**MSc ACSE project: Model reduction using Long Short Term Memory neural networks**
(suitable for 1 or 2 students)

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The goal of model reduction (also known as reduced order modelling [1,2]) is to approximate a high fidelity model (that is, a high dimensional model with many degrees of freedom derived from, for example, a finite element discretisation) using a model of significantly lower dimension (the reduced order model) whilst retaining, as much as possible, the predicting capability of the former. The reduction in dimension can lead to a computational speed up of many orders of magnitude resulting in a model which can be used for multi-query problems and for real-time calculations.

Of recurrent neural networks, Long Short Term Memory (LSTM) networks [3] have shown great promise for time-dependent deterministic problems, for example, in playing chess and for controlling driver-less cars. The 'memory' possessed by these neural networks may have particular importance for model reduction and we expect the combination of these methods to become dominant in the near future for a number of applications including weather prediction, multi-phase flows in pipes and oil & gas reservoir modelling. For example, these methods lead to the prospect of being able to resolve the flows within a building while simultaneously resolving the flows within an entire city. This project will develop the LSTM network with the possible extension of using Domain Decomposition Methods to gain further reduction in computational cost.

The student will join a small team working on this topic. It is expected that the Tensorflow library [4] will be used for the neural networks and IC-FERST [5] or FETCH2 [6] will be used for the high fidelity modelling.

**References**

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[3] Z. Wang, D. Xiao, F. Fang, R. Govindan, C.C. Pain, Y. Guo (2018), Model identification of reduced order fluid dynamics systems using deep learning, *International Journal for Numerical Methods in Fluids*, 86:255-268.

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[5] P. Salinas, D. Pavlidis, Z. Xie, A. Adam, C.C. Pain, M.D. Jackson (2017), Improving the convergence behaviour of a fixed-point-iteration solver for multiphase flow in porous media, *International Journal for Numerical Methods in Fluids*, 84:466-476.

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