

Drag acting on articulated cylinders in pedalling motion : An experimental study towards data-driven modelling

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Université de Liège - Faculté des sciences appliquées

Drag acting on articulated cylinders in pedalling motion : An experimental study towards data-driven modelling

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Thesis presented to obtain the degree of : Master of Science in Aerospace Engineering

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Abstract

In professional cycling, aerodynamic drag represents the dominant source of power loss. As margins between athletes continue to narrow, an accurate characterisation of the aerodynamic forces acting on a pedalling cyclist becomes increasingly relevant for performance optimisation. Yet the continuous motion of the legs generates complex unsteady flow structures that remain only partially understood, motivating the present study.

This thesis investigates the aerodynamic drag acting on articulated cylinders undergoing a pedalling-like motion, as a simplified representation of a cyclist's lower limb. Experiments are conducted in the wind tunnel of the University of Liège, where two circular cylinders mounted on a collaborative robot (UR5e) replicate the kinematics of the thigh and calf segments over a full crank cycle. A total of 110 configurations are tested, spanning a range of Reynolds numbers, reduced frequencies, motion amplitudes and yaw angles. Static measurements first characterise the pressure distribution and drag coefficient of the inclined cylinders, examining the validity of the Independence Principle. The results show that the cosine law holds for the lower (thigh) cylinder but breaks down for the upper (calf) cylinder due to three-dimensional end effects. Dynamic measurements then reveal that the instantaneous drag coefficient cannot be fully described by quasi-steady assumptions alone. A phase shift toward lower crank angles is observed as the reduced frequency increases, interpreted as a memory effect of the unsteady wake. Non-uniform cadence profiles are found to reduce the amplitude of drag fluctuations over a crank cycle, suggesting a potential aerodynamic benefit in long-duration efforts.

Two modelling approaches are evaluated. A quasi-steady moving-leg model captures the global drag behaviour with reasonable accuracy, but overestimates its amplitude at higher reduced frequencies. A two-stage data-driven model, combining an in-cycle Ridge regression with an out-of-cycle Gaussian Process regression, is developed and trained on the experimental dataset. While the framework captures the qualitative trend of the drag coefficient, its predictive performance remains limited by the high inter-dependency of the flow parameters and the relatively small size of the dataset.

This work establishes an experimental and modelling foundation toward the development of reduced-order aerodynamic models for pedalling cyclists, with potential applications in performance analysis and digital twinning of athletes.

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Contents

1	Introduction	1
1.1	Context	1
1.2	State of the art	3
1.2.1	Cycling fluid dynamics	3
1.2.2	Flow around cylinders	4
1.2.3	Flow around cyclists	7
1.3	Objectives	9
2	Experimental set-up and procedure	11
2.1	Set-up	11
2.2	Conventions	13
2.3	Kinematics	14
2.3.1	Inverse kinematics principle and application to the pedalling motion . .	14
2.3.2	Comparison of numerical and analytical results	16
2.3.3	Robot motion with the "freed" ankle	18
2.3.4	Different cadence profiles	19
2.4	Measurements procedure	21
2.4.1	Move/Control the robot	21
2.4.2	Harvest and synchronize data	21
2.5	Parameters space and limitations	23
3	Experimental results	26
3.1	Static cylinders	27
3.1.1	Investigation of Reynolds effect	27
3.1.2	Inclined cylinders	28
3.1.3	Validity of the cosine law	30
3.1.4	Frequency content	33
3.2	Dynamic cylinders	34
3.2.1	Cadence effects	34
3.2.2	Pressure distribution	38
3.2.3	Non-uniform cadence profiles	41
3.2.4	Influence of motion amplitude and yaw angle	42
3.3	Statistical observability	43
3.3.1	Mean drag coefficient in the parameter space	43
3.3.2	Inter- and intra-cycle variability	44
4	Modelling	46
4.1	Quasi-steady moving leg model	46
4.1.1	Moving leg model results	47
4.1.2	Parametric study	49
4.2	Data-driven model	51

4.2.1	Choice of features	53
4.2.2	Discussion	55
4.2.3	Conclusion	57
5	Conclusion	59
5.1	Conclusion	59
5.2	Further work	60
5.2.1	Improved aerodynamic models of the pedalling leg	60
5.2.2	Towards digital twinning of cyclist	61
A	Wind tunnel facility, University of Liège	63
B	List of parameters of dynamic configurations	64

List of Figures

1.1	Ranking and stage profile of the Mountain Individual Time Trial of stage 13 during the Tour de France 2025.	2
1.2	Reference frames definition with forces in relative wind axes (red) and forces and moments in body axes. Wind direction and relative velocities are also defined.	3
1.3	Illustration of the flow around a circular cylinder in the main sub-regimes : (a) Creeping flow, (b) Closed near-wake, (c) Periodic laminar, (d) Transition in wake, (e) Transition in shear layer, (f) Transition in boundary layer, (g) Fully turbulent.	5
1.4	Fluid forces coefficient variation with respect to Reynolds for disturbance-free flows, reproduced from Zdravkovich, 1998 [5]	6
1.5	Contour plot of the streamwise velocity component in the wake of a static cyclist mannequin, from Crouch et al., 2014 [22].	8
1.6	Flow topology visualization by streamwise vorticity around a full-scale mannequin, from Jux et al., 2018 [25].	9
2.1	3D representation of the supports mounted on the robot.	11
2.2	Pictures of the set-up (robot and cobra probe) mounted in TS 2 of the wind tunnel.	12
2.3	Definition of the angles relevant to the kinematics of a pedalling leg.	13
2.4	Simple schematic of the two-degrees-of-freedom robot arm	17
2.5	Comparison of the IK 2 dofs algorithm results with the analytical solution.	18
2.6	Comparison of the joint angles resulting from the IK algorithm for 2 or 3 degrees of freedom.	19
2.7	Comparison of the joint angular velocities resulting from the IK algorithm for 2 or 3 degrees of freedom.	19
2.8	Different cadence profiles considered, at mean cadence of 60 RPM (Variations in Ettema profile are exaggerated to highlight them).	20
2.9	Hip (left) and knee (right) joint angular velocities relative to each cadence profile, with average cadence of 60 RPM.	20
2.10	Pressure signals at stagnation point of both cylinders and airspeed measured at heights corresponding to the mid-span height of each cylinder. Free-stream conditions are stabilised at $V_\infty = 9.45$ m/s.	21
2.11	Filtered pressure signals of first four taps on each cylinder (top: upper cylinder, bottom: lower cylinder) with triggering index shown with red point.	23
2.12	Full parameter space of the configurations tests in the wind tunnel.	24
2.13	Typical reduced frequencies of various men's and women's cycling events, reproduced from [3], with configurations tested in the wind tunnel in blue points.	25
3.1	Static configurations with independently inclined cylinders, air flow comes from the right side.	26

3.2	Pressure distribution around both circular cylinders ($H/D = 2.55$, top : upper/calf cylinder, bottom : lower/thigh cylinder) in vertical position. Measurements performed at mid-span, for three different Reynolds numbers, shown as time-averages with standard deviation and compared with pressure distribution from Achenbach, 1968 [33].	28
3.3	Drag and side force coefficients on both cylinders with respect to inclined angle. Configuration : ϕ_l fixed at 0° and ϕ_u varying from 0 to 60° , $Re = 7 \times 10^4$	29
3.4	Drag and side force coefficients on both cylinders with respect to inclined angle. Configuration : ϕ_l varying from 0 to 60° and ϕ_u fixed at 0° , $Re = 7 \times 10^4$	29
3.5	Drag coefficient with respect to inclined angle ($\bullet$) and expected behaviour from cosine law (- - -) : (a) C_D of calf/upper cylinder for various Reynolds numbers, (b) C_D of thigh/lower cylinder at a single Reynolds	30
3.6	Pressure field around upper/calf cylinder inclined at ϕ_u varying from 10 to 60° while the lower/thigh cylinder remains vertical, $Re = 7 \times 10^4$	31
3.7	Pressure field around lower/thigh cylinder inclined at ϕ_l varying from 10 to 60° while the upper/calf cylinder remains vertical, $Re = 7 \times 10^4$	32
3.8	PSD of the pressure signals at the lateral taps of the upper/calf cylinder	33
3.9	Streamwise component of translational velocity at each cylinder's mid-span due to their rotation in the pedalling motion. Results for 60 RPM motion with 0.11 m amplitude.	34
3.10	Raw force signal from Omega force balance and filtered signal at the corresponding shedding frequency.	35
3.11	Drag coefficient variations over a crank cycle for various reduced frequencies at Reynolds of 4×10^4 , from phase-averaged force balance measurements.	36
3.12	Drag coefficient variations over a crank cycle for a given reduced frequency at different Reynolds, from phase-averaged force balance measurements.	36
3.13	Longitudinal force coefficient variations over a crank cycle for various reduced frequency at Reynolds of 4.5×10^4 , from integrated phase-averaged pressure measurements.	37
3.14	Mean drag coefficient over a full crank cycle with respect to the reduced frequency, from force balance measurements.	38
3.15	Pressure field around both cylinders from dynamic and static configurations relative to a 0° crank angle.	39
3.16	Pressure field around both cylinders from dynamic and static configurations relative to a 100° crank angle.	40
3.17	Pressure field around both cylinders from dynamic and static configurations relative to a 205° crank angle.	40
3.18	Pressure field around both cylinders from dynamic and static configurations relative to a 310° crank angle.	41
3.19	Comparison of drag coefficient over a crank cycle for different cadence profiles at the same mean cadence for two Reynolds number.	42
3.20	Comparison of the mean value and standard deviation in aerodynamic power loss over a crank cycle for the different cadence profile at the same reduced frequency.	42
3.22	Mean drag coefficient versus the flow and motion parameters.	44
3.23	Assessment of the inter- and intra-sample variability at a given configuration.	45
4.1	Illustration of moving leg force model variables. M is the offset distance at the hip, L the thigh/lower cylinder length and S the calf/upper cylinder length. . . .	47
4.2	Drag area predicted by the quasi-steady model for static positions ($k = 0.0$) at intermediate Re (6.9×10^4) compared with experimental data measured.	48

4.3	Comparison of Crouch model prediction with the force balance measurements on dynamic configurations : uniform cadence, same amplitude ($R = 0.11$ m). .	49
4.4	Sensitivity study of the moving leg quasi steady model on the geometry of the leg.	50
4.5	Sensitivity study of the moving leg quasi steady model on the aspect ratio and end conditions corrector for initial C_D	50
4.6	Machine Learning framework for drag prediction of 2 dofs moving-leg.	52
4.7	Example of representation of the non-linear features used in the in-cycle Ridge regression, from one sample in the training dataset.	54
4.8	Predicted C_D of one validation sample compared with true value, from all three variations of the model.	56
4.9	Features weights distribution and relationships with OOC parameters obtained after <i>per condition</i> training of the IC Ridge regression.	57
5.1	General structure of the digital twinning of a cyclist.	62

Chapter 1

Introduction

1.1 Context

Over the last decades, professional cycling has evolved into a highly optimized sport where performance gains are sought in every aspect of the rider–bicycle system. Advances in training methodologies, nutrition, equipment design and biomechanical optimization have progressively reduced the margin separating the best athletes. As a consequence, aerodynamic performance has become one of the primary determinants of success, particularly in time trials and high-speed racing scenarios. While substantial efforts have been devoted to improving the aerodynamics of bicycles, helmets, clothing and rider posture, accurately characterizing the aerodynamic behaviour of a cyclist remains a challenging task. The cyclist is not a static body: the continuous pedalling motion induces complex unsteady flow structures, especially around the legs, which are among the largest moving components exposed to the airflow. Understanding how these moving limbs contribute to aerodynamic drag is therefore an important step toward developing more accurate predictive models of cycling performance.

Drag is the most relevant cause of power consumption in cycling and drag reduction has become one of the main topic of research and innovation. In pro cycling, the emergence of "*marginal gains*" illustrates that even very small improvements in the aerodynamic or mechanical efficiency can turn out to be very important. Although aerodynamic effects are generally associated with flat roads and high-speed racing, they remain relevant in climbing conditions. Recent performances in professional cycling illustrate that riders now reach increasingly high speeds even on uphill time trials. The Mountain Individual Time Trial of Stage 13 of the 2025 Tour de France provides a representative example. This stage was 10.9 km long and featured 645 m of net elevation gain. In order to put in perspective the relevance of aerodynamic gains in this kind of scenario. Figure 1.1 shows the gap in time of the first 12 riders in the stage ranking and their estimated power-to-weights ratios¹. Oscar Onley (7th) is the rider of interest here, as he came close to a podium place in the overall ranking. An estimated power has been computed based on a rolling resistance coefficient C_r of 0.0031, a drag area $C_D A$ of 0.2689 m² for all riders² and following the model described in Meyer et al., 2016 [1] :

$$P = P_{\text{slope}} + P_{\text{roll}} + P_{\text{aero}} \quad (1.1)$$

¹The weight of each rider and stage details are obtained from the website www.procyclingstats.com.

²Data given in the website www.bestbikesplit.com/preview/318704

with

$$P_{\text{slope}} = mg \sin(\tan^{-1} \Delta h) \cdot V_g, \quad (1.2)$$

$$P_{\text{roll}} = C_r mg \cos(\tan^{-1} \Delta h) \cdot V_g, \quad (1.3)$$

$$P_{\text{aero}} = \frac{1}{2} \rho C_D A (V_g - V_w)^2 \cdot V_g \quad (1.4)$$

where Δh is the altitude gain, ρ the air density, g the gravity acceleration, V_g the rider velocity and V_w the wind velocity. The numbers are specified in Table 1.1. In climbing configurations, the aerodynamic part of the total power losses is lower than on flat terrain but are still significant.

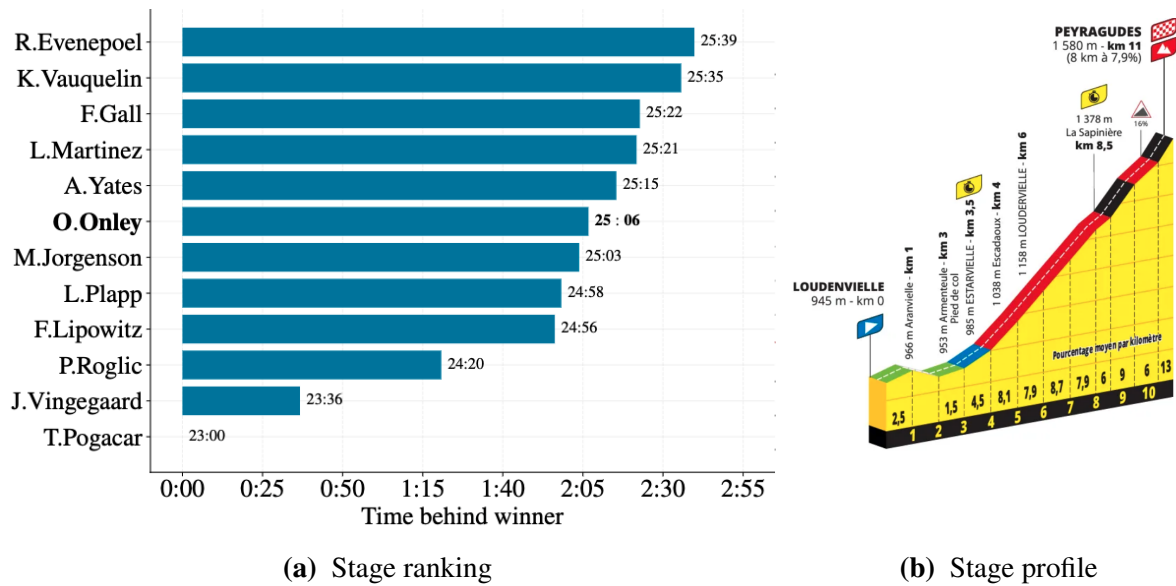


Figure 1.1 : Ranking and stage profile of the Mountain Individual Time Trial of stage 13 during the Tour de France 2025.

	Speed	Est. weight	Est. power	Est. aero loss
F. Lipowitz	26.22 km/h	68 kg	410.5 W	108.4 W
O. Onley	26.04 km/h	62 kg	380.0 W	106.5 W

Table 1.1 : Estimation of key quantities for the comparison of F. Lipowitz and O. Onley during the Mountain ITT in stage 13 of the Tour de France 2025.

Note : This rough estimation is validated by the published power data of O. Onley, who averaged 390 W during this time-trial.

What if O. Onley, initially 10 seconds behind F. Lipowitz had a better position, allowing him to decrease its aerodynamic losses by 5% ? Keeping his power-to-weight ratio constant would have lead him to ride at 26.30 km/h, resulting in a 14.95s faster time at the finish line. This rather crude analysis shows that the aerodynamic losses are significant in pro cycling and motivates the determination of a more accurate aerodynamic model.

1.2 State of the art

1.2.1 Cycling fluid dynamics

The forces acting on a body result from the interaction of the flow with this body. These forces are composed of a pressure term and friction term. Cyclists and bicycles are bodies called *bluff-bodies* such that the flow separates behind the body. Therefore, the magnitude of the aerodynamic forces that act on the body are mainly driven by the pressure term. These forces can be influenced by many parameters. Among them, the flow regime (laminar, turbulent or in transition), the angle of attack or direction of the wind that goes towards the body. The aerodynamics of a single bicycle and a cyclist is very complex due to the intricate shape and the multiple flow separations that occur around different components that acts as bluff-bodies. Additionally, strong flow interactions exist between those bodies. The moving components such as the wheels or the cyclist's legs are also source of unsteadiness and complexity of the flow around a cyclist [2].

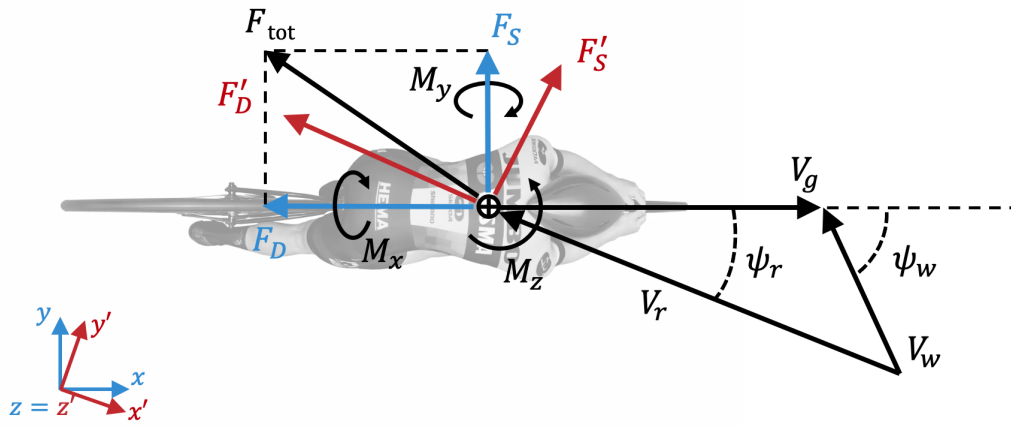


Figure 1.2 : Reference frames definition with forces in relative wind axes (red) and forces and moments in body axes. Wind direction and relative velocities are also defined.

Usually, aerodynamic forces in cycling are decomposed in body axes rather than wind axes (Figure 1.2). The drag force F_D is defined parallel to the ground, positive in the opposite direction of the riding velocity, the lift force F_L (not shown in the figure) is defined positive pointing upward perpendicular to the riding direction and the side force F_S is defined parallel to the ground and perpendicular to the riding direction, positive pointing to the left. Roll (M_x), pitch (M_y) and yaw (M_z) moments are defined positive following the right-hand rule. Forces and moments can be written as

$$F_i = \frac{1}{2} \rho V_r^2 C_i A, \quad i = \{D, L, S\}, \quad (1.5)$$

$$M_j = \frac{1}{2} \rho V_r^2 C_j A l, \quad j = \{X, Y, Z\}, \quad (1.6)$$

with l a characteristic length, ρ the air density, A the frontal area and V_r the relative riding velocity. Dimensionless forms of the aerodynamic forces and moments can be defined from equations (1.5) and (1.6), C_i and C_j . In practice, the drag coefficient C_D and the frontal area A are combined into a drag area variable $C_D A$.

In most studies, the relative riding velocity V_r – defined as the resultant between the absolute riding velocity of the cyclist $-V_g$ and the wind velocity V_w (Figure 1.2) – is used. The angles ψ_w and ψ_r respectively corresponds to the wind direction and the relative riding direction, also called the yaw angle of the flow coming onto the cyclist. Note that the wind velocity is not the only environmental parameter in the computation of the aerodynamic forces, as the air density ρ is a function of the ambient pressure or the temperature, for instance. As an illustration of the influence of these parameters, a few world hour-record attempts have taken place in high altitude places such as Merckx (1976, 2300m) or Campenaerts (2019, 1890m) [2].

Finally, a dimensionless reduced frequency k is used in the literature to consider the pedalling rate parameter. The reduced frequency is defined in Crouch et al., 2016 [3], based on the crank radius, as

$$k = \frac{2\pi f r}{V_r} \quad (1.7)$$

where r is the crank length and f is the pedalling frequency in Hz.

1.2.2 Flow around cylinders

Bicycles and cyclists are bluff-bodies, hence characterized by important flow separations inducing complex flow structures. A first simple approach to bluff-bodies is the flow around cylinders. Cylinders are actually used to simplify the sophisticated geometry of the different parts of a cyclist, such as his legs, in the preliminary design of skinsuit for instance [4].

Among others, Zdravkovich, 1998 [5] investigated the flow around cylinders and described that many different regimes are observed depending on the Reynolds number. The Reynolds number Re is defined as

$$Re = \frac{\rho V_\infty L}{\mu} \quad (1.8)$$

where ρ is the fluid density, μ is the fluid dynamic viscosity, V_∞ is the reference flow velocity and L is a characteristic length (generally the diameter D for a circular cylinder). At low Re , the flow is said to be laminar all around the cylinder, turbulent at high Re and in transition between those two states at moderate Re . Following Zdravkovich, 1998 [5], the transition occurs sequentially in different flow regions as the Re increases : in the wake ($180 < Re < 400$), in the shear layer ($400 < Re < 1-2 \times 10^5$) and in the boundary layer ($1-2 \times 10^5 < Re < 2-4 \times 10^7$). The main flow regimes are illustrated in Figure 1.3, based on the observation described in Zdravkovich, 1998 [5].

First, at very low Reynolds, the flow is creeping (*i.e.* no wake is formed). Increasing the Reynolds results in the formation of Föppl's bubbles in the near-wake behind the cylinder and then to laminar von Karmàn vortex streets in a so-called periodic laminar flow regime. At a larger Reynolds, the laminar periodic flow becomes unstable farther downstream in the wake, this is the first transition (TrW). The laminar eddies in the far-wake become irregular in shape and spacing and this propagates closer to the cylinder as the Reynolds increases. This results in a *laminar wake instability mode* of the eddy formation, at which the shedding becomes a turbulent eddy roll up and shedding. This first transition is reflected by a change in the Strouhal number. The Strouhal number St is defined as the ratio between the oscillations of the flow due to the inertial forces and the flow velocity [6], such as

$$St = \frac{f_{\text{shedding}} D}{V_\infty} \quad (1.9)$$

where f_{shedding} is the eddy shedding frequency. When the Reynolds rises again, transition waves appears as undulations of the free-shear layer. This is the beginning of the sub-critical flow

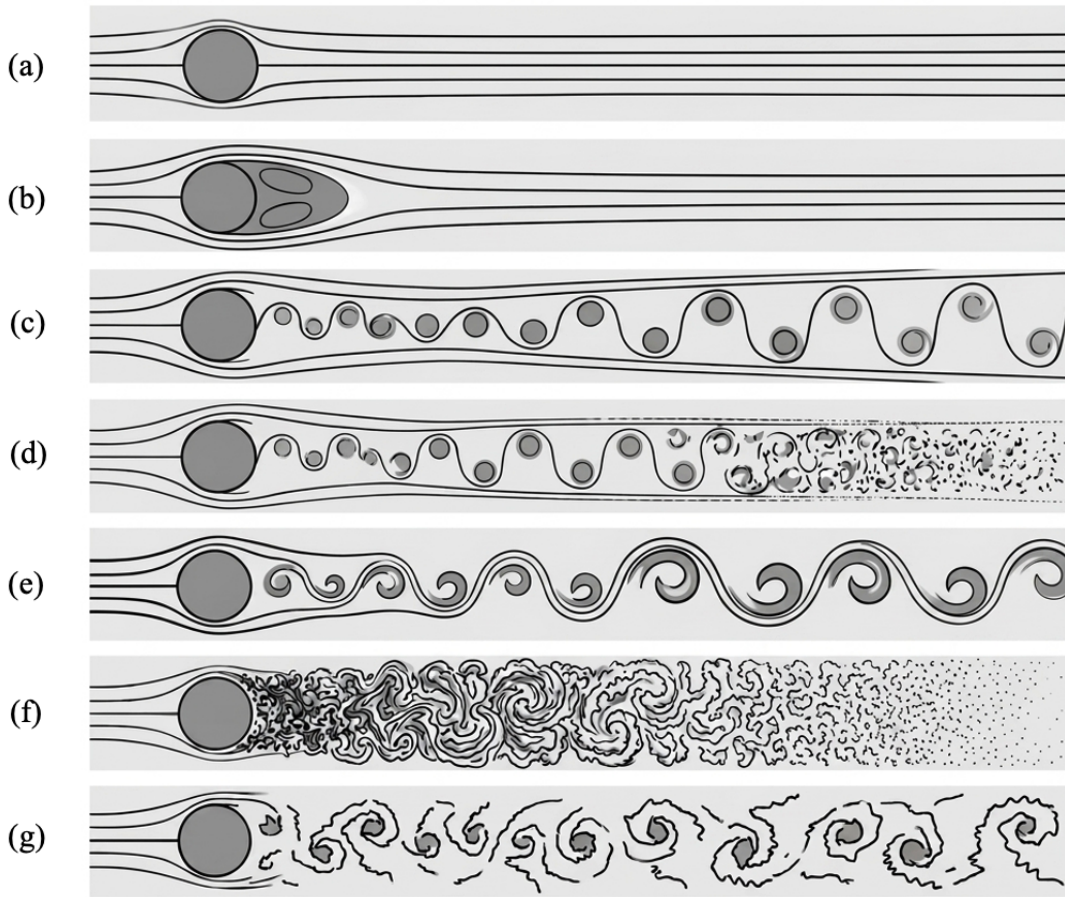


Figure 1.3 : Illustration of the flow around a circular cylinder in the main sub-regimes :
 (a) Creeping flow, (b) Closed near-wake, (c) Periodic laminar, (d) Transition in wake, (e) Transition in shear layer, (f) Transition in boundary layer, (g) Fully turbulent.

regime, which corresponds to a transition from a laminar to a turbulent free-shear layer (TrSL). These transition waves then roll up into discrete eddies along the free-shear layer. The length of the eddy formation region shortens with a larger Reynolds. In these TrSL sub-regimes, there is no significant change in drag coefficient.

At the critical Reynolds number, a sudden burst of turbulence in the free-shear layer near the side of the cylinder causes an asymmetric near-wake. This transition in the free-shear layer close to the cylinder disturbs the near-wake and causes a delay in eddy formation, impacting the position of the stagnation point. This phenomenon initiates the transition in the boundary layer (TrBL). A fall in drag coefficient is expected at this point. The delay of the separation point is partly responsible for the formation of a separation bubble at some location on the cylinder, resulting in an asymmetric single-bubble regime (called TrBL1) and causing another fall in drag coefficient when the second separation bubble appears (in TrBL2). Further increase in Reynolds leads to the fragmentation of separation bubbles along the span of the cylinder, which prevents the periodic eddy shedding. This is the super-critical flow regime (TrBL3). At higher Re , the boundary layer becomes turbulent upstream the separation point and the vortex shedding is allowed again. This is the post-critical sub-regime (TrBL4). Finally, the fully turbulent state of flow is reached when the Reynolds further increases.

The fluid forces that act on the circular cylinder are very dependent on the Reynolds number, as can be observed in Figure 1.4.

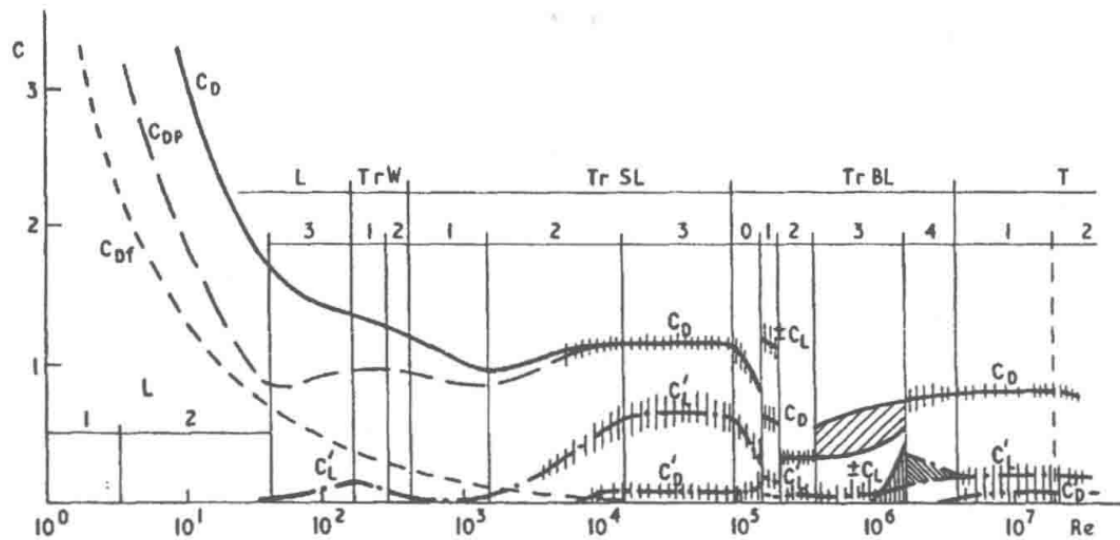


Figure 1.4 : Fluid forces coefficient variation with respect to Reynolds for disturbance-free flows, reproduced from Zdravkovich, 1998 [5]

Additionally, the influence of the geometric parameters has been studied. Norberg, 1994 [7] has investigated experimentally the influence of the aspect ratio on the vortex shedding for a large range of Reynolds numbers (50 to 4×10^4), showing that the aspect ratio and/or different end conditions are a convincing explanation for the data scatter in the literature. In particular, he concluded that different aspect ratios are required in order to obtain an end conditions independent flow at the cylinder's mid-span for flows in transitional sub-regimes. Szepessy et al., 1992 [8] studied the aspect ratio and end plates effects on the vortex shedding flow from a circular cylinder at Reynolds from 8×10^3 and 1.4×10^5 . They observed variations in the fluctuating forces for aspect ratios between 0.25 and 12 .

Since circular cylinders are used to approximate cyclist and bicycle's moving components such as the legs, the flow around statically and dynamically inclined circular cylinders matters. Sears, 1948 [9] derived the boundary layer equations of the flow around a yawed infinite circular cylinder and showed that the important characteristics of the laminar boundary layer are not affected by the yaw angle and that the phenomenon of transition can be controlled by the Reynolds number based on the normal velocity component, through the so-called "cosine law" or "Independence Principle". Several studies consisting of the measurements of the pressure distribution and the shedding frequency on inclined cylinders have been carried out [10, 11, 12] and yielded that the accuracy of this Independence Principle may be limited at large angles of incidence. According to several studies on the flow past inclined cylinders [13, 14], an axial flow develops in the near wake as the angle of incidence increases, resulting in disturbances in the regular von Kármán vortex shedding.

Hoang et al., 2015 [15] investigated the validity of the principle experimentally on a stationary cylinder inclined with the flow in the subcritical regime and observed that the cosine law became inaccurate for inclination angles larger than 40° . Finally, Matsuzaki et al., 2004 [16] investigated the flow structures in the wake of inclined circular cylinders of different aspect ratio (10 , 15 and 30) at low Reynolds and found that even though the structure of von Kármán's vortex becomes stronger in the direction of the cylinder axis as the inclined angle increases for large aspect ratios, the trend is opposite for low aspect ratios. They suggest that the upward flow along the cylinder axis caused by only the inclination of cylinder interferes with the horseshoe vortex behind the cylinder and the interference probably develops the stronger upward flow.

1.2.3 Flow around cyclists

The first studies on the flow around a cyclist were conducted on simple representations of the human body as cylinders [4]. Due to the complexity of a multiple-cylinders configuration, the drag crisis normally observed on a single circular cylinder was not seen on these representations. A moderate influence of the Reynolds number on the drag force acting on cyclists is nevertheless observed by Brownlie et al., 2009 [17]. A strong correlation between the drag coefficient and the leg position is also highly believed. This correlation is indeed observed – among other studies – by Kyle et al., 2004 [18]. Summing up, the flow around a cyclist is, at least, influenced by the riding velocity, the geometry and the kinematics of it.

Lukes et al., 2005 [19] and Malizia et al., 2021 [2] propose a review of the key findings in cycling aerodynamics, related to bike components (helmets, frames, wheels, etc), cyclist's position or even equipment, but also highlight the gaps in the literature on the interaction between these components. Lukes et al., 2005 [19] also insist on the lack of quantitative data on the unsteady flow caused by moving legs. Since then, Baidya et al., 2010 [20] and Crouch et al., 2016 [3] conducted experimental studies on dynamic configurations, respectively on a legs + crank set-up and on a full-scale mannequin. In both papers, the drag force is computed through a wake deficit/integral analysis.

The dominant flow structures that are observed in the wake of a cyclist were investigated by Crouch et al., 2012 [21]. They found that two different flow regimes are observed in the wake and are mainly responsible for the drag of a static cyclist mannequin. A complete flow topology in the wake of a cyclist has then been built based on full-scale static measurements [22]. In the cases with one leg fully stretched, the $C_D A$ shows to be up to 15% larger than the position with a horizontal crank. This large variations in drag coefficient indicates the presence of the different features in the cyclist's wake: a symmetrical flow which would correspond to low drag generation and an asymmetric one which relates to a large drag production. The flow is observed to be symmetrical at each moment with horizontal crank position and then goes towards the asymmetrical regime over the remaining of the cycle. Going further, the effect of the legs motion on the structure of the wake is not constrained to regions near the legs but affects the upper wake of the cyclist as well. Figure 1.5 shows the contour plot of the streamwise velocity component in the wake of the full-scale cyclist mannequin, in which the different flow regimes are clearly visible. The flow is shown to be symmetrical at 15° over the half crank cycle (crank angle defined from the horizontal position).

Moreover, the main wake feature in the hip/lower back region consists of a pair of large streamwise counter rotating vortices of unequal strengths. The low drag/symmetric flow regime is however characterized by very low vorticity.

The authors explain that these asymmetric vortices result from the vorticity generated by the flow separation at two locations :

1. the low part of the hip, when the upper leg is in a raised position, and
2. the upper part of the hip and the side of the torso, when the leg is near-fully extended.

The asymmetry in the location of the flow separation causes a deformation of the vortex streets both in vertical and horizontal directions of the wake. The orientation of the primary vortices is asymmetrical as well, due to the motion of the leg.

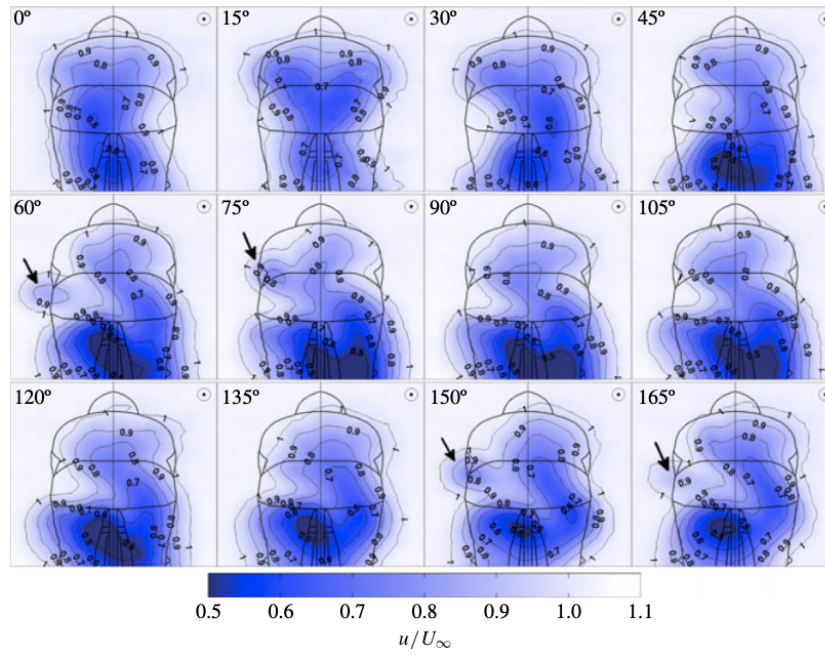


Figure 1.5 : Contour plot of the streamwise velocity component in the wake of a static cyclist mannequin, from Crouch et al., 2014 [22].

Variations in drag area with respect to the legs and trunk positions over a crank cycle were confirmed by numerical studies [23, 24]. Among them, Chi et al., 2020 [24] shows the contributions in drag area of the bike and cyclist components. It can be observed that the thigh and calf segments are those which contribute the most to the variations of drag area over a crank cycle.

The research has been pushed further by considering a dynamic pedalling motion in order to attest the robustness of the quasi-steady results [3]. Dynamic wind tunnel measurements showed that the drag area over a crank cycle is distinct from the static one when the pedalling rate is increased. The variations are generally correlated to the change in strength of the large scale vortices that are observed behind the hip/lower back. These vortical structures are visualized in Figure 1.6.

Small counter rotating vortices are also observed around the pedal/foot when the leg is fully stretched. More recently, Jux et al., 2018 [25] and Terra et al., 2019 [26] have obtained similar qualitative results, respectively from volumetric PIV and large-scale PTV measurements on a full-scale cyclist mannequin. Results were extended to the characterization of the effects of the Reynolds number on the drag of cyclists [27].

Summing up, the position and motion of the legs strongly influence the formation, position and strength of the vortices in the wake of a cyclist and thus the drag that is generated.

Finally, Barry et al., 2016 [28] extended the work on this topic by considering the interactions between multiple cyclists and investigated the flow topology of two drafting cyclists both in static and dynamic configurations. They found that the flow structures downstream the trailing cyclist are similar to those observed on a unique cyclist, while however observing a drag reduction regarding the trailing cyclist. They concluded that the drag reduction is related to the encounter of lower energy flow and not the result of streamwise momentum recovery in the trailing rider wake. Moreover, the transition between a symmetric and asymmetric flow regime during the crank cycle was also seen in both pedalling cyclist.

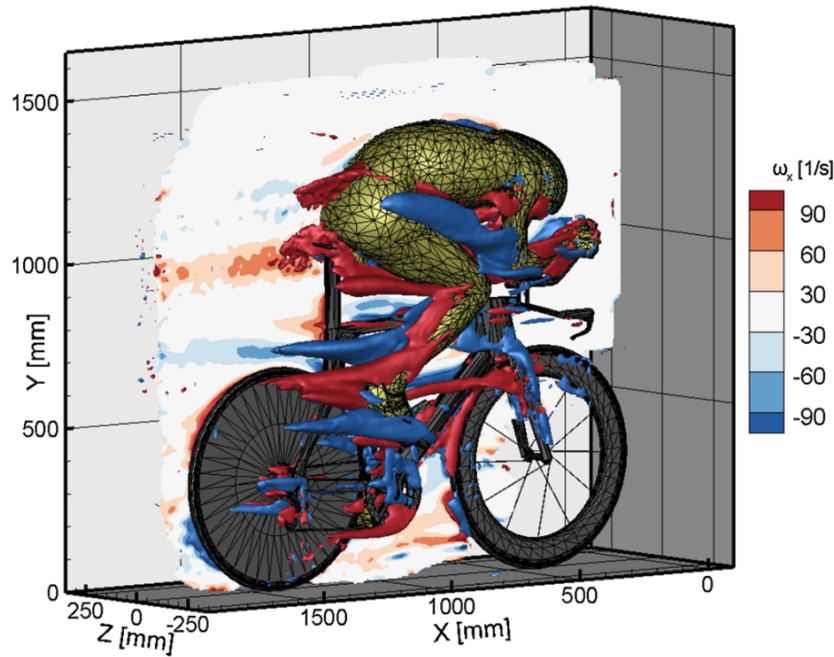


Figure 1.6 : Flow topology visualization by streamwise vorticity around a full-scale mannequin, from Jux et al., 2018 [25].

1.3 Objectives

Cycling aerodynamics has received considerable attention over the last decades due to its direct influence on athletic performance. Previous experimental and numerical studies have demonstrated that the position of the cyclist significantly affects aerodynamic drag and that the lower limbs are among the body segments contributing the most to drag fluctuations throughout a crank cycle. Moreover, investigations conducted on full-scale mannequins have shown that the wake topology of a cyclist evolves continuously during pedalling, alternating between low-drag and high-drag flow regimes associated with changes in the strength and organisation of large-scale vortical structures.

Despite these advances, the influence of pedalling kinematics remains only partially understood. Most available studies focus on quasi-steady approaches, static crank positions or dynamic measurements performed at a limited number of pedalling rates. As a result, the specific role of motion-related parameters such as pedalling frequency, reduced frequency, cadence profile or motion amplitude on the aerodynamic response remains difficult to quantify. Furthermore, the complexity of the cyclist geometry often obscures the physical mechanisms responsible for drag generation, making it challenging to isolate the contribution of the legs from the interactions occurring with the torso, bicycle and other body parts.

The present work aims at addressing this limitation by studying the aerodynamic behaviour of a simplified cyclist leg undergoing a periodic pedalling motion. The leg is represented by two articulated circular cylinders mounted on a collaborative robot and tested in a controlled wind tunnel environment. Such a simplified configuration does not intend to reproduce the complete aerodynamics of a cyclist but rather to isolate the fundamental flow mechanisms associated with the motion of the leg itself.

A first objective of this work is to experimentally characterize the aerodynamic forces acting

on articulated cylinders undergoing pedalling-like motions. Particular attention is devoted to the influence of the reduced frequency, which quantifies the relative importance of motion-induced effects compared with the free-stream flow velocity. Since professional cyclists increasingly ride at high cadences and high speeds, especially in climbing situations, understanding the aerodynamic consequences of pedalling rate becomes relevant for performance analysis and modelling.

A second objective is to investigate how different kinematic parameters affect the drag response of the moving leg. The influence of Reynolds number, motion amplitude and yaw angle is examined through an extensive parametric campaign. In addition, different cadence profiles are considered. While most aerodynamic studies assume a constant pedalling rate throughout the crank cycle, real cyclists exhibit non-uniform angular velocity distributions resulting from biomechanical constraints and force production strategies. The present work therefore evaluates whether these realistic cadence variations can modify the aerodynamic behaviour of the system.

Beyond the global drag force, special attention is paid to the evolution of the pressure field around the cylinders and to the variations of drag throughout the crank cycle. The objective is not only to quantify average aerodynamic losses but also to identify the physical mechanisms responsible for these variations and to assess the importance of unsteady effects in the flow.

Finally, a major objective of this thesis is to evaluate the feasibility of reduced-order drag prediction models based on experimental data. Two complementary approaches are considered. The first one relies on a quasi-steady physical formulation derived from existing moving-leg models. The second one adopts a data-driven strategy combining in-cycle and out-of-cycle regressions in order to predict the drag response from a limited set of kinematic and flow parameters. By comparing both approaches against wind tunnel measurements, the study aims to assess their ability to reproduce the aerodynamic behaviour of moving articulated cylinders and to identify the most relevant quantities governing drag generation.

Overall, this work seeks to improve the understanding of the aerodynamic mechanisms associated with pedalling motion while providing a foundation for the development of predictive models that could ultimately contribute to cyclist performance analysis and optimization.

Chapter 2

Experimental set-up and procedure

2.1 Set-up

Measurements are conducted on a collaborative robot UR5e whose relevant arm segments (*i.e.* from shoulder to elbow and from elbow to wrist) are covered with plastic cylinders. Geometric data of the UR5e are summarized in Table 2.1. The robot is mounted on a force balance and the external cylinders are filled with pressure taps at their mid-span location. Figures 2.1a and 2.1b show the structure that supports the pressure taps and the external cylinders on the robot. In total, 32 pressure taps are used, 16 on each of the cylinders. Cylinders that are mounted on the robot are made of plastic.

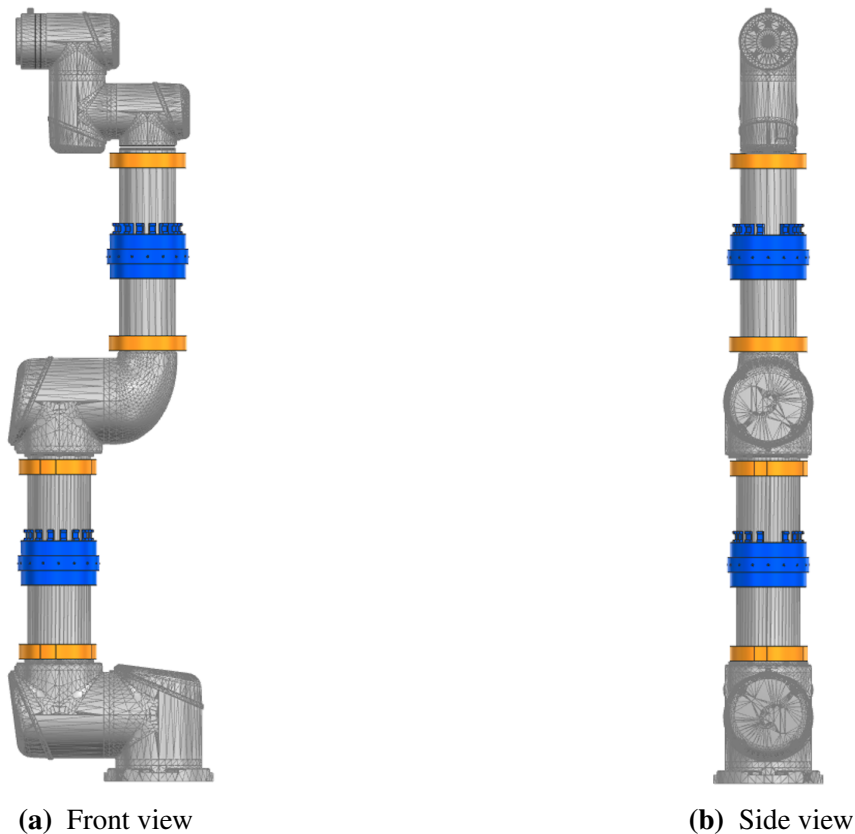


Figure 2.1 : 3D representation of the supports mounted on the robot.

Diameter of the external cylinders		0.11	m
Lengths	Lower cylinder	0.275	m
	Upper cylinder	0.29	m
Total height of the set-up		1.10	m
Projected area	Front plane	0.1102	m ²

Table 2.1 : Geometric data of the set-up. Projected areas are measured from the CAD representation.

Measurements were performed in the low-subsonic wind tunnel at the University of Liège. This low-speed multidisciplinary wind tunnel, built in 1999 on the Sart-Tilman site, is composed of two test sections and can be configured with two different nozzles. Each test section can operate in open or close configuration and is equipped with a rotating test table. The test sections are respectively referred as the Aeronautical test section (TS1), and the Wind engineering test section (TS2). Pictures of the set-up installed in TS 2 are provided in Figure 2.2. The key characteristics of the wind tunnel facility are summarized in Table 2.2. A schematic of the wind tunnel facility is provided in Annex A. The experimental testings were conducted in TS 2 of the wind tunnel, thus yielding a blockage ratio of 2.4%, based on the projected area on the frontal plane. This value is well below the common threshold of 10%, ensuring that the tunnel walls do not interfere with the flow.

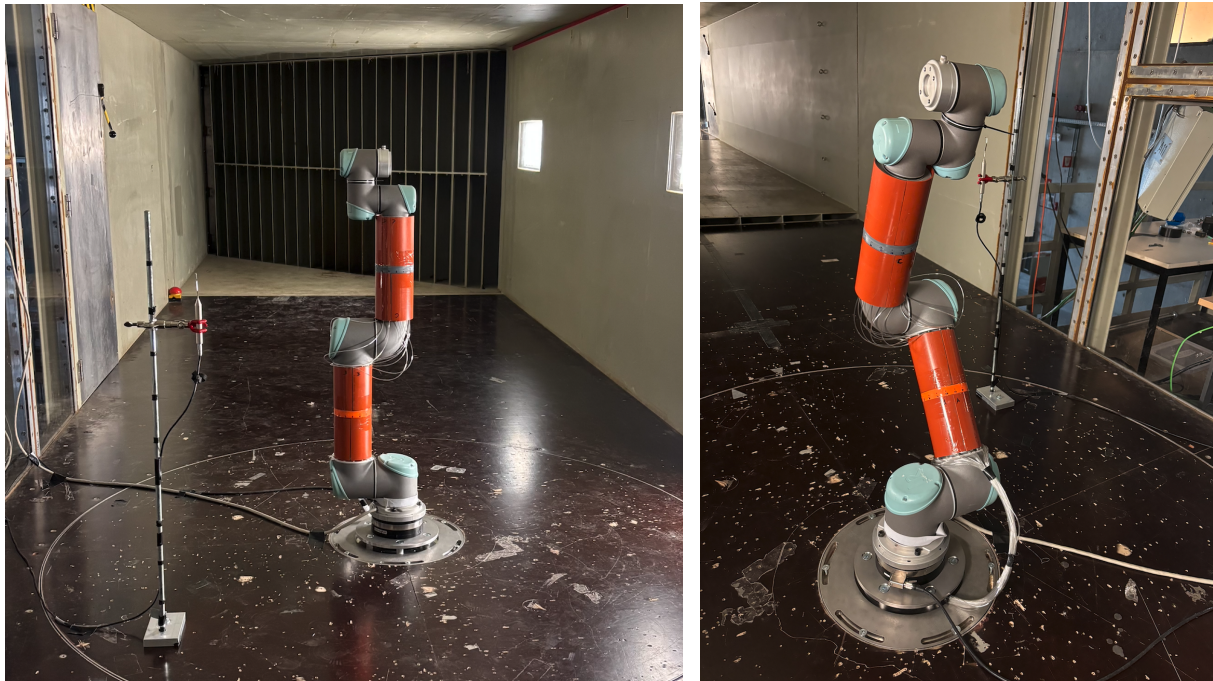


Figure 2.2 : Pictures of the set-up (robot and cobra probe) mounted in TS 2 of the wind tunnel.

Characteristic	Specification	
	TS1	TS2
Dimensions	2 m × 1.5 m × 5 m	2.5 m × 1.8 m × 5 m
Airspeed range (closed loop)	2 - 65 m/s	2 - 40 m/s
Turbulence level	0.15 %	< 0.23 %
Rotating plate diameter	1.5 m	2 m
Streamwise static pressure gradient	0.3 %/m	0.5 %/m
Speed non-uniformity	< 0.5 %	< 0.8 %
Fan diameter	2.8 m	
Maximum flow rate	186 m ³ /s	
Maximum rise in total pressure	1953 N/m ²	
Rotation speed range	25 - 820 RPM	
Power (DC)	440 kW	
Fluid temperature range	15 - 50°C	

Table 2.2 : Characteristics of both test sections and the axial fan of the wind tunnel.

2.2 Conventions

The kinematics of the so-called robotic pedalling leg is represented by the hip and knee degrees of freedom, respectively q_1 and q_2 in the UR5 convention, α and β in biomechanical convention. The hip angle α , while usually defined with respect to the torso line, is defined as the angle of the thigh centreline with the horizontal line since a single leg is considered here not a full mannequin. The relevant angles that describes the kinematics of the pedalling leg are represented in Figures 2.3a and 2.3b. Also in Figure 2.3b are the definitions of an alternative knee angle γ and the crank angle, which is 0 when the pedal is at the front position of the crank.

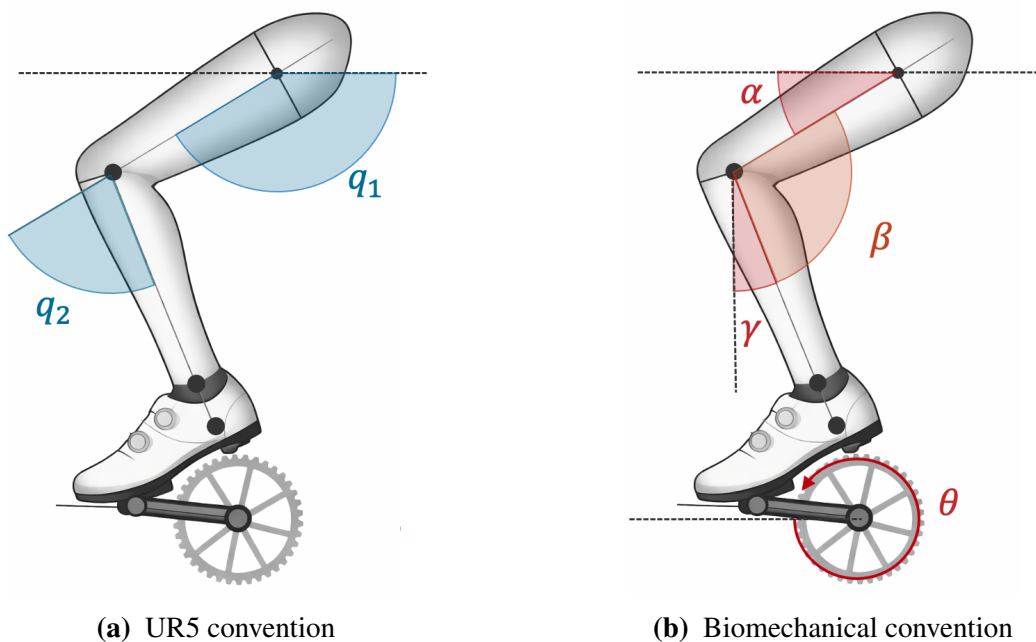


Figure 2.3 : Definition of the angles relevant to the kinematics of a pedalling leg.

2.3 Kinematics

Beforehand, the different trajectories considered of the robot end-tool should be computed, along with the joint motion. In order to add a slight biomechanical input in the global motion, the determination of the latter is realized by implementing a two degrees of freedom inverse kinematics algorithm rather than simply use the analytical expressions. The principle behind the algorithm is presented [29] and its results are compared with the analytical ones. Finally, knowing that the ankle degree of freedom is free to move in practice, the motions of the robotic leg with and without the freed ankle are compared, in order to assess the consequences of the 2 DoFs only assumption on the aerodynamic forces.

2.3.1 Inverse kinematics principle and application to the pedalling motion

Considering a pose vector $\mathbf{p}$ that describes the motion of the robot tool in the operational space and a joint coordinates vector $\mathbf{q}$ that describes the motion in the joint space :

$$\mathbf{p} = [x \ y \ z \ \varphi \ \theta \ \gamma]^T, \quad \mathbf{q} = [q_0 \ q_1 \ q_2 \ q_3 \ q_4 \ q_5]^T$$

where x, y, z are the linear position coordinates and φ, θ, γ the Euler angles. The forward transformation (*e.g.* direct kinematics) is obtained by

$$\mathbf{p} = f(\mathbf{q}).$$

The inverse kinematics consists in the reverse transformation

$$\mathbf{q} = f^{-1}(\mathbf{p}).$$

It is important to be aware that the result $\mathbf{q}$ of the inverse kinematics might not exist or not be unique after the inverse kinematics transformation.

The Jacobian matrix $\mathbf{J}$ of the transformation can be defined such that

$$\dot{\mathbf{p}} = \mathbf{J}_p(\mathbf{q})\dot{\mathbf{q}}$$

where $\mathbf{J}_p$ specifies the Jacobian matrix of the $\mathbf{p}$ with respect to the joint coordinates $\mathbf{q}$.

One must note that two approaches are used to compute the angular velocities. The first one computes the time derivative of the orientation vector ${}^0\dot{\phi} = [\dot{\varphi} \ \dot{\theta} \ \dot{\gamma}]^T$ and the second one directly uses the angular velocity vector ${}^0\omega$. Their expressions are not equal and the relationship between the two is given using a rotation matrix, as

$${}^0\omega = \begin{bmatrix} {}^0\omega_x \\ {}^0\omega_y \\ {}^0\omega_z \end{bmatrix} = \begin{bmatrix} 0 & -\sin \varphi & \cos \varphi \sin \theta \\ 0 & \cos \varphi & \sin \varphi \sin \theta \\ 1 & 0 & \cos \theta \end{bmatrix} \begin{bmatrix} \dot{\varphi} \\ \dot{\theta} \\ \dot{\gamma} \end{bmatrix}.$$

Therefore, one can rewrite the derivation of the direct kinematics state equation and obtain

$$\dot{\mathbf{p}} = \left[\begin{array}{c|ccc} 1 & & & 0 \\ \hline & 0 & -\sin \varphi & \cos \varphi \sin \theta \\ 0 & 0 & \cos \varphi & \sin \varphi \sin \theta \\ & 1 & 0 & \cos \theta \end{array} \right] \frac{\partial f}{\partial \mathbf{q}^T} \dot{\mathbf{q}} = \mathbf{J}_p \dot{\mathbf{q}}. \quad (2.1)$$

This leads to the Jacobian matrix with respect to the velocity $\mathbf{J}_v(\mathbf{q}) \triangleq \mathbf{J}$ as

$$\mathbf{J} = \begin{bmatrix} J_{xq_0} & J_{xq_1} & \cdots & J_{xq_5} \\ J_{yq_0} & J_{yq_1} & & \\ J_{zq_0} & & & \\ J_{\omega_x q_0} & & \ddots & \\ J_{\omega_y q_0} & & & \\ J_{\omega_z q_0} & \cdots & & J_{\omega_z q_5} \end{bmatrix} \quad \text{with } J_{p_i q_j} = \frac{\partial p_i}{\partial q_j}. \quad (2.2)$$

Assuming small variations of joint coordinates, the equation can be linearized into a numerically solvable solution :

$$\Delta \mathbf{p} \approx \mathbf{J} \Delta \mathbf{q} \quad (2.3)$$

Application to pedalling motion

The pedalling motion is a purely bidimensional motion in XZ -plane, composed of only two degrees of freedom of the robot, namely q_1 the shoulder joint and q_2 the elbow joint. The system of equations that describes the inverse kinematics problem can therefore be reduced by considering the operating and joint space constraints related to the motion.

Operating space constraints:

- Motion of the tool is linear such that the angular velocity vector ${}^0\omega$ is not of interest.
- Motion in the XZ -plane : the linear velocity ${}^0\dot{y}$ -component is not of interest.

Joint space constraints:

- The angular displacements of the joints q_0, q_3, q_4 and q_5 are fixed, such that their corresponding velocities are zero.

Therefore, the Jacobian matrix $\mathbf{J}$ as defined in Eq. (2.2) can be rewritten as

$$\mathbf{J}(q_1, q_2) = \begin{bmatrix} \frac{\partial x}{\partial q_1} & \frac{\partial x}{\partial q_2} \\ \frac{\partial z}{\partial q_1} & \frac{\partial z}{\partial q_2} \end{bmatrix}. \quad (2.4)$$

and the pose and joint coordinates vectors become

$$\mathbf{p} = \begin{bmatrix} {}^0x \\ {}^0z \end{bmatrix} \quad \text{and} \quad \mathbf{q} = \begin{bmatrix} q_1 \\ q_2 \end{bmatrix}. \quad (2.5)$$

An initial position at ${}^0y = 0$ ensures to remain in a 2D-plane.

2 DOFs Inverse Kinematics algorithm

For a given transformation $\Delta \mathbf{p}$, the objective is to compute the joint transformation $\Delta \mathbf{q}$ that satisfies Eq. (2.3). Numerically, this is done by minimizing the error e as defined by

$$e = \Delta \mathbf{p} - \mathbf{J} \Delta \mathbf{q},$$

which is realized using the least squares method.

A damping factor is used to avoid singularities that might appear in the Jacobian due to the pedalling motion that is recreated. Typically, some elbow type singularities could be detected

as the links around the wrist of the robot might be collinear. The damped least squares method consist thus in solving the following equation:

$$\min_{\Delta \mathbf{q}} \|\Delta \mathbf{p} - \mathbf{J} \Delta \mathbf{q}\|^2 + \lambda \|\Delta \mathbf{q}\|^2 \quad (2.6)$$

where λ is the damping constant.

The solution of this equation is

$$\Delta \mathbf{q} = (\mathbf{J}^T \mathbf{J} + \lambda \mathbf{I})^{-1} \mathbf{J}^T \Delta \mathbf{p} \quad (2.7)$$

or written as

$$(\mathbf{J}^T \mathbf{J} + \lambda \mathbf{I}) \Delta \mathbf{q} = \mathbf{J}^T \Delta \mathbf{p} \quad (2.8)$$

This latter linear equation is solved numerically. Finally, a relaxation factor is applied to ensure that the step keeps satisfying the small variations of displacement assumption made to linearize the equation and to help the convergence. In fact, large steps might occur without relaxation, leading to divergence or oscillations of the results of the inverse kinematics.

Biomechanical input in the algorithm

In order to direct the result of the inverse kinematics towards robot pedalling motion that is as close as possible to the human motion, boundary values are imposed to the amplitude of the relevant joints. These boundaries, expressed in the biomechanics convention, are chosen based on the work on the kinematic analysis of bicycle pedalling from Garc a-L pez et al., 2017 [30]:

$$\alpha_{\min} = 16.4^\circ, \alpha_{\max} = 64.8^\circ, \beta_{\min} = 67.8^\circ, \beta_{\max} = 145.5^\circ. \quad (2.9)$$

2.3.2 Comparison of numerical and analytical results

Apart from the range of joint angle values that is imposed, the inverse kinematics could be computed analytically. In this case, the analytical form is used to validate the shape of the motion found by the algorithm while remaining aware that the quantitative results will not be the same. Figure 2.4 is a simplified schematic of the 2 degrees of freedom robot arm. Arm are represented by simple rigid links of length L_1 and L_2 , the hip and knee joints are revolute joints labelled as α_r and β_r and the tool of the robot is located at point P.

The position of the tool can be defined from the joint space by the relationship

$$\begin{cases} x_P &= L_1 \cos q_1 + L_2 \cos(q_1 + q_2), \\ y_P &= L_1 \sin q_1 + L_2 \sin(q_1 + q_2). \end{cases} \quad (2.10)$$

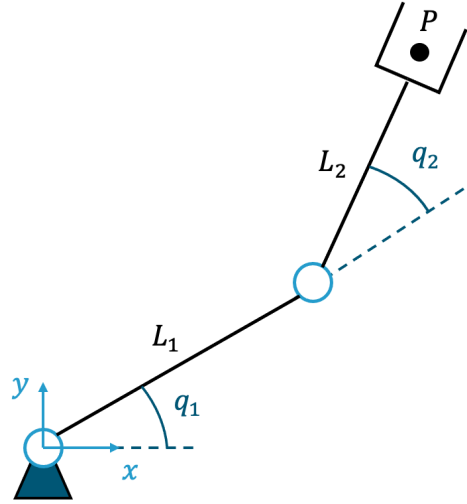


Figure 2.4 : Simple schematic of the two-degrees-of-freedom robot arm

The inverse geometric problem consists in finding the joint coordinates that produce the desired tool trajectory $(x_P(t), y_P(t))$. This problem can be formulated as the vanishing of the so-called *servo-constraints* $\mathbf{g}(\mathbf{q}, t) = \mathbf{0}_{2 \times 1}$ with

$$\mathbf{g}(\mathbf{q}, t) = \begin{bmatrix} L_1 \cos q_1 + L_2 \cos(q_1 + q_2) - x_P(t) \\ L_1 \sin q_1 + L_2 \sin(q_1 + q_2) - y_P(t) \end{bmatrix}. \quad (2.11)$$

Solution of the equations :

Squaring and summing the equation yields

$$x_P^2 + y_P^2 + L_1^2(\cos^2 q_1 + \sin^2 q_1) - 2L_1(x_P \cos q_1 + y_P \sin q_1) = L_2^2(\cos^2(q_1 + q_2) + \sin^2(q_1 + q_2)) \quad (2.12)$$

or

$$x_P^2 + y_P^2 + L_1^2 - 2L_1(x_P \cos q_1 + y_P \sin q_1) = L_2^2. \quad (2.13)$$

Expressing the position of point P in polar coordinates (r_P, θ_P) , the equation becomes

$$r_P^2 + L_1^2 - L_2^2 = 2L_1(r_P \cos \theta_P \cos q_1 + r_P \sin \theta_P \sin q_1) \quad (2.14)$$

$$= 2L_1 r_P \cos(\theta_P - q_1). \quad (2.15)$$

The angle q_1 is then determined by

$$q_1 = \theta_P - \cos^{-1} \left(\frac{r_P^2 + L_1^2 - L_2^2}{2r_P L_1} \right). \quad (2.16)$$

In the triangle composed of the origin O and points K and P , the following relationship is satisfied :

$$r_P^2 = L_1^2 + L_2^2 - 2L_1 L_2 \cos(\pi - q_2) \quad (2.17)$$

such that the angle q_2 can be determined.

Final solutions of the inverse geometric problem are

$$q_1 = \theta_P - \cos^{-1} \left(\frac{r_P^2 + L_1^2 - L_2^2}{2r_PL_1} \right), \quad q_2 = \cos^{-1} \left(\frac{r_P^2 - L_1^2 - L_2^2}{2L_1L_2} \right),$$

$$r_P = \sqrt{x_P^2 + y_P^2}, \quad \theta_P = \tan^{-1} \left(\frac{y_P}{x_P} \right).$$

Figures 2.5a and 2.5b respectively show the comparison between the analytical and numerical (with boundaries) solution of the inverse kinematics for a pedalling motion of 0.11 m tool circular trajectory amplitude at a constant pedalling rate of 60 RPM over one crank cycle. It is observed that the boundaries in joint motions that are imposed in the algorithm do not change much the behaviour of the solution. In some way, this comparison allows to validate the two degrees of freedom IK algorithm for this specific geometry.

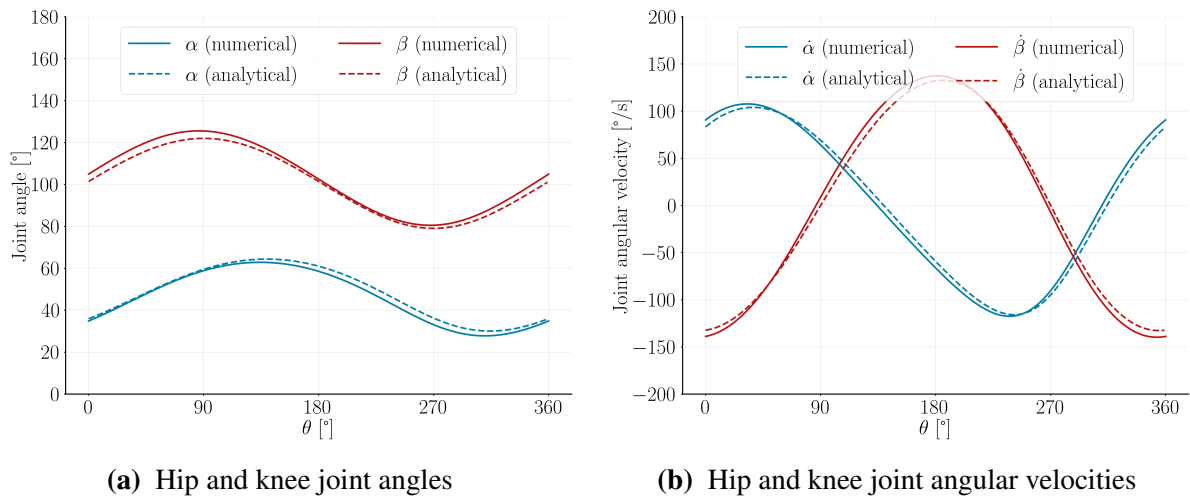


Figure 2.5 : Comparison of the IK 2 dofs algorithm results with the analytical solution.

2.3.3 Robot motion with the "freed" ankle

For simplicity of the experimental set-up, the sole motion of the thigh and calf, modelled as cylinders on the robot, are considered. It is therefore assumed that the effects of the ankle degree of freedom are negligible on the aerodynamic forces acting on articulated cylinders acting as a moving leg. This choice is supported in this section by comparing the joint trajectories across one crank cycle.

To do so, the same Inverse Kinematics principle is used with and without adding the ankle degree of freedom q_3 and the behaviours in hip and knee joint are compared with the initial case. While freeing the ankle joint, an arbitrary range of $[80, 120^\circ]$ (based on observations of different high-level cyclists) is applied at the angle q_3 for the IK procedure, similarly and conjointly as line 2.9.

Figures 2.6 and 2.7 show the joint motion of the pedalling leg for a motion with 0.11 m amplitude and 60 RPM uniform cadence. One can observe that the addition of the ankle degree of freedom causes small variations in the knee angle but a 10° increase in the hip angle. The ankle joint angle itself only varies in a 25° range. The changes in joint motion has little impact on the angular velocities. That said, the qualitative study of the influence of the cadence on the aerodynamic forces acting on the robotic pedalling leg is not believed to be significantly

impacted by the assumption of blocking the ankle degree of freedom.

Moreover, according to Crouch et al., 2016 [3], the small variations in the ankle joint are unlikely to cause a complete reorganisation of the wake flow structures.

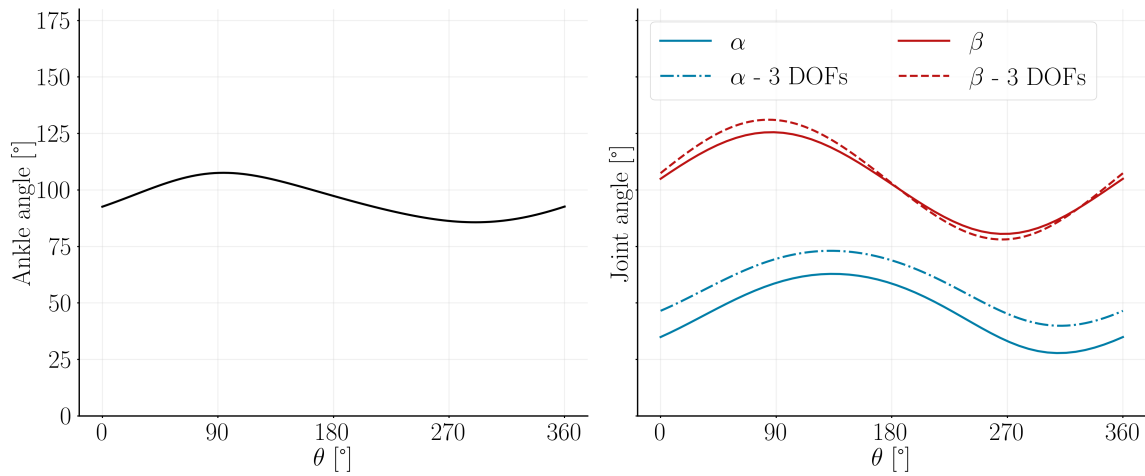


Figure 2.6 : Comparison of the joint angles resulting from the IK algorithm for 2 or 3 degrees of freedom.

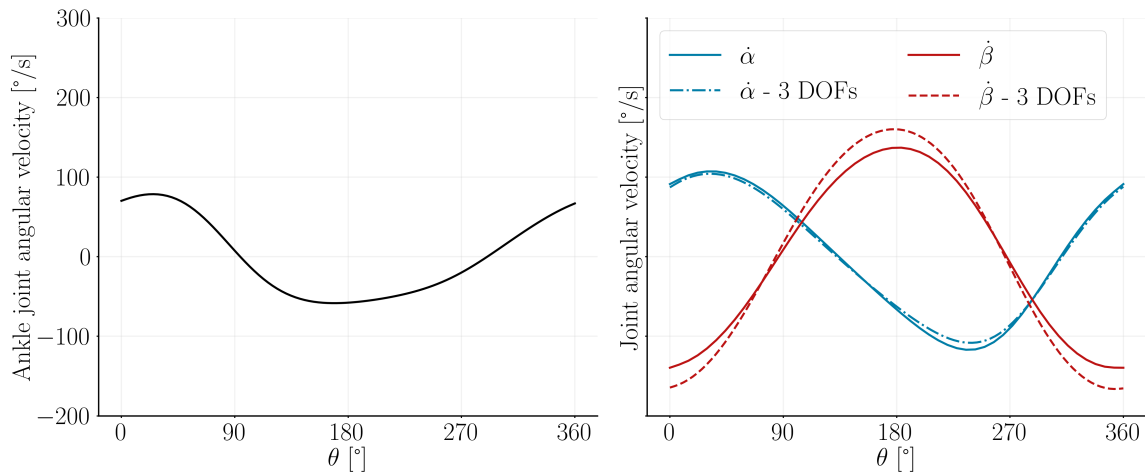


Figure 2.7 : Comparison of the joint angular velocities resulting from the IK algorithm for 2 or 3 degrees of freedom.

2.3.4 Different cadence profiles

Finally, different cadence profiles are considered in order to study the eventuality of non-uniform pedalling rate over a full crank cycle on the aerodynamic efficiency of a moving leg. These profiles are listed below and shown in Figure 2.8.

- Uniform cadence
- *Hull* profile, theoretically obtained while aiming to maintain the total mechanical energy of both legs constant in seated cycling. A reference crank angular velocity is then determined from experimental measurements of the total energy at an average equivalent cadence of 90 RPM. [31].

- *Ettema* profile, obtained from experimental measurements on trained cyclists in steady state at five cadences (60 - 100 RPM) at submaximal power. The objective of these measurements was to detect any differences in the effect of cadence on force, effectiveness and power phases [32].

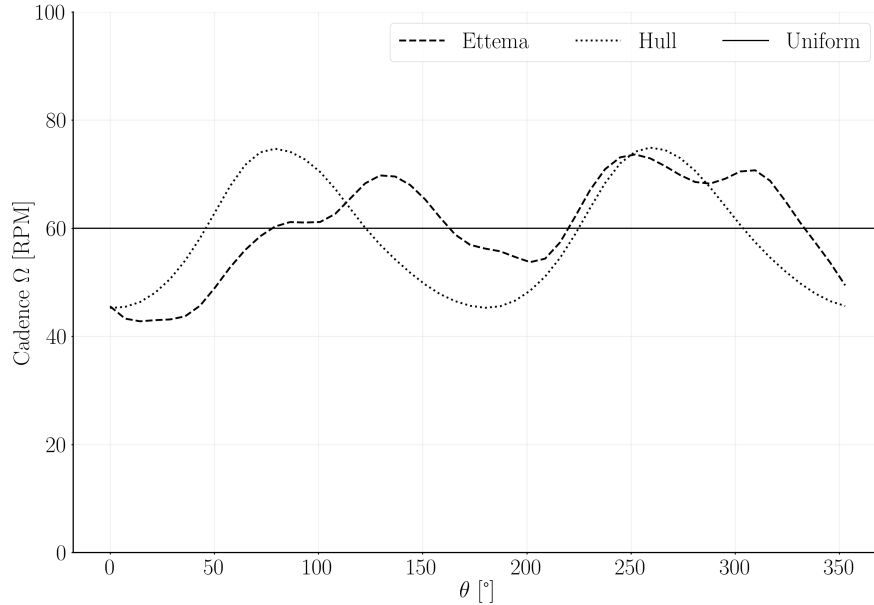


Figure 2.8 : Different cadence profiles considered, at mean cadence of 60 RPM (Variations in Ettema profile are exaggerated to highlight them).

The amplitude of the joint angles is naturally not impacted by a change in cadence profile, contrary to their angular velocities. Figure 2.9 shows the angular velocities of the hip and knee joint, obtained from the application of the Inverse Kinematics. One can see that the *Ettema* profile somehow causes a flattening of the knee angular velocity at its extrema, and that both non-uniform cadence profiles have similar consequences on the hip angular velocity. One might expect that these differences – particularly in hip angular velocity – will affect the true velocity seen by the robotic leg in an airflow, therefore impacting the aerodynamic forces.

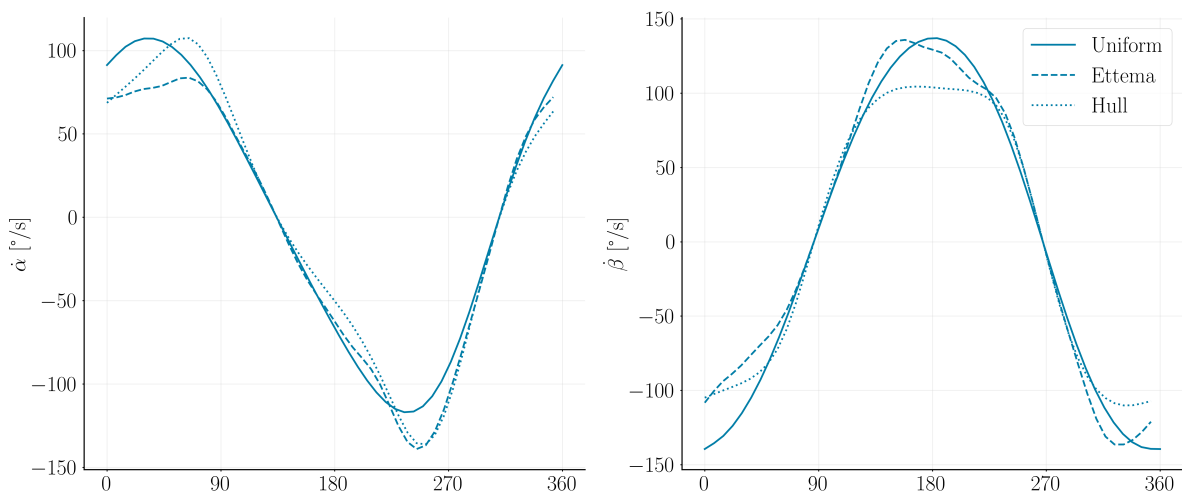


Figure 2.9 : Hip (left) and knee (right) joint angular velocities relative to each cadence profile, with average cadence of 60 RPM.

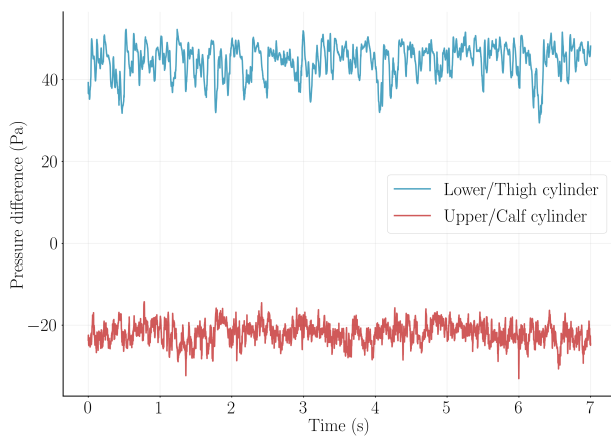
2.4 Measurements procedure

2.4.1 Move/Control the robot

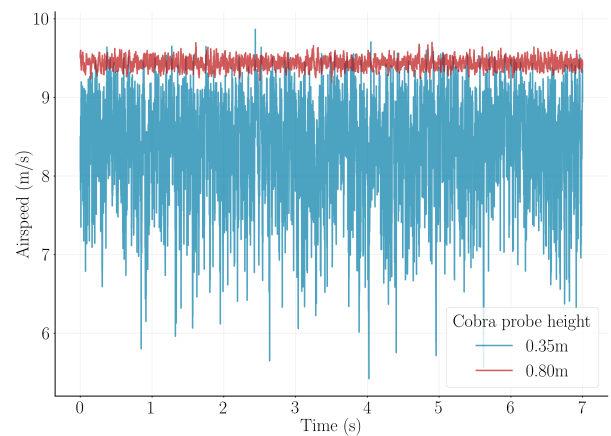
The periodic motion of the robot is pre-computed before the tests using the 2 DOFs Inverse kinematics algorithm presented previously and is communicated by IP link to the robot using a UR script and the python library `python_urx`. In order to both impose the joint motion and keep the variations of the tool pedalling rate during a cycle, the motion is performed through `servoj` commands. The UR script that was sent for each test consists of an infinite loop where each iteration is another loop over all points in the trajectory q (defined in the joint space). This script is sent by socket, using the IP link. The motion stops when the user kills the running of the python code in the terminal. Note that all communication with the robot software are carried out on the primary interface, *e.g.* port 30001, for simplicity. This port, usually used for simple control and feedback usage, has a frequency of 10 Hz.

2.4.2 Harvest and synchronize data

Different kind of data are measured during the tests. First, the aerodynamics forces are measured using a force balance Omega, with a sampling frequency of 1000 Hz. Wind-off measurements are performed for each one of the configurations in order to capture the inertia forces acting on the moving robotic leg. These data allows to isolate the aerodynamic force from the longitudinal one measured with wind. Then, pressure differences are measured at 16 locations on each of the cylinders, at a 1000 Hz sampling frequency as well. Finally, the actual airspeed in the test section of the wind tunnel is measured with a Cobra probe. Even though this instrument has a sampling frequency of 10 000 Hz, the recording is performed at 1000 Hz, in order to match the other measurements. Particular attention is required as the airflow is much dirtier in the region of the thigh/lower cylinder (approximately 35 cm above the ground), resulting in more fluctuating pressure measures around this cylinder than around the upper/calf one. This is illustrated in Figures 2.10a and 2.10b where pressure measurements at the stagnation point at each cylinder are compared, as well as the airspeed measured using the cobra probe at two different height.



(a) Pressure signals at the stagnation point



(b) Airspeed measured by Cobra probe

Figure 2.10 : Pressure signals at stagnation point of both cylinders and airspeed measured at heights corresponding to the mid-span height of each cylinder. Free-stream conditions are stabilised at $V_{\infty} = 9.45$ m/s.

As illustrated by the graphs of the airspeed and the pressure signals, the measurements related

to the upper/calf cylinder are of much better quality. This is also highlighted by the standard deviation of the signals over 7 seconds. These are listed in Table 2.3. One can also see that the free-stream velocity is lower in the lower/thigh cylinder region. The lower cylinder free-stream velocity differs at a ratio of 0.887 that of the upper cylinder one. This corrected ratio is thus applied to all velocities used to compute aerodynamic force and pressure coefficients regarding the lower cylinder. The clean free-stream velocity measured at 0.80 m high is however used for the global coefficients, expressed from the force balance measurements.

	Location	Mean	Standard deviation
Airspeed	0.35m	8.36 m/s	0.64 m/s
	0.80m	9.43 m/s	0.06 m/s
Pressure at stagnation point	Lower/Thigh cylinder	44.58 Pa	3.93 Pa
	Upper/Calf cylinder	47.27 Pa	0.54 Pa

Table 2.3 : Comparison of the mean and standard deviation of the airspeed and pressure at the cylinders' stagnation point time signals in stabilized airflow.

The dynamic configurations (at different pedalling frequency, amplitude and yaw angles) are also realized without wind, in order to capture the inertia forces resulting from the motion of the robot. For these dynamic configurations, the pressures are sampled as follows:

1. Recording starts in initial position ($\theta = 0^\circ$) without wind, to ensure zero bias.
2. Wind speed in the wind tunnel is increased.
3. Once all pressure signals are stabilized, the dynamic motion of the robot starts.

By doing so, the starting time of the dynamic measurements can be easily identified manually. To do graphically so, the pressure signals is filtered at two times the motion frequency and the mean value of the pressure once the robot is static at the initial position and the wind speed is stabilised is computed. This value is reported as an horizontal line on the graph of the pressure signals filtered at the shedding frequency. The starting point of the dynamic pressure measurements corresponds then to the strong deviation of the signal from this value. This procedure, illustrated in Figure 2.11, is simultaneously applied to the pressure signals located at the stagnation taps of both cylinders, since these taps are the most varying with the motion/inclination of the cylinders. Greater priority is given to the upper/calf cylinder as the air stream is of better quality at this height.

Regarding the force measurements, a measure of the voltage out of the robot controller is performed simultaneously with the forces. This voltages remains at 0V during the first 5 cycles and is then set at 5V after that, hence indicating a common starting point of the measurements.

To harvest the kinematics of the robot during the motion, a logger is implemented. The tool position as well as the joints angular position and velocity are recovered each time the robot undergoes the pedalling motion. The positions and velocities are measured by the internal accelerometers of the robot. By doing so, the actual motion can be compared with the trajectory given in the commands. A small time delay is observed in the reproduced motion with respect to the input motion. This is caused by the fact that 1) the logger does not start at the exact same time as the motion, and 2) the input trajectory (built from the IK algorithm) has periodic non-zero boundary conditions for the angular velocities, while the very first cycle begins in practice at rest.

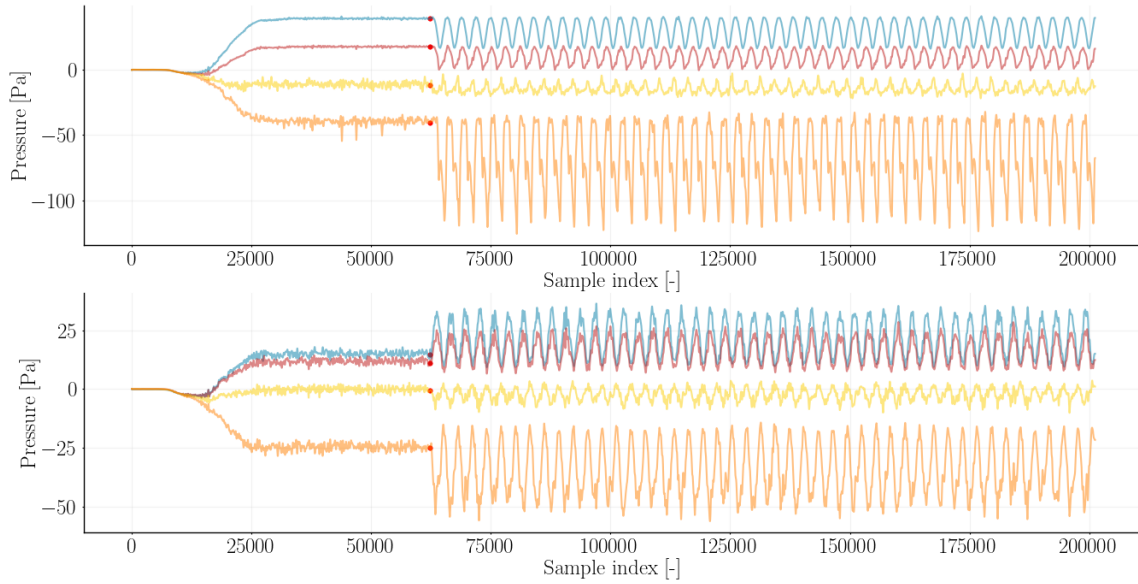


Figure 2.11 : Filtered pressure signals of first four taps on each cylinder (top: upper cylinder, bottom: lower cylinder) with triggering index shown with red point.

The logged motion allows thus to easily compute this phase shift and get back on the good time grid. The small shift in the kinematic position of the robot is computed in post-process using the logged robot motion of each run and all measurements are translated into the same time grid, with respect to the starting points of the measurements. Apart from the phase shift caused at the beginning of the motion, the robot trajectory and velocity are well reproduced, performing the given trajectory with a 0.15% mean error on the tool position and a 0.26% mean error on its angular velocity (data for a 60 RPM motion of 0.11 m amplitude).

2.5 Parameters space and limitations

The different parameters related to the motion and/or the flow conditions are the followings:

- Reynolds number, based on the cylinder's diameter and the mean airspeed measured with the cobra probe :

$$\text{Re} = \frac{V_{\infty} D}{\nu}.$$

- Motion amplitude (*e.g.* crank length) : R .

Note that this parameter has been scaled by the ratio of the external cylinders diameter with the mean diameter of a pro cyclist's thigh, $D_{\text{robot}}/D_{\text{cyclist}}$.

- Reduced frequency, based on the crank length and mean cadence Ω :

$$k = \frac{2\pi\Omega R}{60V_{\infty}}.$$

- Yaw angle (defined in Figure 1.2) : ψ_r .

In order to ensure the diversity in the parameters of the tested configurations, the parameter space of each case is computed randomly in given ranges. The ones that allow for a clean motion of the robot are kept for the tests in the wind tunnel. In total : 110 different runs were conducted. The full parameters space is shown in Figure 2.12.

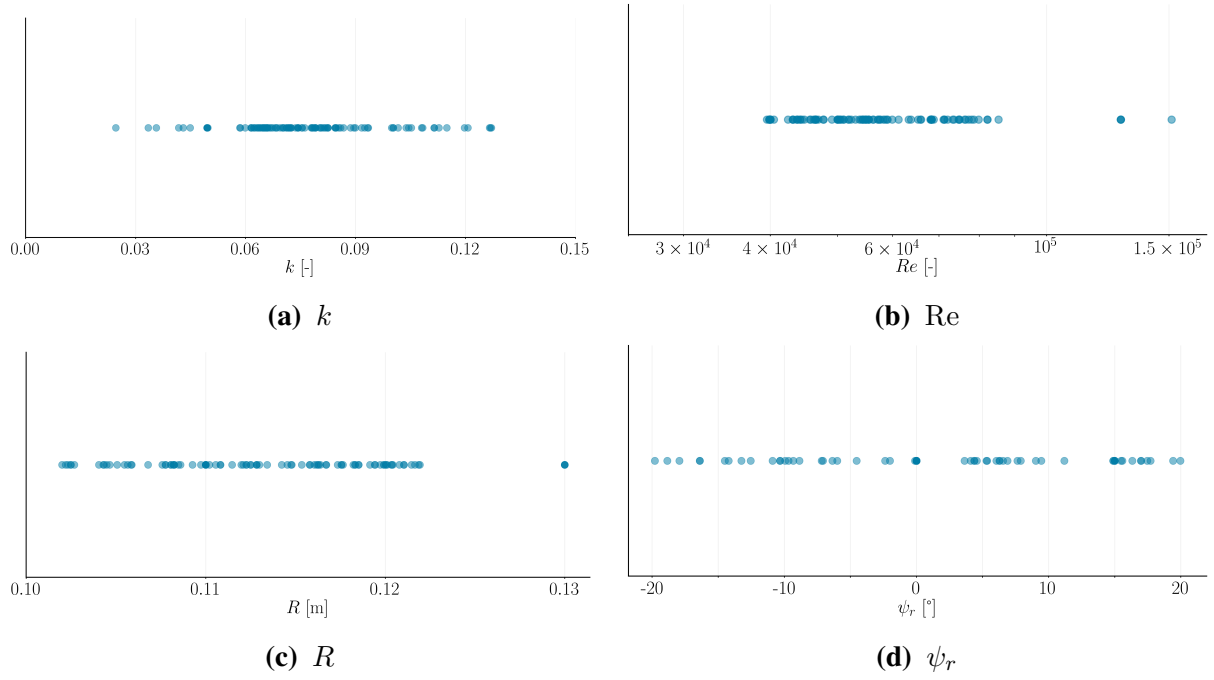


Figure 2.12 : Full parameter space of the configurations tests in the wind tunnel.

Limitations

Due to the physical limitations of the robot UR5, some constraints are unavoidable. The robot has an internal limit on the angular position (min. -360° , max. 360°), velocity (max. $180^\circ/\text{s}$) of the relevant joints and on the translational velocity of the tool (max. 1m/s). These limits highly constraints the robot's ability to perform the pedalling motion at a realistic frequency from a cycling point of view. The maximum cadence realized with the robot lies around 60 RPM. At higher pedalling rates, the internal constraints in the servomotors of the robot take over and the reproducibility of the motion is not ensured any more. The reduced frequency is affected by these constraints. Due to these limitations, the validity of the measurements and the reduced order model built from them is only ensured in the particular case of climbing scenarios, where the aerodynamic still plays a major role (20-30%). Figure 2.13 illustrates the position of this work in the Speed - Reduced frequency regions. As one can observe, the physical limitations of the UR5 robot highly impacts the parameter space regarding flat terrain typical zones.

Force balance accuracy

Finally, the accuracy of the force balance Omega is assessed through a calibration procedure and aiming to quantify the error in longitudinal force F_x measured caused by the coupling with the vertical force F_z and the pitching moment M_y .

Previous work realized in the wind tunnel facility has yielded a calibration matrix $\mathbf{A}$ such as

$$\begin{bmatrix} F_x \\ F_z \end{bmatrix} = \mathbf{F}_{\text{corrected}} = \mathbf{A} \cdot \mathbf{F}_{\text{measured}}. \quad (2.18)$$

This calibration matrix was built by comparing two sets of data obtained by combining axial and vertical loads. It resulted in

$$\mathbf{A} = \begin{bmatrix} 1.011 & 0.021 \\ -0.013 & 0.9938 \end{bmatrix}. \quad (2.19)$$

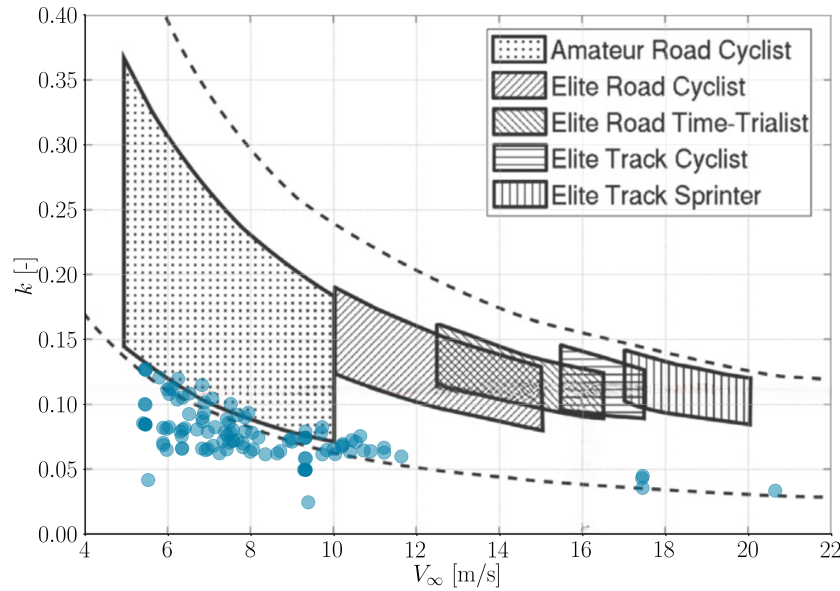


Figure 2.13 : Typical reduced frequencies of various men’s and women’s cycling events, reproduced from [3], with configurations tested in the wind tunnel in blue points.

The root mean square error of the measurements can thus be quantified as $\varepsilon_{F_x} = 0.115$ N for the validation value of 9.81 N longitudinal force.

The error caused by the coupling between with the moment M_y is computed using the data measured on the robotic leg in static inclined positions at different velocities. It is common practice to assume that the error in longitudinal force due to the coupling with the moment is approximately equal to $0.40 M_y$. Table 2.4 presents the results and the corresponding absolute and relative error for static positions at which the upper/calf cylinder is inclined in the free-stream direction at different angles. One can observe that the error remains nearly constant for all inclination angles.

Angle [°]	F_x [N]	M_y [N·m]	Absolute error [N]	Relative error [%]
0	3.867	-1.374	0.550	14.21
10	3.675	-1.355	0.542	14.75
20	3.632	-1.335	0.534	14.70
30	3.455	-1.264	0.506	14.63
40	3.343	-1.184	0.474	14.16
50	3.184	-1.080	0.432	13.57
60	3.019	-0.946	0.378	12.53

Table 2.4 : Summary of F_x -error due to force-moment coupling in the Omega force balance.

The results presented in the next chapter were not corrected for the errors presented here. One should thus remain aware of this while discussing the results.

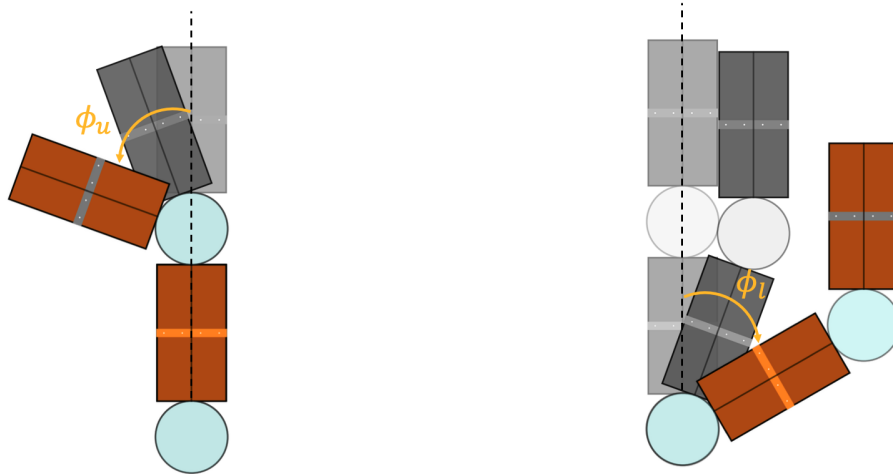
Chapter 3

Experimental results

This section is dedicated to the experimental results observed in various static and dynamic configurations of the pedalling leg in the wind tunnel and aim to gain insights on the flow physics and the influence of the relevant parameters of this work. In each subsection, the goal is to be able to gain relevant informations regarding the behaviour of the flow around the cylinders and more importantly, on the drag force acting on them. This information, highlighted in "Take-home messages" boxes, will be useful in the building of the data-driven model.

First of all, some fixed configurations are considered in order to gain informations about the flow past inclined cylinders in the same flow sub-regime as the one of the pedalling case. These fixed configurations are divided into three parts, listed below and illustrated in Figures 3.1a and 3.1b. Defining ϕ_u as the angle of the calf/upper cylinder with the vertical axis (positive with the cylinder oriented downstream) and ϕ_l as the angle of the thigh/lower cylinder with the vertical axis (positive with the cylinder oriented upstream),

- Lower cylinder fixed at $\phi_l = 0^\circ$, upper cylinder inclined with ϕ_u from 0° to 60° ;
- Lower cylinder inclined with ϕ_l from 0° to 60° , upper cylinder fixed at $\phi_u = 0^\circ$;
- "Cycling configurations" : 8 fixed positions corresponding to the leg position at various crank angles.



(a) ϕ_l fixed at 0° , ϕ_u varying from 0 to 60°

(b) ϕ_l varying from 0 to 60° , ϕ_u fixed at 0°

Figure 3.1 : Static configurations with independently inclined cylinders, air flow comes from the right side.

Then, pedalling configurations are considered at various Reynolds numbers and pedalling rates in the range of interest in order to get valuable informations on the impact that these parameters can have (or not) on the flow. The repeatability and the durability of the dynamic pressure measurements are also studied on the specific case of a 1 Hz pedalling motion at a 9.45 m/s free-stream velocity. The qualitative results obtained from the pressure field are compared with first trends obtained by the force balance measurements. Mainly, the influence of the cadence on the drag force acting on the robotic leg is extensively investigated, first with constant value on the cycle and then using the different cadence profiles described above. Finally, configurations with a wider amplitude and with an applied yaw angle constitute the remaining of the base cases that are analysed in this section.

Disclaimer: Before going any further, one should be aware of some setup characteristics that might have an effects on the measurements conducted. For one, both cylinders are not aligned with each others and the joints at their ends will have a non-negligible influence on the results. While one may not be able to confidently distinguish the true flow field from the what one will call *robot flow perturbations*, one should be careful and critical regarding the results.

Note: The projected frontal area relative to a fully extended robotic leg is used for the force coefficient calculations.

3.1 Static cylinders

Force and pressure measurements on fixed configurations of the cylinders allow to investigate – among other aspects – the possible Reynolds effects on the structure and the validity of the cosine law at high angles of incidence. Furthermore, the time varying signals contain lots of informations on the shedding behind the cylinders. Results are displayed using dimensionless force and pressure coefficients following

$$C_p = \frac{p - p_\infty}{\frac{1}{2}\rho V_\infty^2}. \quad (3.1)$$

Local drag and side force coefficients, respectively C_D and C_S are estimated based on the pressure field around the cylinder using

$$C_D = \frac{1}{2} \int_0^{2\pi} C_p(\theta) \cos \theta \, d\theta, \quad (3.2)$$

$$C_S = \frac{1}{2} \int_0^{2\pi} C_p(\theta) \sin \theta \, d\theta. \quad (3.3)$$

These force coefficients are then projected into the global frame of reference using the orientation of the cylinder's local axes.

3.1.1 Investigation of Reynolds effect

To explore the influence of the Reynolds number on the set-up, three pressure measurements are realized on both cylinders at different free-stream velocity in the wind tunnel. Based on the results on fluid force variations with the Reynolds from Zdravkovich, 1998 [5], no significant Reynolds effect is expected, since the range of interest lies in the Transition in Shear Layer sub-regime, where no drag drop is usually observed.

The pressure field at mid-span of both cylinder is shown in Figure 3.2 for all Reynolds numbers and compared with the literature [33]. As expected, the Reynolds shows no relevant influence on the pressure field on both cylinders. The shape of the pressure distribution is similar to what can be found in the literature. However, the results show a plateau at $C_p = -0.5$ while the C_p distribution from Achenbach observes a plateau around -1.2. This large difference is explained by the fact that the experimental set-up of Achenbach consists of a circular cylinder with a span exactly as high as the wind tunnel height, preventing from any 3D effects. Nonetheless, Norberg, 1994 [7] showed that for circular cylinder of low aspect ratios, the flow at mid-span is very much impacted by the end conditions, partly justifying this quantitative differences.

Larger standard deviations are observed in the pressure data at the lower/thigh cylinder, once again illustrating the difference in flow conditions with respect to the distance with the ground.

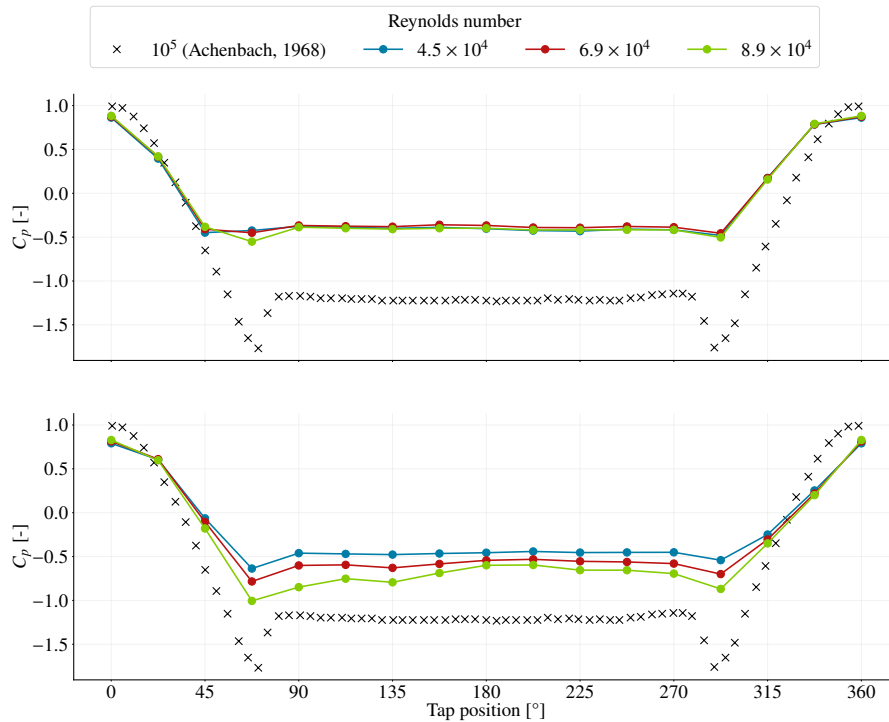


Figure 3.2 : Pressure distribution around both circular cylinders ($H/D = 2.55$, top : upper/calf cylinder, bottom : lower/thigh cylinder) in vertical position. Measurements performed at mid-span, for three different Reynolds numbers, shown as time-averages with standard deviation and compared with pressure distribution from Achenbach, 1968 [33].

3.1.2 Inclined cylinders

Two different configurations are considered (see Figures 3.1a, 3.1b). Results are presented using the following nomenclature : subscript u is used to refer to the calf/upper cylinder and l refers to the thigh/lower cylinder. The drag and side force coefficient in both cases are presented in Figures 3.3 and 3.4. As expected, the drag coefficient of the cylinder inclined decreases with the inclination angle, apart from the upper/calf cylinder where the C_D increases up to an inclination of 20° . It is also interesting to observe that while the vertically fixed lower/thigh cylinder does not seem to be affected by the inclined upper/calf cylinder, a small influence can be observed in the opposite case.

The side force coefficient shows a dependency on the inclined angle as well in both cases, indicating an asymmetry in the pressure field. These observations might be explained by the non-symmetrical shape of the set-up around the cylinders (*e.g.* presence of robot joints and tool). However, it should be noticed that the side force on the fixed cylinder remains nearly constant around zero in both cases, showing that the asymmetry is more the result of the inclination and the flow interaction caused by the latter rather than of the set-up alone.

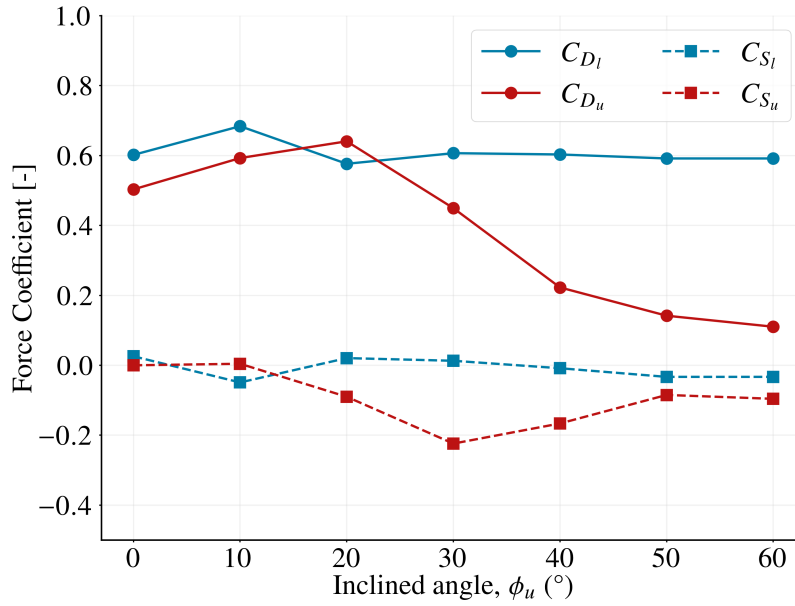


Figure 3.3 : Drag and side force coefficients on both cylinders with respect to inclined angle. Configuration : ϕ_l fixed at 0° and ϕ_u varying from 0 to 60° , $Re = 7 \times 10^4$.

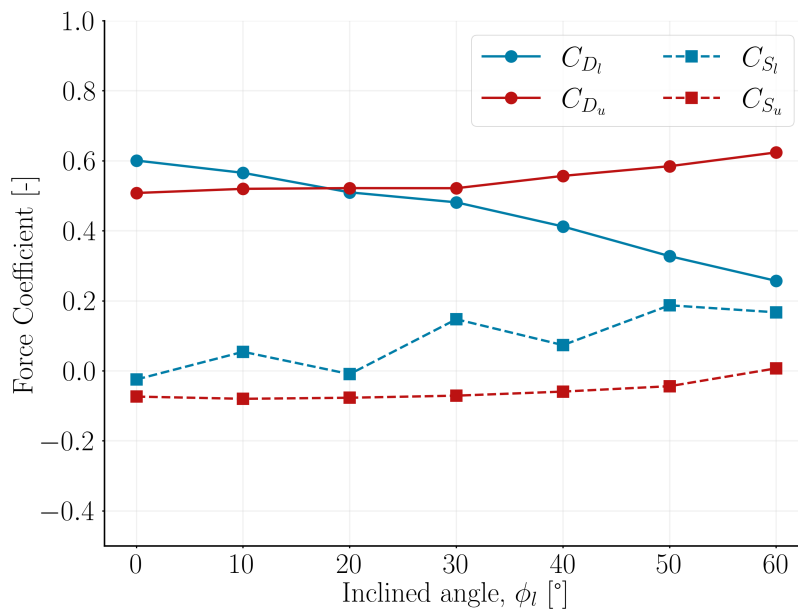


Figure 3.4 : Drag and side force coefficients on both cylinders with respect to inclined angle. Configuration : ϕ_l varying from 0 to 60° and ϕ_u fixed at 0° , $Re = 7 \times 10^4$

Figures 3.6 and 3.7 respectively show the pressure field around the upper and lower cylinders when these are inclined while the other one remaining vertical. First of all, a progressive decrease of the pressure at the stagnation point, following the inclination angle, is observed on both cylinders when they are inclined, as expected. The drag coefficient is then mostly driven by this inclination and projecting the orientation of the cylinder's axis seems sufficient to obtain the decreasing inclination-drag relationship. However, the sides of the upper are largely impacted by the inclination of this latter, experiencing a significant asymmetry in the local pressure field. This lateral asymmetry seems to happen mainly between inclination angles of 20 and 40 degrees, and develops up to $\pm 135^\circ$ with respect to the flow, clearly impacting the pressure difference in the direction of the flow and thus the drag force. The causes of this asymmetry can however not be confirmed at this point even though one can assume that the visible asymmetry in the upper/calf cylinder end conditions may be responsible for it. Finally, no large differences in the pressure field are observed around the lower/thigh cylinder when inclined, showing traditional matching results with the expected behaviour (detailed in section 3.1.3).

3.1.3 Validity of the cosine law

The cosine law (or Independence Principle) states that the flow velocity component that is tangent to the cylinder axis may be ignored because of its minor effects and that the aerodynamic forces of the inclined cylinder can be determined using the force coefficients of the non-inclined cylinder and the flow velocity component normal to the cylinder axis [15]. This principle has been shown to be valid for single circular cylinders inclined up to 40° . Due to the complexity geometry and the significant three-dimensional effects of the robotic leg used in this work, the validity of this principle must be investigated over a large range of angles. Figures 3.5a and 3.5b shows the variations of drag coefficient of the inclined cylinders in each configuration and the expected behaviour of the cosine law based on the C_D at zero inclined angle. The inclination of the thigh/lower cylinder follows quite well the trend expected by the Independence Principle for all angle, indicating the validity of this principle on this part of the experimental set-up. The drag coefficient estimated from the pressure measurement on the calf/upper cylinder do not match the cosine law curve, showing a somehow oscillatory and decreasing behaviour.

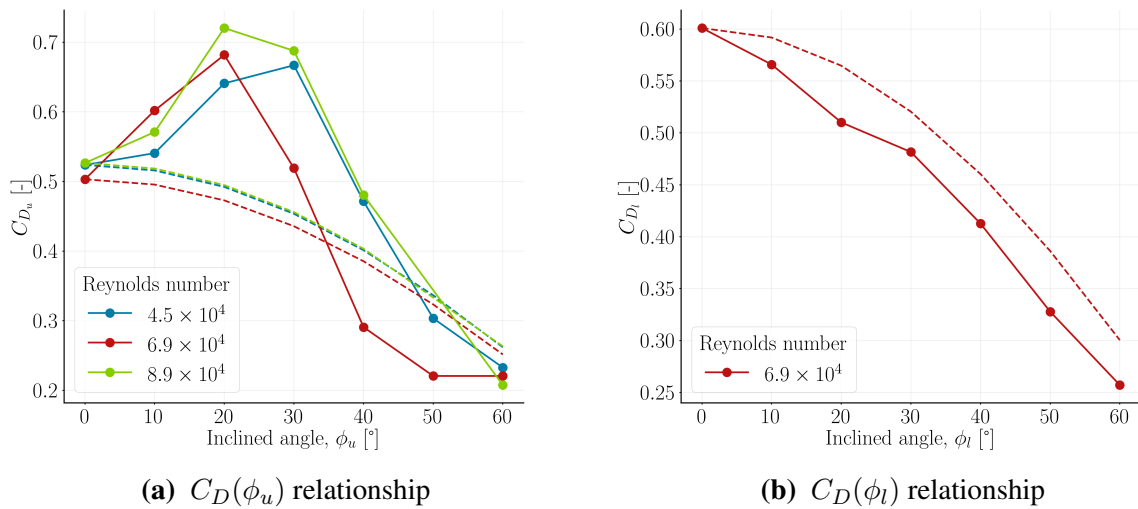


Figure 3.5 : Drag coefficient with respect to inclined angle (●) and expected behaviour from cosine law (---) : (a) C_D of calf/upper cylinder for various Reynolds numbers, (b) C_D of thigh/lower cylinder at a single Reynolds

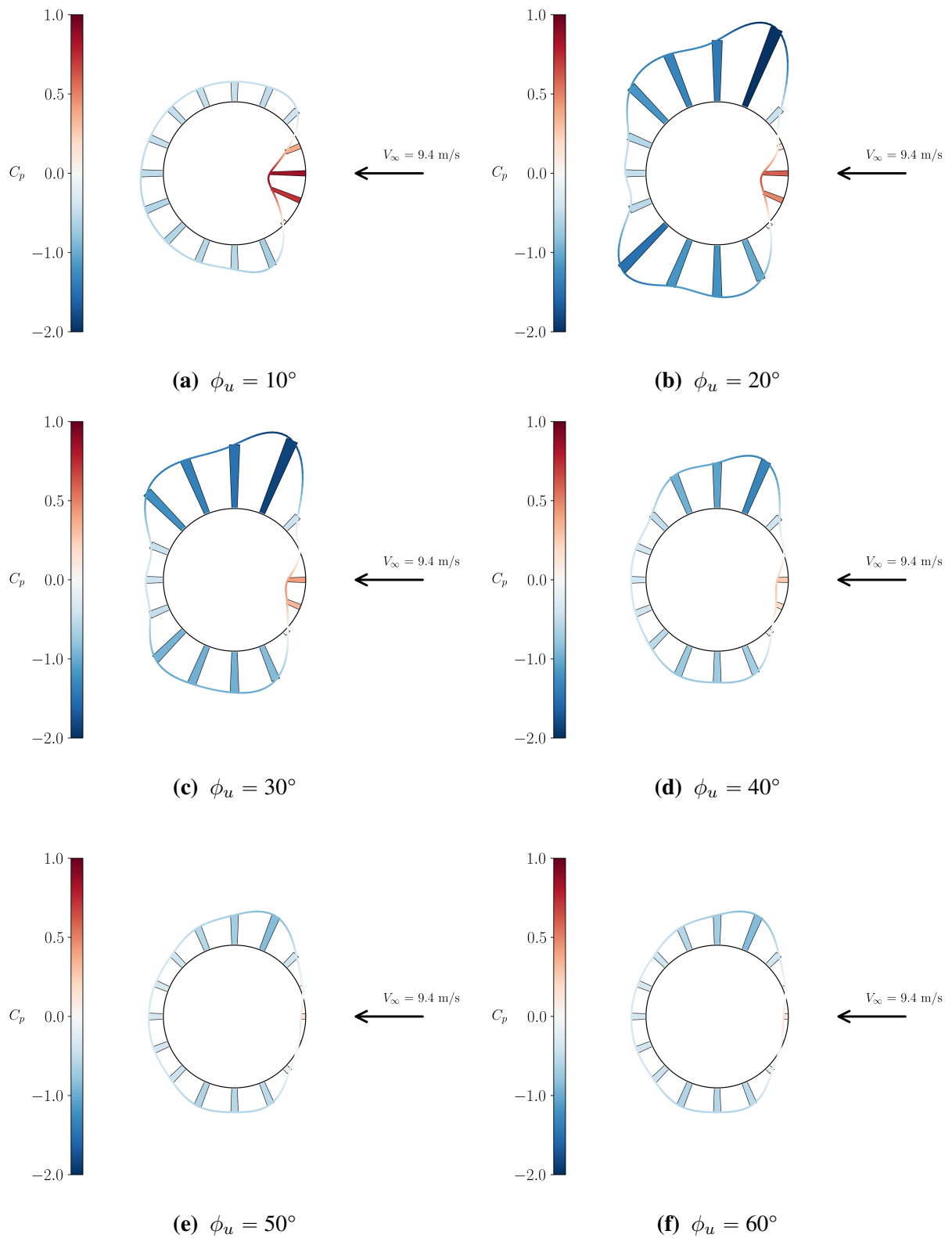


Figure 3.6 : Pressure field around upper/calf cylinder inclined at ϕ_u varying from 10 to 60° while the lower/thigh cylinder remains vertical, $\text{Re} = 7 \times 10^4$.

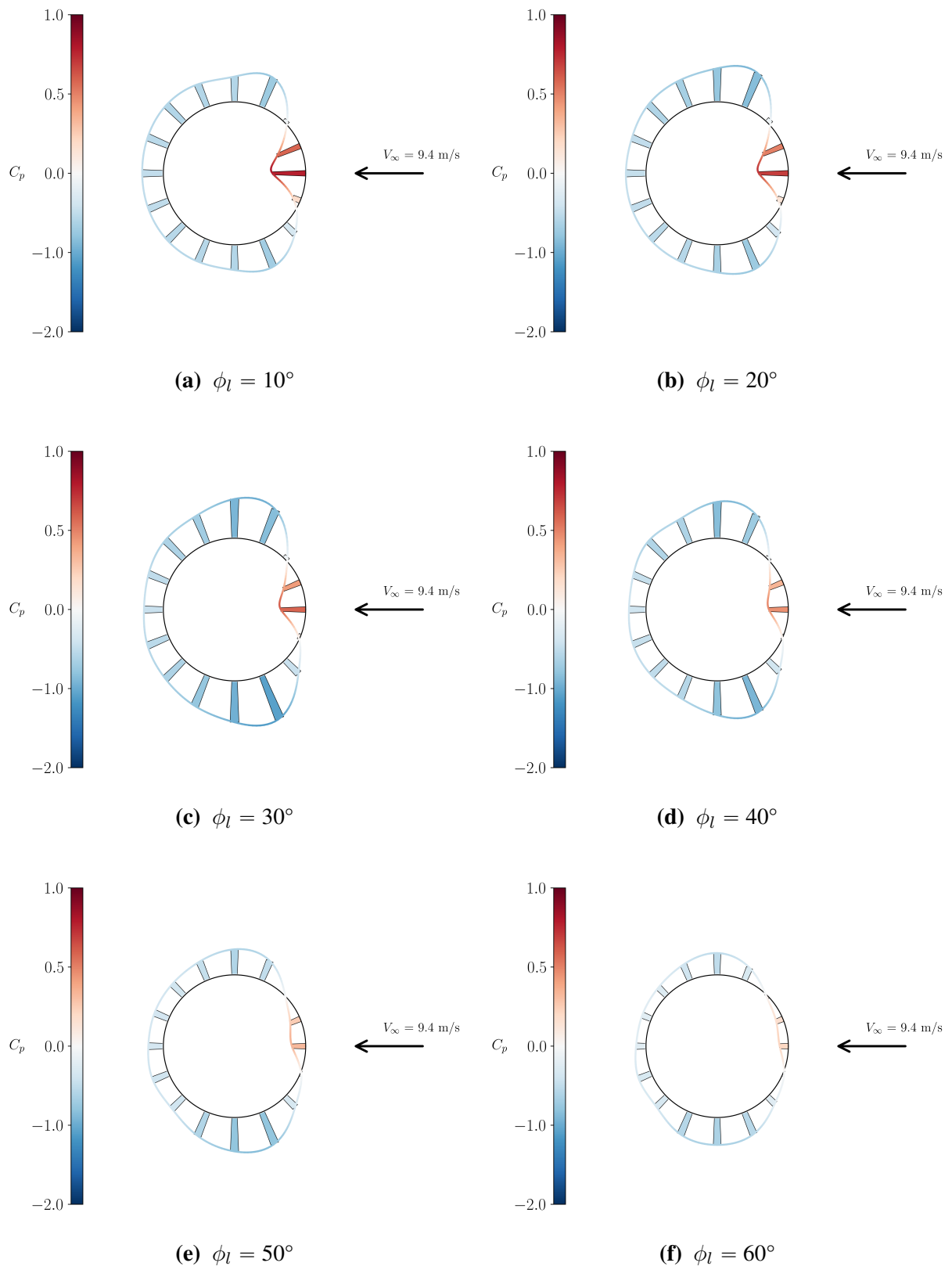


Figure 3.7 : Pressure field around lower/thigh cylinder inclined at ϕ_l varying from 10 to 60° while the upper/calf cylinder remains vertical, $Re = 7 \times 10^4$.

Take-home messages

- The drag coefficient of the upper/calf cylinder is influenced by inclined position of lower $\Rightarrow$ It is likely to be an interaction between both cylinder regarding on lower inclination.
- C_D of lower/thigh cylinder follows the cosine law $\Rightarrow$ Cosine law might be sufficient to model the static component^a of flow past this cylinder.
- C_D of upper/calf cylinder does NOT follow the cosine law $\Rightarrow$ Non-linearities (assumed due to the robotic leg setup) might be required to model the static component of the flow past the upper part of the robot.

^aThe **static component of the flow** refers to the flow characteristics that are only dependent in the position of the cylinders independently and dependently from each other.

3.1.4 Frequency content

The flow past stationary circular cylinders is characterized by coherent vortex structures that shed in the wake. The shedding happens at a specific frequency, defined by the Strouhal number, as written in Eq. 1.9. In the considered range of Reynolds number (*i.e.* in Transition in Shear Layer flow regime), the Strouhal is expected to lie between 0.18 and 0.22. In order to investigate this, the Power Spectral Density (PSD) is computed from the pressure signals measured at the taps located in one half of the upper/calf cylinder (from stagnation point to suction one). Results are shown in Figure 3.8 with the X -axis shown with the Strouhal number. A significant spectral peak is expected to be visible around 0.20, indicating the shedding of the dominant vortex structures in the wake. Additional visible peaks of lower amplitude might also be observed at $2 \cdot St$ and $3 \cdot St$ corresponding to harmonics of the vortex shedding, due to the highly non-linear behaviour in the wake of the cylinder.

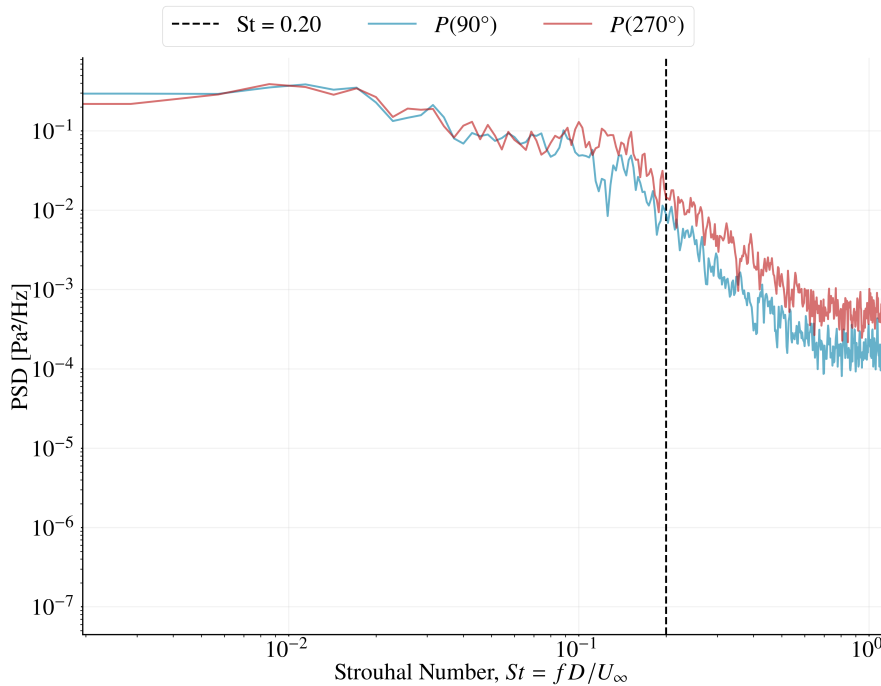


Figure 3.8 : PSD of the pressure signals at the lateral taps of the upper/calf cylinder

No significant peak is observed on the PSD shown in the figure. This is representative of the highly perturbed flow around the robotic leg, which has a more complex geometry than a simple single circular cylinder. One can nonetheless observe that most of the energy is contained before reaching the 0.20 value on the Strouhal axis, before rapidly decreasing at higher frequencies.

3.2 Dynamic cylinders

The results regarding the dynamic tests performed in the wind tunnel are presented here. Pressure and force measurements for basis sets of parameters are used to qualitatively and quantitatively investigate the impact of each parameter on the unsteady drag. Results of static cases in different positions on the pedalling cycle are also shown here.

Disclaimer : One should note that due to the motion of the robot leg segments and their respective inclination with the flow, the true local velocity seen by the cylinder at the pressure tap location is not exactly the free-stream velocity measured by the cobra probe. Figure 3.9 shows the component in the free-stream direction of local translational velocity of both cylinders at their mid-span due to their rotation. The rotation of the cylinders causes a streamwise translation velocity up to 15% of the free-stream velocity for the considered Reynolds numbers. For consistency, this local translational velocity is neglected for the computation of the pressure and force coefficients. Nonetheless, the maximum local velocity encountered by the cylinders is used to estimate the shedding frequency in order to filter the pressure signals. Notice that the inclination of the cylinders does not impact this procedure since the projection of the free-stream velocity only results in reducing the normal velocity.

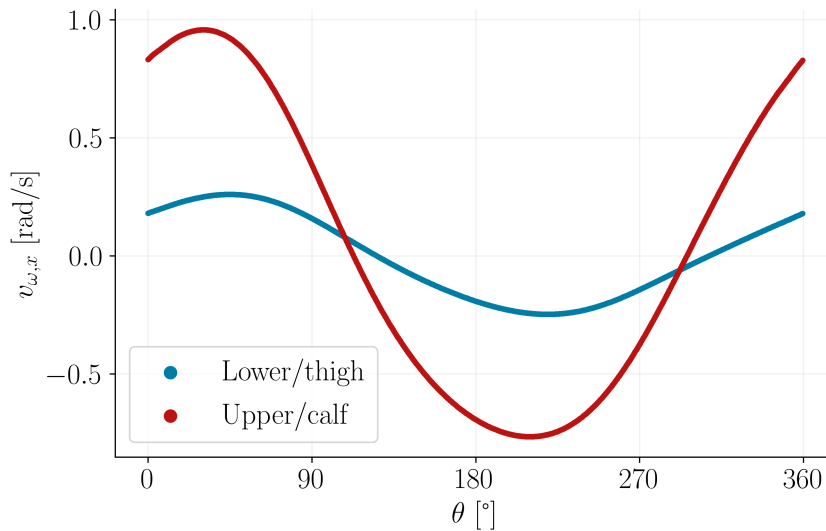


Figure 3.9 : Streamwise component of translational velocity at each cylinder's mid-span due to their rotation in the pedalling motion. Results for 60 RPM motion with 0.11 m amplitude.

3.2.1 Cadence effects

The cadence of a cyclist's pedalling motion is believed to impact the aerodynamic forces acting on it, assuming the motion of the large volume of air and its frequency has consequences on the flow around the cyclist. Its effect is thus thoroughly investigated using a dimensionless form, as defined previously in Eq. 2.5, the reduced frequency k . In order to do that, the drag force directly measured from the force balance and estimated from the pressure measurements on the cylinders is compared for different values of k . All signals are filtered at the estimated shedding

frequency, whose computed based on a Strouhal number of 0.20 and the airspeed measured at 0.80 m above the ground of the wind tunnel, and then phase-averaged over 25 cycles¹. Figure 3.10 shows the raw and filtered drag force of one of the dynamic configurations.

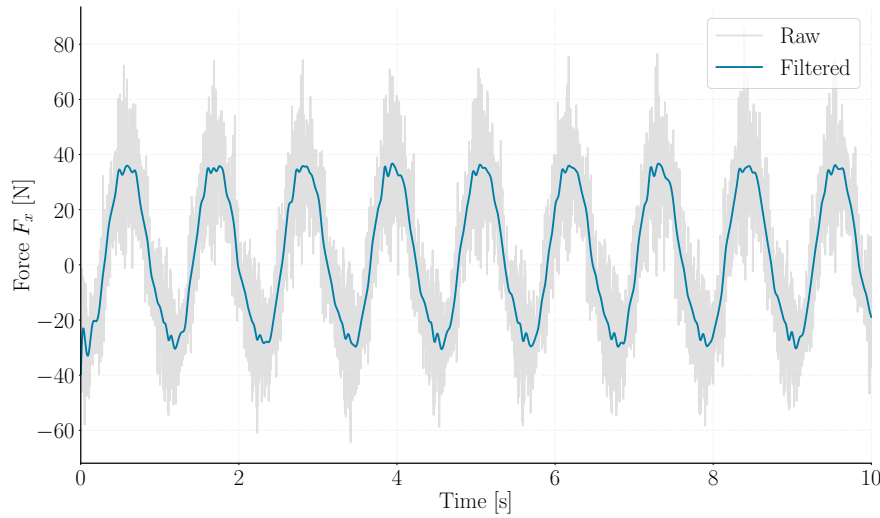


Figure 3.10 : Raw force signal from Omega force balance and filtered signal at the corresponding shedding frequency.

Figure 3.11 shows phase-averaged drag coefficient of the pedalling robotic leg for various reduced frequency while keeping the Reynolds constant. Variations in k are thus achieved by varying the cadence of the pedalling motion from 20 to 60 rounds per minute. First of all, a difference in amplitude of the drag for lower reduced frequencies, even though remaining within an overall similar behaviour for all reduced frequencies. A significant different is noted with respect to the static positions on the pedalling cycle. However due to the small free-stream velocity, the contribution of the translational velocity of the different leg components caused by their rotational motion is not negligible anymore, such that one must remain critical regarding the amplitude of the results. Most importantly, a phase shift is observed on the drag coefficient over the crank cycle. The high drag position on the crank cycle indeed shifts towards lower angles as the cadence increases. A first hypothetical explanation for this phase shift is that the unsteady drag acting on the robotic leg is memory-driven, meaning that the motion of the cylinders and the interactions of their flow structures have consequences on the future flow behaviour. The cylinders are in fact oscillating in their own wakes, perturbing their structures each time.

Figures 3.12a and 3.12b show the drag coefficient of two configurations with the same reduced frequency but different Reynolds, plotted along their respective static results. At higher Reynolds, the reduced frequencies are kept constant by increasing the cadence of the motion. A first observation is that there are less discrepancies on the amplitude at higher Reynolds number, partly explain by the smaller contribution of the local translational velocity. Nonetheless, while static pressure measurements on inclined cylinders did not show signs of Reynolds effects, one can not rule out that the aerodynamic forces of the full set-up with a lot of components that perturbs the flow might be subject to Reynolds effects. That being said, one can look with a critical point of view on the behaviour of the drag at different cadence and Reynolds while keep a constant reduced frequency and observe that a small phase shift is still present. This means that even if the reduced frequency seems to be the most significant parameter regarding cadence

¹One should note that the first 5 cycles of the signals are automatically removed in order to avoid transient measurements.

effect on the drag, the way to vary this parameter is not without consequences on the results, even if small ones.

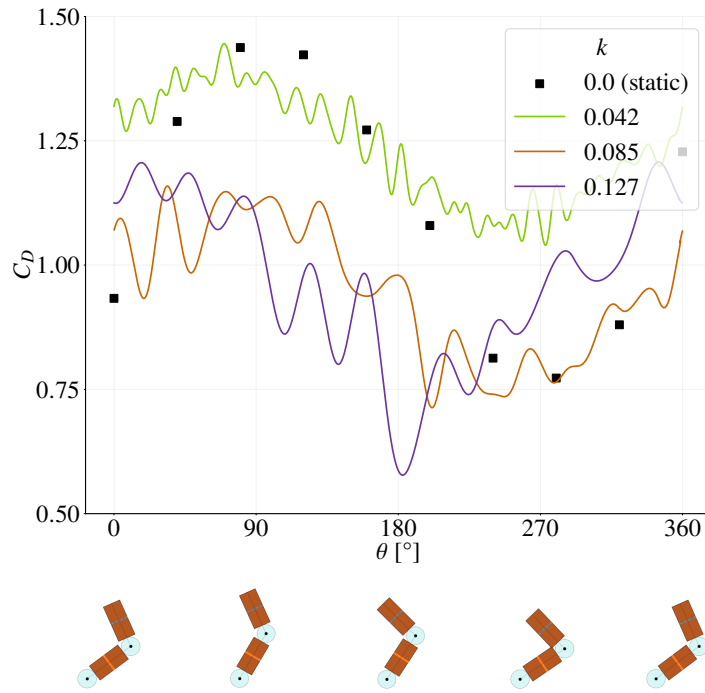


Figure 3.11 : Drag coefficient variations over a crank cycle for various reduced frequencies at Reynolds of 4×10^4 , from phase-averaged force balance measurements.

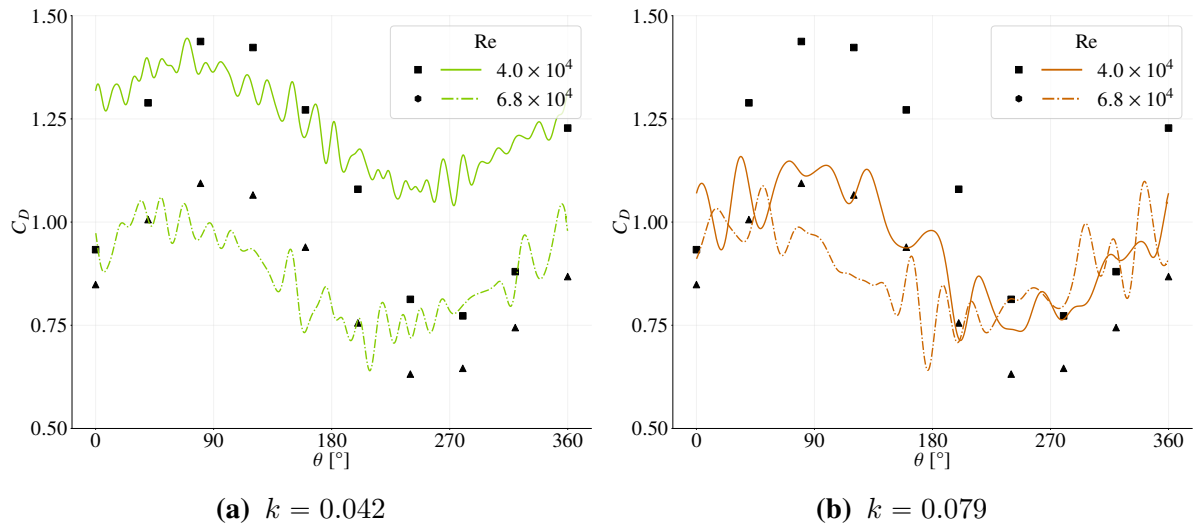


Figure 3.12 : Drag coefficient variations over a crank cycle for a given reduced frequency at different Reynolds, from phase-averaged force balance measurements.

The phase shift is also observed in the longitudinal force coefficient obtained by an integration of the pressure coefficients measured at the taps of each cylinder, as shown in Figure 3.13. However, one should remain cautious while concluding anything based on these results, since the choice of the measurements starting point on the crank cycle has been manually determined, introducing an error. The global shape of the C_{Fx} can however be analysed and compared with the forces data. Also seen on the force balance data, the unsteady drag acting on the dynamic leg does not show any well defined extrema. The high drag portion of the cycle is

indeed flattened a bit, even showing variations in flattened regions in the pressure measurements at small reduced frequencies. One must note that these plateaus are also observed by Crouch et al., 2016 [3], from wake-integral analysis. According to the results presented in this paper, these flatter portions of the drag curves are correlated with pointwise phase-averaged results of the streamwise velocity component with respect to the crank angle. These results have led to the computation of a range of uncertainty on the crank angle lag on the pressure taps and force balance results of $\Delta\theta_{\text{lag}} \approx 30^\circ$ at a reduced frequency of $k = 0.115$. This phase shift aligns with the results obtained above in this work.

Moreover, the C_{F_x} coefficient variations in the crank cycle at the highest reduced frequency leads to conclude that the flow around the articulated cylinders in a dynamic pedalling motion is subject to two different flow regimes depending on the leg position : a high-drag and a low-drag sub-regime. This proposition is also supported by the observations in the wake structures by Crouch et al., 2012 [21].

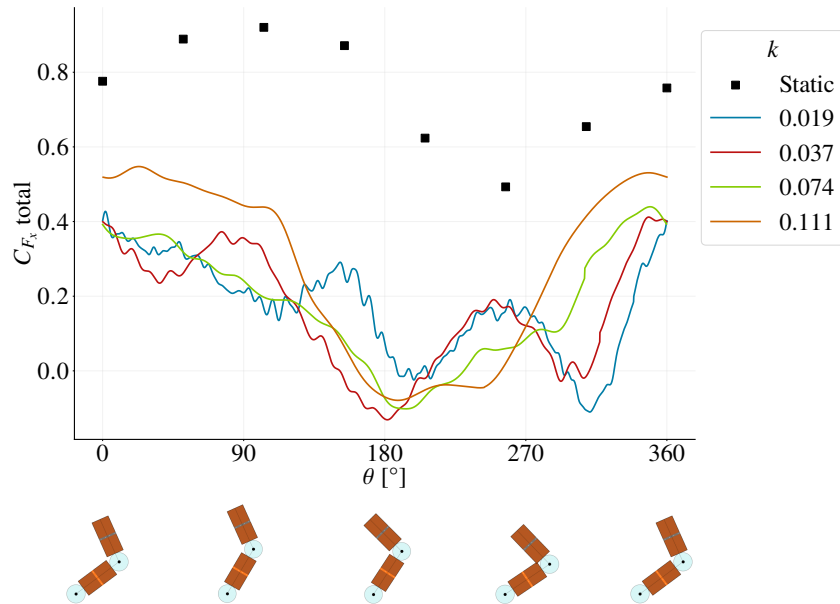


Figure 3.13 : Longitudinal force coefficient variations over a crank cycle for various reduced frequency at Reynolds of 4.5×10^4 , from integrated phase-averaged pressure measurements.

Finally, the mean drag coefficient over a complete crank stroke obtained from the force balance are compared with respect to the reduced frequency at multiple Reynolds numbers, as well as with the wake integrals results from Crouch et al. [3]. These results are shown in Figure 3.14. Compared to Crouch observations, large differences are observed at very low reduced frequencies (also in static configuration). At this point, no explanation for these differences are proposed. One should however know that the experimental set-ups are well different. The model from Crouch et al. is indeed full-scale mannequin while the set-up here is simply composed of a single leg represented by circular cylinders mounted on two segments of an industrial robotic arm.

Looking at the measured data in the wind tunnel at Liège only, one can observe on the figure that the mean drag coefficient globally decreases as k increases but starts to increase a little again at some point, indicating a certain critical reduced frequency at which the mean drag on the pedalling leg would be minimum. However, the increase remains small in amplitude (up to 2% at $\text{Re} = 4.3 \times 10^4$).

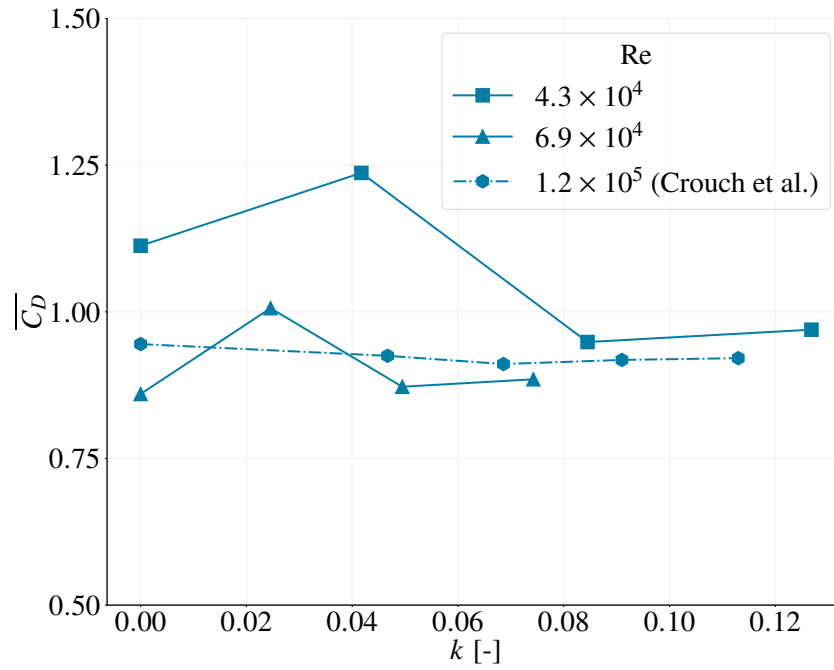


Figure 3.14 : Mean drag coefficient over a full crank cycle with respect to the reduced frequency, from force balance measurements.

Finally, one must note that the points regarding the static configurations in Figure 3.14 correspond to an average of all positions over the cycles. In a cycling point of view, results show that one should remain static with their legs positioned close to 180° crank angle. Assuming that both cyclist's legs operates with a 180° phase shift, summing the obtained drag coefficient would results in a better aerodynamic efficiency at constant riding speed than pedalling at high cadence. Yet, this observation relies on the addition of the results obtained on independent moving leg, thereby disregarding any flow interactions between the legs.

Take-home message

- The global behaviour of $C_D(\theta)$ observed in static configurations is roughly accurate to represent the dynamic behaviour.
- Increasing the reduced frequency results in a phase shift towards smaller crank angles in $C_d(\theta)$. The duration of this phase lag however varies with the way k is changed (*e.g.* keeping V_∞ constant, keeping Ω constant, etc).
- The amplitude of the drag coefficient varies with the reduced frequency. The variations are observed to be more significant at low values of k .

3.2.2 Pressure distribution

It has been proposed in the previous subsection that the unsteady drag acting on the dynamic pedalling leg is memory-driven, in the sense that the history of the flow in the wake affects the instantaneous drag. This hypothesis is further investigated by looking at the phase-averaged pressure field around the cylinders at key positions on the pedalling cycle and comparing them with the pressure fields from static measurements. Figures 3.15, 3.16, 3.17 and 3.18 illustrate this along with a schematic of the robot in the corresponding position. Regarding the results in the in-flow direction, the pressure field on the upper cylinder is very different from the static

case at the initial position on the pedalling cycle. The previous positions of the upper/calf cylinder can be visualized through the shadow of the current position in Figure 3.15 or further before this position with the position at $\theta = 310^\circ$ in Figure 3.18 and show that the so-called knee angle γ of the robotic leg is decreasing towards $\theta = 0^\circ$ and, most importantly, is found to be located in the range of inclination angles that showed non-linear $\gamma - C_D$ relationships (see Figures 3.5a and 3.6). The fact that the pressure field at this given position is still related to a previous configuration, while the pressure field from the static case shows expected instantaneous behaviour regarding the position, supports the idea that the unsteady forces acting on the dynamic moving leg do have a memory characteristic.

The leg motion between 0° and 100° crank angles (Figures 3.15 and 3.16) is mostly driven by a decrease in the hip angle, explaining why the pressure fields around the upper/calf cylinder are close between dynamic and static configurations and the ones around the lower/thigh cylinder are much more different. In this case, the cylinder experiences a larger pressure difference in the in-flow direction than in the static case. Still regarding the lower/thigh cylinder, one can observe on Figure 3.18 that the pressure differences in both in-flow and cross-flow directions are larger in the dynamic case than in the static one, even though the shadow of the leg shows that this cylinder does not move at all in the previous time steps of this particular position. This leads one to believe that the motion of the upper/calf cylinder also has consequences on the flow around the lower/thigh one, mostly through the interactions of the two wakes.

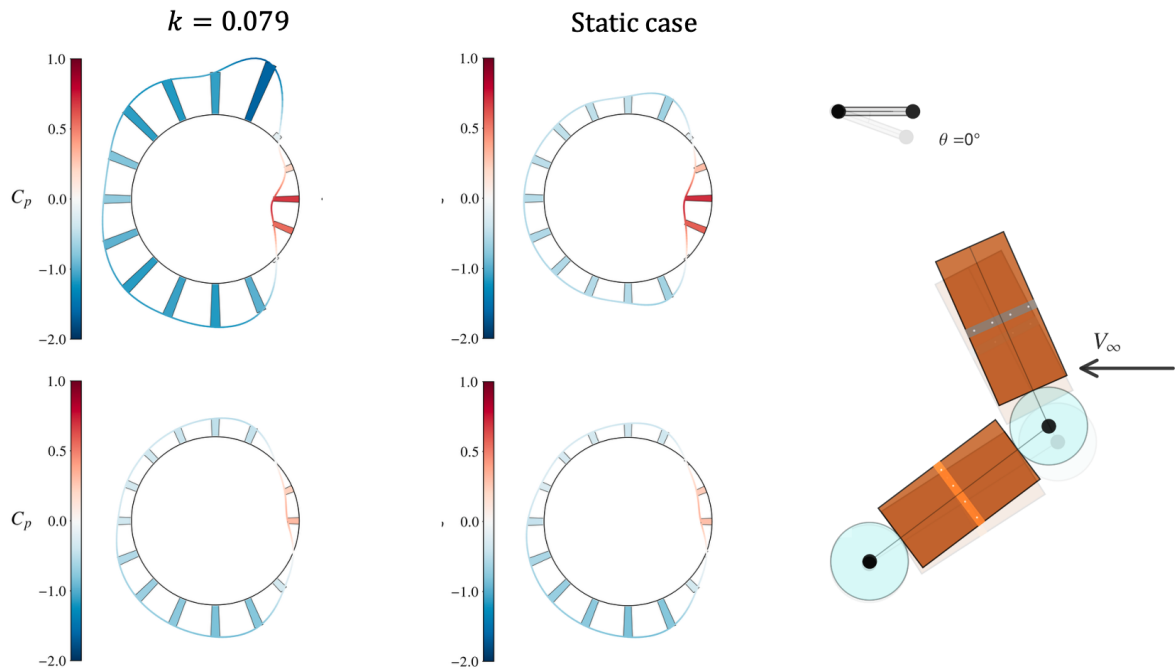


Figure 3.15 : Pressure field around both cylinders from dynamic and static configurations relative to a 0° crank angle.

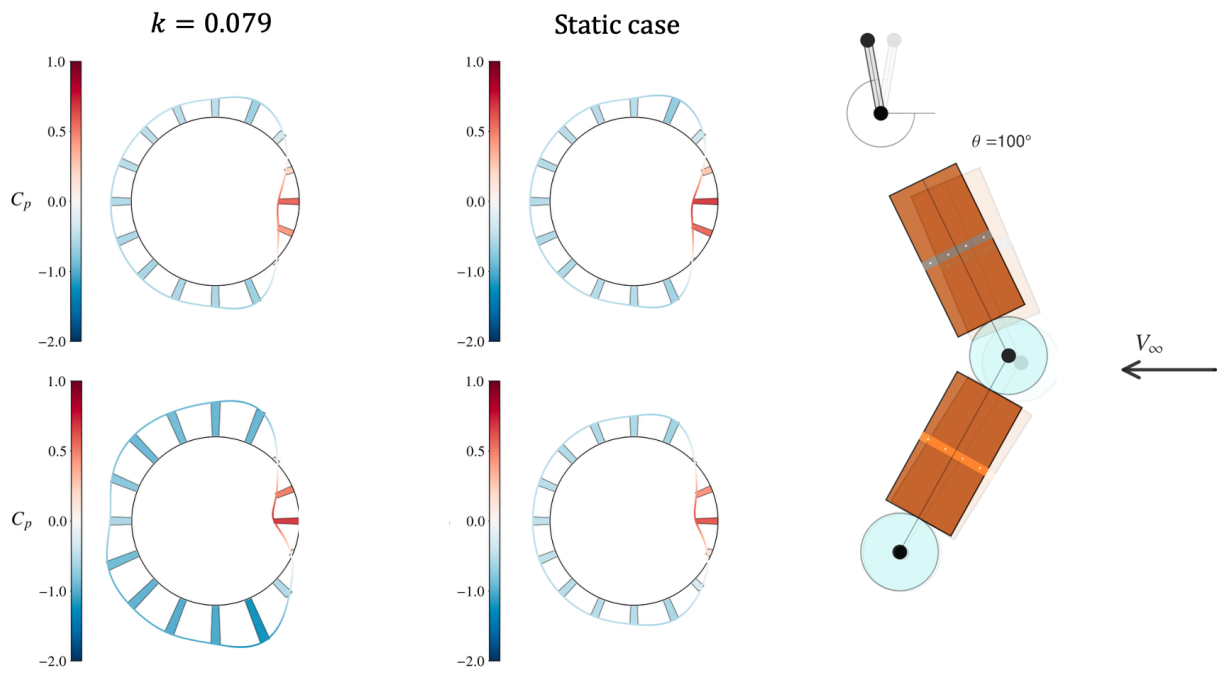


Figure 3.16 : Pressure field around both cylinders from dynamic and static configurations relative to a 100° crank angle.

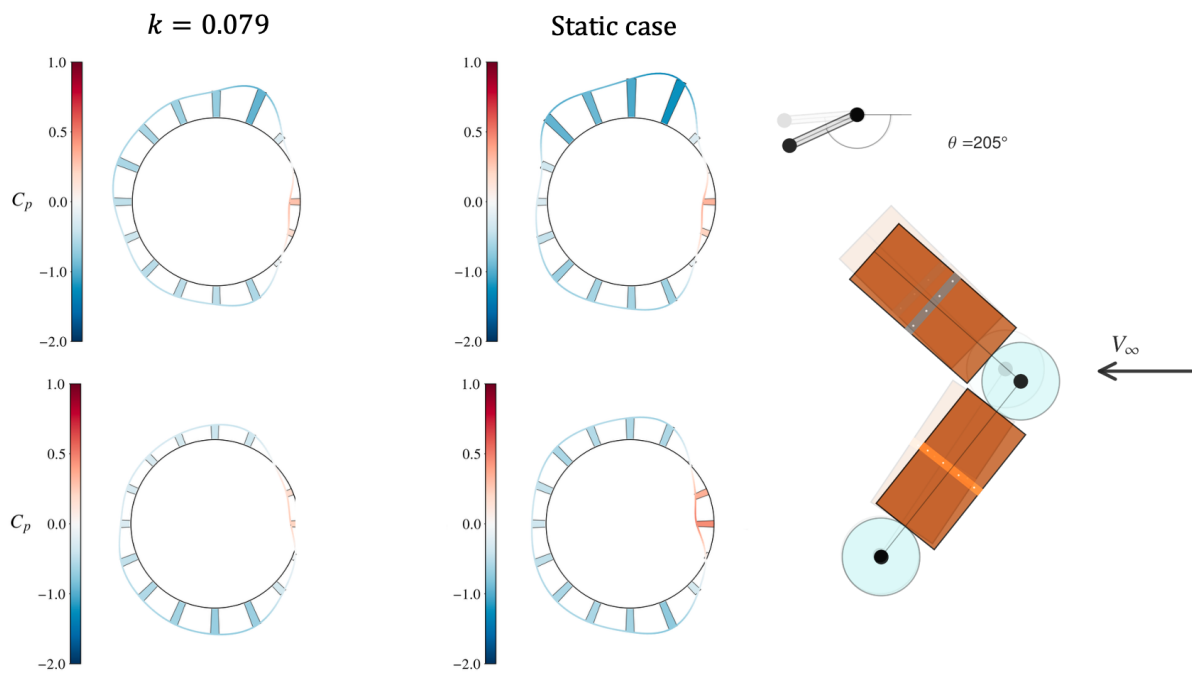


Figure 3.17 : Pressure field around both cylinders from dynamic and static configurations relative to a 205° crank angle.

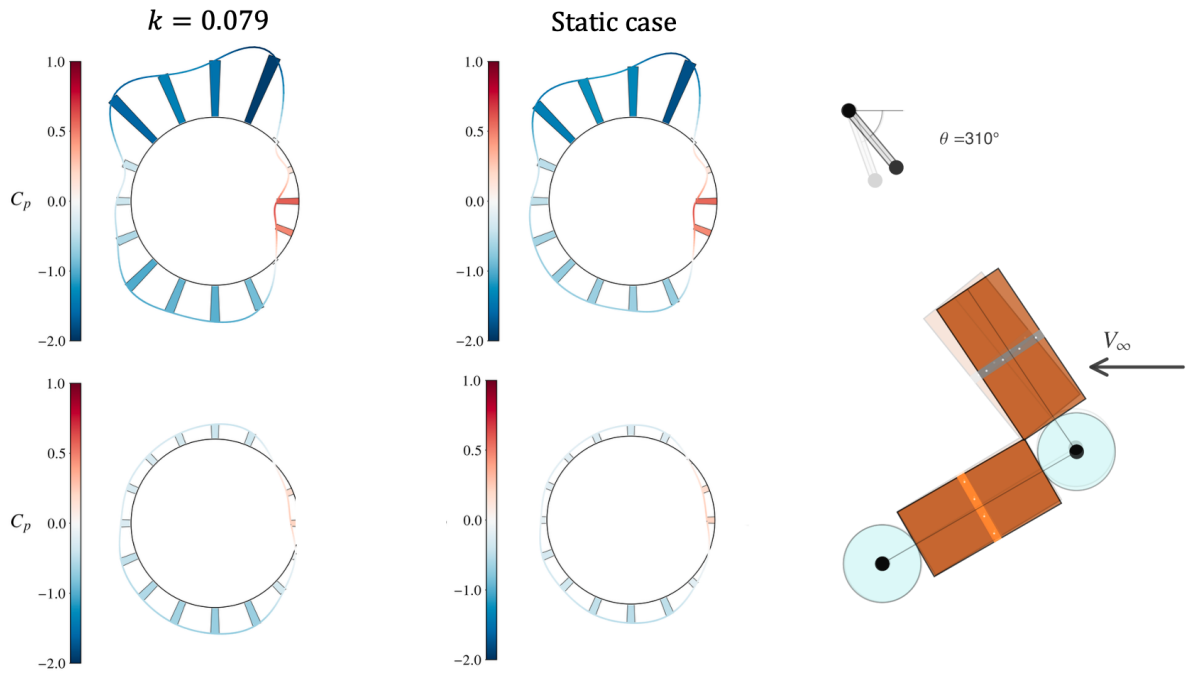


Figure 3.18 : Pressure field around both cylinders from dynamic and static configurations relative to a 310° crank angle.

3.2.3 Non-uniform cadence profiles

According to Crouch et al., 2016 [3], a non-uniform pedalling rate over a pedal stroke will affect the wake structures behind the cyclist and might be more aerodynamically efficient regarding the pedalling motion. Two similar cadence profiles from different sources in the literature are here compared with the constant rate at the same reduced frequency. Figures 3.19a and 3.19b illustrates this comparison at two Reynolds with mean cadence of 60 RPM. One first sees that the Reynolds number affects the differences in aerodynamic performance, yielding lower gaps at higher speeds. Even though the angular velocity of the pedal is clearly changing over the crank cycle, no significant changes are observed in the behaviour of the drag coefficient. The low and high drag regimes are indeed located at similar crank angles. Nonetheless, the non-uniform profiles show much lower deviations between these regimes, which means that the non-uniform profiles might provide a better aerodynamic efficiency.

To further discuss this, the mean and standard deviation values of each drag coefficient variations over a crank cycle are illustrated in Figures 3.20a and 3.20b. Results are expressed in terms of aerodynamic power loss, defined as

$$P_{\text{aero}}(\theta) = \frac{1}{2} \rho C_D(\theta) A V_\infty^3. \quad (3.4)$$

While the constant cadence case yields a lower mean power loss, a non-uniform profile causes significantly lower changes in amplitude during a crank cycle. In long-duration efforts, as in can be the case in mountain time-trials or in triathlons, a smoother power loss/production might provide significant reductions in the energy consumed by the rider. A trade-off does thus appear between the power generated by the rider and the way it is produced, leading to a strong relationship between the aerodynamic efficiency and the biomechanical and physiological aspect.

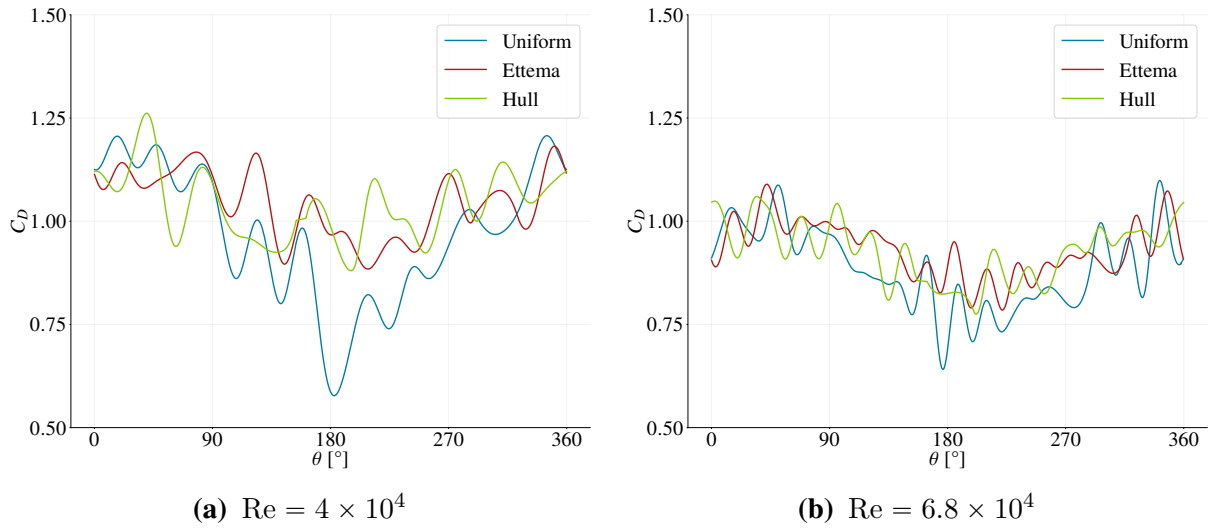


Figure 3.19 : Comparison of drag coefficient over a crank cycle for different cadence profiles at the same mean cadence for two Reynolds number.

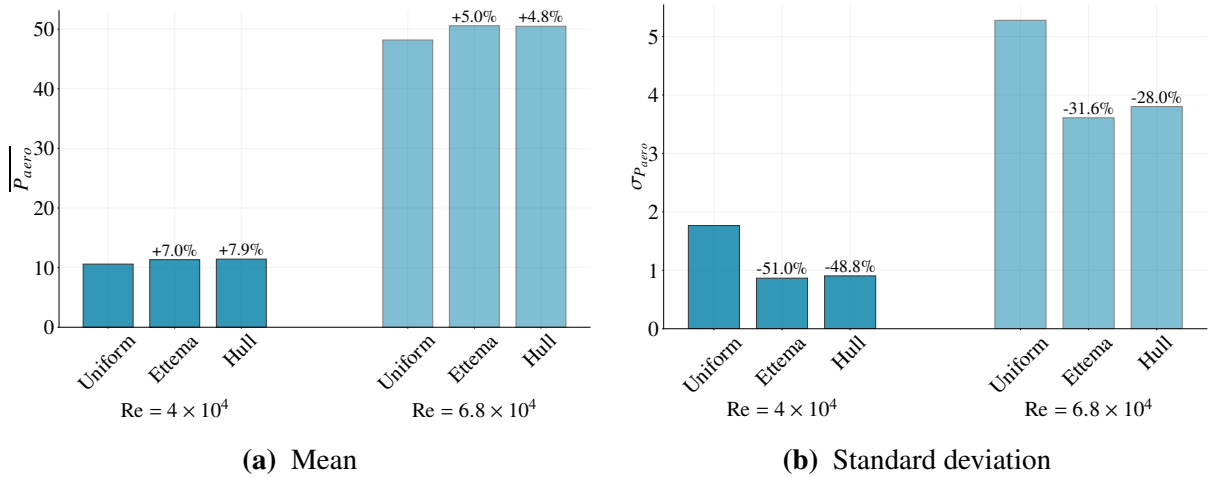


Figure 3.20 : Comparison of the mean value and standard deviation in aerodynamic power loss over a crank cycle for the different cadence profile at the same reduced frequency.

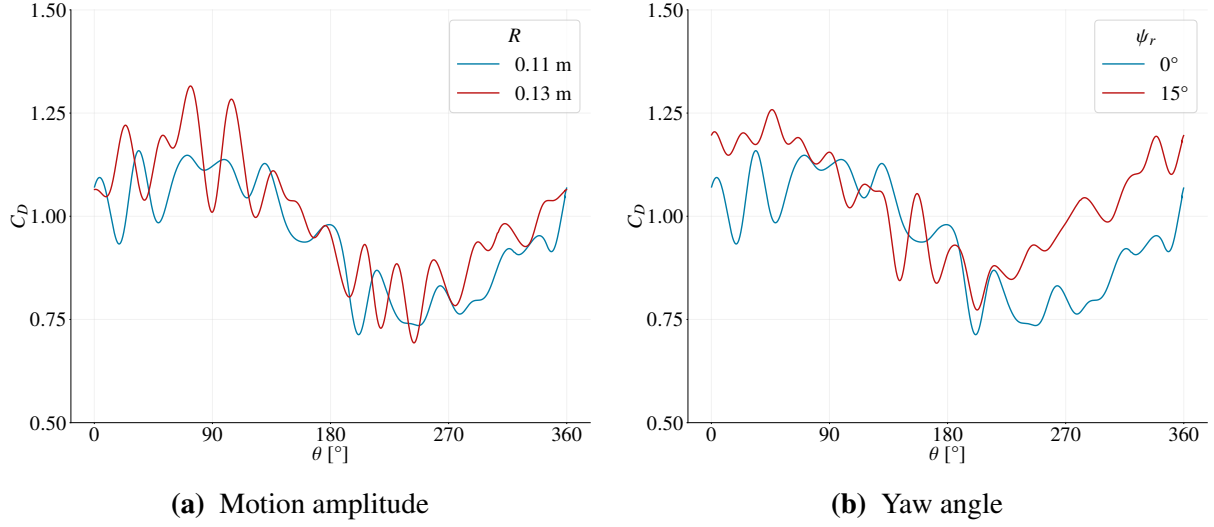
3.2.4 Influence of motion amplitude and yaw angle

Finally, the consequences of varying the amplitude of the motion and the yaw angle of the set-up with the flow are analysed.

Figure 3.21a shows that changing the amplitude of the motion does not much affect in the drag coefficient of the pedalling leg. A very small shift is still observed, yielding similar conclusions as the effects of the cadence on C_D , which is expected since both parameters impact the reduced frequency. One should note that while the variations in R seem small, they correspond to a 3 cm variation after re-scaling into real-life cycling values, which is a range length that is beyond the range in manufactured cranks nowadays.

In contrast, varying the yaw angle shows larger consequences on the drag coefficient of the pedalling leg, as illustrated in Figure 3.21b. As could be expected, imposing a yawed direction to the motion with respect on the flow causes a projection of the force acting on the leg. This

shifts the amplitude of the drag coefficient while the global trend of C_D with respect to the crank angle remains unchanged. A linear trend can be observed on the relationship between the drag coefficient and the yaw angle in the same pedalling conditions : the mean C_D increases for larger positive angles and decreases for larger negative angles. This is further illustrated in section 3.3.



3.3 Statistical observability

This section is dedicated to the characterization of a few statistics of the dynamic pedalling motion dataset that will be used for the modelling. These results provide key information on the robustness and the uncertainty of the experimental data. Global relationships between the mean drag coefficient and the flow and motion parameters are first assessed. The global and in-cycle variability of the drag coefficient are then analysed, followed by more local relationships and eventual trends between the kinematics, the parameters and the drag coefficient. The parameters of the complete dataset are listed in Annex B.

3.3.1 Mean drag coefficient in the parameter space

Relationships between the flow and motion parameters with the mean drag coefficient observed during the experimental measurements from the force balance are a good way to study the consequences of their variations on the aerodynamic performance of the pedalling leg. Figure 3.22 illustrates the possible correlations between the parameters (k , Re , R and ψ_r) and $\overline{C_D}$. Overall, no explicit relationship is observed since the points are shaped as a large single cluster. The yaw angle ψ_r however shows a linear trend as the mean drag coefficient increases as the yaw angle goes from -20 to 20° . A way to quantify these, either non-existent, or very weak correlations with the parameters is the Spearman's rank correlation coefficient ρ . Spearman's coefficient is a non-parametric measure of the monotonicity of the relationship between two datasets. If there are no repeated data values, a perfect Spearman correlation of +1 or -1 occurs when each of the variables is a perfect monotone function of the other. [34]. The Spearman's correlation coefficients are listed here-below:

$$\rho_{Re} = -0.383, \quad (3.5)$$

$$\rho_k = 0.134, \quad (3.6)$$

$$\rho_{\psi_r} = 0.337, \quad (3.7)$$

$$\rho_R = -0.196. \quad (3.8)$$

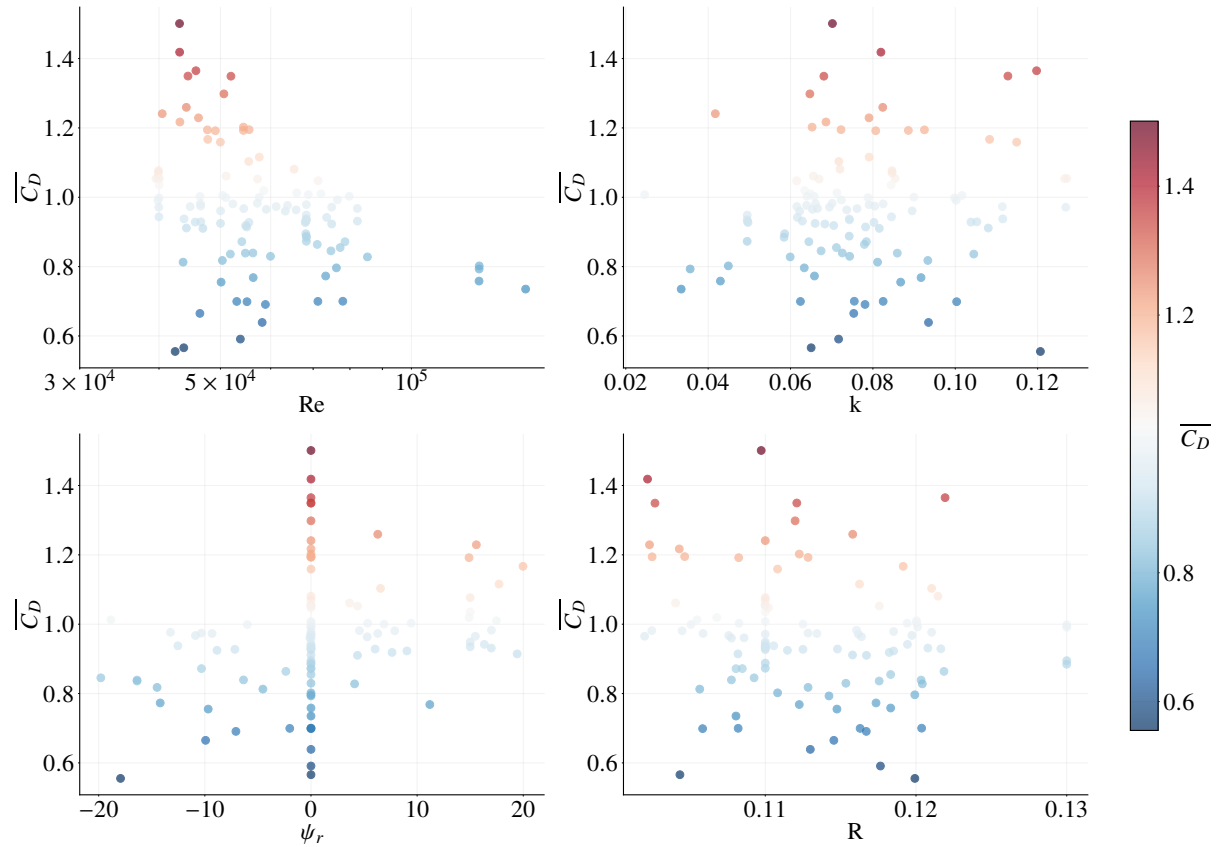


Figure 3.22 : Mean drag coefficient versus the flow and motion parameters.

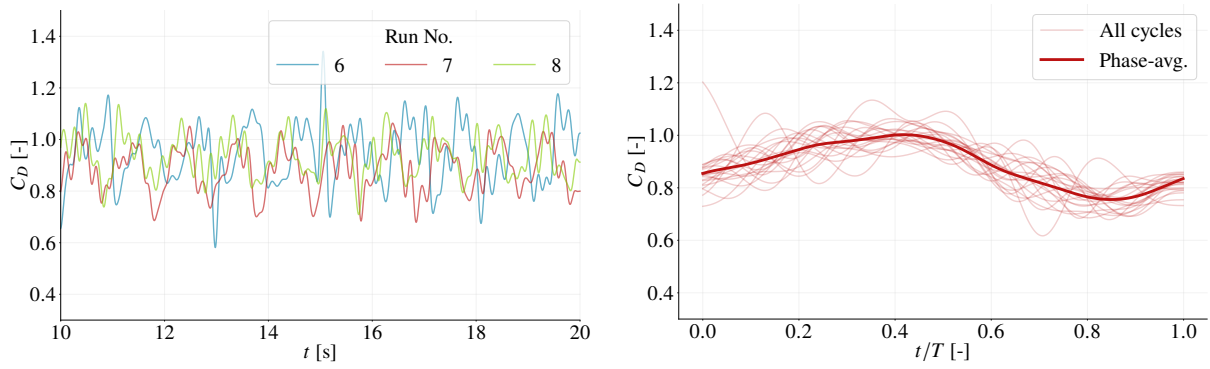
One should note that if one removes the zero yaw angles from the dataset, the Spearman's correlation coefficient increases to 0.501, indicating a better correlation.

These quantitative results confirms that no significant independent relationships is found between the mean drag coefficient and the flow and motion parameters, except from the yaw angle. It also shows that the parameters are inter-dependent. Having said that, it might further be possible to identify relationships between the mean drag coefficient and a (non-linear) function of the parameters.

3.3.2 Inter- and intra-cycle variability

The measurements of unsteady flows on a dynamic structure can lead to differences in the results due to the variability of the data measured. To investigate the high level of uncertainty in the dataset, the inter- and intra-sample repeatability is analysed here by comparing a multiple runs of a given configuration and the behaviour of the drag coefficient throughout the 20 seconds run.

Configuration number 7 in Annex B has been repeated three times, keeping the same parameters. A sequence of the time series of all runs is shown in Figure 3.23a. Although the measurements seem to be qualitatively repeatable, the mean drag coefficient – *i.e.* run 6 : $\overline{C_D} = 0.938$, 7 : 0.889 and 8 : 0.935 – leads to the conclusion that the measurements are not reliably repeatable from a quantitative point of view. Figure 3.23b illustrates the variability inside one drag signal. A smooth global curve is obtained by phase-averaging over a large number of cycles. A significant intra-cycle variability is nevertheless observed, due to the high unsteadiness of the flow around the robotic leg.



(a) C_D time series for three repetitions of the same configuration, low-pass filtered at 10 Hz.

(b) All cycles relative to run 7 with its phase-averaged curve (from data filtered at 10 Hz).

Figure 3.23 : Assessment of the inter- and intra-sample variability at a given configuration.

Finally, a Principal Component Analysis has been performed and has shown that 97.5% of the variability of the drag coefficient curves can be represented by a single mode corresponding primarily to a global shift of the drag level. Variations in Reynolds number and yaw angle are found to be the main contributors to this dominant mode, whereas reduced frequency and pedalling radius exhibit weaker correlations. Another meaningful result is the absence of clear clusters in the PCA score space, which suggests that the investigated parameters do not induce strongly distinct drag signatures. This leads to the conclusion that the experimental parameter space is only weakly observable from drag measurements alone.

Chapter 4

Modelling

Two different approaches to model the drag force acting on a pedalling leg are presented in this section. First, a quasi-steady model developed by Crouch et al., 2016 [3] shows the dominant mechanism of the drag for given leg kinematics and pedalling cadence. A parametric analysis is performed in order to study the sensitivity of the different parameters. Finally, a data-driven model is built from the experimental data of the unsteady drag force.

4.1 Quasi-steady moving leg model

The moving-leg aerodynamic force model allows to explore the influence of the geometry and cadence on the variations of drag area over a crank cycle by considering the a simple quasi-steady drag force model acting on the leg segments. This model is based on the Independence Principle which provides, as developed previously, an estimate of the force acting on an inclined cylinder by projecting the free-stream velocity onto the axis normal to the cylinder. In their paper, the leg segments are simply modelled as tapered circular cylinders, which is convenient with the set-up of this work. While this rather crude model offers a semi-quantitative assessment of the effects of the pedalling cadence on the aerodynamic forces acting on a moving leg over the course of a pedal stroke, it has some limitations. These limitations are listed here-below:

- Inability to capture flow unsteadiness.
- Three-dimensional end effects are neglected.
- Flow interactions between leg segments are neglected : upper and lower leg are considered in isolation from one another while computing the aerodynamic forces.

Also, the flow perturbations produced by other components such as the wheel's rotation are not modelled in Crouch's model but this is not relevant in this work since the representation of a single leg is considered.

Given the leg's kinematics, the model predicts the drag force from the local velocity acting normal to the leg segments. This local velocity is decomposed into the normal free-stream velocity $V_{\infty,\perp}$ and the normal components of the rotational and translational velocities of the leg segments, respectively $(\omega_o Q)_{x',\perp}$ and $V_{x',\perp}$, with ω_o the leg angular rotation rate and Q the distance along the member from the rotation point of reference and the point where F_D is evaluated (here, the centre of gravity of the cylinder). The definition of all global and local axes is shown in Figure 4.1. The drag force at a given crank position and angular velocity is then computed by

$$F_D(\theta, \dot{\theta}) = \frac{1}{2} \rho C_D A \left[V_{\infty,\perp} + V_{x',\perp} + (\omega_o Q)_{x',\perp} \right]^2. \quad (4.1)$$

In the simplest cases, the reference drag coefficient C_D is taken as constant and is an input data of the model. A standard drag coefficient for a circular cylinder is typically taken at 1.1. However, as shown and explained previously, the end conditions and most importantly aspect ratio of the cylinder significantly impacts the value of the drag coefficient of the vertical circular cylinder, due to three-dimensional effects. In order to account for this while using Crouch's model, the reference drag coefficient of 1.1 is multiplied by drag reduction factor κ , defined as

$$\kappa = \frac{C_{D,\text{finite}}}{C_{D,\infty}} = \frac{C_{D,\text{finite}}}{1.1} . \quad [35]$$

While a reduction factor of ~ 0.59 is found in the literature for similar dimensions as the ones of the cylinders mounted on the robot, it has been found that a slightly lower value ($\kappa = 0.50$) shows better accuracy compared to the experimental pressure measurements. This larger drag reduction is most likely due to the complex end conditions around the cylinders.

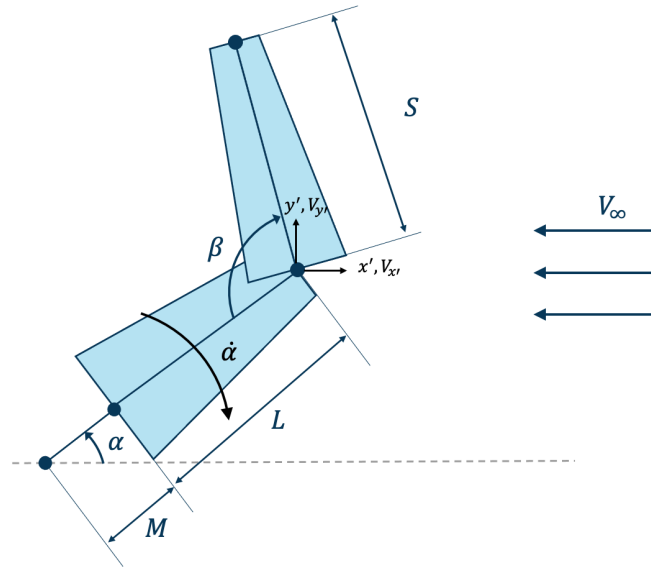


Figure 4.1 : Illustration of moving leg force model variables. M is the offset distance at the hip, L the thigh/lower cylinder length and S the calf/upper cylinder length.

4.1.1 Moving leg model results

First of all, the model results relative to a zero reduced frequency (static case) are compared with those obtained in the wind tunnel with the pressure taps and the force balance. Figure 4.2 shows the global drag coefficient (top), based on the total projected frontal area, and the different contributions of the thigh/lower and calf/upper cylinders (bottom). Since the cylinders' contributions can not be obtained from the force balance, these results are only shown regarding the pressure measurements. As justified above, a drag reduction factor of $\kappa = 0.5$ is used in the model.

The quasi-steady model predicts quite accurately the drag around both cylinders, as shown by the close results with the experimental pressure measurements. A slight misrepresentation of the experimental values is observed for some angles on the crank cycle. These can be correlated with the differences between the model and estimated value from the single cylinders pressure taps shown in the bottom plot. One can see on the bottom plot that the thigh/lower cylinder has the closest results between the model and the experimental while the calf/upper one shows slightly larger discrepancies between approximately 135° and 315° of crank angle. These

positions corresponds to when the knee is inclined at critical angles γ at which the static pressure measurements on an inclined cylinder showed that the calf/upper cylinder does not follow the cosine law (Figure 3.5a). Since the quasi-steady model of Crouch is entirely based on this cosine law, the slight deviation from the experimental results is coherent with the previous observations. Regarding the force balance measurements on static positions, similar conclusions can be drawn on the global behaviour and the measurements amplitude, showing that the assumption of not accounting for the flow interactions mostly affects the amplitude in static positions in the pedalling cycle.

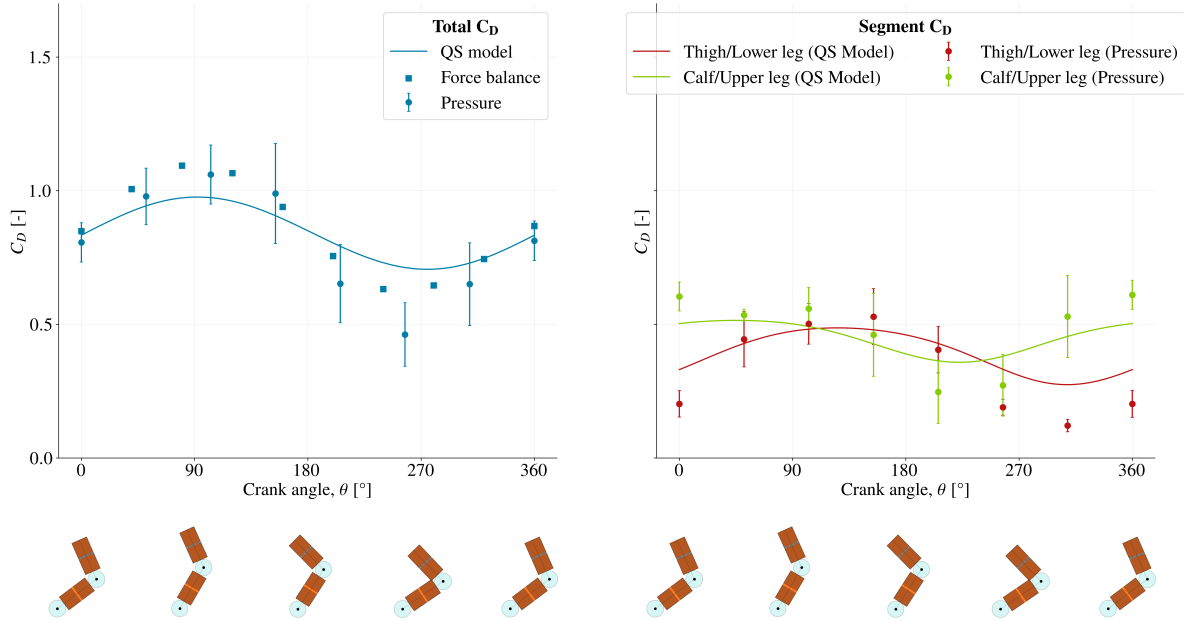


Figure 4.2 : Drag area predicted by the quasi-steady model for static positions ($k = 0.0$) at intermediate Re (6.9×10^4) compared with experimental data measured.

Then, Figures 4.3a and 4.3b show the predictions of the quasi-steady model for different reduced frequency at two different Reynolds. These results are compared with the phase-averaged and filtered at second harmonic (relative to motion frequency) force balance measurements. The most striking observation is that the quasi-steady model is able to reproduce the global behaviour, even though the amplitude of the variations is over-predicted. The ability of the model to reproduce this sinusoidal trend in the drag coefficient is not surprising and can be explained by considering the characteristic times of the wake and the motion. The characteristic time of the motion can indeed be computed by assuming that non-negligible changes in the kinematics occur every 45° . The characteristic time relative to the motion thus corresponds to $1/8$ of the period of motion. For a 60 RPM pedalling motion, it corresponds to

$$\tau_m = 0.125 \text{ s.} \quad (4.2)$$

The characteristic time of the wake can be determined as well using

$$\tau_w = \frac{L}{U_c} \quad (4.3)$$

where L is the distance in the wake that is impacted by the motion and U_c is the convective velocity of the mean flow in the wake. Assuming that the affected distance in the wake is about 5 to 10 diameters of the cylinders and the convective velocity to be half the free-stream one yields

$$V_\infty = 6.20 \text{ m/s} : \quad \tau_w = [0.18 - 0.35] \text{ s} \quad (4.4)$$

$$V_\infty = 9.45 \text{ m/s} : \quad \tau_w = [0.12 - 0.23] \text{ s} \quad (4.5)$$

using the airspeed corresponding to the Reynolds considered in Figures 4.3a and 4.3b. At the lowest airspeed, the convection time in the wake is larger than the characteristic time of the motion of the cylinders, which means that the wake does not have enough time to adapt to the kinematics in the unsteady wake. On the other hand, the highest airspeed considered yields smaller convection time in the wake. This discussion explains why the quasi-steady moving leg model struggles to accurately predict the variations in drag coefficient during a crank cycle for a pedalling motion at relatively moderate-to-high cadence. Looking back at Figure 3.14, this reasoning also partly explains why larger differences are observed at the lowest Reynolds and conversely, smaller differences at higher Reynolds.

One should still remain cautious while comparing the results. At a higher Re , the pedalling rate has in fact a lower contribution to the resulting velocity compared to the free-stream. The over-prediction of the amplitude of the drag coefficient is to be questioned, as the experimental C_D is computed based on the free-stream velocity only.

A flattening of the drag coefficient on the crank cycle – observed on the pressure measurements as well – can nonetheless be thought of as a result of the unsteadiness of the flow. Finally, the phase shift observed in the phase-averaged force balance measurements is quite successfully predicted by the quasi-steady model. Both the model and the wind tunnel data indeed show a shift of the curves to smaller crank angles as the reduced frequency increases.

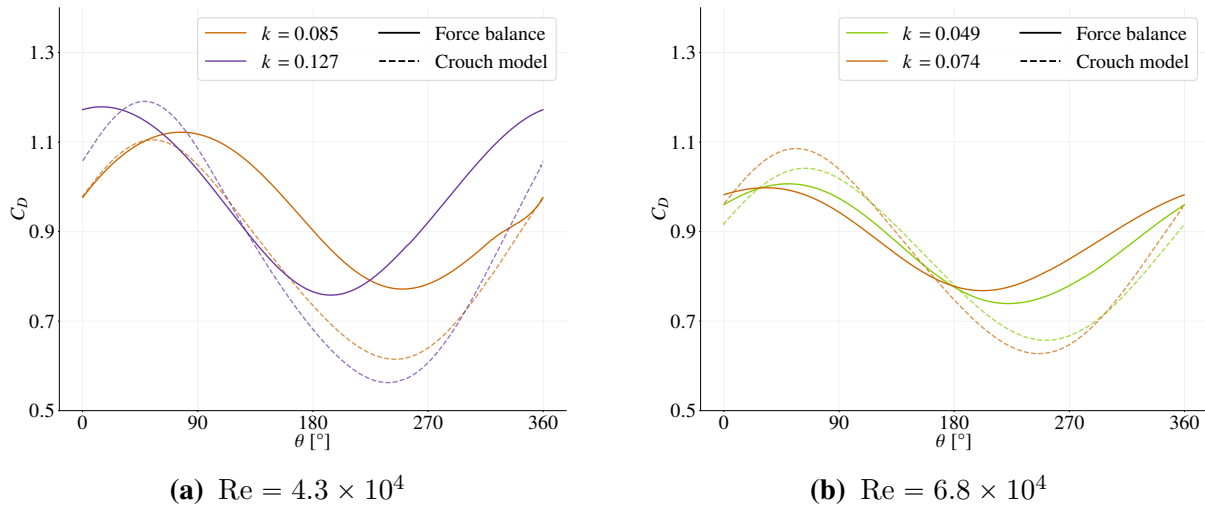


Figure 4.3 : Comparison of Crouch model prediction with the force balance measurements on dynamic configurations : uniform cadence, same amplitude ($R = 0.11$ m).

Overall, a quasi-steady modelling of the drag coefficient acting on the robotic leg is qualitatively and somehow quantitatively accurate for the geometry and flow conditions studied here. The few differences with the experimental data however indicates that the unsteadiness of the flow still impacts the drag and if this particular set-up is conveniently made of two circular cylinders, a more complex geometry and a full cyclist is likely to generate more flow interactions and unsteady behaviours.

4.1.2 Parametric study

The quality of the model prediction for the particular configuration of the UR5e robot mounted with circular cylinder has been investigated in the previous section. It is now worth looking at how the model would deviate from the different characteristics of the set-up were to be modified.

Figures 4.4a and 4.4b illustrate the sensitivity of the drag area predicted by the quasi-steady moving leg model to the geometry of the leg. In particular, the length of each cylinders is varied from 85 to 115% of its initial value. It follows that changing the length of the leg segments mostly affects the extremum of the C_D curve. The high drag regime, to speak in Crouch terms, is particularly sensitive to the length of the leg components. This notably impacts the mean drag coefficient over a crank cycle. Additionally, the sensitivity of the cylinders' diameter has been studied, imposing tapered shape with a taper ratio going from 0.62 to 0.70. This has not yielded any significant changes in the drag coefficient, concluding that the assumption to use circular cylinders of constant diameter is valid regarding the computation of the quasi-steady part of the aerodynamic forces.

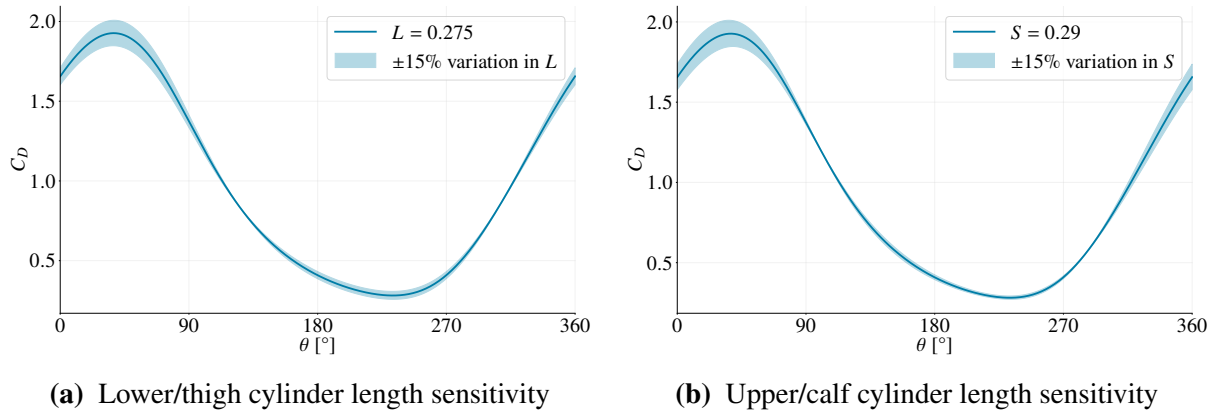


Figure 4.4 : Sensitivity study of the moving leg quasi steady model on the geometry of the leg.

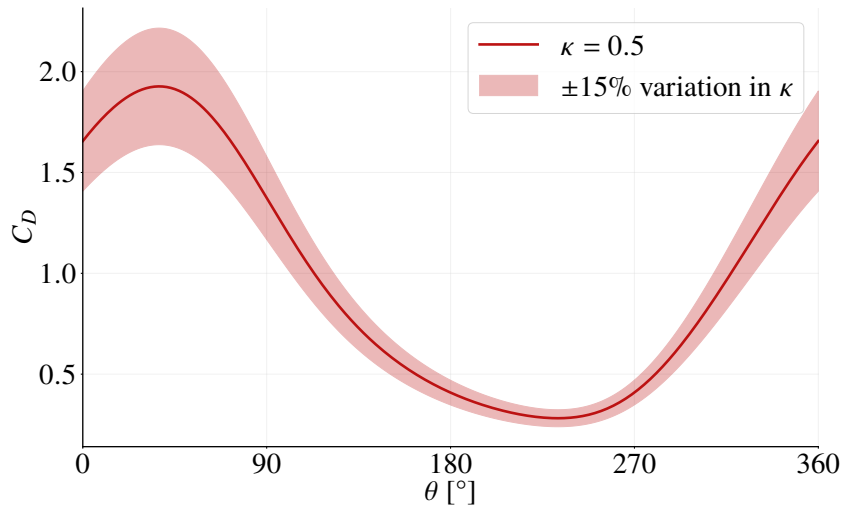


Figure 4.5 : Sensitivity study of the moving leg quasi steady model on the aspect ratio and end conditions corrector for initial C_D .

This rather crude analysis highlights the fact that an aerodynamic model of a dynamic cyclist's leg or cyclist in general should be tailored adequately to the cyclist's morphology and that no universal model can be derived, not to mention that the kinematics of each cyclist is very variable. According to Ettema et al., 2009 [32], the biomechanical pedalling patterns are also subjects to change with a modification in crank length or other geometric quantities.

Finally, the drag coefficient corrector for the end conditions and aspect ratio has been chosen from Potts et al., 2019 [35] but also arbitrarily lowered in order to better match the experimental

data, knowing that flow perturbations caused by the robot parts external to the cylinders exist. The sensitivity of the predicted drag coefficient is thus computed for determining the uncertainty caused by this choice. The drag coefficient corrector κ has been varied from 0.425 and 0.575. Results shown in Figure 4.5 yield a large variation in C_D in the high drag flow regime but also non-negligible ones in the remaining of the crank cycle. The results of Crouch's quasi-steady model should thus be considered cautiously. One should also note that the exact correction on the initial C_D might be subject to change during a full pedalling cycle, since the flow perturbations induced by the robot itself might affect the flow on the cylinders differently depending on the position of the robotic leg.

4.2 Data-driven model

Due to the highly non-linear behaviour of the motion studied, with wake interactions between the cylinders and with the other disruptive components of the robot arm UR5, a classical reduced order model of the unsteadiness of the flow would be difficult to obtain. This difficulties motivate the choice for a data-driven reduced order model. The structure of the model is strongly influenced by the model developed by Calado et al., 2022 [36] for flapping wings, which yielded promising results. The structure and development of the model are detailed in this section. Then, the choice of non-linear features is motivated through the observations realized on the experimental data. Finally, results regarding the training and validation of the model on the experimental dataset are presented and discussed. Particular attention is given to the performance of the model with respect to the model structure.

The model is composed of a two-stages regression based on the leg kinematics and the motion and flow parameters. This framework is illustrated in Figure 4.6. The first stage, so-called 'in-cycle' (IC) regression, consists of a linear regression of non-linear functions. Its role is to map the drag coefficient onto the different kinematics variables (*i.e.* the defined hip and knee angles and the related angular velocity) over one crank cycle. The choice of these functions is detailed in the next subsection. With $\mathbf{f}(t_\star) \in \mathbb{R}^{n_f}$ the vector containing the n_f non-linear features of the model at time $t_\star$, the drag coefficient is built as

$$C_D(t_\star) = \sum_{i=1}^{n_f} f_i(t_\star) w_i = \mathbf{f}^T(t_\star) \mathbf{w}. \quad (4.6)$$

A second stage, an 'out-of-cycle' (OOC) regression is performed, aiming to map the weights obtained from the IC regression onto the the flow and motion parameters. Defining $\mathbf{x} = [k \quad \text{Re} \quad R \quad \psi_r]^T$ as the out-of-cycle flow and motion parameters, the mapping $\mathbf{x} \rightarrow \mathbf{w}$ is conducted through a multivariate Gaussian Process regression, allowing for a formulation of the model uncertainty as well.

The 'in-cycle' regressions is carried out using a Ridge regression. The Ridge regression is chosen over the Lasso one in order to ensure keeping all features in the model during training. The weights $\mathbf{w}^\star$ are computed from a *training* dataset from the experimental force measurements. Denoting $\mathbf{F}(t_\star) \in \mathbb{R}^{n_t \times n_f}$ the IC regression features at times $t_\star$ for all data samples and $\mathbf{c}(t_\star) \in \mathbb{R}^{n_t \times 1}$ (with n_t the number of training sample), the optimal weights are those that minimise the cost function defined as

$$\mathbf{J}(\mathbf{w}) = \|\mathbf{c}(t_\star) - \mathbf{F}(t_\star) \mathbf{w}\|_2^2 + \lambda \|\mathbf{w}\|_2^2 \quad (4.7)$$

where λ is a regularization penalty and $\|\cdot\|_2$ is the L_2 norm of a vector.

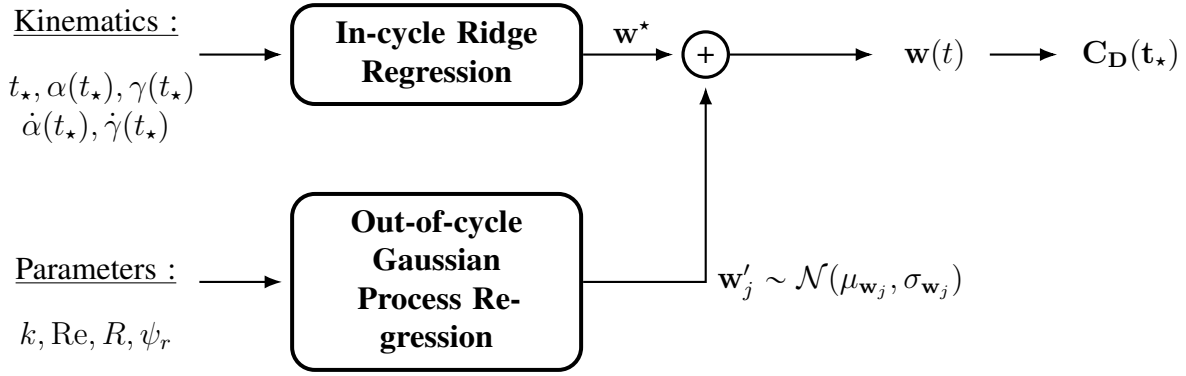


Figure 4.6 : Machine Learning framework for drag prediction of 2 dofs moving-leg.

Minimising the cost function yields the following expression of the weights:

$$\mathbf{w}^\star = \left(\mathbf{F}^T(t_\star) \mathbf{F}(t_\star) + \lambda \mathbf{I} \right)^{-1} \mathbf{F}^T(t_\star) \mathbf{c}(t_\star) \quad \in \mathbb{R}^{n_f \times 1}. \quad (4.8)$$

The '*out-of-cycle*' regression is carried out using a multivariate Gaussian Process. Gaussian processes are stochastic processes characterized by a probability distribution over possible functions compatible with values. They rely on the assumption that any finite sample of these functions evaluated at arbitrary points is jointly distributed. This means that for a given set of parameters $\mathbf{X} \in \mathbb{R}^{4 \times n_p}$ (n_p is the number of Gaussian processes), all candidate functions can be sampled using a 4 dimensional Gaussian distribution

$$\mathbf{w}_j^\star(\mathbf{X}) \sim \mathcal{N}(\mu_j, \mathbf{K}) \quad (4.9)$$

where $\mu_j \in \mathbb{R}^{n_p}$ is the mean of the prediction of the j -th weight for each set of flow and motion parameters and $\mathbf{K}_j \in \mathbb{R}^{n_p \times n_p}$ is the covariance matrix for the j -weight. Following Calado et al., 2022 [36], the multivariate prediction is built using a set of univariate predictions, each independently following its own Gaussian process, yielding n_f processes in $\mathbb{R}^4$.

Theoretical reminder :

For a given stochastic process $s(x)$, first- and second-order statistics are defined as follows:

$$\mu(x) = \mathbb{E}[s(x)] = \int_s s(x) p(s) ds \quad (4.10)$$

$$\text{cov}(x_1, x_2) = \mathbb{E}[(s(x_1) - \mu(x_1))(s(x_2) - \mu(x_2))] \quad (4.11)$$

$$= \int_{s_1} \int_{s_2} s_1 s_2 p(s_1, s_2) ds_1 ds_2, \quad s_i = s(x_i) - \mu(x_i). \quad (4.12)$$

For a stationary Gaussian process, the latter is completely characterised by these statistics. The covariance can therefore be computed using a kernel function $\mathcal{K}$ [37]. Assuming that the data are gathered from a stationary Gaussian process with zero mean, then one can state that

$$\begin{bmatrix} \mathbf{w}_j^\star \\ \mathbf{w}'_j \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \mathbf{0} \\ \mathbf{0} \end{bmatrix}, \begin{bmatrix} \mathbf{K}_j + \alpha \mathbf{I}_{n^\star} & \mathbf{K}'_j \\ \mathbf{K}_j'^T & \mathbf{K}_j'' \end{bmatrix} \right) \quad (4.13)$$

with

$$\mathbf{K}_j = \mathcal{K}_j(\mathbf{X}^\star, \mathbf{X}^\star) \quad , \quad \mathbf{K}'_j = \mathcal{K}_j(\mathbf{X}^\star, \mathbf{X}') \quad , \quad \mathbf{K}_j'' = \mathcal{K}_j(\mathbf{X}^\star, \mathbf{X}^\star)$$

and where α is a regularization variable somehow corresponding to white noise, applied to avoid singularities during the inversion of the covariance matrices and over-fitting on the training

data. Eq. 4.9 corresponds to the prior distribution of each weights computed using the Ridge regression. Assuming zero mean for all weights, their covariances matrices defined by Gaussian kernels for points $\mathbf{x}_l$ and $\mathbf{x}_m$ are written

$$\mathbf{K}_j(\mathbf{x}_l, \mathbf{x}_m) = \mathcal{K}_j(\mathbf{x}_l, \mathbf{x}_m) = \sigma_{w_j}^2 \exp \left(-\frac{\|\mathbf{x}_l - \mathbf{x}_m\|_2^2}{2\gamma_j^2} \right) \quad (4.14)$$

where $\sigma_{w_j}^2$ and γ_j , respectively a regularization on the amplitude of the kernel and the length scale for the j -th process, are hyper-parameters of the model.

Using conditioning rules, one can obtain the probability density function associated with the weights $\mathbf{w}'_j$ associated with any set of parameters $\mathbf{X}'$ as

$$\mathbf{w}'_j(\mathbf{X}') \sim \mathcal{N}(\mu_{\mathbf{w},j}, \Sigma_{w,j}) \quad (4.15)$$

with

$$\mu_{\mathbf{w},j} = \mathbf{K}_j'^T (\mathbf{K}_j + \alpha \mathbf{I}_{n^*})^{-1} \mathbf{w}_j^*(\mathbf{X}^*), \quad (4.16)$$

$$(4.17)$$

$$\Sigma_{w,j} = \mathbf{K}_j'' - \mathbf{K}_j'^T (\mathbf{K}_j + \alpha \mathbf{I}_{n'})^{-1} \mathbf{K}_j' + \alpha \mathbf{I}_{n'}. \quad (4.18)$$

Final results of the model thus consist of the drag coefficient prediction based on the mean weights $\mu_{\mathbf{w},j}$ along with their relative feature. The uncertainty of the prediction is computed through $\Sigma_{w,j}$.

4.2.1 Choice of features

The non-linear features that compose the in-cycle Ridge regression stage are heuristically found with the support of the experimental results. The final functions used are

$$\mathbf{f} = [1 \quad \sin \alpha \quad \cos^2 \gamma \quad \dot{\alpha}^2 \quad \dot{\gamma}^2 \quad \dot{\alpha}\dot{\gamma} \quad \cos^2 \gamma \dot{\gamma}]^T \quad (4.19)$$

These choices are also supported by the simple correlation of these combined functions with the drag coefficient for single independent test samples. A few informations on these functions is given here-below :

- The regression is performed with an intercept (corresponding to $f(\mathbf{X}) = 1$) as it showed better results.
- $\sin \alpha$: This function simply reflects the projection of the thigh/lower cylinder onto the global reference frame using the hip angle α . This choice is supported by the fact that the drag coefficient obtained by pressure signals integration was shown to be in agreement with the Independence Principle while increasing the inclination angle of the cylinder (see Figure 3.5b).
- $\cos^2 \gamma$: This function reflects the projection of the calf/upper cylinder onto the global reference frame using a more sophisticated function of the knee angle γ . By looking at Figure 3.5a, one is reminded that the pressure taps based estimation of the drag coefficient behaviour is non-linear with the inclination angle, which invalidates the Independence Principle. The $\cos^2 \gamma$ function allows a better representation of this trend at higher inclination angles. Even though the non-linear relationship between the local drag coefficient and the cylinder's inclination angle is not perfectly reproduced by this function, the latter has been observed to be already efficient in this form by inspecting the correlation of the function with the drag coefficient of independent samples taken randomly in the dataset.

- $\dot{\alpha}^2$: This function accounts for the angular velocity related to the global robotic arm, by the definition of α . The shape of the $\dot{\alpha}$ –function has been heuristically selected from among higher order polynomials, $|\dot{\alpha}|$ or even trigonometric functions of $\dot{\alpha}$.
- $\dot{\gamma}^2$: This function corresponds to the contributions of the knee angular velocity. Similar procedure and thoughts than for the $\dot{\alpha}$ – function are applied.
- $\dot{\alpha} \cdot \dot{\gamma}$: This function partly models the assumed interactions between the motion of both cylinders. Even if slight interactions were observed in the pressure results regarding static configurations, one considers that these interactions are negligible with respect to the dynamic flow perturbations, hence modelling only these interactions through the angular velocities.
- $\cos^2 \gamma \cdot \dot{\gamma}$: This function, likely to be responsible of additional non-linearities regarding the motion of the calf/upper cylinder. This function has resulted in improvements in the mean square error during training.

Graphical representations of the non-linear features chosen related to a single sample are given in Figure 4.7.

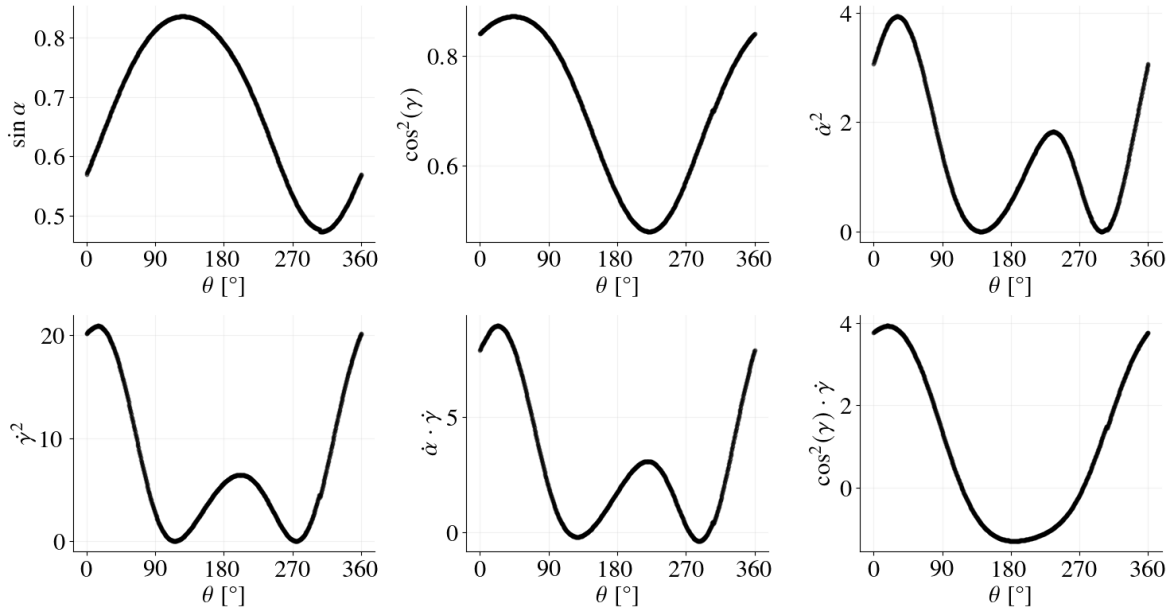


Figure 4.7 : Example of representation of the non-linear features used in the in-cycle Ridge regression, from one sample in the training dataset.

Note on model hyper-parameters : Hyper-parameters are model settings that are not determined by the training data. They control the learning process and the structure of the model. In a linear regression model, hyper-parameters usually refers to L_1 and L_2 regularization parameters. In this case, the model is composed of 12 hyper-parameters, listed in Table 4.1 with their final value. Due to the small amount of training data, it is essential to choose them very wisely, in this case using hyper-parameters optimization tools. The Ridge regularization parameter and the white noise added to the Gaussian Processes are fixed at chosen values. The hyper-parameters present in the Gaussian kernels are however optimized by maximizing the log-marginal likelihood with a BFGS algorithm.

One should note that the Ridge regularization is very low. While a low regularization would typically favour an overfitting of the training data, this is not a constraint – it is even helpful to

Hyper-parameter	Symbol	Value
Ridge regularization	λ	0.1
GP white noise	α	0.01
Kernel hyper-parameters	$\sigma_{w_0}^2, \gamma_0$	$4.46 \times 10^{-4}, 0.552$
	$\sigma_{w_1}^2, \gamma_1$	$1.27 \times 10^{-2}, 0.541$
	$\sigma_{w_2}^2, \gamma_2$	$3.06 \times 10^{-3}, 0.446$
	$\sigma_{w_3}^2, \gamma_3$	$1.25 \times 10^{-2}, 0.133$
	$\sigma_{w_4}^2, \gamma_4$	$10^{-4}, 1$
	$\sigma_{w_5}^2, \gamma_5$	$6.89 \times 10^{-3}, 1$

Table 4.1 : Model hyper-parameters

the model performance – in this case since the Gaussian Process Regression maps a probability distribution on the weights from the out-of-cycle parameters.

4.2.2 Discussion

The Two-Stages Regression model is trained on 80% of the 110 data samples, with the remaining 20% being used for the validation. The samples relative to the boundaries of the flow and motion parameters are ensured to be in the training set. A Min-Max normalization, defined as

$$x_{\text{norm.}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}. \quad (4.20)$$

is applied to the feature matrix.

In order to first confirm the influence of the out-of-cycle parameters and support the need of the OOC Gaussian Processes, the sole in-cycle Ridge regression over the kinematics is applied on the whole dataset as a single sample. Due to the very low variability in the kinematics, even for relatively low variability in drag coefficient between the different samples, it is indeed not expected that the leg's kinematics only would be able to predict the drag coefficient accurately. The results match the expectations as the training shows a very poor performance. In numbers, this poor training translates to a root mean square error of 15.8% and an R^2 score of 0.1197. As stated, the poor training is expected since the kinematics only varies from a few degrees in amplitude (more significant variations in °/s due to the different cadence) and shape. The low variability in the kinematics and the larger discrepancies in the drag coefficient measured inevitably lead to a difficult representation of the true value without any out-of-cycle parameters. Additionally, the green curve in Figure 4.8 is the prediction of a validation sample based on the training over the full dataset. One sees that along with the amplitude, the global trend in C_D is not well predicted by the model of the sole Ridge regression.

A different training of the model for each test sample is thus conducted, called *per condition* training. This training yields n_t sets of weights corresponding to the n_t samples of training data. The per condition training results in much better training performance : 0.21% mean RMSE over the dataset and 0.997 mean R^2 with minimum and maximum values of R^2 respectively at 0.951 and 0.999. Note that this very good training performance is enhanced by the very low regularization on the Ridge regression, which naturally tends to over-fit the training data. Even though the over-fitting would become an issue in a regular regression, it is as stated previously, in this case a desirable characteristic of the regression since it allows a clearer mapping for the Gaussian Processes using the out-of-cycle parameters. With this current variant of the model, the

prediction is made using a nearest neighbour algorithm applied to the out-of-cycles parameters. The prediction on the same validation case is plotted in Figure 4.8. One observes that the prediction is still off in the amplitude of the signal but its global behaviour with the crank angle is much close to the true one. Again, the very low regularization is highly responsible for this.

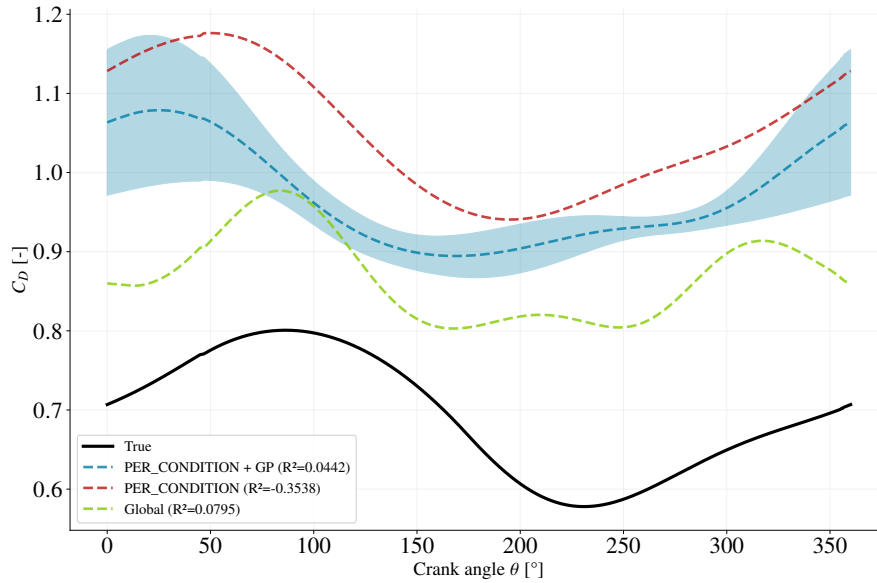


Figure 4.8 : Predicted C_D of one validation sample compared with true value, from all three variations of the model.

Now that a new set of weights is computed for each training sample, some statistical analysis can be performed. Figure 4.9 shows the dispersion of the weight of each feature against the out-of-cycle parameters, as well as the distribution of their value across the complete training dataset. In general, no clear trend is observed between the weights and the parameters, meaning that there is no independent relationships between the in-cycle features and the out-of-cycle parameters. However, the reduced frequency presents first insights of a relationship with the constant value's weight (denoted w_C in the figure). The constant is mostly responsible for the amplitude of the prediction and the experimental results showed a slight increase in amplitude with the reduced frequency. Even if the model is not able to accurately predict the amplitude of the drag coefficient with this per condition training, one could state that it is nonetheless learning that the amplitude of the signal somehow depends on the reduced frequency and, in more details, increases with larger k . Looking at the histograms of the different weights, it strikes one that the largest variability is related to the constant function, while other weights converge towards a unique value for most of them. While the OOC Gaussian Process will mainly constitute a correction term and an uncertainty quantification of the Ridge per condition training for the most of the features, the distribution of the OOC parameters might not be able to easily correct the weight of the constant feature, due to the high inter-dependency of the flow parameters observed in sections 3.2 and 3.3. Finally, the Gaussian Process are applied to the weights obtained after the per condition training in order to map them on their prior distribution given in Eq. 4.9.

Putting the amplitude shift aside, the global behaviour of the drag coefficient is overall well predicted by the Ridge + Gaussian Process model. It nonetheless fails to accurately predict the position of the maximum and minimum of the C_D curve (peaks of the low and high drag flow regimes). Finally, the IC Ridge regression shows better behavioural prediction than the two-stage model, hence suggesting that the out-of-cycle parameters struggles to regress the weights in the Gaussian Processes. Due to the high inter-dependency of the parameters, the assumption

stating that all probability distributions in the multivariate prediction is built from independent univariate Gaussian Process is to be questioned in this case.

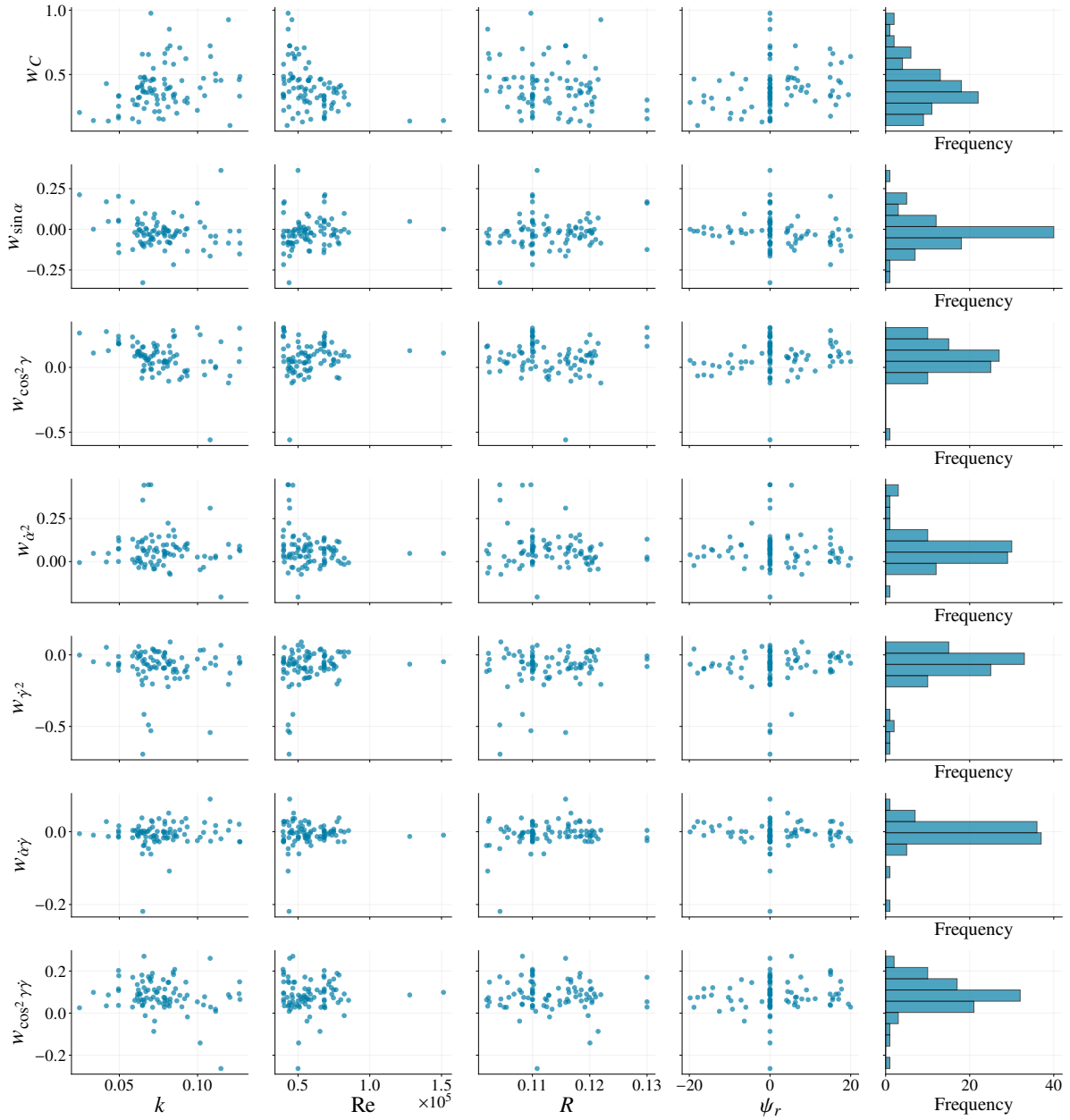


Figure 4.9 : Features weights distribution and relationships with OOC parameters obtained after *per condition* training of the IC Ridge regression.

4.2.3 Conclusion

Summing the drag modelling up, the quasi-steady moving leg model derived by Crouch et al., 2016 [3] shows satisfactory results compared with the experimental measurements, in a given parameter space. The length of this space can be quantified by a characteristic time analysis. Once a given ratio of the motion and wake times is exceeded, it is indeed believed that the unsteady wake cannot adapt enough to the motion of the robot. The model also struggles to be accurate in the amplitude, which is expected since the model only considers two 2D independent cylinders in motion while the set-up is composed of many additional parts (constituting the remaining of the robot) that are very likely to perturb the flow and generate drag.

A two-stages data-driven model is applied to the experimental data and shows poor training and prediction. These results are likely to be consequences of the high interdependency and variability in the experimental data. One also believes, due to the high unsteadiness and complexity of the flow, that the sole kinematics is not sufficient to model the drag force acting on the robotic pedalling leg and that additional aerodynamic information should be gathered in the wake.

Chapter 5

Conclusion

5.1 Conclusion

This thesis investigated the aerodynamic behaviour of articulated cylinders subjected to configurations representative of the lower limbs of a cyclist during pedalling. An extensive experimental campaign was conducted in the wind tunnel of the University of Liège in order to analyse the influence of both geometric and kinematic parameters on the resulting drag coefficient.

The results first highlighted the strong dependence of the aerodynamic drag on the relative positioning of the cylinders. The interaction between the wakes generated by each cylinder was believed to significantly modify the flow structure and, consequently, the drag experienced by the robotic leg. The influence of dynamic pedalling conditions was then investigated through the introduction of time-varying leg kinematics. The phase evolution of the drag exhibited significant fluctuations throughout the pedalling cycle. The results demonstrated that the instantaneous aerodynamic behaviour cannot be fully described by static configurations alone, as the system continuously experiences changing wake interactions and flow conditions. Experimental results showed an increasing amplitude and phase shift to lower crank angles as the reduced frequency increased. It was also observed that the inter-dependency of the flow and motion parameters causes different patterns of variations in drag coefficient with respect to reduced frequency depending on how the latter is varied. Then, a quasi-steady moving-leg model developed by Crouch et al. was used on the robotic leg kinematics and compared with the experimental measurements. It was shown that the model is able to arguably well reproduce the drag coefficient depending on the pedalling cadence and the magnitude of the free-stream velocity.

Finally, the feasibility of developing a predictive data-driven model was assessed. While correlations between the investigated parameters and the drag coefficient were identified, the available dataset did not provide sufficient coverage and statistical robustness to support the development of a reliable machine-learning model. The limited number of experimental configurations, combined with the variability inherent to the measurements, restricts the ability of data-driven approaches to generalise beyond the tested conditions. Consequently, the present work should be regarded as an exploratory study establishing the foundations for future predictive modelling efforts.

Overall, this research improves the understanding of the aerodynamic mechanisms governing simplified cyclist leg representations and highlights the importance of considering both geometric interactions and realistic pedalling dynamics when analysing cyclist aerodynamics.

5.2 Further work

5.2.1 Improved aerodynamic models of the pedalling leg

The most immediate continuation of this work concerns the development of more accurate predictive models for the aerodynamic drag acting on a pedalling leg. While the quasi-steady model adapted from Crouch et al. successfully captures the global evolution of the drag coefficient throughout the pedalling cycle, several limitations were identified. In particular, the model progressively loses accuracy as the reduced frequency increases and struggles to reproduce the amplitude of the drag fluctuations and the precise location of the extrema of the drag coefficient. The characteristic-time analysis introduced in this work suggests that these discrepancies are related to the inability of the wake to instantaneously adapt to the motion of the cylinders. As the ratio between the motion time scale and the wake time scale increases, the quasi-steady assumption becomes less valid and flow memory effects are expected to become increasingly important. This hypothesis is further supported by the phase differences observed between the pressure distributions and the drag response.

A first research direction therefore consists in extending the quasi-steady formulation to account for unsteady aerodynamic effects. Rather than considering the drag coefficient as a function of the instantaneous kinematics only, future models could incorporate quantities describing the recent history of the motion or the state of the wake. Such an approach would preserve the physical interpretability of the current framework while addressing one of its main limitations.

The data-driven modelling framework developed in this thesis also opens several perspectives. The current model relies on a two-stage architecture combining an in-cycle Ridge regression with out-of-cycle Gaussian Process regressions acting on the regression weights. Although the framework provides a physically interpretable decomposition of the drag coefficient, its predictive capabilities remain limited by the high interdependency of the parameters and the relatively small size of the experimental database. Several improvements could therefore be investigated. A first possibility would be to revisit the Gaussian Process formulation itself. The present work employs independent Gaussian Processes with standard kernels for each regression weight. Alternative kernel functions could be explored to better capture the non-linear interactions observed between Reynolds number, reduced frequency, motion amplitude and yaw angle. Composite kernels combining different characteristic length scales or kernels specifically designed for periodic phenomena may provide a more appropriate representation of the underlying aerodynamic behaviour. The assumption of independent Gaussian Processes for each regression coefficient should also be reconsidered. The results suggest that the different regression weights are strongly coupled through the aerodynamic mechanisms governing the flow. Future developments could therefore investigate multi-output Gaussian Processes capable of directly modelling correlations between regression coefficients. Such formulations may allow a more faithful representation of the underlying parameter dependencies.

The presence of flow memory effects further motivates the investigation of machine-learning architectures specifically designed for sequential data. Recurrent Neural Networks and Long Short-Term Memory (LSTM) models are particularly attractive candidates because they naturally incorporate temporal dependencies through internal memory states. Unlike the current framework, these models could directly exploit the history of the motion and may therefore be better suited to capture the delayed aerodynamic response observed experimentally. In particular, the literature shows promising results in the use of Long Short-Term Memory (LSTM) neural networks to predict the hydro- and/or aerodynamic forces acting on a robot undergoing

a reproducible kinematic motion. Han et al., 2025 [38] indeed trained a LSTM-based model to predict the lift and drag forces acting on the legs of a paddling robot and showed good performance.

Another promising direction would consist in combining physics-based and data-driven approaches within a multi-fidelity framework. In such a methodology, the quasi-steady model would provide a first estimate of the aerodynamic forces while a machine-learning correction model would account for the missing unsteady effects. This approach would combine the robustness and extrapolation capabilities of physics-based models with the flexibility of machine-learning techniques. Considering the encouraging performance already achieved by the quasi-steady model, such a correction-based strategy may prove more efficient than attempting to learn the complete aerodynamic response from experimental data alone.

Finally, the generation of additional experimental data represents another important perspective. One of the major outcomes of this thesis is the development of a complete experimental methodology including the robotic pedalling system, force balance measurements and pressure instrumentation. Once this infrastructure has been established, the acquisition of additional data becomes considerably less demanding than the initial development phase. Future campaigns could therefore investigate a broader range of Reynolds numbers, reduced frequencies, motion amplitudes and yaw angles while increasing the density of the parameter space sampling. Such an enlarged database would not only improve the statistical robustness of future machine-learning models but would also allow a more rigorous investigation of the transition between quasi-steady and unsteady aerodynamic regimes. Ultimately, the combination of improved physical models, advanced machine-learning techniques and expanded experimental datasets could lead to the development of a reduced-order model capable of accurately predicting the aerodynamic drag of a pedalling cyclist under realistic riding conditions.

5.2.2 Towards digital twinning of cyclist

Once a performant data-driven model is built for the drag acting on a pedalling leg, one believes that its inherent structure can be successfully applied on full cyclist-like pedalling structure, therefore yielding a very useful tool regarding the prediction of the instantaneous drag during a cycling event, depending on its kinematics, its pedalling cadence, riding velocity and the wind conditions.

This model would however constitute a small part in a larger one, as could be seen as a digital twinning of a cyclist that would characterize the complete behaviour of a cyclist, cross-correlating the environmental conditions, the parcours of the cycling event, the physiological parameters with the power loss in order to optimize the performance. This larger model, whose global simplified structure is proposed in Figure 5.1, could perfectly be applied for individual time trials in pro cycling competitions and long distance triathlon, where the optimization and management of the energy to reach the lowest time possible are fundamentals. Such a digital twin could ultimately be used to build highly individualized race strategies and pacing plans.

A few physiological models have already been developed in the literature ([39], [40]). By combining the different sub-models, the framework would be capable of predicting the evolution of the cyclist's performance throughout an event while accounting for environmental conditions, course characteristics, physiological limitations and aerodynamic losses. The objective would no longer be limited to estimating the drag coefficient or the power output independently, but rather to determine the optimal distribution of effort that minimizes the total race time.

One of the main advantages of such an approach is that the digital twin could continuously evolve throughout the athlete's season. Modern cyclists already generate large quantities of data through power meters, heart-rate monitors, GPS devices, inertial measurement units and other wearable sensors. These measurements could be used to progressively update and calibrate the different sub-models composing the digital twin. In this regard, recent initiatives from companies such as Aeroscale illustrate the growing interest in athlete-specific performance modelling based on continuously acquired field data.

The construction of such a framework would nevertheless require a dedicated calibration phase. In order to accurately characterize the cyclist, several complementary testing campaigns would be necessary. Physiological tests would provide information regarding aerobic capacity, fatigue dynamics, critical power and energy expenditure. Biomechanical analyses would allow the characterization of pedalling techniques, joint kinematics and force production patterns. Finally, aerodynamic assessments performed in wind tunnels, velodromes or field-testing environments would provide the parameters required to calibrate the aerodynamic sub-models. The challenge therefore lies in coupling these different sources of information into a unified framework capable of reproducing the behaviour of an individual athlete. Once calibrated, the digital twin could be used to evaluate race strategies, compare equipment choices, investigate the influence of environmental conditions and optimize pacing decisions under realistic competition scenarios. Such a framework would represent a significant step toward data-driven performance optimization in cycling and triathlon, where the management of energy resources is often as important as the athlete's maximum physical capabilities.

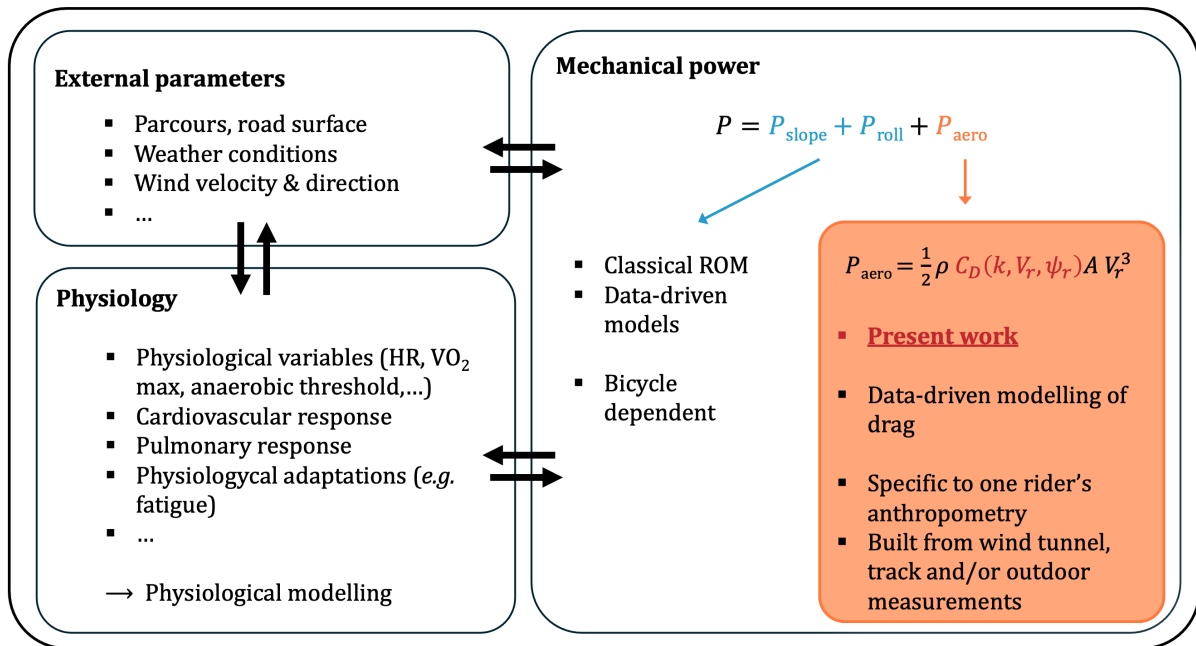
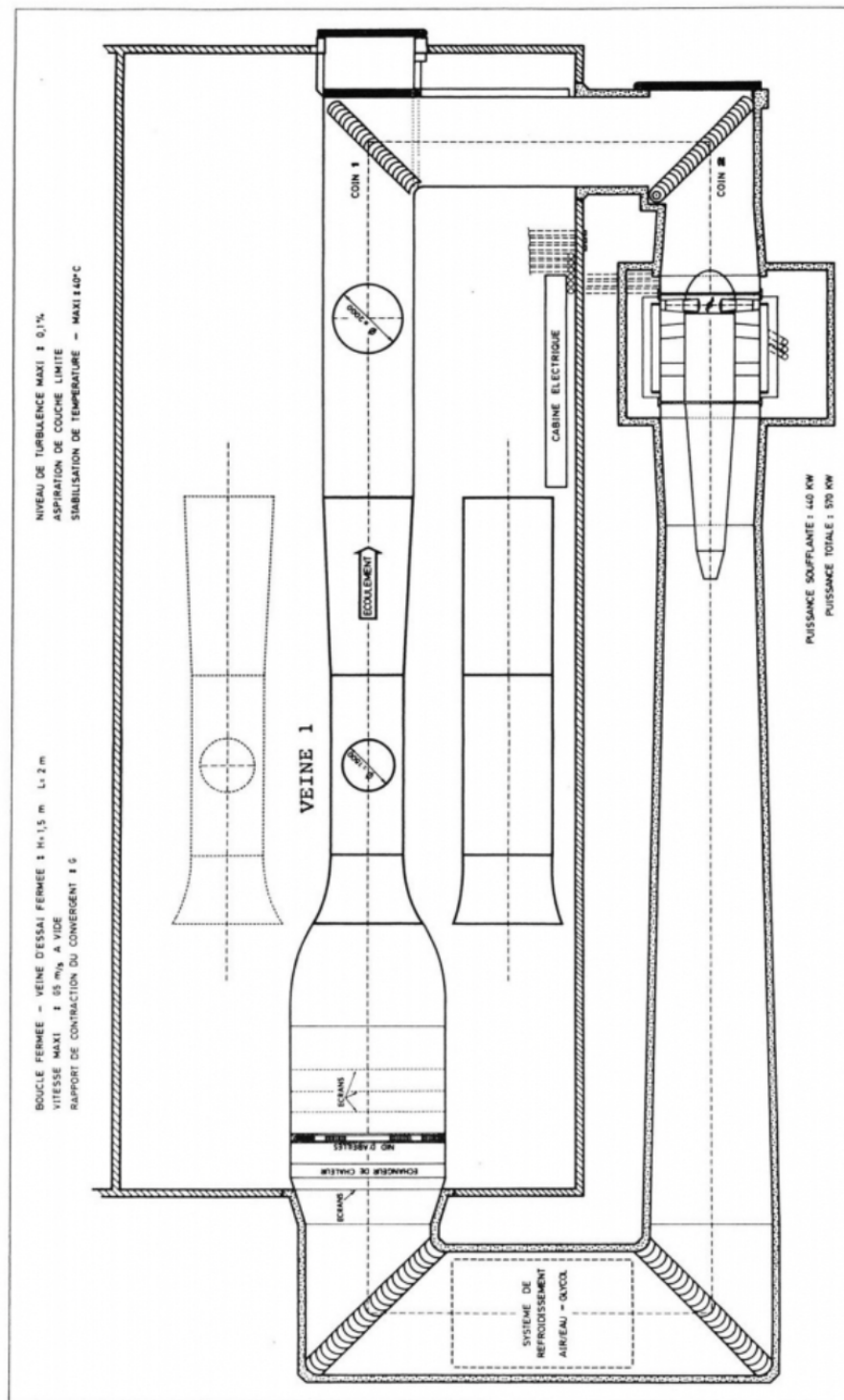


Figure 5.1 : General structure of the digital twinning of a cyclist.

Appendix A

Wind tunnel facility, University of Liège



Appendix B

List of parameters of dynamic configurations

The parameters of the complete dataset related to the dynamic tests in the wind tunnel are specified in Table B.1.

	Reduced frequency k [-]	Reynolds number Re [-]	Motion amplitude R [m]	Yaw angle ψ_r [°]
1	0.0246	6.88×10^4	0.110	0.0
2	0.0417	4.05×10^4	0.110	0.0
3	0.0495	6.83×10^4	0.110	0.0
4	0.0496	6.82×10^4	0.110	0.0
5	0.0497	6.80×10^4	0.110	0.0
6	0.0743	6.83×10^4	0.110	0.0
7	0.0743	6.83×10^4	0.110	0.0
8	0.0743	6.82×10^4	0.110	0.0
9	0.0845	4.00×10^4	0.110	0.0
10	0.0847	3.99×10^4	0.110	0.0
11	0.0854	3.96×10^4	0.110	0.0
12	0.1265	4.01×10^4	0.110	0.0
13	0.1268	4.00×10^4	0.110	0.0
14	0.1271	3.99×10^4	0.110	0.0
15	0.0819	4.31×10^4	0.102	0.0
16	0.0925	4.77×10^4	0.102	0.0
17	0.0681	5.19×10^4	0.103	0.0
18	0.0686	4.32×10^4	0.104	0.0
19	0.0650	4.38×10^4	0.104	0.0
20	0.0723	5.55×10^4	0.105	0.0
21	0.1003	5.51×10^4	0.106	0.0
22	0.0622	6.33×10^4	0.108	0.0
23	0.0335	1.51×10^5	0.108	0.0
24	0.0645	7.86×10^4	0.108	0.0
25	0.0825	7.12×10^4	0.108	0.0
26	0.0702	4.31×10^4	0.110	0.0
27	0.0615	7.13×10^4	0.110	0.0
28	0.0449	1.28×10^5	0.111	0.0
29	0.1149	5.00×10^4	0.111	0.0

30	0.0647	5.06×10^4	0.112	0.0
31	0.1128	4.44×10^4	0.112	0.0
32	0.0652	5.43×10^4	0.112	0.0
33	0.0886	5.43×10^4	0.113	0.0
34	0.0935	5.82×10^4	0.113	0.0
35	0.0356	1.28×10^5	0.114	0.0
36	0.0744	6.00×10^4	0.115	0.0
37	0.1080	4.42×10^4	0.116	0.0
38	0.0695	7.49×10^4	0.116	0.0
39	0.0717	5.37×10^4	0.118	0.0
40	0.0430	1.28×10^5	0.118	0.0
41	0.0711	7.72×10^4	0.118	0.0
42	0.0791	6.83×10^4	0.119	0.0
43	0.0665	8.22×10^4	0.120	0.0
44	0.0633	7.62×10^4	0.120	0.0
45	0.1016	5.04×10^4	0.120	0.0
46	0.0723	7.65×10^4	0.120	0.0
47	0.0755	7.80×10^4	0.120	0.0
48	0.0720	6.53×10^4	0.121	0.0
49	0.1053	4.66×10^4	0.122	0.0
50	0.1197	4.57×10^4	0.122	0.0
51	0.0584	6.83×10^4	0.130	0.0
52	0.0586	6.82×10^4	0.130	0.0
53	0.0999	4.00×10^4	0.130	0.0
54	0.1002	3.98×10^4	0.130	0.0
55	0.0495	6.83×10^4	0.110	15.0
56	0.0495	6.83×10^4	0.110	15.0
57	0.0844	4.00×10^4	0.110	15.0
58	0.0846	3.99×10^4	0.110	15.0
59	0.0674	7.47×10^4	0.109	-19.8
60	0.0713	6.59×10^4	0.105	-18.9
61	0.1207	4.24×10^4	0.120	-17.9
62	0.1045	5.18×10^4	0.118	-16.4
63	0.0859	5.47×10^4	0.120	-16.4
64	0.0933	5.03×10^4	0.113	-14.5
65	0.0658	7.33×10^4	0.117	-14.2
66	0.0639	6.38×10^4	0.121	-13.2
67	0.1115	4.38×10^4	0.111	-12.5
68	0.0761	5.44×10^4	0.108	-10.9
69	0.0805	4.65×10^4	0.113	-10.3
70	0.0784	5.40×10^4	0.108	-10.3
71	0.0754	4.64×10^4	0.115	-9.9
72	0.0867	5.01×10^4	0.115	-9.7
73	0.1114	4.48×10^4	0.113	-9.3
74	0.0660	5.00×10^4	0.111	-8.9
75	0.0803	5.54×10^4	0.113	-7.2
76	0.0781	5.89×10^4	0.117	-7.1
77	0.0726	5.63×10^4	0.108	-6.4
78	0.0788	5.10×10^4	0.105	-6.0
79	0.0811	4.37×10^4	0.106	-4.5

80	0.0779	7.10×10^4	0.122	-2.4
81	0.0624	5.30×10^4	0.116	-2.0
82	0.0895	5.00×10^4	0.109	-0.1
83	0.0656	5.10×10^4	0.104	3.6
84	0.0599	8.52×10^4	0.120	4.1
85	0.0816	4.69×10^4	0.117	4.4
86	0.0669	5.72×10^4	0.118	4.4
87	0.0661	4.65×10^4	0.102	4.6
88	0.0736	6.58×10^4	0.116	5.3
89	0.0658	4.64×10^4	0.108	5.3
90	0.1038	4.56×10^4	0.115	6.0
91	0.0615	6.12×10^4	0.106	6.3
92	0.0824	4.42×10^4	0.116	6.3
93	0.0717	5.54×10^4	0.121	6.6
94	0.0899	5.76×10^4	0.113	6.9
95	0.0705	5.48×10^4	0.118	7.6
96	0.0825	5.23×10^4	0.104	7.9
97	0.0683	7.49×10^4	0.119	9.0
98	0.0640	7.98×10^4	0.119	9.4
99	0.0917	5.63×10^4	0.112	11.2
100	0.0807	4.91×10^4	0.108	14.9
101	0.0634	5.85×10^4	0.107	14.9
102	0.0653	5.90×10^4	0.102	15.5
103	0.0791	4.62×10^4	0.102	15.6
104	0.0617	7.35×10^4	0.119	16.3
105	0.0629	8.22×10^4	0.121	17.0
106	0.0701	5.72×10^4	0.116	17.0
107	0.0648	7.20×10^4	0.120	17.5
108	0.0791	5.76×10^4	0.116	17.7
109	0.0782	5.50×10^4	0.108	19.4
110	0.1083	4.77×10^4	0.119	20.0

Table B.1 : Parameters of the full dynamic dataset.

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