Neural-Network-Enhanced COTSIM: Advancing Predictive Capabilities for Fast DIII-D Simulations

Khadija Shabbir, *Member, IEEE*, Tariq Rafiq, and Eugenio Schuster, *Member, IEEE*

***Abstract*—Sustaining fusion reactions in tokamaks requires heating plasma to thermonuclear temperatures while maintaining confinement and stability. Neutral beam injection (NBI) provides heating, current drive, torque, and fueling, while electron cyclotron (EC) waves are widely used for heating and current drive; together, these actuators shape the plasma current, temperature, and density profiles. The control-oriented tokamak simulator (COTSIM), a predictive, control-oriented code, has been enhanced with neural-network surrogates for transport and sources. Turbulent transport is predicted by MMMnet—a neural-network version of the updated multimode model (MMM 9.0.10)—with significantly reduced computation time relative to MMM; neoclassical transport follows the Chang–Hinton model. NUBEAMnet, a surrogate of the Monte Carlo NUBEAM module, predicts beam-driven heating, current, and torque. EC heating and current drive use a control-oriented, empirically scaled source model; plasma resistivity follows the Spitzer formulation; bootstrap current uses the Sauter model. Equilibrium is computed using both prescribed and fixed-boundary solvers (FBSs), and the pedestal structure is modeled with an empirical pedestal model. For a representative DIII-D discharge, COTSIM predicts electron and ion temperature and safety-factor profiles in close agreement with TRANSP predictive and interpretive simulations while extending predictions through the pedestal region to the plasma edge (versus 80% of the minor radius in TRANSP). The equivalent COTSIM simulation runs in under 3 min compared to about 2 h for TRANSP, enabling rapid scenario planning, optimization of tokamak operation, and between-pulse control design.**

***Index Terms*—Control-oriented tokamak simulator (COTSIM), deep learning, multilayer perceptron, predictive simulation, transport coefficients.**

I. Introduction

THE development of controlled thermonuclear fusion is crucial for realizing clean, abundant, and sustainable energy. Among magnetic confinement devices, tokamaks are the most widely studied because of their effectiveness in confining plasma and their potential to achieve viable fusion power. Like any nuclear reactor, a tokamak requires a reliable simulator to ensure operation planning within safety limits and to optimize performance. The accuracy of the simulator directly influences the relevance of its predictions. In addition, if a simulator has long computation times, it can make scenario optimization impractical or limit exploration to a narrow parameter space. A modular simulator design helps balance speed and accuracy by combining models of varying fidelity, allowing users to select the most appropriate level of complexity for a given task. This flexibility supports control applications and scenario development while maintaining computational efficiency. This motivation led to the development of the control-oriented tokamak simulator (COTSIM), a MATLAB[1] -based, modular, 1.5-D equilibrium and transport code [1], [2]. COTSIM integrates models of different levels of fidelity and complexity for sources, transport, and resistivity to predict the evolution of ion/electron density, ion/electron temperature, poloidal magnetic flux, and rotation profiles. These predictions are achieved by full transport equations or a mix including empirical correlations for some of the profiles. A pedestal model based on [3] is included to predict the edge pedestal height and width. COTSIM also provides three distinct options for computing the plasma MHD equilibrium: prescribed equilibrium (PE), fixed-boundary equilibrium, and free-boundary equilibrium [2]. Neural-network surrogate models for sources and transport [4], [5], [6] have been recently

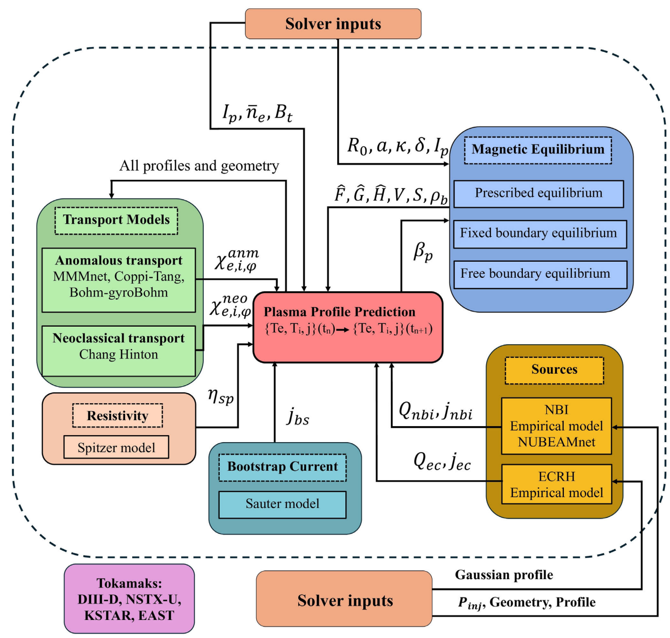

Fig. 1. COTSIM architecture: a structured framework for developing and executing tokamak simulations.

Received 30 September 2025; revised 7 May 2026; accepted 18 May 2026. Date of publication 3 June 2026; date of current version 19 June 2026. This material is based upon work supported by the U.S. Department of Energy, Office of Science, Office of Fusion Energy Sciences, under Award Numbers DE-SC0010661, DE-SC0013977, and DE-FC02-04ER54698. The review of this article was arranged by Senior Editor M. Kovari. *(Corresponding author: Tariq Rafiq.)*

The authors are with the Department of Mechanical Engineering and Mechanics, Lehigh University, Bethlehem, PA 18015 USA (e-mail: rafiq@lehigh.edu).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TPS.2026.3695483.

Digital Object Identifier 10.1109/TPS.2026.3695483

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integrated to improve COTSIM's predictive capabilities and enable both fast and physics-informed tokamak simulations. Fig. 1 shows the COTSIM workflow, highlighting how its modular structure integrates neural-network surrogates and physics-based solvers into a unified predictive framework. COTSIM has been used successfully as an integrated modeling framework in scenario planning for DIII-D [7], EAST [8], and NSTX-U [9].

This work presents an integrated modeling approach that leverages multiple COTSIM modules to predict electron and ion temperatures and q (safety factor) profiles for a representative DIII-D discharge. Predictions are verified against TRANSP predictive simulations and validated against interpretive (analysis/experimental) results. Key differences from [6] include the use of an updated pedestal model, a newer version of the multimode model (MMM), and a fixed-boundary equilibrium solver. Unlike [6], which considered only NBI heating and neglected neoclassical transport, the present study incorporates both NBI and EC heating, accounts for neoclassical transport, and extends predictions to the ion temperature and q-profiles in addition to the electron temperature.

This article is organized as follows. Section II describes the neural-network architecture, training process, and evaluation on unseen data. Section III presents the plasma transport modeling in COTSIM, including the magnetic diffusion equation (MDE), heat transport equation (HTE), heating sources, and current drive. Section IV discusses the validation of COTSIM results against TRANSP using both the PE and the fixed-boundary equilibrium solver. Finally, Section V summarizes the findings and outlines future work, including modeling the L-H/H-L transition for full-discharge simulation.

II. Neural-Network Surrogates

In control-oriented simulations, achieving both high accuracy and fast computation times is crucial for predicting plasma profiles and assessing plasma operating scenarios. Empirical models offer high computational speed at the expense of accuracy, while physics-based models provide greater accuracy but are computationally intensive. Machine learning (ML) techniques are increasingly used to overcome this tradeoff, providing both high accuracy and computational efficiency.

The multimode module is a physics-based transport model developed to improve understanding of anomalous transport in tokamak plasmas [10]. MMM predicts electron and ion thermal transport, particle and impurity transport, and toroidal and poloidal momentum transport, enabling modeling of temperatures, densities, and rotation profiles. MMMnet, a neural-network surrogate for MMM version 9.0.10, was developed to greatly reduce computation time while maintaining high accuracy [11]. The dataset used in this study was generated from TRANSP simulations of 240 DIII-D experimental discharges. From the predictive runs, 600 000 time slices were produced to compute anomalous diffusivities. The input and target data are standardized prior to training by transforming each variable to have zero mean and unit variance. An inverse transformation is then applied to the model's outputs to recover physical units. This preprocessing

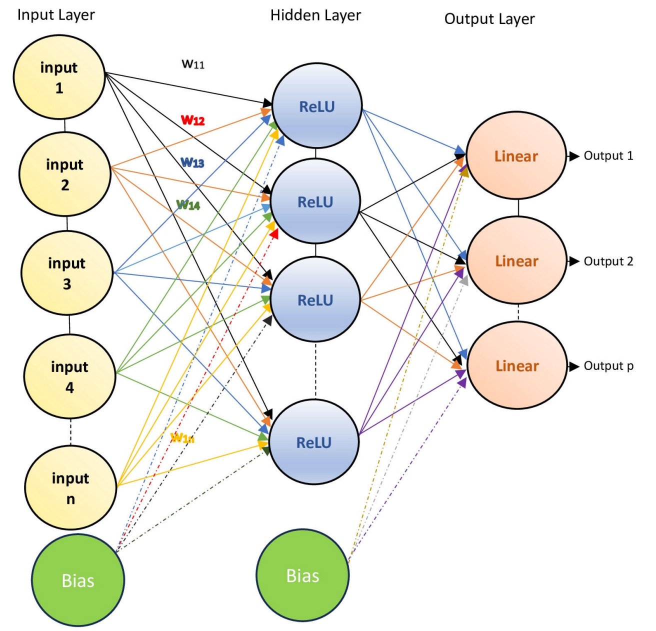

Fig. 2. Neural-network architecture: an MLP with fully connected layers. The network uses nonlinear activation functions to learn complex patterns from input data.

mitigates disparities in feature scales and improves training stability and generalization. MMMnet employs a multilayer perceptron (MLP) architecture with three hidden layers, each containing 51 nodes, as illustrated in Fig. 2. The hidden layers use the rectified linear unit (ReLU) activation function, while the output layer uses a linear activation function. These activation functions introduce nonlinearity, enabling the network to model complex relationships. The network's behavior and learning capability are governed by numerical parameters known as weights and biases.

MMMnet provides surrogate models for all six transport coefficients. Six separate neural networks were trained, one for each anomalous coefficient. The use of separate networks is motivated by the fact that the coefficients exhibit different magnitudes, sensitivities, and noise characteristics; independent training helps avoid negative transfer and improves optimization stability. Although the anomalous transport coefficients in MMM are physically coupled through turbulence dynamics, this coupling is not explicitly enforced in the present formulation. Instead, correlations between coefficients are partially captured by training each model on the same set of input features (e.g., plasma parameters, profiles, and their gradients), and the trained models are validated within integrated simulations. The resulting MMMnet surrogate predicts anomalous transport coefficients with inference times of 0.06–0.15 ms per evaluation, providing orders-of-magnitude speedup relative to the underlying MMM model while maintaining strong agreement with its outputs. This acceleration comes at the cost of reduced interpretability and potential degradation in predictive reliability outside the training domain, as neural networks require sufficiently large and representative datasets for robust generalization. The input structure of all neural

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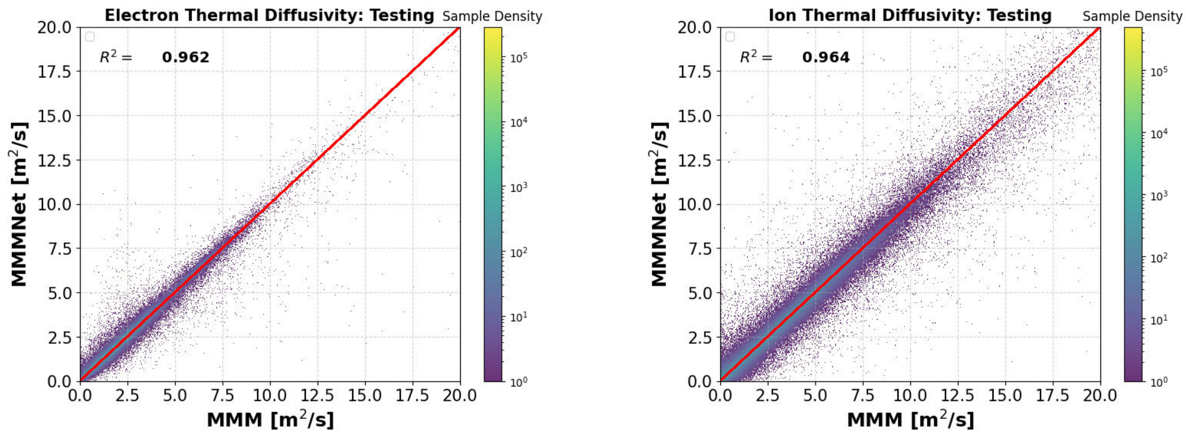
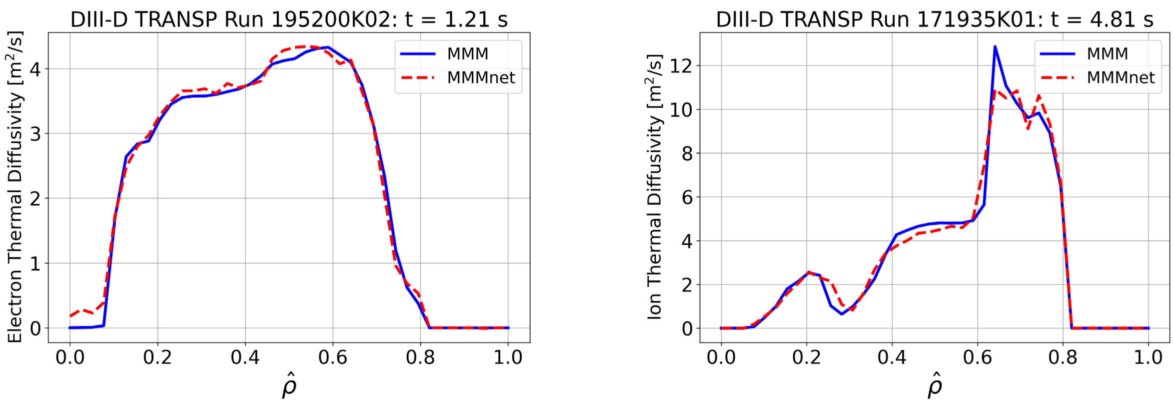


(a) (b)

Fig. 3. Correlation results for (a) electron and (b) ion thermal diffusivities on the testing dataset demonstrate that MMMnet accurately reproduces the transport coefficients predicted by MMM, with improved agreement compared to our earlier work [11].



(a) (b)

Fig. 4. (a) Electron (χ_e) and (b) ion (χ_i) thermal transport coefficients predicted by MMMnet compared with MMM, showing strong agreement.

networks is identical to MMM, and all networks share the same architecture. The performance of MMMnet was evaluated using correlation analysis and tested on previously unseen data. The high correlation between MMM and MMMnet demonstrates consistent model performance on the testing dataset, as shown in Fig. 3. Fig. 4 further demonstrates that MMMnet accurately predicts complex diffusivity profiles from multiple DIII-D TRANSP runs, supporting its use in real-time scenarios. MMMnet's computational efficiency makes it well-suited for integration into COTSIM. In this study, neural-network models for electron and ion thermal diffusivities are integrated into COTSIM. Future work will also extend this approach by integrating neural networks for particle and momentum diffusivities.

NUBEAMnet, a neural-network model for predicting the effects of neutral beam injection (NBI) on DIII-D plasmas, is also implemented in COTSIM [12]. This network was trained and tested on data from TRANSP simulations of DIII-D discharges that include the NUBEAM module [13]. NUBEAMnet effectively reproduces the results of the Monte Carlo NUBEAM code, achieving high accuracy while reducing execution time by several orders of magnitude.

III. Integrated Modeling Within COTSIM Framework

COTSIM includes several 1-D transport models and employs the finite difference method with a fixed time step to discretize the continuous transport PDEs into ODEs.

A. Magnetic Diffusion Equation

The 1-D MDE models the evolution of the poloidal magnetic stream function (ψ). The MDE is given by

$$\frac{\partial \psi}{\partial t} = \frac{\eta(T_e)}{\mu_0 \rho_b^2 \hat{F}^2} \frac{1}{\hat{\rho}} \frac{\partial}{\partial \hat{\rho}} \left(\hat{\rho} \hat{F} \hat{G} \hat{H} \frac{\partial \psi}{\partial \hat{\rho}} \right) + \eta(T_e) R_0 \hat{H} j_{NI} \tag{1}$$

with boundary conditions

$$\left.\frac{\partial \psi}{\partial \hat{\rho}}\right|_{\hat{\rho}=0} = 0, \quad \left.\frac{\partial \psi}{\partial \hat{\rho}}\right|_{\hat{\rho}=1} = -\frac{\mu_0}{2\pi} \frac{R_0}{\hat{G}\left.\right|_{\hat{\rho}=1} \hat{H}\left.\right|_{\hat{\rho}=1}} I_p(t).$$

Here, μ_0 is the permeability of free space; R_0 is the major radius; T_e is the electron temperature; j_{NI} is the noninductive current density; and I_p is the total plasma current. The $\hat{\rho}$ is the normalized effective minor radius, $\hat{\rho} \overset{\Delta}{=} \rho/\rho_b$, used to index flux surfaces. The mean effective minor radius is defined as

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$\rho = (\Phi/(\pi B_{\phi,0}))^{1/2}$, where Φ is the toroidal magnetic flux, $B_{\phi,0}$ is the vacuum toroidal magnetic field at R_0, and ρ_b denotes the effective minor radius at the last closed flux surface. The quantities $\hat{F}$, $\hat{G}$, and $\hat{H}$ are geometrical factors and defined as

$$\hat{F}(\hat{\rho}) = \frac{R_0 B_{\phi,0}}{R B_\phi (R,Z)}, \hat{G}(\hat{\rho}) = \left\langle \frac{R_0^2}{R^2} |\nabla\rho|^2 \right\rangle, \hat{H}(\hat{\rho}) = \frac{\hat{F}}{\left\langle R_0^2/R^2 \right\rangle}. \quad (2)$$

In COTSIM, these geometric factors can be specified from a PE or computed using fixed-boundary or free-boundary equilibrium solvers. In this work, both the PE and the fixed-boundary equilibrium solver are used. In the PE approach, $\hat{F}$, $\hat{G}$, and $\hat{H}$ are held constant throughout the simulations, whereas in the fixed-boundary approach, these geometric factors are recalculated at each time step. The noninductive current j_{NI} includes contributions from NBI, electron cyclotron (EC) current drive, and bootstrap current

$$j_{NI}(\hat{\rho},t) = \sum_{i=1}^{8} j_{nb_i}(\hat{\rho},t) \; + \; \sum_{i=1}^{5} j_{ec_i}(\hat{\rho},t) \; + \; j_{bs}(\hat{\rho},t) \quad (3)$$

where $j_{nbi}(\hat{\rho},t)$ denotes the current driven by the ith NBI source, computed using the NUBEAMnet module in COTSIM. The EC current drive is modeled in this work using the injected power $P_{ec}(t)$ and a simplified efficiency model proportional to T_e^δ/n_e [14]

$$j_{ec}(\hat{\rho},t) = j_{ec}^{ref}(\hat{\rho}) \frac{T_e(\hat{\rho},t)^\delta}{n_e(\hat{\rho},t)} P_{ec}(t) \quad (4)$$

where j_{ec}^{ref} represents the reference deposition profile and δ is the current drive efficiency (here, $\delta = 1$).

The self-generated bootstrap current is calculated using the Sauter model [15]. The plasma resistivity η is modeled as

$$\eta(\hat{\rho},t) = \frac{k_{sp}(\hat{\rho}) Z_{eff}}{T_e(\hat{\rho},t)^{3/2}} \quad (5)$$

where k_{sp} is a reference profile and Z_{eff} is the mean effective charge. Finally, the q-profile, which measures the twist of magnetic field lines and relates to the magnetohydrodynamics (MHD) stability, is given by

$$q(\hat{\rho},t) = -\frac{B_{\phi,0}\rho_b^2\hat{\rho}}{\theta(\hat{\rho},t)}, \quad \text{where} \quad \theta(\hat{\rho},t) \triangleq \frac{\partial\psi}{\partial\hat{\rho}}. \quad (6)$$

B. Heat Transport Equation

The temperature evolution in the core region is governed by the 1-D HTE. The HTE for a plasma species (electron or ion) is given by [16]

$$\frac{3}{2}\frac{\partial}{\partial t}(n_s T_s) = \frac{1}{\rho_b^2 \hat{H}\hat{\rho}} \frac{\partial}{\partial\hat{\rho}} \left[\hat{\rho}\frac{\hat{G}\hat{H}^2}{\hat{F}}\left(\chi_s n_s \frac{\partial T_s}{\partial\hat{\rho}}\right)\right] + Q_s \quad (7)$$

with boundary conditions

$$\left.\frac{\partial T_s}{\partial\hat{\rho}}\right|_{\hat{\rho}=0} = 0, \quad T_s(\hat{\rho}_{ped}) = T_s^{ped}.$$

Here, the subscript $s \in \{e,i\}$ denotes the plasma species (electron or ion), χ_s is the thermal diffusivity provided by MMMnet, and Q_s is the species heat deposition profile. The density profile n_s is computed using a half-dimensional model with a prescribed shape from an experimental time slice

$$n_s(\hat{\rho},t) = n_s^{prof}(\hat{\rho})\, \bar{n}_s(t) \quad (8)$$

where n_s^{prof} is the reference density profile and $\bar{n}_s$ is the line-averaged density and quasi-neutrality implies $n_e \approx n_i$. However, a particle transport equation will also be integrated into COTSIM in future development to enable fully predictive density evolution. The total electron and ion heat deposition profiles combine multiple contributions

$$Q_e(\hat{\rho},t) = Q_e^{ohm} + Q_e^{nb} + Q_e^{ec} + Q^{fus} - Q_e^{rad} - Q_{ie}^{coll} \quad (9)$$

$$Q_i(\hat{\rho},t) = Q_{ie}^{coll} + Q_i^{nb} \quad (10)$$

where Q_e^{ohm} is ohmic heating, Q_e^{nb} and Q_i^{nb} are neutral beam heating to electrons and ions, Q_e^{ec} is EC heating, Q^{fus} is fusion heating, Q_e^{rad} is radiative heat loss, and Q_{ie}^{coll} is ion-electron collisional heating. The ohmic heating term is given by

$$Q_e^{ohm}(\hat{\rho},t) = \eta(\hat{\rho},t)\; j_\phi(\hat{\rho},t)^2 \quad (11)$$

where the total toroidal current density j_ϕ is

$$j_\phi = -\frac{1}{\mu_0\rho_b^2 R_0 \hat{H}} \frac{1}{\hat{\rho}} \frac{\partial}{\partial\hat{\rho}} \left(\hat{\rho}\hat{G}\hat{H}\frac{\partial\psi}{\partial\hat{\rho}}\right). \quad (12)$$

Radiative losses are modeled as

$$Q_e^{rad}(\hat{\rho},t) = k_{brem} Z_{eff}\, n_e(\hat{\rho},t)^2 \sqrt{T_e(\hat{\rho},t)} \quad (13)$$

where k_{brem} is the Bremsstrahlung coefficient.

Ion-electron collisional heating is

$$Q_{ie}^{coll}(\hat{\rho},t) = \nu_e(\hat{\rho},t)\, n_e(\hat{\rho},t) \left[T_e(\hat{\rho},t) - T_i(\hat{\rho},t)\right] \quad (14)$$

where ν_e is the plasma collisionality. The neutral beam heating terms Q_e^{nb} and Q_i^{nb} are obtained from NUBEAMnet. EC heating is modeled empirically using Q_{ec}^{ref} for the profile shape and P_{ec} for the injected power

$$Q_{ec}(\hat{\rho},t) = Q_{ec}^{ref}(\hat{\rho})\, P_{ec}(t). \quad (15)$$

The fusion power density Q^{fus}, based on fusion energy Q_{DT}, deuterium (n_D), and tritium (n_T) ion densities, and the D-T reactivity $\langle\sigma v\rangle_{DT}$, is

$$Q^{fus}(\hat{\rho},t) = Q_{DT}\, n_D(\hat{\rho},t)\, n_T(\hat{\rho},t)\; \langle\sigma v\rangle_{DT}(\hat{\rho},t). \quad (16)$$

C. Pedestal Model

In high-confinement mode (H-mode) operation, a sharp edge transport barrier forms in tokamak plasmas, creating a pedestal region where the pressure, temperature, and density gradients become very steep. The pedestal sets the boundary condition for the core plasma and plays a crucial role in determining overall confinement performance and achievable plasma pressure. The H-mode pedestal temperature serves as a boundary condition in the COTSIM simulations. The height, width, and slope are the key pedestal parameters. These parameters determine the pedestal pressure, $p_{ped} = 2\,k\,n_s\,T_{s,ped}$, where k is the Boltzmann's constant and the pedestal temperature is given by $T_{s,ped} = \Delta\,(\partial p/\partial r)_c\,/\,(2k\,n_s)$. The critical pressure gradient is defined as $(\partial p/\partial r)_c = -B_{\phi,0}\alpha_c/2\mu_0 R_0 q^2$, where α_c is the

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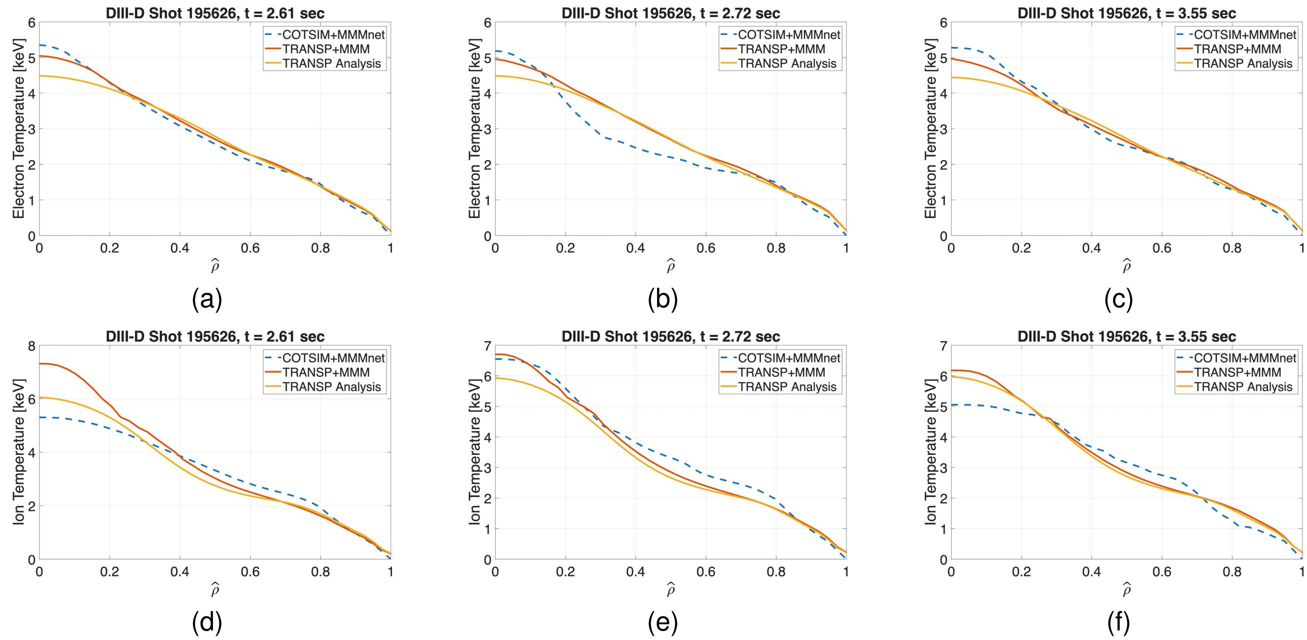

Fig. 5. Comparison of COTSIM-predicted (a)–(c) electron and (d)–(e) ion temperature profiles with TRANSP predictive (TRANSP+MMM) and analysis (TRANSP analysis) profiles using the PE.

normalized critical pressure gradient. The pedestal width Δ is derived from a scaling that accounts for flow shear stabilization

$$\Delta = C_w \sqrt{\rho_i R_0 \, q(r)} \tag{17}$$

where ρ_i is the ion gyroradius and C_w is a tunable parameter.

In COTSIM, the pedestal temperature profile shape is estimated using the normalized pedestal width Δ^* [3]

$$T_s = T_s^{ped} - \frac{T_s^{ped}}{\Delta^*}\left[\hat{\rho} - (1 - \Delta^*)\right]. \tag{18}$$

IV. Results and Discussion

COTSIM's predictions of electron and ion temperatures, as well as the q-profile, have been validated against the integrated modeling code TRANSP. TRANSP is a 1.5-D transport simulation code widely used in tokamak experiments, capable of running in interpretive (analysis) and predictive modes [17]. In analysis mode, TRANSP calculates energy, particle, and momentum transport coefficients using measured equilibrium and plasma profiles together with accurate sources and sinks. In predictive mode, it uses physics-based anomalous and neoclassical transport models to evolve transport equations in time and predict tokamak behavior under different operating scenarios, enabling evaluation and optimization of plasma performance.

The DIII-D experimental discharge 195 626 from the 2023 run campaign was used for both TRANSP and COTSIM simulations. In the TRANSP predictive run, MMM was used for anomalous transport; the NCLASS module handled neoclassical resistivity, bootstrap current, and ion thermal neoclassical transport [18]; the NUBEAM module was used for NBI heating, fueling, torque, and current drive [13]; and the TORAY full-wave model handled EC heating and current drive [19]. Plasma equilibrium was computed using the fixed-boundary toroidal equilibrium code (TEQ) [20].

To validate COTSIM against TRANSP, electron and ion temperatures were predicted using the heat transport (7), while the pedestal height and width were determined using the PEDESTAL model. The q-profile was computed using the magnetic diffusion (1). Turbulent transport was modeled using MMMnet, and neoclassical transport was modeled using the Chang–Hinton formulation. The COTSIM simulation employed the same initial profiles, a simplified EC model (4) and (15), NUBEAMnet for neutral beam actuator trajectories, and either a prescribed or a fixed-boundary equilibrium. The simulations employed a 0.01 s time step, 40 radial nodes, and an implicit numerical scheme.

Figs. 5 and 6 compare COTSIM predictions of the T_e and T_i profiles with TRANSP predictive (TRANSP+MMM) and analysis (interpretive TRANSP) results at different time slices. Fig. 5 employs the PE, while Fig. 6 uses the fixed-boundary equilibrium in COTSIM. The T_e and T_i profiles are derived from experimental diagnostics—primarily Thomson scattering and EC emission (ECE) for T_{e}, and charge-exchange recombination spectroscopy (CXRS) for T_{i}—and are typically provided as fit or reconstructed profiles. In the interpretive (analysis) TRANSP framework, these profiles are prescribed inputs and are not evolved by the transport model; however, in predictive simulations, they serve as independent experimental references for validation of model predictions. The influence of plasma equilibrium formulation on the magnetic flux ψ, and thus on the q-profile, is evident in Fig. 7. In the prescribed-equilibrium case, fixed geometric factors constrain current redistribution, whereas both TRANSP and the fixed-boundary solver (FBS) update the equilibrium self-consistently with the evolving current, yielding q-profiles in closer agreement. The close agreement in the evolution of plasma profiles with

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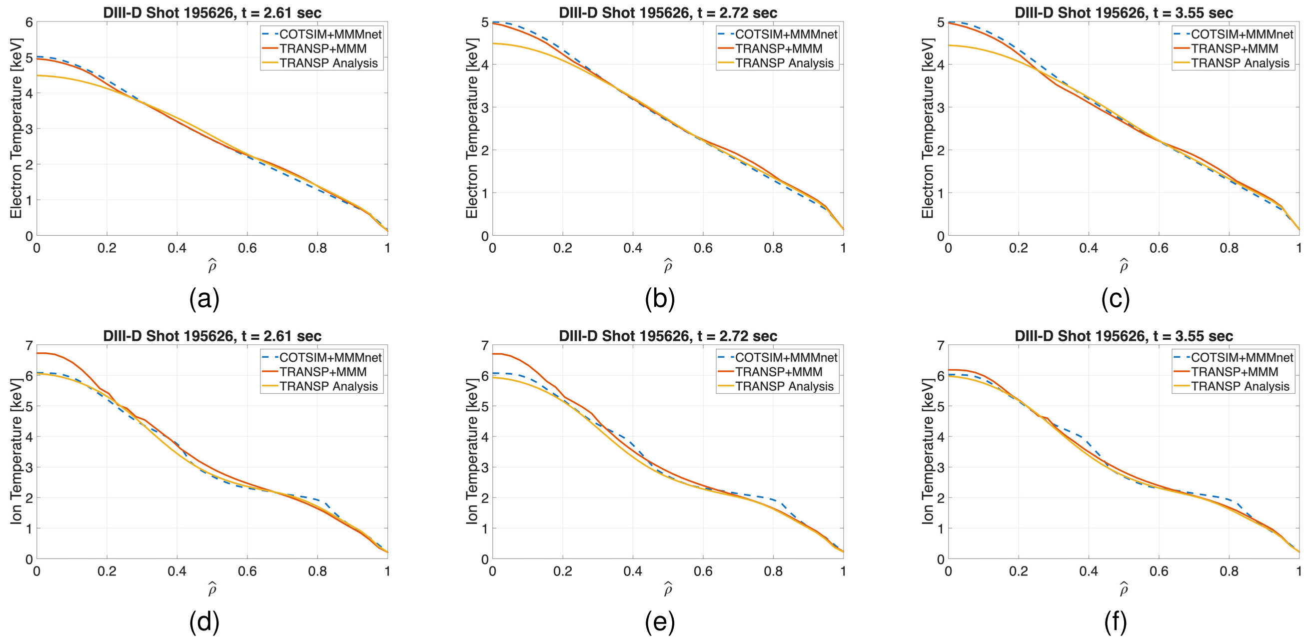

Fig. 6. Comparison of COTSIM-predicted (a)–(c) electron and (d)–(e) ion temperature profiles with TRANSP predictive (TRANSP+MMM) and analysis (TRANSP analysis) profiles using the fixed-boundary equilibrium.

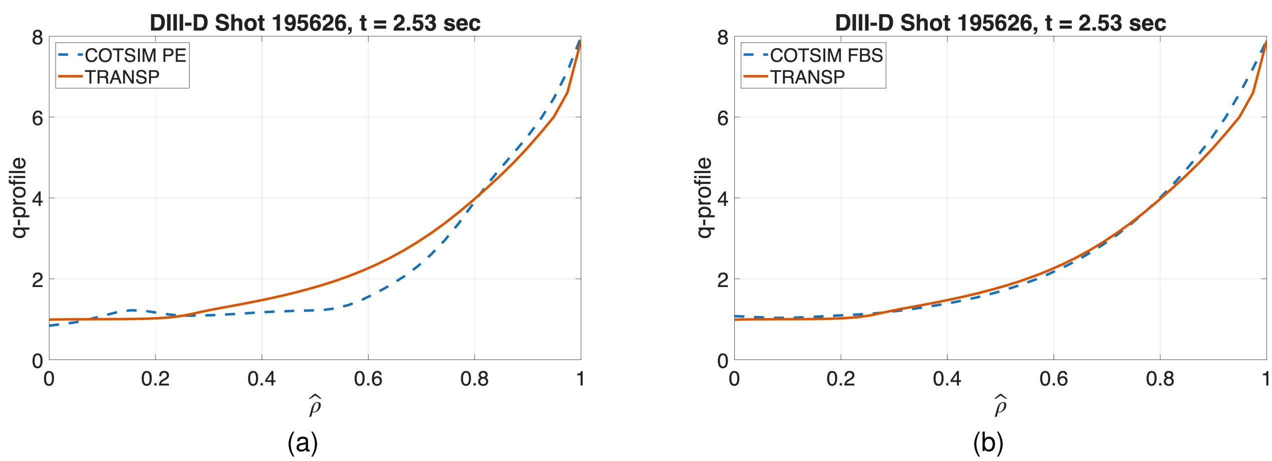

Fig. 7. Comparison of q-profiles from COTSIM with (a) PE and (b) FBS against TRANSP, showing that the self-consistent fixed-boundary approach yields better agreement than the geometry-constrained prescribed case.

the FBS demonstrates that COTSIM can reproduce TRANSP results significantly faster and with comparable accuracy. Note that in TRANSP the prediction boundary is limited to $\hat{\rho} = 0.8$, whereas in COTSIM it extends to $\hat{\rho} = 1.0$, capturing the pedestal region. Fig. 7 further shows that COTSIM reliably reproduces the magnetic q-profile. For this discharge, a full COTSIM simulation is completed in approximately 180 s, compared to about 2 h for the corresponding TRANSP run while maintaining similar predictive fidelity. The COTSIM runs were performed on a laptop with a 2.3 GHz 8-core Intel Core i9 processor.

V. Conclusion

COTSIM is a control-oriented predictive simulation framework developed for fast tokamak scenario development and validation. It integrates neural-network surrogate models to drastically reduce computation time while preserving physics fidelity. MMMnet models anomalous transport based on the MMM, while NUBEAMnet predicts NBI heating, torque, and current drive effects using a surrogate trained on the NUBEAM Monte Carlo code. To maintain consistency with first-principles physics, COTSIM also incorporates self-consistent magnetic diffusion, fixed- and free-boundary equilibrium solvers, heat transport solvers, and empirical/theoretical models for Z_{eff}, pedestal structure, and power deposition. Validation against a representative DIII-D discharge shows that COTSIM-predicted electron temperature, ion temperature, and safety-factor profiles closely reproduce TRANSP predictive and interpretive simulations while extending predictions through the pedestal region up to $\hat{\rho} = 1.0$ (versus $\hat{\rho} = 0.8$ in TRANSP). Whereas a full TRANSP simulation for this discharge requires about 2 h, the equivalent COTSIM run completes in under 3 min, enabling rapid scenario planning and optimization. Future development will

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extend COTSIM to include poloidal momentum transport and L–H transition physics for full-discharge predictive capability.

ACKNOWLEDGMENT

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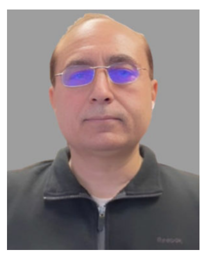
Khadija Shabbir (Member, IEEE) received the M.Sc. degree in computational physics from the Center for High Energy Physics and the M.Phil. degree in space science from the Department of Space Science, University of the Punjab, Lahore, Pakistan, in 2012 and 2018, respectively. She is currently pursuing the Ph.D. degree with the Department of Mechanical Engineering and Mechanics, Lehigh University, Bethlehem, PA, USA.

Her research interests include machine learning, plasma control, and scenario development for tokamak plasmas.



Tariq Rafiq received the M.Phil. degree in plasma physics from Quaid-i-Azam University, Islamabad, Pakistan, in 1998, and the Ph.D. degree in electrical engineering from Chalmers University, Gothenburg, Sweden, in 2004.

He completed a Post-Doctoral Fellowship with the University of Wisconsin–Madison, Madison, WI, USA. He is currently a Research Associate Professor with the Department of Mechanical Engineering and Mechanics, Lehigh University, Bethlehem, PA, USA. He is a Nuclear Fusion Theorist specializing in the development of thermal, particle, and momentum transport models. His research interests include model validation against tokamak experiments, predictive scenario modeling, performance optimization of tokamak discharges, design of new experiments, and extrapolation to reactor-scale devices such as ITER and fusion pilot plants.

Eugenio Schuster (Member, IEEE) received the B.Sc. degree in electronic engineering from the University of Buenos Aires, Buenos Aires, Argentina, in 1994, the B.Sc. and M.Sc. degrees in nuclear engineering from the Balseiro Institute, Bariloche, Argentina, in 1998, and the master's and Ph.D. degrees in aerospace engineering from the University of California at San Diego, San Diego, CA, USA, in 2004.

He is currently a Professor with the Department of Mechanical Engineering and Mechanics, Lehigh University, Bethlehem, PA, USA. He is an expert at nuclear-fusion plasma control and leads the Lehigh University Plasma Control Laboratory.

Prof. Schuster was a recipient of the National Science Foundation (NSF) CAREER Award for his work on "Nonlinear Control of Plasmas in Nuclear Fusion." He has been appointed as a Scientist Fellow in Plasma Control by the ITER Organization. Moreover, he has been designated by the U.S. Department of Energy (DOE) as an Expert Member of the Integrated Operation Scenarios (IOS) Topical Group within the International Tokamak Physics Activity (ITPA), which he is currently chairing. He has served as the Leader of the Operations and Control Topical Group with the U.S. Burning Plasma Organization and as the Founder and Chair of the Technical Committee on Power Generation with the IEEE Control Systems Society.

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