THE EFFECT OF RMP ELM CONTROL FOR ITER ON PEDESTAL PRESSURE COMPARED TO EPED NO-RMP PREDICTIONS

M.E. FENSTERMACHER
Lawrence Livermore National Lab
Livermore, California, USA
email: fenstermacher@fusion.gat.com

O. MENEGHINI, R.J. GROEBNER
General Atomics,
San Diego, California, USA

B. ZYWICKI
University of Michigan,
Ann Arbor, Michigan, USA

C. REA
Massachusetts Institute of Technology,
Cambridge, Massachusetts, USA

Abstract

A new neural network (RMP-NN), trained on measured pedestal data from Resonant Magnetic Perturbation (RMP) ELM control discharges in DIII-D, represents the effect of RMP application on the pedestal pressure compared to EPED1 [1] pressure predictions, in anticipation of the needs of ITER operating scenarios (IOS) analysis. The database shows measured pressure can be below the EPED1 predictions, predominantly for cases with very low ELM frequency (long periods without ELMs), indicative of effective ELM suppression with very strong RMP fields. Predictions from the RMP-NN for cases with ELM suppressed periods longer than an energy confinement time and a range of RMP amplitudes show between zero change and up to a 25% reduction in pedestal pressure within the overall DIII-D dataset, compared with EPED1 predicted pressure, depending on the optimization of the applied RMP fields and other parameters. Random Forest statistical analysis provides guidance on the operational parameters that are most important to the effect of RMP application on the pedestal pressure. All ITER Integrated Operating Scenarios (IOS) desire to use 3D RMP fields to control ELMs. The inclusion of 3D field effects on the pedestal pressure is therefore of paramount importance. The work presented in this paper provides a method to adjust the EPED1 predicted ITER pedestal pressure based on the non-linear effects of the use of RMP fields to mitigate or suppress ELMs.

1. INTRODUCTION

The fusion power output of tokamaks operated with H-mode energy confinement is strongly dependent on the height of the edge pedestal pressure, which forms the boundary condition for the core plasma parameters. Integrated Operating Scenario (IOS) analysis for ITER will therefore need predictions of the dependence of the pedestal height on individual parameters associated with the design of ITER scenarios. Based on present capabilities, predictions of the pedestal pressure height in ITER will be done using the EPED1 model [1] of pedestal height and width being limited by the intersection of peeling–ballooning and kinetic ballooning instability mode constraints. These predictions are made for a given pedestal density, specifications of which will come from other constraints in the IOS modeling such as maximizing fusion power density and requirements for divertor power exhaust control (eg. divertor detachment).

Predictions of the pedestal pressure height and width can be made very quickly using a neural network (EPED-NN) [2] that has been trained on 15,000+ full EPED1 calculations covering parameter ranges found in experimental devices from the ALCATOR CMOD scale to the JET scale, and from EPED1 predictions for ITER parameters. Previous studies [3] with a small database of DIII-D RMP ELM control discharges showed the measured pedestal pressure was near the EPED prediction during ELM mitigation, and near to or somewhat below the EPED prediction for many cases with ELM suppression using strong RMP fields (Fig. 1). The idea of the present work is to make predictions of the difference between the pedestal pressure achieved during the application of RMP fields for ELM control vs the predictions without RMPs from the EPED-NN.
Since there is no first principles theory of RMP ELM control and suppression, this work turns again to neural networks, but this time trained on large sets of DIII-D plasma data at time slices with applied RMP for ELM control, to explore dependencies on individual parameters. The predictions of the NN trained on the RMP data cases (RMP-NN) are then normalized by the predictions from EPED-NN calculations without RMP effects, to provide a tool to allow IOS analysis of ITER scenarios to fold in the effect of applying RMPs for the required ELM control.

2. CONSTRUCTING THE DATA-TRAINED PREDICTIVE NEURAL NET (RMP-NN)

There are four basic steps required to put together the RMP-NN, viz.: 1) a database of time slices with applied RMPs for ELM control must be generated by searching through many years of DIII-D experiments, 2) parameters that are important to pedestal performance with and without applied RMPs must be extracted for all the qualifying time slices, 3) the RMP-NN must be trained on the experimental data with applied RMPs and finally 4) both the RMP-NN and the EPED-NN are used to predict the variation of the pedestal pressure height (here defined as twice the electron pressure at the top of the pedestal) as individual actuator parameters are varied, and the ratio of the two predictions gives the effect of RMP application. These steps and the analysis described below are managed using the OMFIT integrated modeling framework [4].

The analysis presented here makes use of multi-layer feed-forward neural-networks (NNs) as an efficient tool for fully non-linear regression of multi-dimensional data [2]. In these NNs, information flows from a layer of “input” neurons through a layer of “hidden” neurons and out a layer of “output” neurons. Heuristic optimization of the regularity and accuracy of the regression is included [2]. Results from the EPED-NN are the average and confidence levels of an ensemble of 30 sub-NNs, each with 2 hidden layers of 10 neurons each. The RMP-NN uses an ensemble of 32 sub-NNs, each with 3 layers of 30 neurons each. To improve the accuracy of the predictions, supervised training with a backward propagation algorithm is done on a random sample of half of the training datasets, with the other half dataset used as a validation set. Training is only continued as long as the accuracy to the training half dataset is increasing and the error of predictions against the validation set is decreasing.

2.1 Generating Database of Cases With RMPs On for ELM Control

The algorithm to build the RMP-NN first searches the DIII-D shots database for time slices that satisfy conditions defined as RMP “On” and builds a database with each time slice as an independent entry. For the analysis presented here there are three criteria for an RMP “On” case, viz.: 1) the amplitude of the applied current in the internal I-coils on DIII-D is greater than 1 kA, 2) the applied perturbation has toroidal mode number n=3 and 3) the parity between the upper and lower row of I-coils is even (up/down symmetric). For the present work these criteria focus the data to the conditions with highest probability for ELM suppression in DIII-D, but the selection criteria can be adjusted easily for other studies. For time slices satisfying the RMP “On” conditions, the search algorithms also calculate the ELM frequency at that time slice. Here the ELM frequency is defined as $1/T_{ELM}$ where $T_{ELM}$ is the time between the nearest two ELMs. Given that the energy confinement time in DIII-D for RMP ELM control experiments is in the 100-200 ms range, a period of ELM suppression longer than an energy confinement time produces an ELM frequency of less than 5 Hz by this definition. The RMP-NN presented here was trained on more than 38,000 time slices satisfying the RMP “On” conditions from DIII-D experiments over the period 2004-18.
2.2 Calculating EPED Predictions for Conditions Near Database Cases

EPED predictions of pedestal height and width for the RMP database cases, and variations of actuator parameters within the experimental database boundaries near the database cases, are made with the neural net EPED-NN [2]. This neural net has been trained on 20,000+ full EPED calculations of the pedestal height at ELM onset with no RMPs applied, for multiple experimental devices and ITER parameters. Inputs to EPED-NN are the same as for full EPED1 predictions, viz: plasma geometry parameters (major radius \(R\) (m), minor radius \(a\) (m), elongation \(\kappa\), triangularity \(\delta\)), operational parameters (plasma current \(I_p\) (MA), toroidal field \(B_t\) (T)) and characteristic parameters of the plasma (\(\beta_N\), ion mass, pedestal \(Z_{\text{eff,ped}}\), pedestal electron density \(n_{\text{e,ped}}\)). The EPED1 predictions match the measured pedestal pressure height at ELM onset to within a standard deviation of ± 18% for a database with cases from six different tokamaks, including DIII-D data, covering two orders of magnitude in pedestal height [5]. The EPED-NN predictions are accurate to the full EPED1 calculations database to within a standard deviation for the mean relative error of ± 6-10% [2]. From this, the associated error between the EPED-NN predictions and DIII-D pedestal pressure height at ELM onset with no RMP fields might be estimated to be ≤ ± 25%. For the parameters of the RMP “On” cases, Fig.2 shows that the measured pedestal height tends to be from nearly equal to significantly less than that predicted by EPED-NN in cases with strong ELM mitigation or suppression (low ELM frequency – dark blue points in Fig. 2), consistent with the findings from the initial database analysis ([3] and Fig. 1). Fig. 2 also shows that for the parameters of time slices with applied RMP, the measured pedestal height can also be larger than the EPED-NN predictions for many cases with ELM mitigation (high ELM frequency - green and red points). This is possible because the EPED-NN, and the EPED1 calculations on which it was trained, do not include any knowledge of the effect of RMP fields on the pedestal, even for cases that are still ELMing.

2.3 Training the NN_RMP

Pedestal pressure data during ELMing H-mode with 3D RMP fields was used to train the RMP-NN to predict the expected pressure with RMPs compared to EPED calculated pressure without RMP effects (EPED-NN). Input to the RMP-NN includes all the EPED1 parameters (eg. plasma, ...
operational and shape parameters), and other operational parameters observed in experiments to affect the coupling of the applied 3D fields to the pedestal (eg. RMP amplitude, phase and parity, pedestal collisionality and rotation etc.). Multiple (eg. 32) independent neural nets are trained on randomly selected sub-samples of this dataset to form the RMP-NN. The RMP-NN output is then the mean value and standard deviation from this neural net ensemble. Unlike the pedestal response to changes in individual actuators in the actual discharge, in which multiple other parameters also respond simultaneously, this tool allows the effect on the pedestal pressure to be evaluated due to variation of one independent parameter with all the others held fixed, as will be needed for IOS analysis.

2.4 Guidance on Most Important Input Parameters

Random Forest classifier techniques [6] were used to determine the relative importance of the input parameters to the difference between measured pressure with RMPs (RMP-NN) and EPED1 prediction (EPED-NN). Fig 3 shows the strongest dependence on pedestal density as would be expected, since neped is both a strong driver of the EPED-NN predictions, and experimental observations indicated that RMP ELM suppression is strongly facilitated by low density operation. Moderately strong dependence on operational parameters (Ip, BT, δ), and significant dependence on plasma parameters (βN, pedestal rotation, RMP perturbation strength and collisionality) are also indicated, consistent with experimental observations of parameters that impact the effectiveness of ELM mitigation or suppression. This suggests that the strongest dependencies are with parameters input to both the EPED-NN and the RMP-NN.

2.5 Interrogating the RMP-NN

Once trained, the RMP-NN provides a tool to interrogate a multidimensional manifold of pedestal pressure as a function of each of the parameters that were used to train the NN. As a first check, the accuracy of the RMP-NN training is shown in Fig. 4. The experimental pedestal pressure height during RMP application in DIII-D is reproduced by the RMP-NN to within about ±15-20%. Recall that the EPED-NN reproduces experimental pedestal height with no RMP fields to within ±25% for a much broader database of ELMing plasmas in multiple devices, from a theoretical basis using a two-step process of EPED1 calculations and EPED-NN training on a database of those calculations.

The local dependencies of the pedestal height manifold on variations of any of the independent parameters will depend on both the location of the local starting point in the multidimensional parameter space, and the direction (which parameter used) for the variation. For ITER IOS analysis the local starting point will be the set of input parameters representing an ITER operating point of interest, and the RMP-NN will then provide the effect of RMP application on pedestal pressure normalized to the EPED1 prediction at that point, plus the variation of the pressure ratio as one of the input parameters is varied. To make the extrapolation to ITER cases in the future, theory based normalizations of the dimensional input parameters in the present training set will need to be developed; examples are described in Section 4. For the DIII-D examples shown below, the local starting point is chosen to highlight the possible effects of RMP application on the pedestal pressure, vis. the plots in Section 3 use as a local starting point a time slice with low ELM frequency, indicative of effective ELM suppression, and pedestal pressure below the EPED-NN prediction (shot 175896 at 3075 ms, as identified by the red cross in Fig. 2). In each figure below, within the
variation of an input parameter, the value of that variable at the local starting point is marked by the vertical dashed line, and the fixed values of the other input parameters in the training set are taken from the conditions of the local starting point time slice, viz.: major radius R=1.71 m; minor radius, a=0.6 m; βₙ=0.7; toroidal field, Bₜ=1.96 T; average triangularity, δ=0.5; 1-coil current=3.82 kA; plasma current, Iₚ=1.52 MA; elongation, κ=1.81; pedestal density, nₑₚₑₐₜ=4.6×10¹⁹ m⁻³; pedestal toroidal rotation, vₑₚₑₐₜ=4.0 km/s; pedestal electron temperature, Tₑₚₑₐₜ=356 eV; pedestal Zₑₑₐₜₑₚₑ=1.67.

3. PEDESTAL DEPENDENCE DURING ELM CONTROL FOR DIII-D PARAMETERS

Consistent with the Random Forest analysis (Fig. 3), the RMP-NN shows strong dependence of the reduction in achieved pressure vs. EPED-NN predictions on several parameters not input to EPED1 analysis. As expected there is a strong dependence on applied RMP amplitude (represented by the Icoil parameter in Fig. 3). Fig. 5 shows RMP-NN (red) and EPED-NN (blue) predictions over the range of RMP currents in the database. In each case, the solid curve is the average prediction from the ensemble of 32 sub neural nets, and the shaded band is the 1-sigma confidence level of that average prediction. The vertical dashed line shows the value of the independent parameter for the local starting point. The black lines at the bottom of each plot show the range of that independent variable in the training database. Neural nets are efficient and precise for predictions within their training parameter regimes, but the confidence bands indicate that reliability of extrapolation decreases rapidly away from the training regimes. RMP coil currents with ELM frequencies less than 5 Hz produce periods without ELMs greater than an energy confinement time (Fig. 5b). For those RMP currents Fig. 5a shows the reduction in pedestal pressure outside the confidence bands can be up to 20% with RMPs on (red curve) compared with the EPED-NN predictions (blue curve), in the parameter space near the local starting point with strong RMP fields and ELM suppression.

As a check on the results with RMP “On”, Fig. 5a (green curve) also shows the pedestal height prediction from a NN trained on experimental data without strong RMP fields (RMP-OFF-NN), ie. 0 < Icoil < 1 kA-t. Fig. 6 shows that the level to which the RMP-OFF-NN predictions accurately reproduce the RMPs “Off” training data. For these weak perturbation fields the predicted pedestal height is only slightly less than the EPED-NN predictions as expected. This supports the interpretation that the larger difference between the EPED-NN (blue) and RMP-NN (red) predictions in Fig. 5a is due to the strong RMP fields and ELM suppression conditions near the local starting point. Note that far from the local starting point, eg. for Icoil=0 kA-t, the average prediction of the
RMP-NN (solid red line) under-predicts the physically realistic pedestal height given by the RMP-OFF-NN and the EPED-NN. This again emphasizes that extrapolating NN predictions outside their training set can produce unreliable results.

The pedestal pressure with RMPs also shows dependence on pedestal toroidal rotation (Fig. 7). Here the rotation velocity is measured by the tangential CER chord at the top of the pedestal (Te symmetry point minus half the pedestal Te width). There is substantial evidence from DIII-D and other RMP experiments that ELM suppression by RMPs depends on RMP penetration and pedestal state bifurcation physics [7-9]. These publications suggest that simultaneous alignment of 1) the zero crossing of either the electron perpendicular velocity or the ExB velocity with 2) the top of the pedestal and 3) a strong resonant component of the applied RMP spectrum modified by the associated plasma response, are very important for optimizing effective RMP ELM control [10]. The electron perpendicular velocity at the top of the pedestal is the difference between the diamagnetic and ExB velocities, the latter of which depends strongly on the toroidal velocity through the radial force balance in the pedestal. For the range of pedestal top toroidal rotation values that yield ELM frequencies less than 5 Hz (ELM periods longer than an energy confinement time – Fig. 7b), the RMP-NN results in Fig. 7a show up to a 20% reduction in the pedestal pressure (red curve) compared with the EPED-NN predictions (blue curve) in the parameter regime near the ELM suppressed local starting point with strong RMP fields.

Finally, the RMP-NN results suggest the experimental observation of a window of edge safety factors (q95) for effective ELM suppression with RMPs. Significant dependence of the pedestal pressure in the RMP-NN results on either plasma current (Ip) or toroidal field (BT) variations is shown in Figs. 8 and 9. Variation of either Ip or BT, with other geometry parameters fixed in the RMP-NN, results in a variation of edge safety factor (q95). The RMP-NN suggests that within the q95 window producing ELM suppression for periods longer than an energy confinement time (ELM frequencies less than 5 Hz in Figs 8b and 9b) there is also a reduction in the pedestal pressure (red curve) compared with EPED-NN predictions (blue curve) in the parameter regime near the ELM suppressed initial starting point with strong RMP fields. This qualitative prediction with either Ip or BT varied, and all other parameters held fixed, is consistent with experimental observations during q95 scans in which other parameters are varying simultaneously with q95.
4. IMPLICATIONS FOR ITER

Extrapolation of the RMP-NN results in terms of normalized input parameters suggests the use of RMPs for ELM control in ITER may reduce the pedestal pressure to somewhat less than EPED-NN predictions of the ITER pedestal height. As examples, Figs. 10 and 11 show the dependence of the pedestal pressure as functions of the RMP coil current normalized to either the plasma current or the toroidal field, for extrapolation to future devices. Normalization to plasma current implies an assumption that the RMP effect scales with poloidal field. Normalization to toroidal field implies an assumption that the effect of RMP scales with the background radial field. An ITER baseline operating point with \( I_p = 15 \) MA, \( I_{coil} = 90 \) kA in the RMP coils, \( B_T = 5.3 \) T, \( a = 2.0 \) m and \( R = 6.2 \) m gives normalized coil current parameters in the units of these plots of \( I_{coil}/I_p = 6 \) (kA/MA) and \( I_{coil}/(B_T a R) = 1.4 \) (kA/(Tm²)). In both cases (Figs 10 and 11) the RMP-NN pedestal pressure predictions for these ITER values are 10-15% below the EPED-NN predictions for the parameter regime with strong RMP fields near the initial starting point.

5. SUMMARY AND CONCLUSIONS

Neural network analysis techniques have been used to make predictions of the pedestal pressure height both for the case of ELMing H-mode without 3D perturbations and for H-mode cases with ELM control by 3D magnetic perturbations. A neural net trained on thousands of EPED1 calculations of the pedestal height, from multiple devices spanning two orders of magnitude in pedestal height, will be used to predict the ITER pressure pedestal for a given pedestal density in ITER Operating Scenario analysis. This work adds predictions from a separate neural net trained on a database of experimentally measured pedestal heights in DIII-D plasmas with applied 3D perturbations for ELM control, and normalized to the EPED-NN predictions, to allow the effect of the RMPs to be predicted for ITER scenarios. Results for DIII-D parameters show the impact of RMP fields on the pedestal height can be from nearly no difference with the EPED-NN predictions to up to about 25% below the predictions of EPED-NN, depending on the parameter regime. Results also show strong dependence of any reduction on 1) applied RMP amplitude, 2) the pedestal toroidal rotation contribution to the edge electron perpendicular or ExB velocities through the radial force balance in the pedestal, and 3) on edge safety factor through either BT or Ip variations at fixed geometry parameters. Future goals of this work include 1) expanding the RMP-NN training dataset to include experimental results from multiple devices with RMP fields, and 2) using the NN tools to try to determine those parts of ITER parameter space for which ELM control can be achieved with very minimal reduction of the pedestal pressure height compared to EPED1 no-RMP predictions.

ACKNOWLEDGEMENT

This work was supported in part by the US Department of Energy under DE-FC02-04ER54698, LLNL DE-AC52-07NA27344 and the Science Undergraduate Laboratory Internship (SULI) program and under DE-FC02-
REFERENCES


