PREDICTION OF THE ITER H-MODE POWER THRESHOLD BY MEANS OF VARIOUS STATISTICAL TECHNIQUES

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1. Introduction

The prediction of the additional heating power required to reach the H-mode regime is a key issue in the design of ITER. This prediction is usually based on power law scalings calculated from the data provided by different tokamaks. An enhancement of the international threshold database has allowed a refinement of the existing scalings [1-5]. However, even if more parameters (a, κ, δ and S_{plasma}) are taken into account, than in the former list of parameters (n_e, B_ϕ and R), and more tokamaks are represented in the database (now 10 tokamaks: ASDEX, AUG, ALCATOR C-MOD, COMPASS-D, DIII-D, JET, JFT-2M, JT-60U, PBX-M, TCV), some scattering in the data does still exist (RMSE≅25-30%), leading to a large uncertainty in the ITER power threshold prediction: P_{thr}(ITER)=90MW with a 95% confidence interval of [-40 +80]MW. With the final goal of reducing this uncertainty, completely different approaches have been investigated. This paper presents the first results obtained by 3 other statistical techniques: discriminant analysis, system identification and neural networks.

2. Discriminant Analysis

Discriminant Analysis consists of finding a new set of co-ordinates, that are linear combinations of the input parameters and which minimises the correlation between data from different classes and maximises the correlation within a class. In the case of a “two classes” discrimination, one axis of the new set is enough to represent the classification: along this axis, the data from the two classes appear as histograms, more or less separated. The classification ability along this new axis is characterized by two quantities. One of these represents the distance between the average values of the two classes, divided by the average of the standard deviation of the two classes. The other is the rate of well classified data over the total amount of data, expressed in %. For every classification attempt, a subset (typically 80% of the data, randomly chosen) of the selected data is used for the calculation of the classifier. The remainder of the data is used as a test population. The quality of the classification is then characterised by its ability to succeed on this test population. Finally, some kind of stability of the classification is tested by repeating the calculations several times, the dataset each time being slightly different because of its random selection.

From the two histograms obtained along this new axis, a probability function is deduced [6]. By fitting a hyperbolic tangent to this function, using weights corresponding to the number of points in each bin, a smooth function is determined which is well defined all over the space. If the RMSE of the fit is too high the classification is rejected.

Knowing the co-ordinate transformation and the mapping between the new axis and the probability function, it is possible to determine the probability of being close to the LH transition as a function of the Loss Power ($P_L = P_{heat}$ -dW/dt). This can be done for existing data, see

Figure 1.a-c; for new points in actual machines in order to predict the necessary additional power; or for future machines like ITER, see Fig. 1.d. When applied to existing data, the actual loss power and phase (L-mode, H-mode or “at the LH transition”) is compared with the probability function to give an estimate of the success rate. A time slice is estimated to be in L-mode if the probability is below 0.5. When the model is applied to ITER design values, (R=8.1m, a=2.8m, B_t=5.5T, $\bar{n}_e=5*10^{19}m^{-3}$, κ=1.7, S_{pl}=1100m^2), the loss power which gives a probability of 0.5 is considered as the threshold power. In order to estimate the stability of the model, the probability function has been calculated for points around the design values (random 10% perturbations). The ITER predicted threshold power is then an average of 20 different power values corresponding to these random perturbations around the design values. The uncertainty in the threshold power is the standard deviation of the threshold powers.

3. Results from Discriminant Analysis

At first, discriminant analysis was applied to data from the ITER threshold database and the input variables were those from the conventional scaling laws: n_e, B_t, R and P_{Loss}. The two

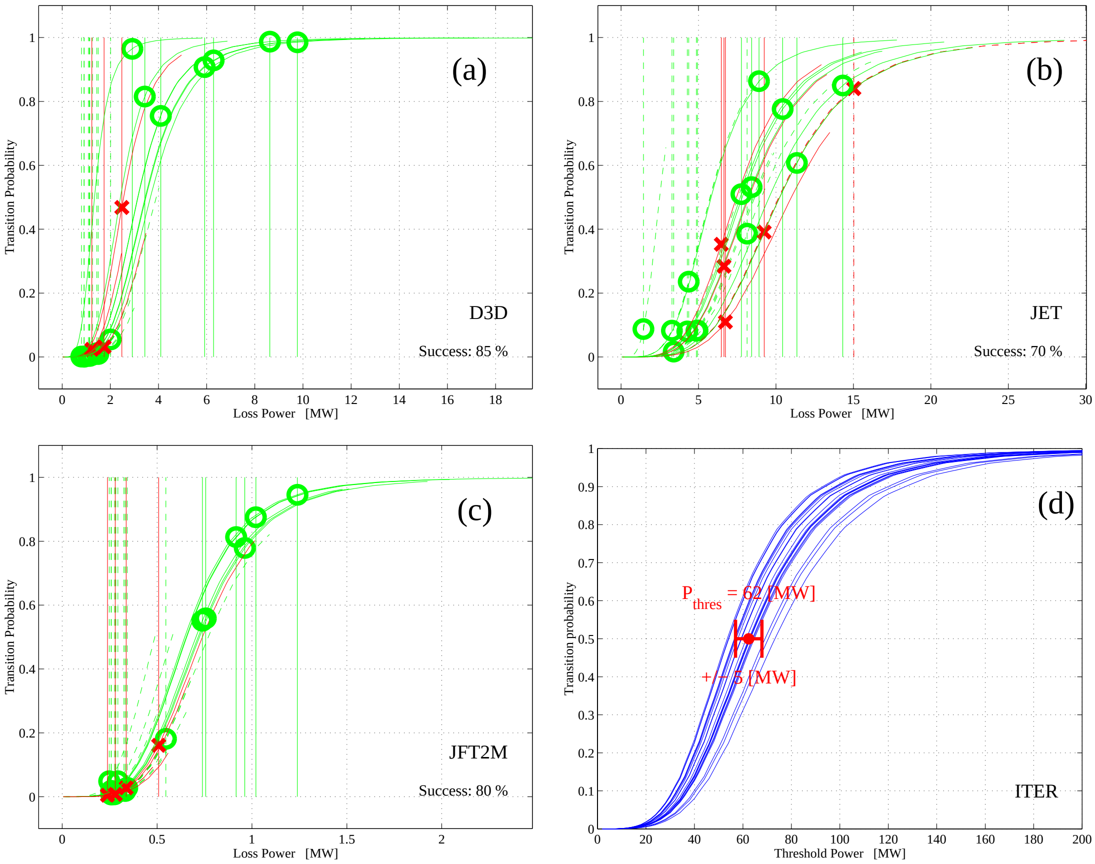

Figure 1*: Prediction of the transition probability.*
a-c: tests for 3 tokamaks: DIII-D, JET and JFT2M. For each tokamak, 10 time slices in L-mode (dashed lines) and 10 in H-mode (plain lines) are randomly chosen. For each time slice, the Loss Power is scanned from 0 to twice the experimental value (vertical line) and the transition probability calculated over this range (curved lines). The intersection between the corresponding lines is shown by a symbol: A circle when the prediction is in agreement with the experimental phase and a cross if the test is negative.
d: application to ITER. The different lines correspond to 10% random perturbations around the ITER design values. The model described in row 3 from Table 1 has been used for these tests and application.

classes consisted of time slices taken during the L mode phase and those at the LH transition. The classification ability was not good. An improvement was gained by adding the plasma elongation and surface area as well as incorporating all the pair products of the input parameters. With these additions, the classification succeeded for about 70 % of the test data, but the extrapolation to ITER values was diverging because of the linear characteristics of the classifier. This problem disappeared when the logarithm of the input parameters was used in the calculation. Utilising the SELDB2 selection criterion (SELDB2 is based on the experience gained by the experimentalists of each device to define data at the transition which are supposed to yield low power threshold values for each tokamak) and using a model without the pair products, a reasonable classifier has been found. The numbers associated with this classifier are summarised in the first row of Table 1.

The second row in Table 1 corresponds to the discrimination between the L mode and H mode time slices, with the “strong” SELDB2 selection criteria generally used [1] replaced by a condition which keeps dW/dt small only. The ITER power threshold lowered but the precision gained by the increase in statistics is lost by the larger diversity of the data, due to the absence of the SELDB criteria.

In order to increase the statistics without deteriorating the quality of the data, all 3 global databases (i.e. standard datasets of L-mode, H-mode and Threshold databases) have been merged together. However, only data from tokamaks represented in the L- and H-mode databases were kept. The predicted threshold power in ITER prediction based on this combined database is 63+/-5MW (row 3 of Table 1) . Figure 1 shows the transition probability for 3 tokamaks and for ITER. However, the fraction of H-mode data compared to L-mode data was rather large (80%); the reduced classification quality is due to this unbalanced population. In the 4th case, we restricted the data in H-mode to a randomly selected subset with its size equal to the L-mode subset and all the pair products were used in the model. The quality of the discrimination is quite good and the uncertainty of the ITER prediction is also rather low.

	Asdex	AUG	C-MOD	Compass	DIII-D	JET	JFT2-M	JT60-U	TCV	Test 1	Test 2	Test 3	ITER
1	135 85 %	87 60 %	181 50 %	8 100 %	216 65 %	303 55 %	109 50 %	25 50 %	66 50 %	0.33 65%	0.34 53%	65%	191 +/- 75
2	298 65 %	315 70 %	465 60 %	15 55 %	309 50 %	241 55 %	778 95 %	10 100%	34 50 %	.48 72%	.47 69%	59%	103 +/- 69
3	712 85 %	302 70 %	471 70 %	31 0 %	609 85 %	902 75 %	522 80 %	19 80 %	48 50 %	.64 66%	.61 65%	70%	63 +/- 5
4	235 80 %	103 75 %	172 70 %	4 0 %	236 95 %	291 85 %	154 40 %	12 65 %	33 90 %	.97 83%	1.02 82%	75%	111 +/- 35

***Table 1**: ITER prediction results for different cases of data selection, described in the text, and numbered from 1 to 4. Under the tokamak names appear the number of points used in both classes and the rate of success of the prediction of the power threshold. The “Test 1” column shows the two quality estimators of the classification caculated on the data set. “Test 2” contains the same estimators but calculated on the test population. “Test 3” presents the global success rate of the LH power threshold on the experimental data. In the ITER column appear the predicted value of power threshold and its uncertainty (for its determination: see text)*

From Table 1, the determination of a unique value of the ITER power threshold appears as a trade-off between the classifier quality and the uncertainty in the prediction. Different tests have been performed in an attempt to get a better determined value for the ITER prediction: a) when removing one tokamak at a time, small variations in the ITER predictions have been observed (less than 25% in all the above mentioned models), b) when adding noise to the input data, the classification and the ITER prediction diverge with a certain rate from the values shown in Table 1. This rate indicates the stability of the prediction value. These different tests, performed on the 4 different models, give a large number of predicted values for the ITER threshold power. A weight, function of the classification quality, the model stability and the prediction variance, has been assigned to these predicted values. The weighted average leads to a prediction of the ITER threshold power of 80 MW +/- 25 MW.

4. System Identification and Neural Networks

Almost all the presented classifiers so far are of the 1st degree, and therefore all the parameters are important. Since the major advantage of the system identification technique [6] is the removal of unnecessary parameters, nothing is gained by this method and the results are quite similar to those obtained by discriminant analysis. Neural networks with different architectures, number of hidden layers and selection of input parameters have also been tried. With resulting success rates between 60 and 70 %, none of these models gave better results than discriminant analysis. Nevertheless, the ITER predictions were in the same range as that obtained from discriminant analysis.

5. Discussion - Conclusion

The discriminant analysis, as a tool to predict the threshold power for ITER, has some advantages and disadvantages. The mathematical expression of the function is much more complicated than a simple power law (3 terms per parameter plus a mapping function between the new co-ordinate and the probability function). However, this method gives rise to more confidence in the scaling law results. The predicted values from the two methods converge to approximately the same value and the simple scaling laws are based on data taken <u>at</u> the transition whereas the results obtained with discriminant analysis used only L-mode and H-mode data.

Acknowledgements

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