

An Integrated Data Analysis Model for the W7-AS Stellarator

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Abstract

This paper describes the first implementation of a new diagnostic analysis model in which a number of previously separate diagnostic models are integrated into a single comprehensive model. The linkage of information from these different models is done using Bayesian probability theory, which allows information about physical parameters inferred from one separate model to be utilised *without losses* in another model. Since interdependencies between diagnostic models are common for fusion diagnostics, inference of physical parameters from several diagnostic models treated as a whole can be expected to give an increase in accuracy and robustness.

One major interdependency between diagnostic models is the common mapping to a magnetic coordinate system, which itself has to be inferred from measurements. Here a fast self-consistent 3D stellarator equilibrium calculation based on function parameterization is used as part of the overall integrated model, which additionally includes a Nd:YAG Thomson scattering system, diamagnetic loop measurement and microwave interferometer. The self-consistent inclusion of a magnetic coordinate reconstruction adds influences from uncertainties in the position of inferred flux surfaces to quantities such as n_e -, T_e - and pressure profiles. From the reconstructed magnetic mapping itself error bars on quantities like effective radius, iota profiles and plasma volume can be derived. These error bars will reflect both statistical and systematic uncertainties from the whole system.

Introduction

In traditional diagnostic data analysis, physical parameters are evaluated through separate models/codes tied to individual diagnostics. Interdependencies between such models are then usually treated in a sequential fashion, that is, the output from one diagnostic model is directly used as input for another (figure 1). This leads to a suboptimal utilisation of the measurements: When many diagnostic models are interdependent through common physical parameters, those diagnostic models could all *provide* information about (and thus modify) parameters that are currently used merely as fixed inputs from previous analysis. In a sense, there are multiple models of aspects of the plasma where there should optimally only be one model, evidenced by data from a number of diagnostics, treated as a whole.

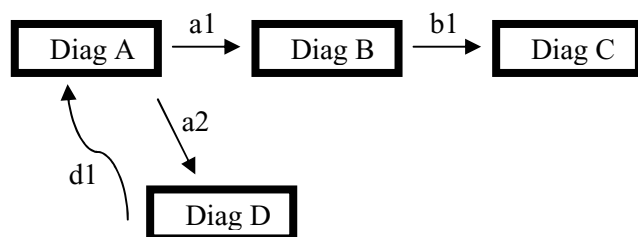


Figure 1. Physical parameters (a_1, b_1 etc) estimated from one diagnostic model is used directly in another. Between diagnostic models A and D there is a mutual dependency.

In a Bayesian framework [1,2], knowledge about parameters and observations are represented by probability distributions. The establishment of all relationships (probabilistic and functional) between all entities in the entire integrated system defines a joint probability density in the space of all parameters and all observations. From this high dimensional probability distribution inferences can then be made about marginal distributions, expected values or standard deviations of parameters given the total of diagnostic observations.

Specific advantages of this approach include: 1) possibility of automatic consistency between all included diagnostics by inclusion of systematic uncertainties in the joint model, 2) n_e , T_e and pressure profiles directly fitted as function of magnetic coordinates, 3) error bars on the magnetic mapping itself and derived quantities (r_{eff} , i profiles, plasma volume etc).

Bayesian Model

In a real model where several diagnostics are considered, the interrelationship between physical parameters, nuisance parameters (for example: systematic errors), measurements and measurement errors can be quite complex. In figure 2 these relationships are represented by a Bayesian Graphical Model [3], in which each node represents a probability distribution conditioned on the parent nodes, or a deterministic functional dependency on the parent nodes. The main free parameters of the model are: n_e -, T_e -and ion pressure profiles parameterized as a function of magnetic coordinates (toroidal flux) (top left of the graph), and some systematic errors, mainly calibration factors c_{geom} from the Thomson diagnostic [4,5] at the bottom left. At the centre of the graph an equilibrium calculation is done using a function parameterization approach [6], based on the calculated total pressure profile and coil currents. Observations giving evidence on the values of the free parameters are given at the bottom nodes of each diagnostic at the bottom of the graph. The graph together with a specification of the functional form of all dependencies specifies a joint probability density over the free parameters of the model conditioned on the data. From this density samples can be generated using Markov Chain Monte Carlo (MCMC) methods [7]. These samples are then used for all inferences about the parameters of interest and their marginal distributions.

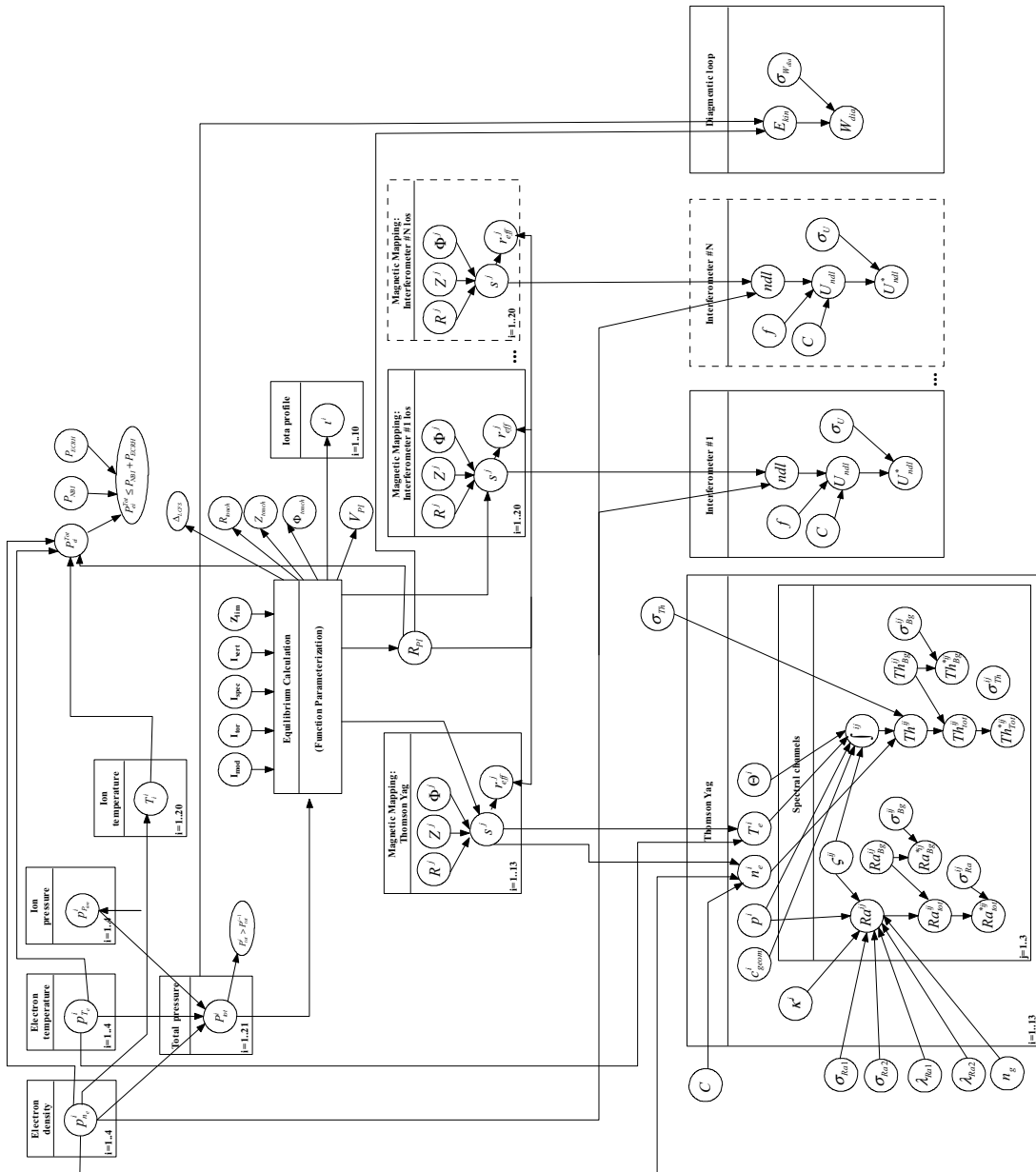


Figure 2. Bayesian Graphical Model of implemented integrated model for W7-AS.

Results

All nodes in figure 2 represent parameters that can be inferred from the model in the form of marginal posterior distributions. The distribution for such a parameter will reflect uncertainties from all parts of the system, including the uncertainty with which the magnetic coordinate mapping can be known given all measurements. We will only give two examples here, first the inferred T_e -profile distribution (figure 3), and then the distribution for inferred effective radii for the Thomson channels (figure 4).

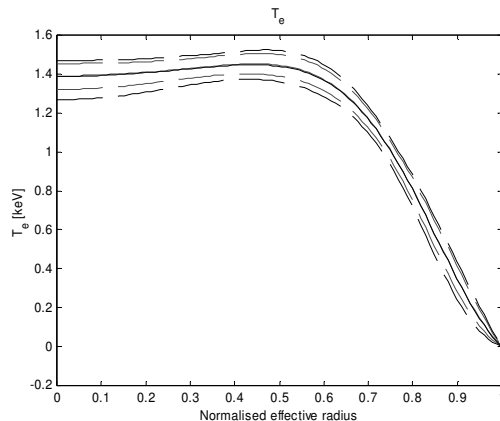


Figure 3. T_e -profile as a function of normalised effective radius. Dashed curves show the one and two standard deviation limits.

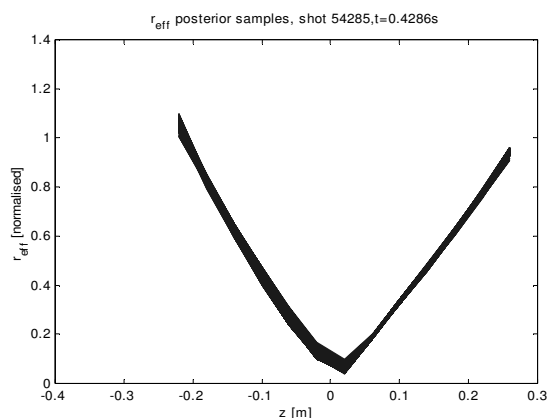


Figure 4. Distribution of normalised effective radius for 12 Yag Thomson channels along z -axis. $s > 1$ indicates Thomson channel outside last closed flux surface.

References

- [1] Jeffreys, *Theory of Probability*, Oxford University Press, 1939
- [2] Gelman et al, *Bayesian Data Analysis*, Chapman & Hall, 1995
- [3] S L Lauritzen, *Graphical Models*, Clarendon Press, 1996
- [4] R Fischer, A Dinklage, E. Pasch, Plasma Phys. Contr. Fusion 45, 1095 (2003)
- [5] A Dinklage et al, contribution P1-52, this conference
- [6] H Callaghan, P Mc Carthy, J Geiger, Plasma Phys. Contr. Fusion 42, 1013 (2000)
- [7] Gilks, Richardson, Spiegelhalter, Markov Chain Monte Carlo in Practice, Chapman & Hall, 1996