BI-STABILITY IN THE WAKES OF PLATOONING AHMED BODIES

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ABSTRACT

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Daniel Morgan Stalters

Autonomous heavy vehicles will enable the promise of decreased energy consumption through the ability to platoon in closer formation than is currently safe or legal. It is therefore increasingly important to understand the complex and dynamic wake interactions between vehicles operating in close proximity for aerodynamic gains. In recent years, a growing body of research has documented a bi-stable, shifting wake generated behind the Ahmed reference bluff body. At the same time, studies of platooning Ahmed bodies have focused on changes to the body forces and moments at different following distances or lateral offsets, typically based around time-averaged measurements or steady-state CFD. The present study attempts to understand the implications of bi-stability in the wake of two square-back, platooning Ahmed bodies, given the potential for transient instabilities. Temporally-correlated static pressures were measured on two identical wind tunnel models at various following distances to uncover the time-dependent interactions between platooning vehicles. Bi-stability is highly dependent on symmetry and the uniformity of oncoming flow, and it is shown that a shifting bi-stable wake behind the lead vehicle leads to correlated, bi-stable flow patterns on the following vehicle, even in the absence of a lateral offset. At a following distance of 0.25L, pressure data indicated there may be a point where this bi-stable behavior reaches a critical point between suppression and amplification, significantly affecting the aerodynamic
loads on the lead vehicle. This leads to the conclusion that bi-stable wake interactions between vehicles may be useful to consider in the context of real-time organization of vehicle platoons.

Keywords: [Platooning, Convoy, Semi-trucks, Bi-Stability, Aerodynamics]
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Chapter 1
INTRODUCTION

The transportation and freight sectors make up a large fraction of the world economy with many millions of miles driven by large transport vehicles, including semi-trucks. With a total of 169.8 billion miles traveled by combination trucks in 2014, class 8 tractors account for 12-13% of petroleum consumption in the United States [1,2]. According to the National Renewable Energy Laboratory, 65.9%, or 111.4 billion, of those miles may be platoonable [3]. Additionally, electrically powered trucks, recently becoming practicable for the short to medium-haul range, impose new energy requirements and demand better aerodynamic efficiency from the vehicle’s shape. Platoons of semi-trucks, alternatively referred to as convoys, offer a solution to designers.

Driverless, automated vehicle systems have allowed for vehicles to travel much closer than before as reaction times and safety of these systems have been shown to exceed that of a human driver. Reduced following distances have shown theoretical drag reductions on the order of 20% at highway speeds for the largest vehicles such as semi-trailers when platooning [1]. This method of drag reduction is not new to vehicle aerodynamics and has been exploited for competitive advantage in motorsports for years. Emerging technologies may soon make vehicle platoons practical on public roads and highways to save on fuel and energy costs.

This requires more investigation into fundamental aerodynamic behavior in such scenarios, and the use of the Ahmed reference body is one means to uncover
the relevant phenomena. The Ahmed reference body has become a standard shape in automotive aerodynamics and is used to reproduce a simplified wake characteristic of ground vehicles [4]. The square-back Ahmed body, with a bluff trailing edge approximates the wakes of SUVs and large trucks.

![Figure 1.1: Original schematic of simplified automotive bluff body characterized by Ahmed in 1984, dimensions in mm [4].](image)

In recent years, a growing body of research has indicated the presence of a bi-modal, shifting wake structure behind the Ahmed body, illustrated in Figure 1.2 [5,6,7,8]. The toric structure previously thought to describe the recirculation region in the wake of the Ahmed reference body has been shown to be a time-averaged
result and misrepresentative of the shifting, bi-stable nature of the wake [8]. Additionally, this bi-stable behavior has been shown to be largely Reynolds independent [5,7]. Multi-stable wake behavior has been observed on multiple production vehicles in wind tunnel tests, indicating this type of wake behavior extends beyond the Ahmed model research body [9]. Indeed, it has become clear that wake aerodynamics in the zero-yaw case can no longer be assumed quasi-steady in the design of automotive shapes. Passive methods to suppress the bi-stable behavior using cylinders in the horizontal and vertical shear layers as well as in the wake of the square-back Ahmed body showed a potential drag reduction of 4-9% depending on cylinder placement [6]. This method, while effective, may have limited application to on-road scenarios. Others have shown that feedback control methods using side-mounted flaps can stabilize the wake to the symmetric case and reduce drag on the body by 2% [10].

![Figure 1.2: Streamlines of bi-stable modes in wake of Ahmed reference body compared to spatially averaged wake exhibiting traditional, time-averaged unimodal symmetry.](image)
Further work on bi-stability has identified a number of factors affecting shedding patterns. Work carried out by Volpe et al. [7] has identified fragility in bi-stable wake shedding behind the square-back Ahmed body. At yaw angles less than 1°, bi-stability in the wake is maintained, albeit at increasingly disproportionate temporal significance between the two modes. A steady, asymmetric wake forms at yaw angles larger than 1°. However, despite the presence of bi-stable modes, when pressure data is time-averaged, force coefficients and pressure fields are found to agree with previous values. Meile et al. has shown that for the 35° slant Ahmed body, multi-stable wake behavior is seen at a narrow, but critical $\beta$ range of 12-13° [8]. Grandemange et al. has also shown that below a critical ground clearance, $0.10H$, bi-stable shedding in the wake of the square-back Ahmed model is suppressed [5].

Studies conducted on simplified vehicle models have shown that dynamic events such as a gusting crosswind differ from the quasi-steady state estimate [11,12,13]. These events exhibit strong time dependent evolution and can differ significantly from quasi-steady force and moment estimates [12,13]. Additionally, self-excited frequencies due to wake shedding patterns have been observed when model motion is not prevented by rigid model supports [14].

To date, many studies on the effect of platooning have studied steady state or transient lane-change maneuvers [15,16,17,18,19,20,21]. Many of these studies were conducted on 25-35° rear slant Ahmed bodies, or simplified shapes which more closely approximate the wake features of a typical sedan car.
A summary of selection of important studies to date is found in Table 1.1. Studies of platoons up to four bodies have been conducted to measure the optimal spacing of vehicles based on individual and global drag reduction. Drag values show improved platoon performance at closer spacings with California Partners for Advanced Transportation Technology (PATH) researchers identifying non-linear drag trends around 0.2L vehicle spacing on van-shaped models shown in Figure 1.3 [19].

![Figure 1.3: Two-vehicle platoon results showing non-linear drag coefficient behaviour around 0.2L vehicle spacing.](image)
Transient and asymmetric forces on platoons become important when considering these platoons operate in a dynamic environment. Destabilizing side forces and moments were measured in mis-aligned platoons and studies show significant (up to several times the nominal value) asymmetric body forces during passing and lane change maneuvers depending on vehicle following distance and lateral spacing [19,20,21,22]. When bluff bodies are used instead of the more streamlined passenger vehicle shapes, forces and moments are magnified due to the larger wake and greater vorticity induced by the leading bodies. And as the following distance is reduced, the interaction between the lead and following models increases due to the greater strength of the lead vehicle’s wake at that distance [21,22]. This dynamic stability question becomes ever more important to understand as pressure to reduce following distances in platoons of large transport vehicles increases in order to realize greater aerodynamic benefits.

Table 1.1: Summary of selection of important platooning studies to date.

<table>
<thead>
<tr>
<th>Study</th>
<th>Date</th>
<th>Re_H</th>
<th># Vehicles</th>
<th>Following Distance (x/L)</th>
<th>Ahmed Geom.</th>
<th>Numeric/Exp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bruneau et al. [15]</td>
<td>2017</td>
<td>1.50x10^4</td>
<td>1-3</td>
<td>0.2,0.5,1</td>
<td>90°</td>
<td>DNS</td>
</tr>
<tr>
<td>Ebrahim et al. [16]</td>
<td>2016</td>
<td>7.68x10^5</td>
<td>2</td>
<td>0.125,1</td>
<td>25°</td>
<td>RANS</td>
</tr>
<tr>
<td>Pagliarella et al. [17,18]</td>
<td>2007/9</td>
<td>5.10x10^5</td>
<td>2</td>
<td>0.125,0.25,0.5,0.75,0.875,1,2,3</td>
<td>25°,35°</td>
<td>Exp.</td>
</tr>
<tr>
<td>Zabat et al. [19]</td>
<td>1995</td>
<td>2.82x10^5</td>
<td>1-4</td>
<td>0-3</td>
<td>Chevy Lumina</td>
<td>Exp.</td>
</tr>
<tr>
<td>Chen et al. [20]</td>
<td>1997</td>
<td>0(10^5)</td>
<td>4</td>
<td>0.21,0.41,1</td>
<td>Buick LeSabre</td>
<td>Exp.</td>
</tr>
<tr>
<td>Tsuei et al. [21]</td>
<td>1999</td>
<td>0(10^5)</td>
<td>4</td>
<td>passing manuevers</td>
<td>Buick LeSabre</td>
<td>Exp.</td>
</tr>
</tbody>
</table>

Other studies of platooning tractor-trailer combinations and sedan vehicles have been conducted on closed courses and public freeways. [23,24,25]. In all cases, a reduction in fuel burn is shown when compared to the single vehicle case.
However, these values vary between studies and repeatability suffers due to changing atmospheric conditions between tests [23]. The farthest distances tested exceed one vehicle length while the closest following distances are around 0.2s at 65 mph, corresponding to a following distance of about 5.8m. It is acknowledged that technical and safety limitations prevented testing closer vehicle spacings [23].

Tests conducted on California roads in the San Francisco Bay Area and Los Angeles show on-road fuel consumption to decrease by 5 – 14% for a three-vehicle platoon depending on vehicle spacing [24]. The closest vehicle separation tested was 0.6s at 55 mph (14.6 m). Despite the relatively close following distances for typical interstate traffic, this is still greater than the distances considered in most aerodynamic studies.

It is clear that an understanding of the transient aerodynamics of platooning vehicles is necessary as the potential for connectivity among vehicles poses increasingly complex challenges in vehicle stability, passenger comfort, and safety. As recent studies of bi-stability over single Ahmed reference models have shown, significant side forces and moments are experienced as a result shifting wake dynamics, leading to a modification to the understanding of a “steady” flow condition [5,6,7,19,20]. Measuring and understanding bi-stability in the context of a large vehicle platoon is one step forward in better understanding the transient and connected interactions of a complex and dynamic system. Pioneering work by Bai et al. has shown that machine learning techniques from the broader data science field can be successfully used to classify and identify fundamental flow features in aerodynamic data of a backwards facing ramp [26]. Researchers have for years used
proper orthogonal decomposition (POD) on aerodynamic data to extract important turbulent structures from wake data of the Ahmed model in both experimental and numeric studies [7,27,28,29,30]. More recently, POD has been used to analyze bi-stable aerodynamic data [7,29,30], though researchers have stopped short of pairing these techniques with clustering algorithms to sort and classify aerodynamic data.

1.1 Goals of Current Research

In light of the above works, the goals of this thesis are:

1. Measure bi-stability in the wake of two platooning, square-back Ahmed reference models at multiple following distances.
2. With this data, build algorithmic models classifying the wake behavior of both vehicles based on bi-stable patterns.
3. Correlate behavior in the platoon to statistically assess the level of vehicle to vehicle, aerodynamic interaction.
Chapter 2

EXPERIMENTAL SETUP

Test were conducted in the Cal Poly low speed wind tunnel. The tunnel is an open return design with a 1.19 m x 0.88 m test section. Freestream turbulence levels were measured to be < 1%. Based on the original Ahmed dimensions [4], the 0.588:1 scale Ahmed models used in the present study are assumed negligibly impacted by blockage effects given the model frontal area blockage ratio of 3.76% is below the commonly accepted limit of 5% for bluff bodies [31]. The dimensions of the model are $H = 169.2\text{mm}$, $W = 228.6\text{mm}$, and $L = 613.5\text{mm}$. A description of the numeric blockage study follows below.

2.1 Model Sizing

A computational study exploring the impact of blockage on force and pressure values in the Cal Poly test section was undertaken in Star-CCM+. Interests for a larger model, preferred for ease of manufacture and instrumentation, and concerns over model frontal area blockage formed a dueling set of requirements for model size. The internal structure of the models also needed to be large enough to house a pressure transducer for future studies using these models.

2.1.1 Domain Setup

A computational domain was created with the original Ahmed model dimensions in order to provide validation of the numeric model as well as form a control case used
to make comparisons later in this sizing and blockage study. The “unbounded” domain is shown in Figure 2.1. The symmetry of the Ahmed model and test section was exploited by splitting the domain with a symmetry plane and doubling force values when validated against literature. Pressure taps are not modeled as they have little to no impact on the boundary layer. Model supporting struts are also not modeled to reduce complexity of the study. A velocity inlet specification and pressure outlet boundary conditions were selected and set at 44.704 m/s (100 mph). It was desired to effectively eliminate communication between fluid domain boundaries and the model while keeping the ground clearance constant between the control case and the blockage study as it has a significant impact on the resultant body forces. Full-scale dimensions were used for this study to ensure Reynolds similarity for comparison with literature.

Figure 2.1: Computational domain used for the “unbounded” comparison case.
Blockage ratios were tested in single percent increments from one to five percent frontal area blockage. Maintaining the original Ahmed dimensions of the reference model, the outer domain walls were scaled to replicate the Cal Poly wind tunnel test section for each blockage ratio. These results were then compared to experimental results from Ahmed [4] and Strachan [32]. For all tests, ground clearance was kept constant with the original Ahmed experiment and a single body was used for comparison to literature. The modeled Ahmed body is located 0.91 m (3ft.) from the test section inlet boundary. The inlet and diffuser sections of the wind tunnel were modeled as upstream and downstream extensions of the test section domain to prevent pressure communication to the inlet or outlet boundaries. A no-shear slip condition was specified for all walls in the fluid domain to prevent the growth of a boundary layer and more directly isolate the effects of increasing model blockage. The diffuser section of the wind tunnel was modeled as a pressure outlet 10 characteristic lengths from the downstream boundary of the test section, allowing for pressure recovery before the flow exits the fluid domain. While different than the installed wind tunnel diffuser section, no flow angularity is expected in the experimental test section and the driving pressure drop across the fan can equally be modeled by a velocity specification. An initial inlet velocity of 44.704 m/s (100 mph) was used for similarity to the control case. It is assumed that the trends found for different blockage ratios using the original Ahmed body dimensions would hold under scaling to the actual dimensions of the Cal Poly wind tunnel test section.
2.1.2 Grid Description

A trimmed cell mesh was selected for this study as the geometry of the Ahmed reference body and the primary flow direction in the domain allowed for good overall flow alignment and would minimize skew related numeric diffusion.

Each mesh was constructed with the same surface cell size constraints on the outer boundaries and allowed to grow unrestricted except for an area of volume refinement around the body. Within this region, surface and volume controls were maintained across all simulations. Twelve prism layers were used to resolve the boundary layer on the body using a geometric growth rate of 1.2, ensuring the volume difference between layers is no greater than 20%. An approximation of the boundary layer height on both the Ahmed body and the test section walls was computed using the 1/5th power law for turbulent boundary layer growth over a flat plate. These values at the final length of the model and Ahmed body were used to set the first prism layer height to no greater than a $y^+$ of 30 across the entire test section. Given the transition from the inlet to the test section of the Cal Poly low speed wind tunnel, the boundary layer is assumed to be turbulent at the onset. The grid used in the blockage study is shown below in Figure 2.2.
2.1.3 Turbulence Model

A turbulence intensity of 4% and a turbulence length scale of 5 cm is selected to model the flow conditions of the tunnel [33]. It was later measured that the turbulence intensity in the Cal Poly test section is less than 1% though this should have negligible impact on the conclusions here regarding frontal area blockage. The turbulence length scale is based off the largest considered Ahmed model characteristic height. The segregated flow model was selected as the testing speeds were incompressible and lowered required computational resources.

The test cases were run on a local machine with 16 GB of RAM and up to four computer processors. Monitors of drag and lift coefficients were setup to assess the
stability of the solution. A minimum residual threshold of $10^{-3}$ was established as the requirement for convergence. In all cases, convergence to levels below this was achieved. At these residual levels, drag and lift monitors showed steady behavior for 500 iterations.

Two different turbulence models, realizable $k$-ε and $k$-ω SST, were used to evaluate differences in drag and lift predictions and determine the most accurate model for the current test set up. These two-equation models were selected for their robust performance accurately modeling highly separated flow fields and the relative speed of solving over higher order RANS solutions. A comparison of the wake region is shown in Figure 2.3. Values for drag and lift coefficients are compared between the models and indicate large differences in solutions when solved on the same mesh. The $k$-ω SST model shows clear indications of the presence of a lower vortex off the underside of the Ahmed reference model. While predicted by some computational studies and found experimentally, Strachan [32] reports this lower vortex to dissipate within 0.198 m of the rear face of the body. Here the numeric prediction shows indications of this vortex 0.456 m from the rear face of the body. Additionally, the $k$-ω SST model shows a narrower wake downstream of the body, potentially explaining the lower drag prediction.
2.1.4 Blockage Study Results

The results of the blockage study show that there is overall good agreement between experimental values found in literature and those values obtained here using the realizable k-ε turbulence model. Table 2.1 contains a summary of the Reynolds numbers for the experimental comparison cases as well as the current computational study.

Table 2.1: Test Reynolds numbers of reference studies.

<table>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>4.26 x 10^6</td>
<td>1.7 x 10^6</td>
<td>3.19 x 10^6</td>
</tr>
</tbody>
</table>
Comparing the experimental results of Ahmed and the more recently Strachan, several comments can be made. First, model differences such as the absence of cylindrical supports on the computational model must be noted as contributing to differences. As Figure 2.4 shows, drag is consistently over predicted compared to experimental studies. The inclusion of model support struts or a single overhead strut like those used in the comparison to Ahmed [4] and Strachan [32] respectively would only increase this difference. Unlike the zero-shear floor boundary used for this blockage study and the moving ground plane of Strachan, the drag value measured by Ahmed was obtained over a stationary ground plane where a boundary layer could develop. While not provided in Ahmed’s work, the boundary layer height at the start of the model can be approximated from the provided dimensions. At the leading edge of the Ahmed body, the boundary layer height assuming theoretical flat plate conditions apply would be 22mm. While this is less than the 50mm ground clearance height of the model there is an associated displacement thickness that would affect the pressure distribution under the model. The results of Strachan [32] are more interesting because they involve a moving ground plane and an above mounted strut. Due to the model’s influence on the surrounding flow field, there is a small boundary layer at the leading edge of the model despite the moving ground plane. Strachan reports this to have a 99% dynamic pressure recovery height of 1mm. And while the model is supported by an above-mounted strut, the aerodynamic shape of the strut makes this a more comparable experimental point. Strachan [32] reports that the counter rotating vortices that form over the slanted face of the fast-back Ahmed model are weakened
by the supporting strut. Compared to the numeric results of the blockage study the lift value reported by Strachan is higher, not lower. It is possible that in the case of the square-back Ahmed geometry, the overhead strut could form low pressure vortices where the strut connects to the model, leading to higher lift values and lower pressures. However, the agreement is still found to be quite good considering the use of RANS equations to model a bluff body with a large wake region.

Figure 2.4: Lift and drag comparison between numeric results (solid lines) and experimental reference studies at multiple blockage ratios. Final model blockage indicated by dotted line.
2.2 Ahmed Model Design

The Ahmed models constructed for use in this research were conceived as standard Ahmed models to be used by Cal Poly students conducting current and future vehicle aerodynamic work. Therefore, design choices were made that provide flexibility and modularity to accommodate changing research goals while not immediately contributing to the research aims of the present study. An interchangeable rear section allowing testing on shapes other than the square-back geometry is the primary reflection of this effort. Additionally, pressure taps on the front and side surfaces of the model were installed to give future researchers more measurement options covering the entire model. The models are composed of three main sections hereafter referred to as the nose, main tray, and rear tray shown in Figure 2.5.

![Figure 2.5: The three main sections of the Ahmed reference model.](image)
2.2.1 Material Selection

Extruded acrylic sheet was selected for the planar surfaces of the model for its ease of machinability and exceptionally smooth surface finish. 5.08mm (0.200 in.) thick acrylic sheets were laser cut to ensure dimensional accuracy and the highest degree of similarity between the models. The laser printer used to cut the acrylic was measured to have dimension accuracy better than 0.075mm. Using the results of this study, laser thickness and tolerances were included in the final engineering drawings used to cut the acrylic sheets. Pressure tap and fastener locations were “piloted” while the parts were still on the printer bed. A cordless drill was later used to enlarge and finish the holes.

Initially plastic nose pieces were printed on the Cal Poly Aerospace department’s 3D printers. This was motivated by the success of other master’s thesis projects at Cal Poly using 3D printed parts in wind tunnel models [34]. The need for high quality flow over the front of the model made it necessary to print the nose as one part to prevent the creation of seams. A total of five nose cones were printed with differing bed temperature and print settings in an effort to remedy the warping the plastic pieces experienced when removed from the print bed. Unfortunately, this was never overcome, and the final nose cones were milled on a HAAS three-axis mill in the Cal Poly Aerospace machine shop. A composite MDF sandwich block was used. The five front pressure ports were located and drilled at the time of machining the outer profile, ensuring their exact location relative to the part axes. The two machined nose pieces were sanded, primed, and painted with multiple coats of matte black paint.
2.2.2 Model Assembly

All acrylic pieces were joined with a chemical weld using a solvent based acrylic glue. This method was selected as it minimizes the number of fasteners needed to assemble the model. Simple tooling was made of angle iron and acrylic pieces clamped in place during the curing process so that perpendicular joints were replicated between models.

The nose cones were joined to the main trays using double-sided 3M VHB 5952 mounting tape, selected because of its strong bonding performance with low surface energy materials such as acrylic. Using tape creates a narrow (0.045 in.) seam the thickness of the tape. The seam is later filled in with caulk.

Sixteen static pressure ports were arranged in a grid on the rear of each model to capture pressure fluctuations (Figure 2.6). The sides of both models are tapped along the centerline with nine static pressure ports on either side. A total of eight static ports, four on each side, are located on the rear tray to provide higher resolution side pressure measurements near the bi-stable wake region. This was done as authors have reported significant changes to yaw moments on the body during wake shifts [8]. Five pressure ports are arranged in a cross on the nose of each model. These front-facing ports are intended to make dynamic pressure measurements and record directionality changes in the oncoming flow. All pressure taps are made with 0.063 in. aluminum tubing lengths, cut, smoothed and installed flush with the model surface. Figure 2.6 shows the rear pressure port layout over the model.
The lateral breaking characteristic of the bi-stability phenomenon prioritized minimally disturbed flow over the sides of the model. Therefore, fasteners and seams were located on the top and bottom surfaces of the model where possible to help preserve flow quality over the sides of the model. Six counter-sunk, flat-head screws were used to attach the rear tray to the main tray. Four of the screws were located on the underbody surface of the model behind the support struts where flow is already disturbed. The other two screws were located on top of the model as can be seen in Figure 2.6. All screws were countersunk to a depth below the surface of the model and then covered and smoothed over with acrylic latex caulking to further hide the screw head from the flow. An opposing tab system was used on the sides of the model to ensure side seams were flush, preventing any backward or forward steps from disturbing the boundary layer in this critical region. The same
caulking used to cover the screw heads was used to fill any remaining gaps or seams across the model.

Platoon testing necessitated routing tubing outside of the models to a common pressure transducer housed underneath the test section. Tubing was routed through the model legs to underneath the test section in equal 1.22m (4ft.) lengths to synchronize readings between the models.

Non-load bearing, hollow legs were made from 15.88mm (5/8in.) acrylic extruded tubing and used to shield the pressure tubing and preserve the underbody flow. An internal structure, separate from the legs, forms the mechanism by which the models were secured to the tunnel floor. A threaded rod system was used to allow continuous height adjustability at each corner of the model. Figure 2.7 shows this structure and the connection of the model to supports beneath the test section floor. Internal and external “bridges” provide attachment points for the load-bearing structure and the vertical separation necessary to route the tubing into and out of the hollow acrylic legs. This method of non-load bearing, external legs and a rigid internal load bearing structure also allows for future conversion to a load cell configuration for force measurements. The internal hex nuts are tightened and “locked” into place with lock washers on the upper surface of the internal acrylic bridge. This prevents the threaded rod from spinning during height adjustments. Height changes are made beneath the tunnel floor through tandem adjustment of the two hex nuts underneath the test section floor. These two nuts, when tightened, provide the bulk of the stiffness in the system. With a total four supports, the models are found to be both rigid and vibrationally isolated at testing conditions.
Models are shown installed along the center line of the test section (Figure 2.8) with the first model located 0.68L (0.42m) from the test section inlet. Ground clearance is set at 0.17H (29.4mm), scaled to the original Ahmed experiment [4].
Figure 2.8: Ahmed models in 1L following distance configuration.

2.3 Instrumentation

Body force measurements were not made in this study. Instead an emphasis was placed on identifying and understanding the time-dependent behavior of the bi-stable wake at various following distances. Pressure measurements were made with a Scanivalve ZOC33/64Px pressure transducer having a measurement range of 1 psid and an accuracy of ±0.0008 psid. In total, 32 low range, high resolution pressure ports were available to accommodate the rear static pressure ports on both models. Tunnel velocity measurements and front-of-model ports were connected to the remaining high range ports. Tubing length was sized to accommodate the 1L formation but kept to a minimum in order to reduce the signal filtering effects of the pressure tubing.
A balance between a higher signal to noise ratio and longer duration bi-stable shedding periods was struck at a height-based Reynolds number \((\text{Re}_H)\) of \(2.0 \times 10^5\) \((U_0 \approx 18.0 \text{ m/s})\). Reference tests by Grandemange et al. [5] and Volpe et al. [7] were conducted at \(\text{Re}_H = 9.2 \times 10^4\) and \(\text{Re}_H = 5.1 \times 10^5\) respectively and show the average, non-dimensionalized bi-stable shedding period in the wake of the Ahmed reference body to be independent of Reynolds number.

### 2.4 Flow Uniformity

Flow quality measurements were taken in the test section of the Cal Poly low speed wind tunnel to ensure symmetry in the onset flow at the location of the first model. Measurements at \(\text{Re}_H = 1.0 \times 10^5\) and \(2.1 \times 10^5\) were made using a total pressure rake at the location of the lead model. Velocities were normalized with respect to the pitot-static probe used to set tunnel velocity. Overall flow uniformity across the test section is acceptably within less than \(\pm 1\%\) deviation from the measured test section velocity. Figure 2.9 shows the measured region of the test section with a frontal area overlay indicating the location of the Ahmed models during testing. Flow uniformity ahead of the models is shown to be better than \(\pm 0.5\%\) \((0.1 \text{ m/s})\).
Figure 2.9: Flow uniformity in positive x-direction at $Re_H = 2.1 \times 10^5$.

## 2.5 Boundary Layer

Prior to testing, a new wind tunnel floor was installed in the Cal Poly low speed wind tunnel to ensure low boundary layer growth over buoyancy concerns considering the length of the two-model platoon. A raised floor, common in other studies of ground vehicles where a moving ground plane is not available, was not pursued. This was over concerns about overall size of a ground plane to accommodate a two-vehicle platoon and the complexity of routing tubing for different formations.

A 20-probe boundary layer rake was used to measure the boundary layer 0.42m downstream from the start of the empty test section. The onset boundary layer thickness at the first model was measured at $\delta^* = 7.38$mm, $\theta = 4.19$mm,
substantially larger than the theoretical flat plate thicknesses of $\delta^* = 1.48\text{mm}$, $\theta = 1.14\text{mm}$. Boundary layer thicknesses shown here were computed using a discreet trapezoidal integral method. The slight kink in the boundary layer profile seen at 4 mm in Figure 2.10 is due to a test section floor panel seam 0.125m upstream of the model. The displacement thickness was used to compare effective ground clearance with the threshold provided by Grandemange et al. [5].

Using the notation of Grandemange et al. [5] and considering the displacement thickness of the measured boundary layer, these current tests were conducted at an effective ground clearance of $0.13H$. This is found to be adequately above the critical value of $0.10H$ identified by Grandemange et al. and below which bi-stable shedding patterns were observed to be suppressed. Therefore, no boundary layer suction system needs to be employed. This is further supported by experimental validation on a single Ahmed reference body (Chapter 4).
Boundary layer rake measurements at downstream stations were not made as the boundary layer that develops in an empty test section and the boundary layer that would develop ahead of the following model while an upstream model is installed would be significantly different. Instead, for insight into onset flow conditions for downstream models in a platoon, the boundary layers provided in the numeric study conducted by Ebrahim et al. [16] are considered. However, boundary layer height is not expected to be the most influential flow feature determining the flow over the following model given the complexity of the upstream wake behind the lead model.
A comparison to published bi-stability data over a single square-back Ahmed model is made to establish the ability to measure this phenomenon in the Cal Poly wind tunnel with the current models before beginning platoon testing. Single model data is taken at the farthest following distance of 1L to establish that boundary layer growth does not suppress the bi-stable shedding behavior as ground clearance has been shown to limit this behavior at lower effective clearances. Additionally, single model measurements in both locations were made with both models and bi-stability was observed over both.

2.6 Following Distances
The following distances considered in this study include distances already practicable for on-road tests as demonstrated by the work of Lammert et al. and others [23,24]. It also includes following distances that are not currently possible but warrant further investigation as closer following distances become feasible. All following distances were normalized to the characteristic length of the models (613.5mm). The following distances 1L and 0.5L are within current, on-road capabilities while the closer distances, 0.25L and 0.05L, represent future following distances.
Figure 2.11: 1L (a), 0.5L (b), 0.25L (c), and 0.05L (d) following distances.

2.7 Test Details

All tests were conducted over a minimum of 900s with platooning tests conducted in excess of 1000s to ensure sufficiently settled bi-stable wake signals and reduced uncertainty in the results. Measurements were taken at 20 Hz for single-body tests and 10 Hz for multi-body tests. The difference in measurement rate was driven by LabVIEW processing speeds and the number of ports sampled. It was found that changing the number of ports written to a file would impact the effective sample frequency. During platoon testing, where a larger number of pressure ports were sampled, the sample frequency was necessarily relaxed. If higher frequency data is desired for future research efforts, a more efficient file writing process will need to be found. Considering previous studies of bi-stable wake behavior artificially resample data at 1Hz, this has no impact on results presented here.
Chapter 3

ANALYSIS METHODS

Grandemange et al. [5] and Volpe et al. [7] found that sample durations on the order of, or greater than, $10^3$ s are required when measuring bi-stable behavior as the random nature and long period of bi-stable modes takes a long time to settle to a global average. Additionally pressure measurements are taken at 20 Hz for single model testing and 10 Hz for platoon configurations. Because of the large amount of data to be processed, techniques are borrowed from the fields of data science and machine learning. Bai et al. [26] demonstrated the capability of these techniques for fundamental aerodynamic flows. Here dimensionality reduction and classification techniques are used to provide flexibility and demonstrate the scalability of these techniques for more complex aerodynamic applications. Unsupervised methods are favored as they form a robust data flow pipeline that can be used to quickly process aerodynamic data and inform models with minimal user input. Once these unsupervised techniques have identified and labeled data, regression models are fit to the platooning data to draw conclusions and build predictive models.

3.1 Principal Component Analysis

The first unsupervised method used on the raw pressure data is principal component analysis, also referred to as PCA. PCA is fundamentally a dimensionality reduction technique often used to extract the most important features of a set of...
data. Mathematically, proper orthogonal decomposition (POD) is a similar technique used in aerodynamics research for decades [7,27,28,29,30].

The derivation of finding the principal components of a set of data is summarized from Jolliffe [35]. The PCA algorithm takes a $n$-dimensional data set $\mathbf{x}$ and converts it into up to $n$ uncorrelated, linear functions of the form $\mathbf{a}_k' \mathbf{x}$. The first function $\mathbf{a}_1' \mathbf{x}$ is found by maximizing the amount of variance accounted for by the function in $\mathbf{x}$. The next function, $\mathbf{a}_2' \mathbf{x}$, is found by looking for an uncorrelated function that again maximizes the remaining variance unaccounted for in $\mathbf{x}$. This is repeated up to $n$ times, forming the process for determining the principal components returned by the PCA algorithm. The first component is shown below.

$$
\mathbf{a}_1' \mathbf{x} = \alpha_{11} x_1 + \alpha_{12} x_2 + \cdots + \alpha_{1p} x_p = \sum_{j=1}^{p} \alpha_{1j} x_j
$$

(1)

If the first PCA vector of coefficients, $\mathbf{a}_k$, is to account for the most variance of the data, $\text{var}[\mathbf{a}_1' \mathbf{x}] = \mathbf{a}_1' \Sigma \mathbf{a}_1$ must be maximized. Applying a normalization constraint $\mathbf{a}_1' \mathbf{a}_1 = 1$ and using Lagrange multipliers

$$
\mathbf{a}_1' \Sigma \mathbf{a}_1 - \lambda (\mathbf{a}_1' \mathbf{a}_1 - 1)
$$

(2)

Then differentiating with respect to $\mathbf{a}_1$

$$
\Sigma \mathbf{a}_1 - \lambda \mathbf{a}_1 = 0
$$

(3)

$$
(\Sigma - \lambda \mathbf{I}_p) \mathbf{a}_1 = 0
$$

(4)

Thus, the value to be maximized is

$$
\mathbf{a}_1' \Sigma \mathbf{a}_1 = \mathbf{a}_1' \lambda \mathbf{a}_1 = \lambda \mathbf{a}_1' \mathbf{a}_1 = \lambda
$$

(5)
It is shown that $\mathbf{a}_1$ is the eigenvector corresponding to the largest eigenvalue $\lambda$ of $\Sigma$. Ultimately it is shown that PCA returns the eigenbasis of the covariance matrix $\Sigma$ of the input data.

If all dimensions determined by PCA are retained in the eigenbasis representation of the data, the original data can be reconstructed exactly. However, from this eigenbasis it is possible to truncate the least important dimensions based on the amount of variation they account for in the original data. With each dimensional reduction, the maximal amount of information about the original data is maintained.

Figure 3.1 shows this decomposition clearly in two dimensions where the original data is transformed into its principal components $Z_1$ and $Z_2$. Represented in this new set of coordinates, it is apparent that more information about the distribution of the original set of data is contained in the first principal component $Z_1$ than in $Z_2$. In fact, a better description of the separation of the original data can be found in the variable $Z_1$ than in $X_1$ or $X_2$. If this same set of data were to be reduced to one dimension, the most informationally efficient way to perform this task would be to represent each data point by its first principal component.
Figure 3.1: 50 data points in $X_1,X_2$ (a). Same 50 data points with respect to their principal components $Z_1,Z_2$ (b).

To avoid confusion, the definition of these terms as provided in Jolliffe [35] is used in this study. A principal component is the product of the linear function $\alpha'_k x$ while the vector $\alpha_k$ is referred to as the vector of coefficients.

3.2 Clustering

Clustering methods vary in method and complexity and are used to intrinsically and algorithmically group individual data points based on dimensional similarities within in a larger data set. The simplest methods are based on multi-dimensional distance formulas such as the familiar Euclidean distance formula while more complex models may rely on statistically derived distributions of the data. A simplified discussion of the internal process used in distance-based clustering
models is provided to familiarize the reader with the principles of clustering techniques.

For every new point, cluster membership is based on the shortest distance between it and all other cluster centroids. Once this point has been assigned a cluster, cluster centroids are re-computed, and the next point in the data set is considered. This is done may times over with randomized initial cluster centers until the best initial seeding of clusters found. However, a limitation of these distance-based techniques is their inability to handle sets of data where clusters of data are not uniformly shaped in $n$-dimensional space. In the case of the Euclidean distance formula, the shape of a cluster is an $n$-dimensional sphere. For more flexible clustering of data sets where natural partitions in the data may not be best described by uniformly shaped groups, a different type of clustering technique is needed.

The Gaussian mixture model addresses this problem by clustering based on a probabilistic mixture model derived from the gaussian distribution [36]. At each cluster, the model assigns a gaussian distribution in each dimension of the data, overcoming the limitation of simpler, distance-based methods by allowing non-uniform distributions among the clusters. To assign a new data point to a cluster, the model queries the location of the point in the $n$-dimensional space and assess the likelihood of belonging to any of the clusters based on the distributions of each cluster. While not as computationally fast as distance-based methods, this type of clustering is more flexible for a wider array of applications.
Another layer of flexibility is added by incorporating variational inference methods in the classification of data, such as in the Bayesian-Gaussian mixture model used for data analysis in this study. This model applies the Dirichlet initial condition allowing the model to determine the most appropriate number of clusters for a given data set before clustering [37]. Based on a set of randomly sampled points, a prior probability distribution of cluster centers is generated, allowing the model to probabilistically determine the number of clusters best describing the given set of data. Because the clustering technique used in this study is required only to identify bi-stable shifts in the pressure data, an upper limit of two potential data groupings is set as an upper limit. In the case where bi-stable wake patterns may be suppressed and a symmetric wake forms, the Dirichlet initial condition allows the model to detect a single cluster in the distribution of data points, preventing the separation of the data set into two clusters otherwise not statistically warranted.

### 3.3 Regression Models

Two types of regression model are used for the platooning data gathered in this research. Fundamentally, linear and logistic regression differ by the type of data they seek to model. Linear regression models a continuous output variable while logistic regression models a categorical output variable, typically with a binary state. The binary nature of a bi-stable wake makes logistic regression particularly well suited this application.
As a supervised learning method, training data is required to “build” the equations that form the model. This is typically done by using a subset of a complete data set and solving the linear equations in reverse to generate values of known coefficients in the models. Once this has been done, it is possible to apply the linear models to the entire data set and assess, quantitatively, their accuracy by comparing the predicted outputs to measured values. This provides the engineer a quantitative measure of the performance of the model and provides confidence in applying the models to sets of data where the outputs may be unknown.

3.3.1 Logistic Regression

Logistic regression is a linear function of input variable $x$ that describes the probability of a given binary output $Y$. To ensure the function $p(x)$ is linear, the logistic transformation of $\log(p(x))$ is performed, giving the form:

$$
\log \frac{p(x)}{1 - p(x)} = \beta_0 + x \cdot \beta
$$

Solving for $p$,

$$
p(x) = \frac{1}{1 + e^{-(\beta_0 + x \cdot \beta)}}
$$

Internally, the logistic model determines which binary label it assigns based on two “dueling” probabilities corresponding to the two possible outputs. Because the sum of the two probabilities must equal 1, the decision threshold can be thought to be 0.5. Whichever outcome is the most likely at a given moment is assigned for that
data point. An extension of this form, used in this analysis, is multivariate logistic regression where the linear function \( p(x) \) is solved for the input vector \( x \).

### 3.3.2 Linear Regression

Linear regression seeks to model a set of points \((X_i, Y_i)\) by a line of best fit of the form

\[
\hat{Y}_i = a + bX_i
\]

where \( \hat{Y}_i \) is a predicted, or “modeled,” output. The values of \( a \) and \( b \) in the function are found by minimizing the sum of squared errors in \( Y \). Thus, the quantity to be minimized is

\[
\sum_{i=1}^{n} (Y_i - a - bX_i)^2
\]

Due to the nature of the function, linear regression models are only capable of modeling continuous data. As with logistic regression, linear regression models can be extended to accommodate multivariate inputs. Linear regression provides a convenient output in the form of the \( R^2 \) value. Ultimately, \( R^2 \) is a ratio, always 0 to 1, of the variance in the predicted output over the variance of the original data,

\[
R^2 = \frac{\text{var} (\hat{Y})}{\text{var} (Y)}
\]

allowing the user to interpret the value as the variance in \( Y \) explained by the model of inputs \( X \).
3.4 The Data Analysis Pipeline

Raw pressure data for a given following distance is processed into its principal components. The coefficients of the three most important dimensions of the data are kept and clustered using a Bayesian-Gaussian mixture model. Based on cluster membership of the individual data points, labels corresponding to an instantaneous wake state, left or right mode, are assigned. The labels of the data are used to build and train both linear and logistic regression models. The outputs of the regression models provide a quantitative assessment of the level of correlation between the wake aerodynamics of the two models in the platoon. By using recognizable features identified in the PCA decomposition of wake pressure data as inputs, it is also possible to determine which wake features are most responsible for any observed correlations. This process is illustrated below in Figure 3.2.
Figure 3.2: Data analysis pipeline flowchart illustrated with data drawn from current study.
Chapter 4
RESULTS

Tests over a single Ahmed reference body were conducted at two locations using both models to establish independence and baseline values. Additionally, these single body results are validated against published data on bi-stability. The two locations tested are the lead position, unchanged throughout the testing campaign, and the position of the second model in the 1L following distance case.

4.1 Single-Body Results
Bi-stable shifting patterns in the raw static pressure measurements are seen in Figure 4.1, confirming the existence of two wake states for the models tested at both locations. Ports 6 and 10 are shown on the model. Power density functions of the measured pressure coefficient are shown for both models, clearly indicating the presence of a bi-modal, largely symmetric distribution of pressure data between two levels. What asymmetry is present in the pressure coefficient PDFs of both models is due to a preference towards one stable wake mode over the other. This preference may be due to imperceptible geometric asymmetries of the model or the alignment with the flow. Between the two positions, buoyancy effects are noticeable in a shift of approximately 0.04 $C_p$ in both the raw pressure data and the $C_p$ distribution plots.
Figure 4.1: Summary of single-body results. Model 1 raw pressure signal (a), PDF of filtered model 1 pressure signal (0.5s moving avg. window) (b), model 2 (by itself) at 1L following distance (c), PDF of filtered, model 2 pressure signal (d).

The temporal preference for one wake mode is shown in Figure 4.2 where the average 38.1% distribution of the initial wake state leads to a roughly 60-40 split between the two modes. Over 900s this split is shown never to reach the theoretical 50-50 distribution. Volpe et al. [7] conducted an in-depth study of this asymmetry using PIV and demonstrated that an observed preference of the wake for one mode may be caused by yaw angles of less than a degree but that the pressure
The topology of the wake is unaffected at these small yaw values. Even with extreme care aligning the models with the flow in the test section, slight asymmetries were observed in all tested cases. However, distributions provided in by Volpe et al. indicate that the models here are yawed less than ±0.5°. Additionally, the data analysis methods used for both the single model and platooning tests are robust to asymmetries, provided a statistically significant number of wake switches occur. Given the sample duration of the tests are on the order of $10^3$s and the average mode duration during single-body tests is 10s and during multi-body tests, around 3s, a statistically significant number of samples is reached.

![Figure 4.2: Time distribution of initial phase behind lead model.](image)
Single body results from the lead position and 1L following distances and values of average bi-stable shedding interval reported in literature are shown in Table 4.1. Raw pressure data from these tests was resampled at 1 Hz to match the reported results from both Grandemange et al. [5] and Volpe et al. [7].

**Table 4.1: Summary of single-body, bi-stability timescales.**

<table>
<thead>
<tr>
<th>Study (@ 1Hz)</th>
<th>Re$_H$</th>
<th>$t_{phase}$ (s)</th>
<th>$V_\infty/H$</th>
<th>$t_{phase}$ (s)</th>
<th>$V_\infty/H$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grandemange et al. (2013)</td>
<td>$9.2 \times 10^4$</td>
<td>5.3</td>
<td>1472</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volpe et al.</td>
<td>$5.1 \times 10^5$</td>
<td>11.82</td>
<td>1092</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Present Work</td>
<td>$2.0 \times 10^5$</td>
<td>13.42</td>
<td>1497</td>
<td>10.20</td>
<td>1108</td>
</tr>
</tbody>
</table>

Resampled data from the present work agrees well with the range of non-dimensional shedding period values established by other researchers. Model 2 installed at the 1L following distance absent the leading model shows a slight reduction in the average shedding period, though the mechanism for this difference cannot be readily understood from the current test set up. It is thought that there could be some impact from the growth of the boundary layer along the test section floor, but because boundary layer and/or $V_\infty$ measurements were not made at such a developed position, this cannot be confirmed. Additionally, while power density functions over a range of ground clearances were provided by Grandemange et al. [5] no temporal data was provided to suggest average wake shedding behavior was modified at clearances above the critical ground clearance value.
4.2 Platoon Results

Platoon testing was conducted in the same manner as single body testing and indicated significant, non-linear changes to bi-stable behavior at the tested following distances. Repeatability data was taken for the most important following distances. At each position, dependence on model order within the platoon was checked by switching the position of the models.

Results of the multi-body tests are summarized in Table 4.2. It is observed that the average bi-stable shedding period of the single model case is significantly modified at every following distance tested, with the largest differences seen at the closest following distances.

Table 4.2: Summary of multi-body, bi-stability timescales.

<table>
<thead>
<tr>
<th>Study (@ 1Hz)</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ReH</td>
<td>$t_{phase}$ (s)</td>
</tr>
<tr>
<td>Grandemange et al. (2013)</td>
<td>$9.2 \times 10^4$</td>
<td>5.3</td>
</tr>
<tr>
<td>Volpe et al.</td>
<td>$5.1 \times 10^5$</td>
<td>11.82</td>
</tr>
<tr>
<td>Present Work</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single Body</td>
<td></td>
<td></td>
</tr>
<tr>
<td>@ 1.00L</td>
<td></td>
<td></td>
</tr>
<tr>
<td>@ 0.50L</td>
<td></td>
<td></td>
</tr>
<tr>
<td>@ 0.25L (symmetric)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>@ 0.25L</td>
<td></td>
<td></td>
</tr>
<tr>
<td>@ 0.05L</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 4.3 summarizes the multi-body platoon testing in the form of raw pressure signals and the associated PDFs of the test case at ports 6 and 10 on each
model. At a following distance of 0.25L, a highly sensitive, lead model wake exhibits either suppressed or amplified bi-stable wake patterns depending on the model order. This behavior was confirmed in repeatability data and is discussed in greater detail in following sections. At the 0.05L following distance, the bi-stable wake behavior of the lead model is suppressed while the following model continues to show switching between two stable wake modes, indicated by the two peaks in pressure signal at the levels seen behind the following model in all other platoon tests.

In all cases where bi-stable, shifting patterns are observed in the wake of the lead model, the wake of the following model shows an opposite mirroring of this behavior. This suggests that the wake of the lead model might condition the flow over the following model, impacting the wake of the following model in predictable ways. Literature points to the importance of oncoming flow symmetry for bi-stable wakes to exist. The results presented here indicate asymmetries in the oncoming flow may force selection of a stable wake mode behind a downstream bluff body. It is also seen that average pressure coefficients measured over the rear of the lead model increase with decreasing following distance. This is a well-documented trend supported by many studies that attribute the reduction in dynamic pressure in front of following vehicle and the rise in base pressure behind lead vehicle to the measurable drag reduction over the entire platoon.
Figure 4.3: Summary of multi-body results. 1L (a), 0.5L (b), 0.25L “symmetric” (c), 0.25L “bi-stable” (d), and 0.05L (e) following distances.
The magnitude of pressure fluctuations in the wake of the individual platoon models is shown in Figure 4.4. The average $C_p$ value over the left side of the models (left eight pressure ports on the rear face) was conditionally averaged based on the two stable modes observed in the wake. The difference between the averages and the associated standard deviation for both models in the platoon is shown in Figure 4.4. A near linear trend is observed in the lead model average fluctuation data while fluctuations in the wake of the following model do not appear affected by following distance. However, the results of this study point to a critical region of sensitivity in the wake behind the lead model at a following distance of 0.25L.
Figure 4.4: Magnitude and standard deviation of average shift in $C_p$ between left and right wake modes. Lead/follow model trends shown by dotted lines.
4.2.1 Repeatability

Repeatability tests were conducted at following distances 0.5L and 0.25L, selected based on the significance of the findings at these locations. The 0.25L following distance was of particular interest as two different wake interactions were measured and the amplitude of fluctuations on the lead model differed significantly from other following distances considered. All models were removed and reinstalled in the test section between repeatability tests. Table 4.3 provides a summary of timescale data and conditionally averaged $C_p$ values at ports 6 and 10 for each model and following distance. Pressure fluctuations between modes are shown to be highly repeatable. Timescales of bi-stable switching measured in the 0.5L and 0.25L symmetric tests show slightly more sensitivity. The timescales of switching during the 0.25L bi-stable tests in particular appear to be more variable than the other following distances tested. This may be the result of a strong gradient or sensitivity in the wake behind the lead vehicle as evidenced by the two significantly different flow patterns observed at the 0.25L following distance.

Table 4.3: Timescale repeatability data at selected following distances.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$Re_H$</td>
<td>$t_{phase}$ (s)</td>
</tr>
<tr>
<td><strong>Platooning</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>@ 0.50L</td>
<td>$2.0 \times 10^5$</td>
<td>2.57</td>
</tr>
<tr>
<td>Repeat</td>
<td>3.06</td>
<td>328</td>
</tr>
<tr>
<td>@ 0.25L (sym.)</td>
<td>$2.0 \times 10^5$</td>
<td>2.06</td>
</tr>
<tr>
<td>Repeat</td>
<td>1.99</td>
<td>223</td>
</tr>
<tr>
<td>@ 0.25L</td>
<td>$2.0 \times 10^5$</td>
<td>15.00</td>
</tr>
<tr>
<td>Repeat</td>
<td>9.70</td>
<td>1056</td>
</tr>
</tbody>
</table>
4.2.2 Visualization

Smoke visualization was performed to confirm the wake structures inferred from pressure data in the two 0.25L following distance cases. A Sony Alpha A7R II camera was positioned on top of the test section and directed through a circular cutout made in the ceiling panel above the wake of the lead model. A continuous green laser was positioned beside the test section and the beam was split into a horizontal plane at \( z = 0.5H \) on the rear face of the Ahmed models. Still images were taken at 42MP resolution and HD video at 60FPS. A “control” visualization of the wake behind a single model in the lead position was also tested and compared with the platooning results. The images were converted into digital coordinate systems based on the known dimensions of the Ahmed models and the wake features measured in that reference frame. It should be noted that the values reported only reflect the measurements made on images where the most clearly defined wake regions could be identified and as such do not represent a time averaged value. A more complete study of this sensitive wake region would need to be made using PIV or another optical technique to obtain a time averaged value.

Figure 4.5 shows the right, bi-stable mode of the single Ahmed model installed in the lead position. An outline of the wake feature is provided in the same figure as a reference for how the longest axial length of the wake was measured. Figure 4.6 shows the three different wake cases for the 0.25L platooning tests.
Figure 4.5: Single-body, right wake mode (left), annotated (right).

Figure 4.6: Left mode (a), right mode (b), and “symmetric” wake (c) at 0.25L following distance.

The axial length of the bi-stable mode for the single model case is measured to be roughly 275mm, or 0.45L. One possible explanation for the amplified pressure fluctuations seen at the 0.25L following distance is that nose of the following model “splits” the two vertical shear layers forming off the sides of the lead model, effectively holding them apart, rather than allowing the wake to develop normally as may be the case for larger following distances. This behavior is shown best in in
Figure 4.6 (a) where the left vertical shear layer of the lead model is shown to impinge on the outer leading radius of the following Ahmed model. Amplified, lateral pressure fluctuations measured on the rear face of the lead model may then be due to a wider wake. How the radius of the leading surface of the following model impacts this wake interaction is not understood from this study. It is also possible that these larger differences in pressure between stable wake modes require larger upstream disturbances or fluctuations to upset the current modal selection, causing wake switches to occur over a noticeably longer average period.

The 0.5L following distance pressure data does not show a magnification in peak pressure fluctuation between modes from the single model data. This finding would make sense if the following model in the platoon impacts the pressure fluctuations in the wake of the lead model only through interacting at a distance closer than the maximum axial length of the recirculation region. At a following distance of 0.05L, it is more likely that the distance between the two models is so short that shifting simply cannot occur, and the flow, instead of forming a typical wake, is directed down the sides of the second model in the platoon. The entire platoon at this following distance could be thought of as a single body. Given that bi-stable behavior was still observed in the wake of the second model at a following distance of 0.05L, this is a reasonable hypothesis. However, more testing is required to fill in the gaps of understanding between the length of the bi-stable wake features and the role of shear layers on wake formation between vehicles in a platoon. It is reinforcing that PATH researchers appear to have found similarly non-linear behavior at following distances near the range of 0.25L as shown in Figure 1.3.
Models borrowed from the data science field are used to separate and classify the raw data. This is particularly useful as the selected models are able to mathematically identify patterns within multi-dimensional data sets and process incredibly large volumes of data more quickly through dimensionality reduction. As will be shown later in this section, the models are also able to identify correlations between vehicles within the platoon and exploit these correlations to successfully predict wake aerodynamics with limited input data. This begins to lay the groundwork for efficient real-time, on-road sensing in platoons with reduced instrumentation needs.

First, the pressure data is dimensionally reduced using PCA and then classified using a Bayesian-Gaussian mixture model. The first step is intended to identify the primary features of the data and reduce the quantity of data sorted by the clustering model, important for decreasing computational time in an active aerodynamics environment. It is found that left-right, bi-stable shifts of the wake are successfully identified as primary wake features in the pressure data during the dimensionality reduction process. Pairing known wake features of the Ahmed model to identified principal dimensions in the wake allows regression models to capture and correlate otherwise complex features in aerodynamic data with relatively few dimensions. Using the feature information extracted by PCA, clustered data is labeled and sorted. What results is a data analysis pipeline that is shown capable of
correctly labelling and sorting aerodynamic data. This sorting based on features, rather than pressure values, is the distinguishing outcome of this method and is done without manual selection or threshold setting by the engineer.

5.1 Filtering the Data

All classification and regression models that follow in this section were built on data that was filtered with a 0.5s, symmetric, moving average window. This window was found to significantly reduce noise in the pressure signal while maintaining the bi-stable shifting behavior characteristic of the Ahmed body wake. Applying a moving average window increases the ability of the PCA/clustering pipeline to separate the data based on the bi-stable behavior of the wake. Figure 5.1 (d) shows more distinct and separate peaks in the filtered PDF decomposition while Figure 5.3 shows the actual output of the clustering algorithm where it is possible to see the clusters are more defined, leading to greater certainty in the final classification.
However, it is important to ensure this type of filtering does not obscure the meaning of the original data. If too large a window is used in the averaging filter, bistable shifts over a period shorter than the window may be smoothed to the point of being unidentifiable. An example of over-smooth data, generated using a window of 2.5s, is shown in Figure 5.2. It would appear within the circled segment of time there is a third, stable pressure level and no “switch” of wake mode occurred. Using the
raw data as a comparison, this is shown to misrepresent the actual wake behavior, leading to potentially inaccurate conclusions.

![Figure 5.2: Pressure signal of a single model in the lead position with a 2.5s moving average window, showing effects of over-filtering.](image)

As described in the derivation of the principal components, variation is the quantity maximized in each new component. Filtering the raw pressure data and reducing noise in the signal increases the relative proportion of variation in the input data due to bi-stable shifts of the wake. In the case presented here, the moving average window filters both random noise and removes smaller fluctuations in the pressure signal that do not directly correspond to the bi-stable switching of the wake. In Figure 5.3 this is seen in both the reduction in scatter among the data points after clustering and the decrease in explained variance of the second and
third principal components, corresponding to physically coherent characteristics of the wake. As the mixture models used in this study to classify the data consider the distribution of data in forming and adjusting the cluster boundaries, an increase in model certainty through increased separation of cluster centers and a reduction in the scatter within clusters is achieved. Figure 5.3 shows the difference between the clusters generated with the filtered and unfiltered data. The vector of coefficients and their associated explained variance of the input data are provided for the first three principal components, arranged to match the physical layout of the 16 pressure ports on the rear of the model to which they correspond.

Figure 5.3: Raw (a) and filtered (b) pressure vector of coefficients (left) clustered in component space (right).
A physical interpretation of the vector of coefficients is possible since each coefficient within the vector applies to a known pressure port location. The vector of coefficients corresponding to the first principal component shows the model’s detection of the bi-stable behavior of the wake as the main contributor to variation in the pressure signals. The second vector of coefficients shows a central, static pressure fluctuation uncorrelated with the bi-stable behavior. The third vector of coefficients identifies a general top-bottom asymmetry with a noticeable wishbone pattern formed by the lower corners and upper-center of the rear face. Figure 5.4 indicates that the largest distinction between the two identified clusters is along the $X_1$ axis. In fact, if only $X_2$ and $X_3$ are used to differentiate between the two clusters, shown in Figure 5.4 (b), there is virtually no difference between the two clusters. In fact, a valid interpretation of Figure 5.4 (b), is that fluctuations of the central pressure bubble and top-bottom distribution are independent of the bi-stable shifting of the wake. Considering the principal component decomposition ensures uncorrelated variation among modes, this is perhaps an obvious conclusion.
This highlights one of the difficulties of this approach in physically interpreting all but the most important principal dimensions of the data. Wake features with weak physical correlations may not be clearly identified by separate dimensions and instead become “blurred” into aspects of two or more principal dimensions to which they are all weakly correlated. Conversely, wake features with strong physical correlations may be grouped together into a single principal dimension, making it difficult to identify the separate wake features without prior knowledge of the wake physics. However, despite these limitations, Figure 5.5 demonstrates that the unsupervised PCA/clustering pipeline conforms closely to expectations by classifying the discrete data points based on bi-stable shifts in the wake. It is relevant to emphasize that no previous knowledge of the wake physics or expected thresholds were set before the labelling of aerodynamic data was
completed. The PCA/clustering pipeline reflects an unsupervised classification of aerodynamic data based on intrinsic patterns and variation in the input data. In the case of separating data based on bi-stable modes, the models used here are shown to be highly successful.

Figure 5.5: Filtered pressure signal port 10 (a), output of PCA/clustering pipeline represented in the physical domain demonstrating selection along expectations of bi-stable wake behavior.

5.2 Platoon Study
The vector of coefficients, corresponding to the first three principal components for each model in the platoon, are presented in Figure 5.6. A 0.5s moving average window is again used to filter the raw pressure data. The explained variance is documented above each vector of coefficients and is included mainly as a reference for the reader indicating the relative “importance” of each dimension. It is noted that the first three dimensions do not account for a consistent level of explained variance among the retained dimensions of the data. Instead this is allowed to vary among
the following distances and models to simplify the analysis. This is considered appropriate as the current study attempts to classify the data based on bi-stable wake behavior, identified in the first principal dimension of the data. In cases where bi-stability is not identified in the first principal dimension, it is found that the phenomenon is not present, as in the 0.05L following distance case.
Figure 5.6: PCA coefficient vectors: 1L lead model (a), 1L following model (b), 0.5L lead model (c), 0.5L following model (d), 0.25L bi-stable lead model (e), 0.25L bi-stable following model (f), 0.25L symmetric lead model (g), 0.25L symmetric following model (h), 0.05L lead model (i), and 0.05L following model (j).
At a following distance of 1L, the three primary wake features identified by PCA in the wake of the lead model are nearly identical to those identified in the wake behind the single model (Figure 5.3 (b)). The bi-stable switching of the wake is identified in the first dimension and a central pressure rise, possibly related to the roughly central meeting between the two, asymmetric recirculation regions in the wake of the Ahmed body, is captured in the second. The third mode shows a strong similarity to the wishbone shaped distribution of the third principal dimension identified by the PCA algorithm in the wake of the single model. As expected from the raw pressure data gathered for the following model at 1L following distance, PCA identifies the bi-stable characteristic in the wake as the first principal dimension. However, in this case (Figure 5.6Figure 5.3 (b)), the second and third principal dimensions differ from those of the lead model.

The dimensions identified in the wakes of the 0.5L following distance platoon (Figure 5.6 (c,d)) show a unique similarity between lead and following models. Additionally, at following distances of 0.5L and closer, the central pressure bubble is no longer identified in the wake of the lead model, though it is identified in the wake of the following model. Instead, either the wishbone or an asymmetric, top-bottom distribution make up the second and third principal dimensions. This is likely due to some influence of the following model on the formation of the wake behind the lead model.

In the “symmetric” 0.25L following distance case (Figure 5.6 (g,h)), it is possible to see that there is still a prevailing bi-stable pattern towards the top and outer edges of the rear face of the Ahmed model. What this suggests is that portions
of the wake behind the lead model may be experiencing stronger inter-model interaction than at larger following distances, leading to uneven suppression of a bi-stable wake. This observation of uneven, bi-stable suppression supports the observed sensitivity of the lead model wake in the 0.25L following distance configuration. It shows that in both the “bi-stable” and “symmetric” cases, bi-modal characteristics are present and hints at a similarity between the wakes that may only be upset through minute differences in model alignment or construction.

The 0.05L following distance case (Figure 5.6 (I,j)) shows complete suppression of any bi-stable behavior in the wake of the lead model while the principal dimensions in the wake of the following model show a strong likeness to the single body case.

The principal dimensions in the wake of the following model at all following distances shows a similarity between the 1L and 0.5L cases and the 0.25L and 0.05L cases though it is not possible to say why this may be the case from the PCA analysis alone.

5.3 Correlative and Prediction Models

Regression models were built using the labeled pressure data and wake features identified by the PCA/clustering pipeline. Two types of regression model, linear and logistic, were built and assessed in this analysis. A more complete discussion regarding the differences between the two regression models is found in Section 4.3.

Input data for the regression models is drawn from raw pressure data or a combination of principal components identified in the wake of the lead model. The
outputs from the regression models are pressures or principal components of the following model. The used of regression techniques allows a more quantitative analysis of the level of correlation between the wake aerodynamics of the individual models in the platoon.

5.3.1 Logistic Regression

Two types of input data are used for the logistic models. The first model used raw pressure data from the entire rear face of the lead model while the second used combinations of the principal components from the wake of the lead model. The wake mode (left or right) of the following model is the output in both cases. The first 500s, or 5000 discrete data points, of each test were used to train the models.

The internal “decision” process of the logistic regression model is illustrated for a segment of the 0.25L “bi-stable” test in Figure 5.7. “True” labels are assigned to the following model by the PCA/clustering pipeline when only data from the following model is considered. “Predicted” labels are the output of the regression model that used the 16 pressure signals of the lead model as input data to predict the wake state of the following model. A shift of 0.6s between the input and output data resulted in the highest model accuracy, suggesting there may be a delay in communication between the two wakes. At a test velocity of ≈18 m/s, flow around the outside of the model takes 0.04s to travel from the rear face of the lead model to the rear face of the following model at a following distance of 0.25L. Therefore, it is likely another mechanism is at least partially responsible for the observed correlation between the wakes of the two platooning models. The overall accuracy
of the model is reported with the data. A value of 98.8% is remarkably high, leading to the conclusion that the pressure distribution in the wake of the first model is highly correlated with the wake of the second model.

Figure 5.7: Logistic Regression decision process for binary classification of second model wake mode based on raw pressures from model 1 (ports 1-16).

A summary of the results of the logistic regression models is provided in Table 5.1. Models are listed according to following distance and the type of input
data used. The overall accuracy of the model is listed as well as the physical time of
the shift used to achieve the highest model score.

5.3.2 Linear regression
Because linear regression models predict continuous values, it is not possible to
simply predict the wake state as in logistic regression. Instead, a linear regression
model is built to predict the first principal component value of the following model.
This first principal component most directly corresponds to the bi-stable wake
behavior as shown in Section 6.2. The reported $R^2$ value allows the user to directly
interpret the amount of variation in the output variable accounted for by the input
variables. However, compared to the accuracy score of a logistic regression model,
the $R^2$ value is a harsher metric to judge the success of the model since a linear
regression model encodes more information about continuous levels of the output
whereas a logistic regression model which chooses between two binary states.

The 0.25L “bi-stable” test is again used to show the performance of the linear
regression model in Figure 5.8. The inputs to the model are the 16 pressure signals
of the lead model rear face and the output variable is the first principal component
($X_1$) in the wake of the following model. Based on the $R^2$ value, pressure fluctuations
in the wake of the lead model account for over 90% of the variation in bi-stable
behavior observed in the wake of the following vehicle. Given the complexity and
dynamic nature of the flow field in the wake of any bluff body, it can be said with
certainty that a strong correlation between the wake dynamics of the lead and
following models in a platoon exists and is dominated by bi-stable, modal selection in the wake of the lead vehicle.

Figure 5.8: Predicted versus measured $X_1$ value in the wake of the following model.

The results of all linear regression models and the associated $R^2$ scores is provided in Table 5.1. At a following distance of 0.05L, regression models do not provide a meaningful output as a result of the symmetric wake behind the lead model. Therefore, these results are excluded from the summary.
Table 5.1: Summary of regression methods predictive capability at all following distances.

<table>
<thead>
<tr>
<th>Input Data</th>
<th>Logistic Regression (C_{P,1-16})</th>
<th>Logistic Regression (% correct)</th>
<th>Linear Regression (R^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Platooning</td>
<td>C_{P,1-16}</td>
<td>X_1</td>
<td>X_1, X_2, X_3</td>
</tr>
<tr>
<td>@ 1.00L (shift 0.6s)</td>
<td>93.1</td>
<td>93.1</td>
<td>93.1</td>
</tr>
<tr>
<td>@ 0.50L (shift 0.2s)</td>
<td>88.7</td>
<td>88.7</td>
<td>88.7</td>
</tr>
<tr>
<td>@ 0.25L (shift 0.2s)</td>
<td>98.8</td>
<td>98.8</td>
<td>98.8</td>
</tr>
<tr>
<td>@ 0.25L symm. (shift 0.3s)</td>
<td>64.3</td>
<td>64.2</td>
<td>64.2</td>
</tr>
<tr>
<td>@ 0.05L</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
</tbody>
</table>

In cases where a bi-stable wake is present behind the lead vehicle, the models are successful in predicting the wake behavior of the following model and indicate a strong correlation between the wakes of the lead and following models. The following distance 0.5L appears to perform more poorly than the bi-stable following distances of 1L and 0.25L. Indeed, the “bi-stable” 0.25L following distance case shows the best overall model performance. However, this is likely the result of the strength of pressure fluctuations dominating the wake of the lead model of the platoon in that configuration. Excepting the “bi-stable” 0.25L following distance case, it would appear decreasing following distance negatively impacts the predictive capability of the regression models. This trend aligns well with the linear trend identified in Figure 4.4 relating the decreasing magnitude of bi-stable pressure fluctuations in the wake of the lead model with decreasing following distance. It appears the strength of bi-stable pressure fluctuations in the wake of the lead model are the strongest indicator of regression model success. These results
also point to bi-stability as one of the most important aerodynamic features in a steady-state platoon of bluff bodies.
Wind tunnel tests of square-back Ahmed models in two-vehicle platoons show bi-stable wake patterns in the wake of the lead vehicle directly impact the bi-stable wake modal selection of the following vehicle. Pressure measurements indicate this interaction leads to opposite and asymmetric forces and moments on each model similar to the alternating pattern of opposing forces and moments researchers have identified in misaligned platoons. It is therefore crucially important to understand this aerodynamic interaction and ensure flow regimes and dynamic excitations or frequencies in a platoon do not reinforce each other in an on-road environment.

A critical region of sensitivity between the two models at the following distance 0.25L has been identified. At this following distance, an amplification of the bi-stable shifting pattern in the wake of the lead vehicle was measured. An explanation of this behavior was offered as the result of interaction between the vertical shear layers of the lead model and the nose geometry of the following model. A more thorough examination of this interaction is necessary to causally confirm this hypothesis. Additionally, it is likely that a region of increased wake sensitivity may extend to other following distances around 0.25L as the current study was not exhaustive of all possible following distances.

A linear reduction in amplitude of pressure fluctuations between averaged wake modes was observed in the wake of the leading platoon model. The wake of
the following model appears unaffected by the magnitude of upstream fluctuations. This was highlighted in the 0.25L following distance case where the exceptionally different strength of pressure fluctuations in the wake of the lead model showed little influence on the fluctuations observed in the wake of the following model.

It has been shown that algorithmic, variance maximizing methods to separate multi-dimensional pressure fields are capable of detecting bi-stable wake behavior and can be used with success to classify aerodynamic data. Additionally, predictive regression models are capable of using a single input from the wake of the lead vehicle to successfully predict the bi-stable aerodynamic characteristics of following vehicles in a platoon. This promotes confidence that sparse sensing methods are in fact possible in platoons of vehicles.

A slight temporal delay between input and output data sets improved regression model predictive success, indicating a lag between bi-stable modal shifts in the wake of the lead vehicle and the corresponding response in the wake of the following vehicle. This lag was found to be longer than the expected time for flow to travel around the outside of the models. A potential explanation for this points to flow from inside the wake of the lead model as the mechanism by which the disturbance is propagated. However, a more thorough study of this effect is needed to conclude with any certainty.

Finally, platoons of more than two vehicles need to be studied to understand the extent to which lead vehicle wake selection impacts the wake dynamics over longer convoys of vehicles. Force and moment measurements on each vehicle in the platoon would provide a more complete understanding of how the magnitude of
body forces and moments may be modified from single-body tests and if they differ for individual vehicles within the platoon.
REFERENCES

1. U.S. Federal Highway Administration, “Highway Statistics - Annual Vehicle Distance Traveled in Miles and Related Data.”


