Bayesian multi-diagnostic inference for divertor physics studies in MAST-U

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As the performance of magnetic-confinement fusion (MCF) devices has improved toward fusion-relevant plasma conditions, the problem of handling the exhaust power of these devices has become much more challenging. Currently, it is not clear that a 'divertor', the conventional exhaust system used by MCF devices, will be sufficient to handle power exhaust for a reactor-scale device without destroying plasma-facing material surfaces.

Consequently, significant research effort is focussed on potential alternatives or modifications to the divertor concept which will reduce peak heat loads on material surfaces. One such modification, the 'Super-X divertor', will be tested in the MAST-Upgrade spherical tokamak which will begin operations in 2019. Understanding the impact of the Super-X divertor on plasma exhaust conditions is a major goal of MAST-Upgrade, and obtaining robust estimates of plasma temperature and density across the Super-X will be key in achieving this goal. This is challenging however, as direct measurements of the temperature and density are limited to isolated points (e.g. Thomson scattering, Langmuir probes), and diagnostics which do offer good spatial coverage (e.g. filtered cameras) measure 'higher-level' quantities such as atomic line emissivities. Consequently, no individual diagnostic system can provide the requisite information.

We aim to solve this problem by using a Bayesian approach to combine information from all available divertor diagnostics. By parametrising the plasma state throughout the divertor (i.e. the fields of temperature, density ect.), we are able for a given diagnostic system to construct a probability distribution which describes the likelihood of obtaining the observed experimental data given this set of parameters. By repeating this process for each diagnostic system, the basic rules of probability theory allow us to combine the likelihoods for each individual diagnostic into a single multi-diagnostic likelihood describing the probability of simultaneously obtaining all observed divertor data for a given plasma state. Finally, a 'posterior' distribution for the plasma state parameters themselves can be obtained by combining this multi-diagnostic likelihood with a 'prior' distribution which allows us to impose physicality constraints.

We will present a description of the Bayesian approach to combining diagnostic information, an overview of the system design for the multi-diagnostic inference system and the results of preliminary numerical tests of the system.