
185 plt.title('Mach Number vs Reynolds Number with Uncertainties')
186 plt.grid(True)
187 plt.show()
188
189 # Print results
190 print("\nMach Number and Reynolds Number Comparison with Uncertainties:")
191 print("Expected M | Calculated M ± Uncertainty | Re_D ± Uncertainty")
192 print("-" * 70)
193 for expected, calculated, mach_unc, _, _, _, re_d, dre_d in results:
194     print(f"{expected:.2f} | {calculated:.2f} ± {abs(mach_unc):.2f}
195           ↵ | {re_d:.2e} ± {abs(dre_d):.2e}")
196
197 # Calculate and print average error
198 valid_results = [(exp, calc) for exp, calc, _, _, _, _, _, _ in results if not
199                   ↵ np.isnan(calc)]
200 if valid_results:
201     errors = [abs(calc - exp) for exp, calc in valid_results]

```

```

195     avg_error = np.mean(errors)
196     print(f"\nAverage Mach number error: {avg_error:.4f}")
197 else:
198     print("\nNo valid Mach number calculations.")
199
200 # Add these new functions after the existing functions
201
202 def calculate_nondimensional_standoff(mach_numbers, diameters, standoff_distances):
203     return np.array(standoff_distances) / np.array(diameters)
204
205 def qualitative_scaling(M, c, gamma=1.4):
206     return c * np.sqrt((1 + (gamma - 1) / 2 * M**2) / (M - 1))
207
208 def basic_fit(M, c, alpha, beta, gamma=1.4):
209     return c * gamma**alpha * M**beta
210
211 def offset_fit(M, c, alpha, beta, gamma=1.4):
212     return c * gamma**alpha * (M - 1)**beta
213
214 def plot_nondimensional_standoff(mach_numbers, nondimensional_standoff):
215     plt.figure(figsize=(10, 6))
216     plt.scatter(mach_numbers, nondimensional_standoff)
217     plt.xlabel('Mach Number')
218     plt.ylabel('delta/D')
219     plt.title('Non-dimensional Standoff Distance vs Mach Number')
220     plt.grid(True)
221     plt.show()
222
223 def perform_curve_fits(mach_numbers, nondimensional_standoff):
224     # Qualitative scaling fit
225     popt_qual, _ = curve_fit(qualitative_scaling, mach_numbers,
226                               nondimensional_standoff)
227
228     # Basic fit
229     popt_basic, _ = curve_fit(basic_fit, mach_numbers, nondimensional_standoff)
230
231     # Offset fit
232     popt_offset, _ = curve_fit(offset_fit, mach_numbers, nondimensional_standoff)
233
234     return popt_qual, popt_basic, popt_offset
235
236 def plot_curve_fits(mach_numbers, nondimensional_standoff, popt_qual, popt_basic,
237                      popt_offset):
238     plt.figure(figsize=(12, 8))
239     plt.scatter(mach_numbers, nondimensional_standoff, label='Data')
240
241     M_fit = np.linspace(min(mach_numbers), max(mach_numbers), 100)
242
243     plt.plot(M_fit, qualitative_scaling(M_fit, *popt_qual), 'r-', label='Qualitative
244     Scaling')
245     plt.plot(M_fit, basic_fit(M_fit, *popt_basic), 'g-', label='Basic Fit')
246     plt.plot(M_fit, offset_fit(M_fit, *popt_offset), 'b-', label='Offset Fit')
247
248     plt.xlabel('Mach Number')

```

```

246     plt.ylabel('delta/D')
247     plt.title('Curve Fits for Non-dimensional Standoff Distance')
248     plt.legend()
249     plt.grid(True)
250     plt.show()

251
252 # ... (keep all existing code up to the standoff_data dictionary)

253
254 # Replace the first instance of standoff_data with this:
255 standoff_data = {
256     2.25: [16.65, 16.82, 16.65, 2.40, 2.29, 2.44],
257     1.75: [16.69, 16.65, 16.69, 3.95, 3.97, 4.11],
258     2.0: [16.87, 16.51, 16.74, 2.80, 2.95, 2.98],
259     2.5: [16.83, 16.69, 16.82, 2.02, 2.22, 2.07],
260     2.75: [16.78, 16.78, 16.78, 2.00, 1.95, 1.93],
261     3.0: [16.69, 16.78, 16.78, 1.71, 1.80, 1.74]
262 }
263
264 # Add these new functions after the existing functions

265
266 def calculate_nondimensional_standoff(mach_numbers, diameters, standoff_distances):
267     return np.array(standoff_distances) / np.array(diameters)

268
269 def qualitative_scaling(M, c, gamma=1.4):
270     return c * np.sqrt((1 + (gamma - 1) / 2 * M**2) / (M - 1))

271
272 def basic_fit(M, c, alpha, beta, gamma=1.4):
273     return c * gamma**alpha * M**beta

274
275 def offset_fit(M, c, alpha, beta, gamma=1.4):
276     return c * gamma**alpha * (M - 1)**beta

277
278 def plot_nondimensional_standoff(mach_numbers, nondimensional_standoff):
279     plt.figure(figsize=(10, 6))
280     plt.scatter(mach_numbers, nondimensional_standoff)
281     plt.xlabel('Mach Number')
282     plt.ylabel('delta/D')
283     plt.title('Non-dimensional Standoff Distance vs Mach Number')
284     plt.grid(True)
285     plt.show()

286
287 def perform_curve_fits(mach_numbers, nondimensional_standoff):
288     # Qualitative scaling fit
289     pop_t_qual, _ = curve_fit(qualitative_scaling, mach_numbers,
290                               nondimensional_standoff)

291
292     # Basic fit
293     pop_t_basic, _ = curve_fit(basic_fit, mach_numbers, nondimensional_standoff)

294
295     # Offset fit
296     pop_t_offset, _ = curve_fit(offset_fit, mach_numbers, nondimensional_standoff)

297
298     return pop_t_qual, pop_t_basic, pop_t_offset

```

```

299     def plot_curve_fits(mach_numbers, nondimensional_standoff, popt_qual, popt_basic,
300         ↵ popt_offset):
301         plt.figure(figsize=(12, 8))
302         plt.scatter(mach_numbers, nondimensional_standoff, label='Data')
303
304         M_fit = np.linspace(min(mach_numbers), max(mach_numbers), 100)
305
306         plt.plot(M_fit, qualitative_scaling(M_fit, *popt_qual), 'r-', label='Qualitative
307             ↵ Scaling')
308         plt.plot(M_fit, basic_fit(M_fit, *popt_basic), 'g-', label='Basic Fit')
309         plt.plot(M_fit, offset_fit(M_fit, *popt_offset), 'b-', label='Offset Fit')
310
311         plt.xlabel('Mach Number')
312         plt.ylabel('delta/D')
313         plt.title('Curve Fits for Non-dimensional Standoff Distance')
314         plt.legend()
315         plt.grid(True)
316         plt.show()
317
318     # ... (keep the rest of your existing code)
319
320     # After your existing code, add:
321
322     # Process the standoff data
323     mach_numbers = list(standoff_data.keys())
324     diameters = [[d for d in data[:3]] for data in standoff_data.values()]
325     standoff_distances = [[s for s in data[3:]] for data in standoff_data.values()]
326
327     # Calculate average values
328     avg_diameters = [np.mean(d) for d in diameters]
329     avg_standoffs = [np.mean(s) for s in standoff_distances]
330
331     # Calculate non-dimensional standoff
332     nondimensional_standoff = calculate_nondimensional_standoff(mach_numbers,
333         ↵ avg_diameters, avg_standoffs)
334
335     # Plot non-dimensional standoff distance
336     plot_nondimensional_standoff(mach_numbers, nondimensional_standoff)
337
338     # Perform curve fits
339     popt_qual, popt_basic, popt_offset = perform_curve_fits(mach_numbers,
340         ↵ nondimensional_standoff)
341
342     # Plot curve fits
343     plot_curve_fits(mach_numbers, nondimensional_standoff, popt_qual, popt_basic,
344         ↵ popt_offset)
345
346     # Print table of fit constants
347     print("\nFit Constants:")
348     print("Qualitative Scaling: c =", popt_qual[0])
349     print("Basic Fit: c =", popt_basic[0], ", alpha =", popt_basic[1], ", beta =", popt_basic[2])
350     print("Offset Fit: c =", popt_offset[0], ", alpha =", popt_offset[1], ", beta =", popt_offset[2])

```

B.3 calibration.py

```

1   import cv2
2   import numpy as np
3   import matplotlib.pyplot as plt
4
5   def onclick(event):
6       global points
7       if event.button == 1 and len(points) < 2: # Left mouse button
8           points.append((event.xdata, event.ydata))
9           plt.plot(event.xdata, event.ydata, 'ro')
10          plt.draw()
11          if len(points) == 2:
12              plt.close()
13
14  def calculate_calibration_factor(image_path, grid_spacing_mm=5):
15      global points
16      points = []
17
18      # Read the image
19      img = cv2.imread(image_path)
20      img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
21
22      # Display the image and wait for point selection
23      fig, ax = plt.subplots()
24      ax.imshow(img_rgb)
25      ax.set_title("Click on two points 10 grid spaces apart")
26      fig.canvas.mpl_connect('button_press_event', onclick)
27      plt.show()
28
29      if len(points) != 2:
30          print("Error: Two points were not selected.")
31          return None
32
33      # Calculate distance between selected points
34      distance_px = np.sqrt((points[1][0] - points[0][0])**2 + (points[1][1] -
35          points[0][1])**2)
36
37      # Calculate calibration factor (pixels per mm)
38      calibration_factor = distance_px / (10 * grid_spacing_mm)
39
40      # Visualize the selected points
41      fig, ax = plt.subplots()
42      ax.imshow(img_rgb)
43      ax.plot([points[0][0], points[1][0]], [points[0][1], points[1][1]], 'r-')
44      ax.plot([p[0] for p in points], [p[1] for p in points], 'ro')
45      ax.set_title(f"Calibration: {calibration_factor:.2f} pixels/mm")
46      plt.show()
47
48      return calibration_factor
49
50      # Usage
51      calibration_image_path = "Lab 1\\Data\\Images\\Wind_off_calibrate.bmp"
52      cal_factor = calculate_calibration_factor(calibration_image_path)

```

```
52     if cal_factor:  
53         print(f"Calibration factor: {cal_factor:.2f} pixels/mm")
```