MACHINE LEARNING AIDED NEUTRON YIELD FOR DUD DETECTION BASED ON JET AND TFTR DEUTERIUM-TRITIUM PLASMAS

[1,2]L. Piron, [3]A. Pau, [3]O. Sauter, [4]M. Baruzzo,[5]C. Challis, [6]R. Dumont, [7]D. V. Eester, [5]M. Fitzgerald, [2]D. Frigione, [8]E. Fredrickson, [5]Z. Ghani, [9]M. Gambrioli, [5]L. Garzotti, [10]J. Hobirk, [10]A. Kappatou, [5]K. Kirov, [5]D. Keeling, [7]E. Lerche, [5]M. Maslov, [5]M. Lennholm, [5]F. Rimini, [11]V. K. Zotta, [5]D. F. Valcarcel and TCV contributors (*) and JET contributors (**) and WPTE contributors (***) and TFTR contributors (****)

[1]Università degli Studi di Padova, Padova, Italy
[2]Consorzio RFX, Padova, Italy
[3]Ecole Polytechnique Federale de Lausanne (EPFL), Lausanne, Switzerland
[4]ENEA, Fusion and Nuclear Safety Department, C.R. Frascati, Rome, Italy
[5]Culham Science Centre, Abingdon, United Kingdom
[6]CEA, IRFM, St-Paul-Lez-Durance, France
[7]Laboratory for Plasma Physics, LPP-ERK/KMS, Bruxelles BE
[8]Princeton Plasma Physics Laboratory, Princeton, USA
[9]CRF- University of Padova, Italy
[10]Max-Plank-Institut für Plasma Physik, Garching, Germany
[11]Sapienza University of Rome - DIAEE, Italy

See the author list in (*) B. P. Duval et al 2024 Nucl. Fusion 64 112023 for the TCV Contributors, in (**) C.F. Maggi et al 2024 Nucl. Fusion 64 112012 for the JET Contributors, in (***) E. Joffrin et al 2024 Nucl. Fusion 64 112019 and in (****) R. J. Hawryluk et al 1998 Phys. Plasmas 5, 1577–1589 for the TFTR Contributors.

Email: lidia.piron@unipd.it

Fusion reactors will be the most intense and powerful sources of fast neutrons. Each deuterium-tritium reaction will produce a 3.5 MeV energetic helium atom and a 14.1 MeV neutron. While the charged helium is confined within the plasma, where it contributes to plasma heating thanks to Coulomb collisions, the neutron will escape toward the wall of the plasma chamber.

The counting of 14.1 MeV neutrons produced by fusion reactions per second, known as the neutron yield, will be one of the most important metrics in a burning plasma, as it directly measures the device's efficiency in energy and tritium production.

Nevertheless, this is not the only reason why the neutron measurements [1] are of special interest for fusion devices. Neutron diagnostics play also a crucial role in determining the plasma composition, i.e. the deuterium-tritium fuel ratio, the ion temperature and density [2]. Neutron emission can also be useful to monitor plasma position, its extent and shape [3]. This requires measurements of spatial emission profiles, so that neutron emissivity distribution can be reconstructed using special tomographic methods.

In future burning plasma fusion devices, measurements of the neutron yield will be exploited in real-time to determine whether the discharge should be terminated, because the plasma is not reaching the target fusion power. This deviation with respect to the expected plasma performance can be due to various causes, such as off-normal events or a system fault.

In this context, at JET already in its first deuterium-tritium campaign, named the DTE1, which took place in 1997, a controller has been used to save the limited neutron and tritium budgets. This controller monitored whether the neutron yield remained above a predetermined curve [4]. In the DTE2 campaign, which took place in 2021, a more sophisticated algorithm, named the dud detector, has been exploited in real-time to detect underperforming baseline plasmas [5-7]. The algorithm relied on performance metrics, i.e. the neutron yield normalized to the plasma stored energy to the square and the confinement time normalized to the H_{98} scaling [5].

However, out of 16 deuterium-tritium baseline plasmas, as documented in [7], the dud detector raised only one false positive alarm due to a failure in the real-time Rnt signal. This could have been avoided if multiple neutron yield signals from various neutron diagnostics had been available in real-time. This approach ensures a degree of redundancy, which can help account for potential problems within the diagnostic equipment itself and/or in the acquired signals. Another strategy to avoid this kind of issue is to rely on a real-time data-driven model, which can generate synthetic neutron yield data, as proposed in [8].

In this work, we present a first-of-its-kind surrogate model for neutron yield. This model has been developed using JET deuterium and tritium discharges from the DTE2 and recent DTE3 campaigns (2023), applying various machine learning methods such as Support Vector Regression, Decision Tree Regression, K-Nearest Neighbors, Random Forest, Gradient Boosting Machines, eXtreme Gradient Boosting, LightGBM, Neural Networks, and Gaussian Processes & Bayesian Neural Networks. These methods have proven to be robust and reliable in supplementing missing neutron rate data and forecasting it. A comparison between the experimental and modelled neutron yield, as predicted using the Bayesian Neural Network method, is shown as an example in Fig. 1. The Rnt model has also been validated against DTE1 and TFTR deuterium-tritium pulses to assess its portability.

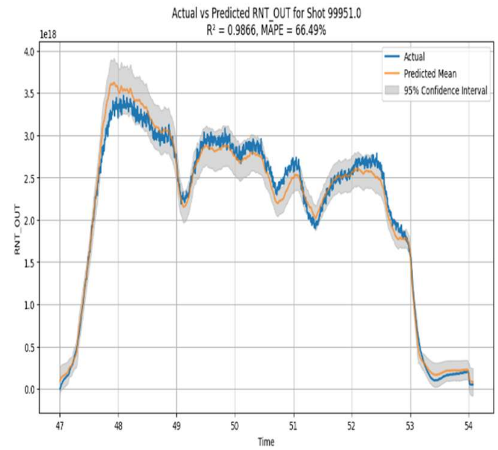

Fig.1 Time behaviour of the neutron rate as measured (in blue) and as foreseen by a surrogate neutron rate model based on a Bayesian Neural Network (in orange). The grey shaded area corresponds to the 95 % confidence interval. The experimental data refers to the ITER deuterium-tritium JET discharge #99951.

Moreover, the neutron rate surrogate model's ability to predict neutron production can be leveraged for real-time plasma performance monitoring. This approach will be tested in TCV, where a dud detector, based on the Rnt machine learning model, will be integrated into the plasma control system. The detector will monitor plasma performance based on its trajectory in the operational space. If the plasma deviates from the expected behavior (i.e., underperforms), an alarm will be triggered, and a controlled plasma termination will be initiated.

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