## Influence of Machine Learning-based active flow control on the turbulent statistics of the flow over a circular cylinder

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The aim of the present paper is to investigate the capabilities of Machine Learning (ML) to reduce the aerodynamic drag of a circular cylinder in cross flow, by actively controlling its wake with a synthetic jet. The control of the wake behind bluff bodies has a great relevance in several engineering applications not only for the purpose of drag reduction, but also for the suppression of vortex shedding. Many flow control strategies have been adopted in previous researches, which can be categorized into two main groups: passive and active flow control techniques. The latter group includes SJ actuators which have been proven an efficient flow control technique thanks to their advantageous features, such as reduced size and weight, improved manufacturability, low cost and high reliability. Previous works <sup>1 2</sup> have analysed the performance of a synthetic jet-based control of a cylinder wake varying essentially two control parameters, the momentum coefficient and the dimensionless frequency. On the other side, few attempts have been made to evaluate the effects of the input signal waveshape <sup>3</sup>. In these works, the signal waveshape was defined in a parametric way. In the present study, Machine Learning, in the form of Linear Genetic Programming, is 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. Once obtained the optimal waveform, Particle Image Velocimetry is used to obtain instantaneous two-dimensional velocity fields measurements in a plane containing the synthetic jet slot and to characterize the mean flow quantities and turbulent statistics of the phenomenon, as reported in Figure 1.



Figure 1: Left: Distribution of the costs during the ML optimization process; Middle: timeaveraged streamwise velocity field for the ML-based control law; Right: Turbulent Kinetic Energy map for the ML-based control law.

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<sup>&</sup>lt;sup>2</sup>Carlo Salvatore Greco et al. J. Fluid Mech. **901**, (2020).

<sup>&</sup>lt;sup>3</sup>Li Hao Feng et al. J. Fluids Struct. **26** 900-917, (2010).