

# Comparative analysis of machine learning methods for active flow control

## 7000 Industrial Applications

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Machine learning frameworks such as Genetic Programming (GP)[1] and Reinforcement Learning (RL)[2] are gaining popularity in the flow control community. This work presents a comparative analysis of the two, bench-marking some of their most representative algorithms against global optimization techniques such as Bayesian Optimization (BO) and Lipschitz global optimization (LIPO). First, we review the general framework of the flow control problem, bridging optimal control theory with model-free machine learning methods. Then, we test the control algorithms on three test cases. These are (1) the stabilization of a nonlinear dynamical system featuring frequency cross-talk[3], (2) the wave cancellation from a Burgers' flow and (3) the drag reduction in a cylinder wake flow[4]. Although the control of these problems has been tackled in the recent literature with one method or the other, we present a comprehensive comparison to illustrate their differences in exploration versus exploitation and their balance between 'model capacity' in the control law definition versus 'required complexity'. We believe that such a comparison opens the path towards hybridization of the various methods, and we offer some perspective on their future development in the literature of flow control problems.

The extended version of this work is presented in [5].

## REFERENCES

- [1] JR Koza, *Genetic programming as a means for programming computers by natural selection*. Statistics and Computing 4 (1994), 10.1007/bf00175355.
- [2] R.S. Sutton, A.G. Barto, *Reinforcement learning: An introduction*. (MIT press, 2018).
- [3] T. Duriez, S.Brunton, B.Noack *Machine learning control-taming nonlinear dynamics and turbulence* - 2017 - Springer
- [4] H. Tang, J. Rabault, A. Kuhnle, Y. Wang, T. Wang, *Robust active flow control over a range of Reynolds numbers using an artificial neural network trained through deep reinforcement learning*, Physics of Fluids, 2020
- [5] F.Pino, L.Schena, J.Rabault, A.Kuhnle, M.A.Mendez, *Comparative analysis of machine learning methods for active flow control*, submitted to Physics of Fluids