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

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Abstract

In future fusion reactors, measuring the neutron production rate from Deuterium-Tritium (DT) fusion reactions will be crucial as it indicates fusion performance. To optimize Tritium consumption and limit neutron activation, a support function included in the plasma control system called a dud detector will trigger an alarm if the plasma fails to achieve expected fusion performance. This function has been developed and routinely employed at JET during DT campaigns. This study presents advanced dud detectors that build upon experience from JET DT operations and incorporate machine learning methods.

Towards DT operations in BEST, ITER and SPARC, we have investigated the portability and the inherent limitations of these new detectors by analyzing similar Deuterium-Tritium experiments conducted at TFTR.

1. INTRODUCTION

Fusion reactors will be the most intense and powerful sources of fast neutrons. Indeed, each Deuterium-Tritium (DT) 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.

In the blanket, neutrons will slow down and release thermal power that will produce electrical power, via a two-loop cooling circuit, and will breed tritium, by reacting with Lithium6 and Lithium7.

The counting of 14.1 MeV neutrons produced by fusion reactions per second, known as the neutron rate (R_{nt}), 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 extend 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, the neutron rate will be exploited in real-time to determine whether the discharge is behaving as expected or should be terminated, because the plasma is not reaching the target fusion power due to an abnormal event related to the plasma itself or a system fault.

In this context, at the Joint European Torus (JET) device, already in its first DT campaign, named the DTE1, which took place in 1997, to save the limited neutron and tritium budgets, a controller, named dud detector, had been used that monitored whether the neutron rate remained above a predetermined curve [4]. In the DTE2 campaign, which took place in 2021, a more sophisticated dud detector algorithm has been exploited in real-time to detect underperforming baseline plasmas [5-7]. The algorithm relied on performance metrics, i.e. the neutron rate normalized to the plasma stored energy to the square (R_{nt}/W_p^2) and the H_{98} , the ratio between the energy confinement time and the expected energy confinement time from the empirical, multi-machine energy confinement time scaling law [5].

However, over 16 deuterium-tritium baseline plasmas, as documented in [7], the dud detector raised a false positive alarm due to a failure in the real-time R_{nt} signal. This could have been avoided if multiple neutron rate 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 machine learning (ML) model, which can generate synthetic neutron rate data, as proposed in [8].

In this paper, we present a first-of-its-kind surrogate model that predicts the time evolution of the neutron production. Such a model has been developed considering JET DT discharges performed during DTE2 and the recent DTE3 campaign, carried out in 2023. Various ML methods, such as Support Vector Regressor (SVR) [9], Gaussian Process Regression (GPR) [10], Bayesian Neural Network (BNN) [11], have been considered and the one which shows to be most robust and reliable in supplementing missing R_{nt} data is the GPR method. An excellent accuracy, about 98.3% of the coefficient of determination (R^2) has been achieved. Besides this purpose, the ML model's capability in forecasting the neutron production can be deployed for real-time monitoring the plasma performance.

The experience gained during JET DT operations also allows the design of novel dud detectors which rely, for example on the thermal neutron rate calculations. The applicability of these new dud detection methods, including the one based on machine learning, has been tested against (Tokamak Fusion Test Reactor) TFTR data [12] in preparation to next future DT experiments in BEST, ITER and SPARC.

The paper is structure as follows: in section II the neutron rate features in JET DT plasmas are described, in Section III the machine learning approaches for synthetic neutron rate model identification are presented, together with the quality assessment of the generated data with the original data, in Section IV the insights that have been gathered in this work are discussed together with the application of the surrogate machine learning models in reproducing the neutron rate in DTE1 and DT-TFTR plasmas. In Section V, the design of a novel dud detector based on the thermal neutron production is presented. Section VI provides the conclusions.

2. NEUTRON RATE IN JET AND TFTR DEUTERIUM-TRITIUM PLASMAS

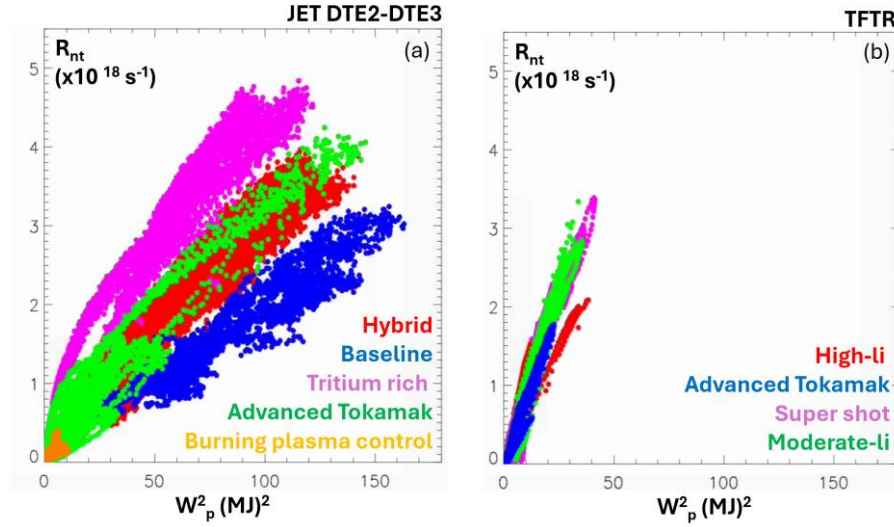


FIG. 1. Neutron rate as a function of stored energy to the square in (a) JET DT plasmas and (b) TFTR DT plasmas. The color code has been used to distinguish the various scenarios explored during DT operations.

During DTE2 and DTE3 campaigns, plasma dynamics were investigated in three main plasma scenarios, which have been carefully optimized over the last decades to maximize fusion performance, to study the critical physics issues associated with DT fuel and alpha-particles, to test burning plasma controllers and to extrapolate the knowhow towards ITER and the next step magnetic fusion devices.

These scenarios are known as the hybrid, baseline, and advanced tokamak and all used a 50/50 D/T ratio [13]. The hybrid scenario produced most neutrons per MJ of plasma stored energy by operating in low density, high temperature plasma regimes [14, 15], while the baseline scenario achieved high neutron rate by reaching the highest plasma stored energy, by operating at high plasma current, up to 4 MA [16, 17]. Conversely, the advanced tokamak scenario used a combination of high plasma current and magnetic field with internal transport barriers formation to achieve the high neutron rate [18].

For these different DT plasma scenarios the neutron rate, measured by three $^{235}\text{U}/^{238}\text{U}$ fission chambers located outside the vacuum vessel [2], is reported in Figure 1(a) as a function of the stored energy to the square. Hybrid plasmas are reported in red, baseline plasmas in blue, and advanced tokamak plasmas in green. The same figure also includes hybrid plasmas with a Tritium rich content, which was approximately 15/85 D/T mixture instead of 50/50 D/T [19, 20]. This dataset is represented in magenta. Additionally, the figure includes data points for experiments conducted at low plasma current, toroidal magnetic field and auxiliary power, which were part of burning plasma control studies [21, 22].

Note that the slope of R_{nt} versus W_p^2 varies depending on the plasma scenario. This variation reflects the different approaches to achieving fusion production in each scenario, as previously aforementioned. This feature has been exploited as a performance metric for dud detection in baseline plasmas, as documented in [5, 7].

The same analysis reported in Figure 1(a) has been carried out for DT plasmas performed in TFTR from 1993 to 1997. As at JET, the neutron rate was measured by ^{235}U detectors [23].

DT TFTR experiments explored various plasma scenarios, including super-shot, advanced tokamak, high-li and moderate-li [12, 24-27]. The super-shots demonstrated enhanced confinement and performance, thanks to the strong beam particle fueling of the plasma core, peaked density profiles, high ion temperature in the core, around 2-4 times the electron temperature. Additionally, lithium coating was used to further suppress the influx of deuterium and carbon [26]. The advanced tokamak plasmas were characterized by reversed shear near the plasma core accomplished by ramping up the plasma current to create a hollow current profile, coupled with a staged neutral beam injection power profile, strongly peaked electron density profile, and significant bootstrap current. TFTR also investigated other methods to enhance confinement and fusion production. The high-li scenario involved peaking the current density profile by manipulating plasma current growth or ramp-down, leading to a temporary increase in plasma internal inductance. A less extreme approach, known as the moderate-li regime, involved rapidly increasing the plasma minor radius just before neutral beam injection.

Figure 1(b) shows the behavior of the neutron rate as a function of the squared stored energy in TFTR discharges, considering the various scenarios described previously. Note that, differently from JET, there is less variation in the R_{nt} versus W_p^2 in the TFTR DT database. This is associated with the fact that all TFTR discharges had relatively peaked pressure profiles.

3. SURROGATE MODELS FOR NEUTRON RATE

JET plasmas performed during the DTE2 and DTE3 have been analyzed with the purpose of developing new dud detectors in preparation for upcoming DT experiments in BEST, ITER and SPARC. The new detectors, based on machine learning models and straightforward analytical formulas, can be used for supplementing missing R_{nt} data and for distinguishing between well-performing plasmas and duds.

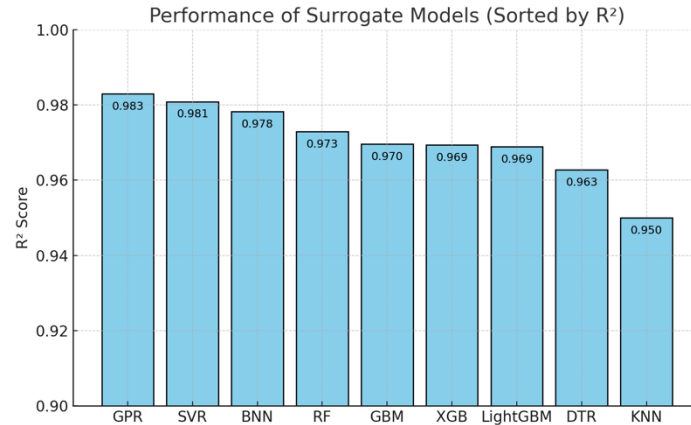
For this purpose, a dataset containing 101 DTE2/DTE3 discharges has been created including data collected during the main heating phase of DTE2 and DTE3 discharges. Table 1 presents the key plasma parameters of the main plasma scenarios described in the previous Section. Importantly, the database also includes DT plasmas operating below full power. This deliberate inclusion of lower-performance data ensures the dataset encompasses a wide range of neutron rate outputs, enhancing its utility for dud detection.

TABLE 1. Main JET DT plasma parameters in the various scenarios analyzed.

Scenario	I_p (MA)	B_t (T)	Density (m^{-3})
Hybrid	2.3	3.43	2-6
Baseline	3/3.5/3.8	2.8/3.35/3.6	2-8/2-8
Advanced Tok.	2.5	3.8	1.5-3
Tritium-rich	2.45	3.85	2-6
Plasma Control	1.4	1.8	3-4

The features that have been included when creating the dataset are the auxiliary heating power, the core electron temperature from Electron Cyclotron Emission diagnostic (T_e), the electron density from interferometer (n_e), the Deuterium and Tritium mixture from passive spectroscopy, the Deuterium density (n_D) and Tritium density (n_T), the stored energy, the neutron rate and the reactivity $\langle \sigma v \rangle$ defined as $3.68 \cdot 10^{-18} T_e^{-2/3} e^{-19.94 T_e^{-1/3}}$ [28, 29].

TABLE 2. Summary of the model performance in the regression task.



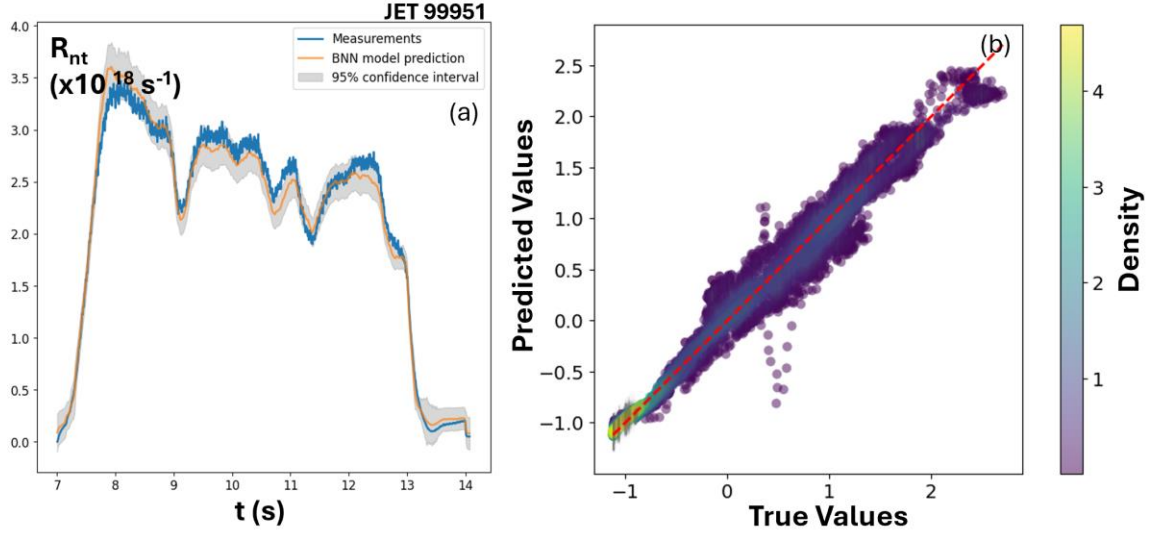


FIG. 2. (a) Neutron rate as a function of time from measurement (in blue), from BNN model prediction (in orange) and the grey shaded region represents the 95% confidence interval. (b) Normalized density plot with normalized with predicted vs true measurements values.

Several machine learning methods have been evaluated for the regression task of reconstructing R_{nt} , most of which were instance-based and did not account for temporal dependencies. The models included the Gaussian Process Regressor (GPR) [10] and Bayesian Neural Network (BNN) [11], which uncertainty estimates, Support Vector Regressor (SVR) [9], Random Forest (RF) [30], K-Nearest-Neighbors (KNN) [31], Decision Tree Regressor (DTR) [32], eXtreme Gradient Boosting (XGB) [33], Gradient Boosting Machine (GMB) [34] and Light-GBM [35].

As commonly used in machine learning studies, the dataset has been divided into training and test shot sets. The DTE2-3 dataset included 101 discharges, out of which 11 were left out for testing. All the machine learning models reached good performance in the regression task, achieving $R^2 > 0.95$, as demonstrated in TABLE2.

Figure 2 shows on the left, as an example, the capability of the BNN model in predicting the R_{nt} within 95% confidence level in the 99951 high performance baseline plasma with 3 MA plasma current and 2.8 T toroidal magnetic field. The R^2 value reached is quite good, around 0.987, and 95% confidence interval remains tight throughout the main heating phase, reflecting the reliability of the surrogate model. The scatter plot, on the right part of the figure, further demonstrates the excellent correlation between measured and reconstructed values, confirming the consistency of the surrogate across the test set.

These results demonstrate that the ML methods applied in this study can accurately reconstruct missing neutron rate data. When integrated into the plasma control system, these methods can act as monitors for detecting underperforming plasmas.

4. APPLICATION OF THE SURROGATE R_{NT} MODEL TO JET DTE1 AND TFTR HIGH PERFORMANCE DISCHARGES

ML models developed from the DTE2 and the DTE3 datasets were applied to predict the performance DTE1 and TFTR discharges. The goal of this analysis was to evaluate the portability of these models to another devices in preparation for future DT experiments. The DTE1 database was selected because, during that campaign, JET operated with a different wall conditioning and wall/divertor materials with respect to DTE2 and DTE3 campaigns, and limited auxiliary heating, conditions that influenced the neutron rate. On the other hand, TFTR used the same fuel, but with different fuel mix, and featured a different neutral beam injection angle, beam voltage and relatively peaked density profiles, both of which impact neutron production.

Representative results are shown in Figure 3 for a JET DTE1 discharge, on the left and for a TFTR discharge, on the right. While the models retain some predictive capability, clear systematic deviations arise, especially for TFTR, where predicted rates consistently underestimate the measurements. Predictive intervals widen considerably in these cases, signaling the increased model uncertainty.

The reduced performance on DTE1 and TFTR can be traced to distribution shifts in input features (see conclusions).

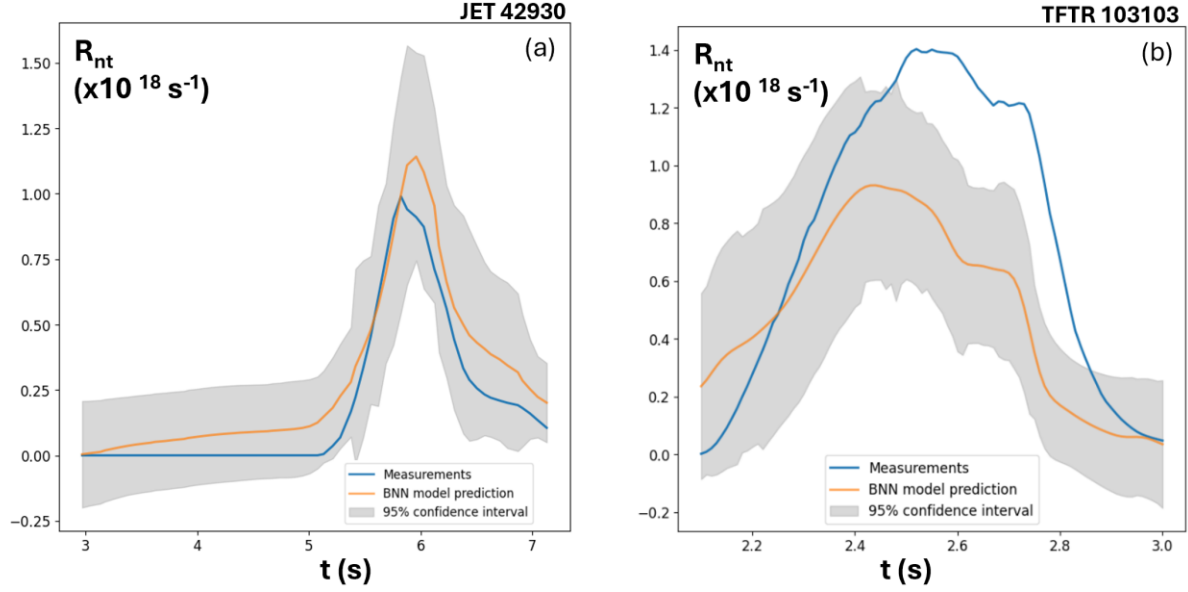


FIG. 3: “Zero shot” BNN reconstructions for (a) a JET DTE1 and (b) a TFTR discharges using the model trained on DTE2-DTE3.

5. DESIGN OF A DUD DETECTOR BASED ON THE THERMAL NEUTRON RATE

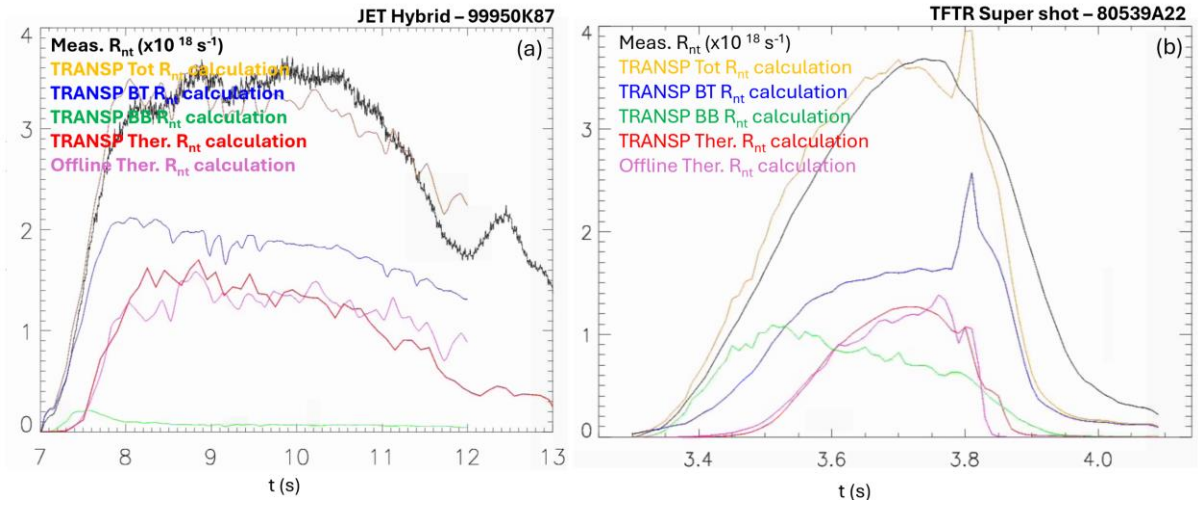


FIG. 4. Neutron rate as a function of time from measurement (black), together with TRANSP run calculations of the beam-target (blue), beam-beam (green), and thermal (red) contributions, as well as their sum (orange). The signal in magenta represents the offline-calculated thermal neutron rate content. The data on the left refer to the JET 99950 Hybrid DT plasma and its corresponding TRANSP K87 run, while the data on the right refer to the TRTR 80539 Super shot and its corresponding TRANSP A22 run.

In the context of developing novel dud detectors, neutron production contributions in DT plasmas have been analyzed using data from JET and TFTR, including outputs from the TRANSP code [36], which models beam-beam, beam-target, and thermal neutron contents.

Figure 4 presents examples from this analysis: the neutron rate in the #99950 JET Hybrid discharge alongside its K87 TRANSP simulation, and the #80539 TFTR Super shot with the corresponding A22 TRANSP run. The

thermal neutron rate has also been evaluated offline using the formulation proposed in [28, 29], i.e. $R_{nt}^{Ther} = n_D n_T < \sigma v >$, which successfully reproduces the thermal neutron content predicted by TRANSP. This capability supports the design of a dud detector dedicated to monitoring neutron production from thermal fusion reactions. Such a detector has been incorporated into the Simulink framework shown in Figure 5, with potential application to future burning plasma control.

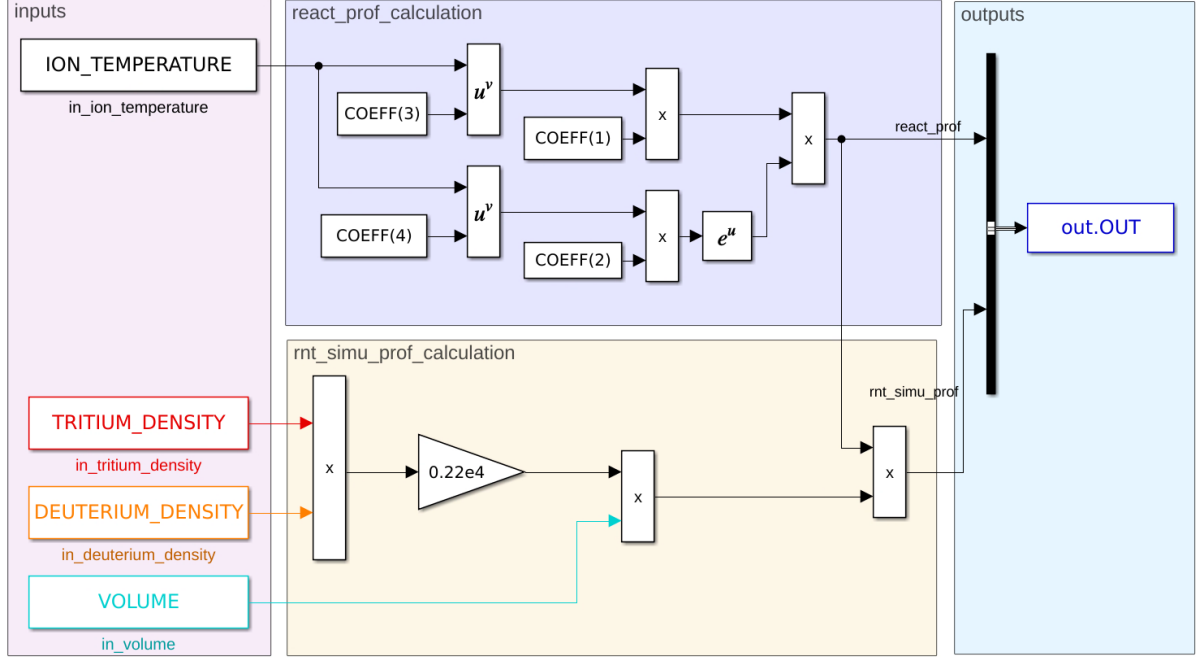


FIG. 5. Design of a novel dud detector based on thermal neutron rate calculation.

6. CONCLUSIONS

As far as the reconstruction via ML surrogate modeling is concerned, the reduced performance in extrapolating on JET DTE1 and TFTR can be traced to distribution shifts in input features. Figure 6 compares the distributions of key plasma parameters (NBI, T_e , density, stored energy, isotope fractions) across DTE2–3, DTE1, and TFTR datasets.

Distinct differences are evident: TFTR discharges populate regions of feature space scarcely represented in the JET training set, while DTE1 also shows systematic offsets relative to DTE2–3. Such out-of-distribution inputs explain the broader predictive intervals and highlight the value of uncertainty-aware models in identifying extrapolation regimes.

In conclusion, GPR and BNN emerge as the most promising surrogate approaches, combining excellent regression accuracy with principled uncertainty quantification. These methods demonstrate readiness for deployment in plasma control systems at JET-like conditions, while their performance on DTE1 and TFTR underscores the importance of addressing portability challenges through future work on domain adaptation and transfer learning. The GPR model was optimized via Bayesian optimization, while BNN training in PyTorch proved computationally more efficient, making it well suited for fast simulators and integrated modelling. Equivalent results were obtained with a JAX implementation, which exploits automatic differentiation and provides efficient runtimes on CPUs and GPUs, enabling “faster-than-real-time” simulations in many scenarios.

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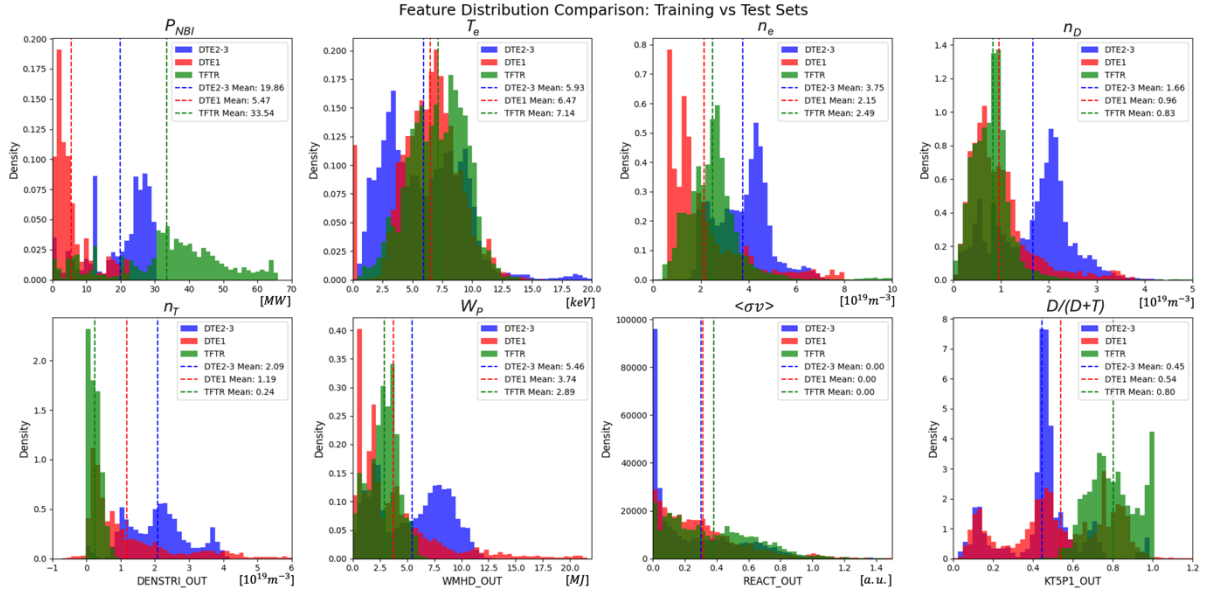


FIG. 6: Feature distribution histograms comparing DTE2 and DTE3 (in blue), DTE1 (in red), and TFTR (in green) datasets.

REFERENCES

- [1] O. N. JARVIS et al Neutron measurement techniques for tokamak plasmas 1994 Plasma Phys. Control. Fusion 36 209
- [2] P. BATTISTONI et al 14 MeV calibration of JET neutron detectors-phase 1: calibration and characterization of the neutron source Nuclear Fusion 58 2018 026012
- [3] A. SPERDUTI et al Plasma position measurement with collimated neutron flux monitor diagnostics on JET Fusion Engineering and Design 168 2021 112597
- [4] M. LENNHOLM et al Real time control developments at JET in preparation for deuterium-tritium operation Fusion Engineering and Design 123 2017 535
- [5] L. PIRON et al The dud detector: an empirically-based real-time algorithm to save neutron and T budgets during JET DT operation, Fusion Engineering and Design 146 2019 133364
- [6] L. PIRON et al Progress in preparing real-time control schemes for Deuterium-Tritium operation in JET Fusion Engineering and Design 166 2021 112305
- [7] L. PIRON et al Innovative dud detection based on JET DT experience Fusion Engineering and Design 200 2024 114155
- [8] A. ZHAROV Exploring the potential of machine learning for real-time neutron emissivity tomography using the Vertical Neutron Camera of ITER Fusion Engineering and Design 204 2024 114519
- [9] H. DRUCKER et al Support vector regression machines Advances in Neural Information Processing Systems 9 (MIT Press, 1996).
- [10] E. RASMUSSEN C. and WILLIAMS C.K.I. 2006 Gaussian Processes for Machine Learning (The MIT Press)
- [11] Z. GHAHRAMANI Probabilistic machine learning and artificial intelligence Nature 521 2015 452–9
- [12] K. M. MCGUIRE et al Review of deuterium–tritium results from the Tokamak Fusion Test Reactor Physics of Plasmas 2 1995 2176
- [13] E. R. Solano Fusion research in a Deuterium-Tritium tokamak Fundamental Plasma Physics 15 2025 100096
- [14] J. HOBIRK et al The JET hybrid scenario in Deuterium, Tritium and Deuterium-Tritium Nucl. Fusion 63 2023 112001
- [15] A KAPPATOU et al Overview of the third JET deuterium-tritium campaign Plasma Phys. Control. Fusion 67 2025 045039
- [16] L. GARZOTTI et al Development of high-current baseline scenario for high deuterium–tritium fusion performance at JET Plasma Phys. Control. Fusion 67 2025 075011

- [17] L. GARZOTTI et al Development of a high-current, high fusion performance scenario on JET: physics insights and operational challenges to be submitted to Plasma Phys. Control. Fusion
- [18] M. FITZGERALD et al Stability analysis of alpha driven toroidal Alfvén eigenmodes observed in JET deuterium-tritium internal transport barrier plasmas Nucl. Fusion 63 2023 112006
- [19] M. MASLOV et al JET D-T scenario with optimized non-thermal fusion Nucl. Fusion 63 2023 112002
- [20] M. MASLOV et al Insights of the JET high fusion power scenario in the final DT campaign 7-11 July 2025, EPS Conference on Plasma Physics, Vilnius, Lithuania
- [21] M. LENNHOLM et al Fusion Burn Regulation via Deuterium Tritium Mixture Control in the Joint European Torus PRX ENERGY 4 2025 023007
- [22] M. BARUZZO et al The contribution of JET on deuterium-tritium plasma control, 13-18 October 2025, 30th IAEA Fusion Energy Conference, Chengdu, China
- [23] H. W. HENDEL et al In situ calibration of TFTR neutron detectors Rev. Sci. Instrum. 61 1990 1900–1914
- [24] R. J. HAWRYLUK et al Fusion plasma experiments on TFTR: A 20 year retrospective Physics of Plasmas 5 1998 1577
- [25] M. D. Williams, D-T operation on TFTR Fusion Engineering and Design 36 1997 135–142
- [26] D. K. MANFIELD et al, Enhancement of Tokamak Fusion Test Reactor performance by lithium conditioning Phys. Plasmas 3, 1892 1996
- [27] M.C. ZARNSTORFF et al, Controlled Fusion and Plasma Physics, Proceedings of the Sixteenth European Conference, Vol. 13B, Part 1, Venice, 1989, European Physics Society, Petit-Lancy, Switzerland, p. 35.
- [28] J. WESSON, D. J. CAMPBELL, Tokamaks, Clarendon Press, 2004
- [29] S. GLASSTONE, R. H. LOVBERG, Controlled Thermonuclear Reactions, Van Nostrand 1960
- [30] C. REA et al Disruption prediction investigations using machine learning tools on DIII-D and Alcator C-Mod Plasma Phys Control. Fusion 60 2018 084004
- [31] T. COVER et al 1967 IEEE Trans. Inf. Theory 13 21–27
- [32] A. MURARI et al Prototype of an adaptive disruption predictor for JET based on fuzzy logic and regression trees Nucl. Fusion 48 2008 035010
- [33] T. CHEN T. and C. GUESTIN 2016 XGBoost: a scalable tree boosting system Proc. 22nd ACM SIGKDD Int. Conf. on Knowledge Discovery and Data Mining KDD'16 (New York, NY, USA, 13–17 August 2016) (Association for Computing Machinery) 785–94
- [34] T. HASTIE, R. TIBSHIRANI, AND J. FRIEDMAN. The elements of statistical learning. Springer, 2 edition, 2009
- [35] Y. ZHONG et al Disruption prediction and model analysis using LightGBM on J-TEXT and HL-2A Plasma Phys. Control. Fusion 63 2021 075008
- [36] R. J. GOLDSTON et al J. Comput. Phys. 43 1981 61. <https://transp.pppl.gov/index.html>