Bring fusion energy closer: challenges for probabilistic inference in the multiphysics, multiscale environment of fusion devices

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Abstract

Fusion energy research can be greatly accelerated by probabilistic inference that reliably combines multimodal diagnostics with physics simulators to estimate plasma and device state. Probabilistic inference is becoming more routine across fusion devices worldwide, but can be greatly expanded in both the data and techniques used. We outline some of the open challenges in this path, inherent to the multiscale, multiphysics nature of fusion devices, namely high-dimensional, time-dependent posteriors; fidelity hierarchy of physics simulators for forward models; and wide range of multimodal diagnostics at varying spatiotemporal resolutions. We highlight some potential techniques, machine learning and related, to begin to tackle these problems.

1 Introduction

Nuclear fusion, the process that powers the sun, offers a path to clean, carbon-free energy, yet building terrestrial fusion power plants that produce net energy remains elusive. However, accumulated progress and novel technologies have led to a current state where a large multinational experiment and also many fusion companies funded by private investors are nearing key milestones to demonstration power plants. These plants have to overcome the historical challenges faced by fusion energy, namely the need to tame a hot, fusing plasma at 100 million degrees °C, next to machine components which can withstand the harsh nuclear environment. This is a quintessential multiscale, multiphysics problem, which manifests in the range and variety of both experimental diagnostic measurements and physics models/simulation codes used in fusion energy research, as highlighted in Figure 1. A key challenge in fusion energy research is the ability to assimilate sensor measurements with physics models/simulations in order to, for example, create real-time controllers for the plasma, interpret the plasma state for improved operations, and ultimately establish the scientific understanding of plasma and device behavior to enable a successful fusion power plant design.

1.1 Current Approaches

The current dominant approach to assimilating sensor data with physics models in fusion experiments is siloed, individual diagnostic analysis, with error propagation done (if at all) by hand. An example of this is magnetic equilibrium reconstruction, where magnetic sensor measurements and Thomson scattering measurements of plasma density/temperature are used to constrain the plasma magnetic force balance equilibrium, whose results are in turn for example used to map the same plasma density/temperature to other diagnostics. Consistency is obtained (in principle) by iteration, but can face non-convergence issues, and neglects cross-diagnostic dependencies which can be valuable for both consistent solutions and true error uncertainty for predictions Fischer et al. [2024].

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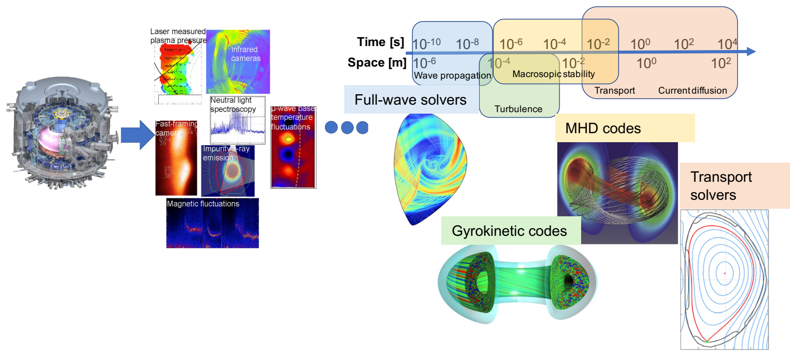

Figure 1: Example multimodal diagnostics and physics simulators spanning a wide spatiotemporal range in fusion energy devices

More sophisticated modeling termed "Integrated Data Analysis" (IDA) Fischer et al. [2024], Fischer and Dinklage [2007]) is currently spreading in use in fusion experiment. IDA uses Bayesian probabilistic modeling, defining likelihoods for each diagnostic of interest and combining with Bayes rule to determine a posterior for plasma state physics parameters given multiple diagnostics. Typically a diagnostic forward model is combined with an analytic noise model to form the likelihood, and Maximum A Posteriori (MAP) for parameter estimation. Markov Chain Monte Carlo (MCMC) is utilized for full coverage of the PDF, but due to computational constraints is often only used for select time slices and diagnostics.

Likelihood-free methods using normalizing flows for neural density estimators have been used for Simulation-Based Inference (SBI) Furia and Churchill [2022] extracting anomalous transport coefficients from diagnostic measurement in the edge, but these works have been proof of principle, and focus on a relatively small number of physics parameters ($\sim$60).

1.2 Bottlenecks and Opportunities

A number of difficulties intrinsic to the nature of fusion energy experiments/simulation are also opportunities for applying and developing novel sampling techniques focused on probabilistic inference. First, experiments are inherently time-dependent, and desired interval for parameter inference is at least on millisecond timescales. Informing machine operators and researchers quickly of derived physics from the experiments in a timely manner is critical for optimal use of machines. Usage of MCMC for this volume of data is therefore limiting, and opportunities to utilize neural density estimators Papamakarios [2019] to speed up inference is very attractive. Second, combining the myriad of diagnostics generating different data modalities (scalar time-series, image, video, line-integrated diagnostics, etc.) at different spatiotemporal resolutions is a challenge. Development of useful diagnostic data encoders and best practices for joint latent space diffusion Bao et al. [2023] or other means to meaningfully perform probabilistic inference leveraging many different modalities is needed. Ability to restrict latents to produce physically realizable values would be invaluable, utilizing for example work done on formal verification methods for numerical algorithms Gorard et al. [2025]. Third, the ability to perform high-dimensional spatiotemporal inference, for example time-dependent overlaid meshes of local divertor wall temperature from infrared video measurements plus other diagnostics with models for multiple reflections. Work on plug-and-play diffusion priors for scientific video inverse problems Zhang et al. [2025] could provide a path to tackle this challenge if paired with multimodal capabilities and geometric deep learning architectures. Fourth, diagnostic measurements are ultimately sparse, and simulation is relied on heavily to fully interpret current devices and predict future devices. This will become even more pronounced in next step devices and future power plants, as the nuclear environment will further limit the diagnostics available, for example ITER will need to reconstruct the magnetic equilibrium often without internal current measurements. Fusion has a variety of simulators covering different physics, with a hierarchy of fidelity. Enabling the use of expensive simulators in the forward models for SBI would ultimately be ideal, through AI surrogates, emulators, amortization, or intelligent sampling through the parameter space. In reality multifidelity models Rosen et al. [2022] leveraging data from simulators at increasing levels of fidelity may be needed to stay within realistic computational budgets.

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