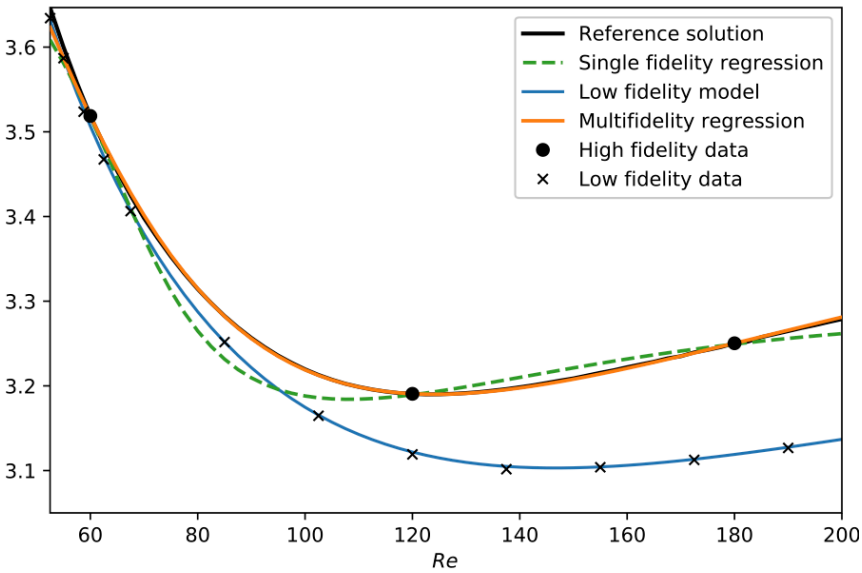
Highly accurate numerical or physical experiments can often be very time consuming and expensive. When time or budget restrictions prohibit the generation of additional data, the amount of available information may be too limited to provide a generic overview of the analyzed situation. Multifidelity methods deal with such problems by incorporating information, which can be obtained at lower cost from other sources, but are ideally well-correlated with the accurate high fidelity data. By exploiting correlations between different data sets, multifidelity methods often yield superior generalization capacities when compared to models solely based on a few high fidelity data. In my master thesis, we presented the use of artificial neural networks applied to multifidelity regression problems. By elaborating a few existing approaches, we proposed new neural network architectures for multifidelity regression. A collection of artificial benchmarks highlighted the potential of the analyzed models. Finally, we also showed an application of multifidelity regression in the context of an engineering problem, involving an incompressible fluid flow around a circular cylinder. Drag and lift coefficients for a range of Reynolds numbers are obtained using multifidelity models. The results showed that the prediction error on the drag coefficient can be reduced by as much as 98% by leveraging less reliable, but cheap data. The different benchmarks showed remarkable results; in every single test, the proposed models consistently outperformed traditional multifidelity schemes.



2-D flow around a circular cylinder: Maximum drag coefficient of the high and low