Presentation Abstract:

Within structural systems, as is the case across many areas of engineering, it is often difficult (if not impossible) to describe the dynamic behaviour of the system exactly in closed from first principles. The problem of system identification then is to determine effective models which can predict behaviour of interest over a sufficiently broad range of operating conditions. One powerful approach may be to build a physical model of the system and attempt to calibrate the parameters of that model from measured data. Alternatively, one may decide to purely use observational data in combination with tools such as machine learning to build a *black-box* model of the system. In this talk, one methodology which sits between these two extremes will be shown. Using some partial knowledge of the physics, a model will be constructed and coupled with a Gaussian process (a machine learning regression tool) in order to provide insight into the physics of nonlinear dynamic systems from data. This insight is subsequently used to build more effective nonlinear models which can extrapolate beyond the already seen data. Examples will be shown for three cases, first a single degree of freedom input-output system, then an extension for output-only (blind) identification and finally some preliminary results for higher order models with multiple degrees of freedom. The key takeaway of this talk will be how, as engineers, imposing physical knowledge in data-driven modelling not only allows more accurate models but that black-box components can reveal unknown physical phenomena.

Presenter's Biography:

Tim Rogers is a senior lecturer in the Dynamics Research Group, Department of Mechanical Engineering at The University of Sheffield. He is interested in optimal use of data within engineering applications, particularly those associated with dynamic systems. His research is focussed on applications of statistical machine learning and Bayesian approaches to solve problems in (nonlinear) system identification and structural health monitoring. This work covers applications in offshore energy, aerospace and civil infrastructure, where the need to build reliable dynamic models and to infer the condition of engineering assets from data is of key importance. A particular area of interest is in how to appropriately quantify and use uncertainty, in a probabilistic setting, to improve methodologies and ultimately help engineers to make informed decisions.