# Machine Learning-based active control and PIV measurements of a circular cylinder wake

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The aim of the present paper is to investigate the fluid dynamic evolution of a circular cylinder wake controlled by a synthetic jet (SJ) to reduce the related aerodynamic drag via Particle Image Velocimetry (PIV).

In the field of flow manipulation, the control of the wake of bluff bodies, characterized by vortex shedding phenomena, has a great relevance due to its importance in several engineering applications. Many strategies have been adopted by researchers to pursue this aim and categorized into two main groups: passive and active flow control. The latter group includes SJ actuators which have been proven as an efficient flow control technique thanks to their advantageous features, such as reduced size and weight, improved manufacturability, low cost and high reliability, as reported also by Greco et al. (2020). Several works (e.g., Feng and Wang, 2010) explored the possibility to improve the performance of synthetic jets varying the input signal shape, however in these works the signal was defined in a parametric way (sinusoidal signals with varying suction duty cycle were investigated).

In the present study, Machine Learning (ML) algorithms, in particular Genetic Programming, are used to overcome the limitations inherent to the assumption of a parametric waveshape and to find the optimal waveshape of the input signal for the drag reduction of the cylinder body.

The experiments are carried out in a subsonic open circuit wind tunnel with a rectangular test section of 300 mm $\times$ 400 mm and a low turbulence intensity level (0.1 %). The test body is a hollow cylinder, whose inner and outer diameters are 24 and 30 mm, coupled with a loudspeaker driven by an electrical signal which is generated using a wave generator coupled with a four-channel power amplifier. Thanks to the oscillation of the loudspeaker, the fluid is periodically ejected and sucked from a slot placed on the cylinder surface at the rear stagnation point, generating the synthetic jet. The cylinder aerodynamic drag is measured by two LAUMAS single point load cells, located at the basis of the cylinder, whose output signals are amplified and then acquired through a LAUMAS TBL4 RS485 weight transmitter. The wind tunnel facility is equipped with a planar PIV system used to carry out velocity measurements of the wake in a plane orthogonal to the cylinder axis. Such a system consists of a Quantel Evergreen laser (Nd-YAG, 200 mJ/pulse) and an Andor Zyla 5.5 mega-pixels sCMOS camera equipped with a 50 mm focal length lens, thus obtaining a resolution of 24.85 pixel mm$^{-1}$. The flow is seeded with oil droplets, generated by a Laskin nozzle, having a nominal diameter of 1 µm and the wind tunnel is operated at a free-stream velocity of 10.4 m/s, as also measured by PIV.

The gradient-enriched machine learning control (gMLC) algorithm developed by Maceda et al. (2021) is used to find the best open-loop control law in terms of the input voltage signal. This algorithm is based on a Genetic Programming framework to build control laws starting from a selected library of analytical functions, which are evolved through genetic operations. The minimum of the objective function is found via a downhill simplex method. In the present case, in a first analysis, the starting population of analytical functions consists of 12 sine and cosine functions and the algorithm combines these laws using several operations (sum, difference and multiplication) and mathematical operators (sine and cosine). Figure 1 illustrates the learning process of gMLC algorithm for the aerodynamic drag reduction of a circular cylinder by reporting the trend of the cost function with respect to the number of tested individuals (left panel) and the optimal waveshape of the voltage input signal (that corresponding to the individual with the minimum cost) compared to a sinusoidal signal with the same frequency and amplitude. In the present case, the ML algorithm has found an optimal waveshape exhibiting a non-sinusoidal trend; on the contrary, the best individual has a shape that resembles more a square wave, still characterized by a duty cycle equal to 50%.

Figure 2 reports the maps of the streamwise-normal components of the Reynolds stress tensor for three configurations analyzed via PIV measurements: the uncontrolled one, the reference sinusoidal waveshape and the ML-based. High values of Reynolds stresses can be observed along the shear layers, in the vortex core region of the time-average von Karman vortices for the uncontrolled case and along the centreline

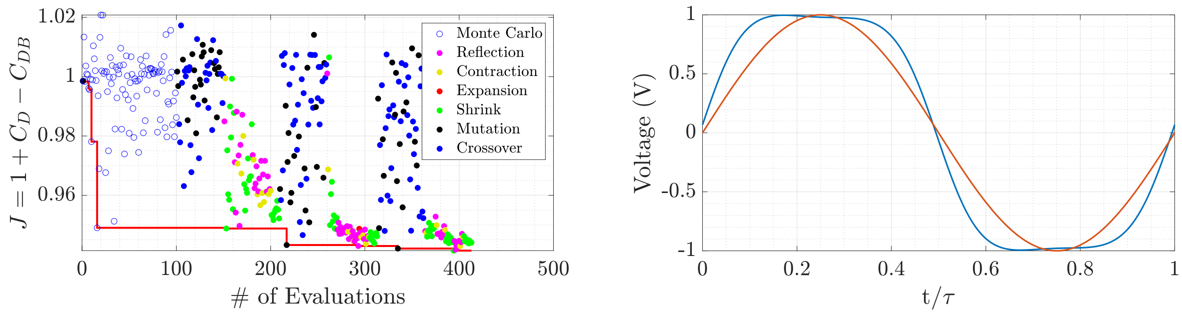


Figure 1: Left: Distribution of the costs during the gMLC optimization process; right: waveshape of the best-individual voltage control law found via the gMLC algorithm (blue curve) compared with the sinusoidal one (red curve). $\tau$ is the period of the sinusoidal wave.

where the synthetic jet is issued; in this region, a peak for the streamwise-normal Reynolds stresses can be observed for both the controlled cases. ML-based actuation reports higher values of the normal Reynolds stresses in the shear layers and at the rear stagnation point with respect to the sine controlled actuation and this implies a better suppression of vortex shedding phenomenon.

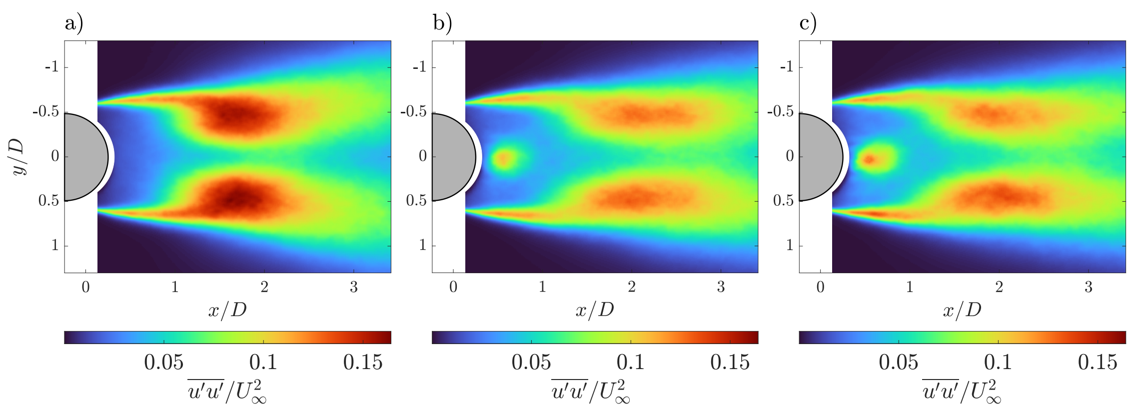


Figure 2: Dimensionless streamwise-normal Reynolds stress maps for: (a) baseline case, (b) controlled configuration with sinusoidal waveshape, (c) controlled configuration found via gMLC algorithm.

This study demonstrates the effectiveness of the synthetic jet in controlling the von Kármán Street when applied in the cylinder rear stagnation point. The optimization procedure allowed to identify an optimal waveshape found via gMLC algorithm able to reduce efficiently the aerodynamic drag with respect to natural case better than the sinusoidal conteurpart. In fact, the gMLC control law leads to a percentage drag reduction with respect to the uncontrolled configuration $\approx 1.25$ times greater than the sinusoidal control law.

# References

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