DEEP LEARNING SURROGATE MODELS FOR NEUTRONIC IRRADIATION OPTIMISATION IN IFMIF-DONES

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The IFMIF-DONES project, which aims to pave the way for understanding the effects of high-energy and high-flux neutronic irradiation on materials, is a crucial step for the future of fusion reactors. Traditionally, Monte Carlo simulations have been employed to study neutronic transport and interactions; however, their computational cost hinders the ability to optimise and control elements of the environment, such as geometry or accelerator configuration, in the case of IFMIF-DONES. In this work, we propose an approach based on Deep Learning Surrogate Models, which employs a Neural Operator known as MIONet to predict neutron-related tallies such as flux, damage energy, hydrogen (H) and helium (He) production, and heating. By using a custom differentiable version of the MIONet, we enabled the ability to optimise the initial Gaussian parameters that define the deuteron footprint on the lithium curtain. Several optimisation techniques were tested, including Gradient Descent, Bayesian Optimisation and Multi-Objective Evolutionary Optimisation, allowing for a more efficient parameter space exploration and the creation of multidimensional Pareto Fronts based on customizable optimisation functions. The results of this work demonstrate that these models achieve speedup factors of around 10^6, compared with Monte Carlo simulations, with Coefficients of Determination (R^2) above 0.986 for every model, up to 0.996. Additionally, the integration of optimisation techniques allows for inverse design where desired outcomes are set through custom loss functions, and the model is utilised to discover optimal input parameters. Through this work, we highlight the computational efficiency achieved by these models, as well as their potential for advancing real-time control systems and design optimisation within fusion facilities. Future work will focus on refining the 3D High Flux Test Module model according to the improved configurations, integrating more parts of the system, such as the accelerator, to explore integral control of the device, and updating the model's architecture to achieve its most efficient configuration.

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