EUROPEAN FUSION DEVELOPMENT AGREEMENT

EFDA–JET–PR(05)30

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** See annex of J. Pamela et al, "Overview of JET Results ", (Proc.20th IAEA Fusion Energy Conference, Vilamoura, Portugal (2004)).*

Preprint of Paper to be submitted for publication in
IEEE Transactions on Plasma Science

ABSTRACT

An accurate and general regime identifier is considered an important tool for future real time applications in JET. In this perspective, a traditional approach based on Discriminant Analysis was tested, using various sets of JET real time signals. Unfortunately no combination of signals managed to provide a success rate higher than 90%. To improve the performance and increase the generalisation capability, an identifier based on fuzzy logic was developed, which allowed quite naturally to include also information on the time evolution of the D_α, a quantity normally not exploited by more traditional solutions. With this technique a success rate of 95% was achieved using only D_α and the derivative of β normalised diamagnetic as inputs. A Support vector Machines approach, based again on a suitably defined distance like Discriminant Analysis, provided slightly inferior results with exactly the same inputs but matched the fuzzy logic method with the inclusion of the absolute value of β normalised diamagnetic. This comparative performance assessment of the various methods is an important first step on the route to identify the best solution for a regime identifier for JET and in perspective for ITER.

1. INTRODUCTION

In the last decades, real time control has assumed an increasingly important role in experimental fusion devices. Since the scenarios are becoming more complicated every day, with higher shaping and input power, feedback on various parameters is necessary to stabilise the configurations and to maximise performances. As a consequence, in JET nowadays practically all the main diagnostics produce real time outputs [1,2] to allow integrated identification of the plasma state. Moreover various tools are also available to close the feedback loop: from the magnetic coils, acting on the magnetic topology, to the gas valves and all the heating systems (LH, ICRF and neutral beams). Moreover other emerging techniques, using new generation of real time visual processors, offer promising strategies for efficient real-time control [3]. All these technical means allow a great variety of control scheme to be implemented [4].

On the other hand, one of the main limitations of present day control schemes is their static nature, i.e. the fact that the plasma is assumed to reach a certain confinement state at a certain time "a priori", i.e. before the shot and on the basis of the pre-programmed discharge parameters. The actual real time control strategy is then determined on the basis of this assumption about the regime reached by the plasma at the time of the feedback. As already reported in ASDEX Upgrade [5], in case of unexpected variations in the plasma confinement state, the real time controller can on certain occasions apply a non optimal strategy, which can be counterproductive, contribute to the degradation of the plasma performance and even induce disruptions. This problem has motivated the development of automatic techniques capable of determining in real time the confinement regime of the plasma and therefore giving the opportunity to adopt the best feedback strategy for the actual scenario and not for the one assumed a priori before the shot.

In JET experiments, where the vast majority of the diagnostics provide already real time signals, the identification of certain regimes is relatively straightforward. The advanced scenarios for example, being reached when the ρ* attains a certain value, are very simple to identify, since this parameter is already available in real time [6]. To control the radiation fraction, a Digital Neural Network has already been developed, which determines the total emitted power in the main plasma and in the divertor from the line integrals of bolometry [7].

Discriminating if the plasma is in the L or H mode of confinement remains a more difficult issue. First of all there is no single quantity providing a unique discrimination. Moreover the most useful measurement, typically used by the specialists in their off line analysis, is the D_{α}, which is difficult to analyse automatically because the relevant information resides in the time history of the signal and not in its absolute value. Therefore, to solve this problem the traditional approach consisted of trying to discriminate the regime on the basis of a series of magnetic and kinetic measurements. The first attempt was made by Franzen et al. [5], who devised a fast online regime identification algorithm for ASDEX upgrade. By using scaling laws and 14 online-available signals, L-mode and H-mode in low and high radiative scenarios were discriminated, achieving an identification rate of over 95%. The system was able to react dynamically to plasma regime transitions within a cycle time of 2.5ms. This allowed unexpected regime transitions to be detected and corrected. The first group to use discriminant analysis and non-linear system identification to localise the L-mode / H-mode boundary in multidimensional operational space, were Martin and B¸hlmann [8] on the TCV Tokamak. This was followed by an extensive project by Giannone et al. [9] on ASDEX upgrade who developed a regime identification system with online signals using Scaling laws as well as Discriminant analysis. Using a linear combination of two to five plasma variables, with this approach it was possible to distinguish between L-mode and H-mode with an error as low as 1.3%. The system was also applied to the improved the distinction between H-mode and advanced H-mode yielding a failure rate of 5.3%.

At JET an implementation of this approach of Discriminant Function Analysis for L/H mode identification has been attempted. The results were quite good but some weaknesses of the method, which is based on defining a suitable distance in the parameter space of the measurements, became quite apparent. First of all the number of parameters required for the classification is quite high and the discrimination is based on their absolute value, requiring specific tuning of the thresholds depending on the range of the main plasma parameters like the current and the toroidal field. Secondly the main quantity used by the specialists, the D_{α}, is not included because the relevant information resides in the time history and not in the absolute value of this signal. Moreover the final success rate in the classification is good but not excellent (see section 2), reflecting the difficulties in devising algorithms general enough to cope successfully with the great variety of JET scenarios and experimental programmes. In order to improve performances and identify methods more suited to JET needs, the scope of the entire classification task was redefined and new solutions, based on soft computing approaches, were tried.

With regard to the scope of an automatic regime identifier at JET, it was considered important for the final solution to satisfy the following requirements:

1) Being able to discriminate on a ms time scale between the L and H mode of operation
2) Require a small number of input data
3) Provide a high rate of identification
4) Include D_α in the set of parameters describing the plasma
5) Use as much as possible signal derivatives in order to reduce the dependence of the performance from the engineering parameters of the discharge

Given the nature of the L-H mode transition and the requirements for the identifier, fuzzy logic appeared from the beginning as a good candidate. Fuzzy set theory, contrary to boolean logic, does not use sharp distinctions but, on the contrary, is based on continuous degrees of membership. It is therefore particularly suited to solve vague problems for which the expert opinion is essential. With this method a significantly better success rate was obtained with a reduced number of measurements, using mainly signal derivatives. In order to further address the relative merits of this approach with respect to more traditional solutions, the results were compared with another technique, using so called Support Vector Machines (SVMs). A Support Vector Machine is a learning algorithm for pattern classification and regression. A SVM classifier finds the optimal hyperplane that correctly separates (classifies) the largest fraction of data points while maximising the distance of either class from the hyperplane (the margin). With almost the same inputs (all the inputs less one) SVMs perform slightly less well than fuzzy logic but by addition of one more signal, they reach the same level of success

As the main objective of the work was to asses the relative merits of more advanced methods, like fuzzy logic and SVMs, for the identification of the plasma confinement state, it was decided to produce a Database incorporating a large variety of conditions, in terms of plasma density, plasma current and heating power, but without including an excessive large number of shots (the selection of a wider database to be used in a more comprehensive validation analysis of the method is already in progress). The chosen pulses were considered by various experts of JET team to evaluate the correct L-H and H-L transition times. This information was used to validate the results obtained with the different automatic methods.

The pulses used for the analysis described in this paper are reported in Table 1, together with the main plasma parameters, i.e. the plasma current (Ip), the Toroidal Field (TF), the integrated density (Ne), the Neutral Beam Injection power (NB), the Radio Frequency power (RF), the neutron fluence (Neutrons) and the Diamagnetic Energy (Wdia).

With regard to the structure of the paper, the next session is devoted to the Discriminant Analysis approach, describing the way it was implemented at JET and the obtained results. The importance of the D_α, as an indicator of ELMs, is mentioned in section three, where the approach used to include this signal in the fuzzy logic identifier is reported in detail. Section four describes the approach based on Support Vector Machines. Finally summary and conclusions are given.

2 . CLASSIFICATION BASED ON DISCRIMINANT ANALYSIS

Discriminant Analysis, a recognised branch of statistics, is a technique concerned with the identification of patterns, described by a set of features. Its main objective consists of devising the best rule to classify experimental observations into distinct groups so that the membership of subsequent data can be optimally determined. This approach is based on discriminant functions that need to be maximised to achieve the required partitioning of this feature space. In our case the feature space is defined by a selection of plasma parameters. The samples have then to be mapped to the class labels, L-mode and H-mode, in different multivariate plasma parameter spaces. The parameter space was partitioned by a Discriminant Function using a Bayesian approach. In particular, a classifier was set up to use the “maximum posterior” (MAP) decision rule. This means, the criterion for assigning a label or class to a given sample was to maximise $p(\ldots_i|\mathbf{x})$, the “posterior probability” of a class, ω_i, that is its probability, given a particular sample, **x**, in n-dimensional feature space.

$$g_i^{MAP}(x) = p(\omega_i \mid x) \tag{1}$$

By using Bayes’ rule, the MAP discriminant functions can be written in terms of the posterior probability, $p(\mathbf{x}|\omega_i)$. This is the probability that **x** is observed given that the class is known:

$$g_i^{MAP}(x) = p(\omega_i \mid x) = \frac{p(x|\omega_i) * p(\omega_i)}{p(x)} \tag{2}$$

By assuming that the likelihood densities follow a multivariate normal distribution, it is possible to write $p(\mathbf{x}|\omega_i)$ in terms of statistical parameters such as mean, $\boldsymbol{\Sigma}_i$ and covariance matrix S_i of the given class:

$$g_i^{MAP}(x) = \frac{1}{(2\bullet)^{n/2}\,|\Sigma_i|^{1/2}} * \exp[-\frac{1}{2}(x - \grave{\imath}_i)^T \Sigma_i^{-1}(x - \grave{\imath}_i)]\,\frac{p(\grave{u}_i)}{p(x)} \tag{3}$$

In relation (3) $p(\omega_i)$ is the prior probability of a class to occur and $p(\mathbf{x})$ is the probability of observing **x**, which is constant, when considering a given sample. Simplifying by eliminating constant terms and taking logs, the Discriminant Function becomes:

$$y_i(x) = -\frac{1}{2}(x - \grave{\imath}_i)^T \Sigma_i^{-1}(x - \grave{\imath}_i) - \frac{1}{2}\log(|\Sigma_i|) + \log(p(\grave{u}_i)) \tag{4}$$

It can be seen that the classifier depends strongly on the quadratic term, $(\mathbf{x} - \boldsymbol{\mu}_i)^T \Sigma_i^{-1} (\mathbf{x} - \boldsymbol{\mu}_i)$, called the Mahalanobis distance. This is a vector distance normalised to the covariance Σ_i^{-1}, which is a way of quantifying the spread of the various quantities in the training set. By maximising $y_i(\mathbf{x})$, the Mahalanobis distance of an observation to a class centre approaches zero; $y_i(\mathbf{x})$ is therefore a minimum distance classifier. The second and third terms in (4) were neglected, in order to simplify coding. The second term can indeed be neglected, provided the difference in $|\Sigma_i|$ is small for L-mode and H-mode, which is normally verified at JET. Equal prior probabilities were assumed for L-mode and H-mode classes, that is $p(\omega_1) = p(\omega_2)$ and therefore the third term results in the simple adding of a constant which can be ignored.

In order to classify a set of samples using discriminant analysis in the way described above, it is necessary to know the following statistical parameters of the classes: Class means $^{o}{}_{I}$ and covariances Σ_i. These parameters were obtained from a **training set**, a subset of the data base described in the previous section.

Since at JET a series of quantities is available in real time, a systematic investigation was performed to determine the most suited to the classification under study. The list of tested parameters is reported in **Table 2**.

The one-to-five dimensional mappings, for which the Discriminant Analysis algorithm has the highest success rates, are given in **Table 3**. The success rate is the fraction of the observations in the validation set for which the Discriminant Analysis classifier gives the same estimate as the expert. The best success rate appears to depend strongly on the number of parameters. For mappings with spaces as small as 1 parameter, the algorithm produces a vague indication of whether a discharge is in L-mode or H-mode, for larger sets, around 3-5 parameters, a fairly clear indication is given. On the other hand no combination of inputs was able to provide a success rate higher than 90%. It is also worth pointing out that no improvement in the classification was obtained by using other signals in table 1. This seems to indicate a redundancy in the information contained in the table. This was additional evidence that motivated the inclusion of D_α in the set of input signals as described in the next section.

3. A FUZZY LOGIC APPROACH TO THE REGIME IDENTIFICATION

The results obtained with the Discriminant Analysis approach, were not as satisfactory, as those reported on other machines. This is probably due to a particularly wide operation space and the great variety of plasma scenarios of JET. These aspects are an additional obstacle to overcome when assessing whether an already difficult and not clear cut phenomenon such as L-H transition is taking place, which always requires a close look by the experts in order to be properly determined. These difficulties motivated on the one hand the inclusion of the D_α in the set of inputs, since this is one of the main signals used by the experts. On the other hand, the somehow uncertain nature of the L-H transition suggested the adoption of a Fuzzy Logic approach to the identification problem.

3.1 ELMS AND REGIME IDENTIFICATION

Edge Localized Modes (ELMs) [10] are instabilities occurring in the edge of H mode plasmas in toroidal magnetic fusion experiments, producing a loss of confinement. As a result, the lost energy flows along the field lines to the divertor plates, causing a peak in the D_α radiation. Monitoring the D_α radiation in the divertor region can provide, then, useful information on the presence of ELMs. In particular, at JET there are two signals which are particularly suited to this purpose, the S3AD/

AD35 and the S3AD/AD36, which monitor the D± radiation in the outer and inner divertor respectively as shown in figure 1.

In addition to revealing the presence of ELMs, a very good indicator of the plasma confinement state, the other main advantage of the D_α signal is that it can also help a lot in identifying the transition point between the L and H mode. In particular it was observed that often the L-H transition is accompanied by a drop in the D_α signal while the transition back to the L-mode is denoted by a little step up of the signal itself (Figure 2).

Unfortunately the individuation of the transition time on the basis of the D_α signal is not completely unambiguous, because it is strictly dependent on the plasma configuration and the divertor conditions. Indeed, in discharges with a detached divertor or if the strike points are too far from the D_α lines of sight, the above mentioned conditions for the transition are not always clearly distinguishable. Moreover, depending on the scenario, H-mode discharges can exhibit ELMs free phases or type-I ELMs with very low frequency. In these plasma conditions the D_α signal is not always enough to evaluate the plasma confinement mode.

In order to overcome these problems additional measurements are required. In this perspective, it was observed that a L-H transition is accompanied by a change in the slope of Bndiam (β_N), Wmhd or the electron density Dens1 (see Table 2). It is worth pointing out that also the absolute value of these quantities can be used for regime identification. However, although the absolute value allows estimating quite accurately the confinement modes in a single plasma experiment or at maximum in experiments from the same session, it results difficult to extrapolate a general rule that could be applied to shots from different experimental sessions. Indeed, the absolute value of these signals is strictly dependent from the engineering parameters chosen by the physicists to perform a specific plasma experiment. Therefore, in order to keep the approach as general as possible and eliminate the need of re-tuning of the algorithm in dependence from the plasma parameters, only the derivative of the aforementioned three signals was retained in the set of input signals. In particular Bndiam proved to be the best suited because, being a normalised quantity, is the less affected by the plasma parameters. In figure 3 it is possible to observe the trend of the abovementioned signals for shot 58816.

3.2 THE FUZZY MODE IDENTIFIER

The reported considerations on the nature of the L-H transition and the interest in devising a quite general solution, both point in the direction of adopting the approach of fuzzy logic. Fuzzy logic indeed is now an established and rigorous mathematical discipline in which knowledge representation is based on degrees of memberships rather than on the crisp membership of classical binary logic. Fuzzy logic is multivalued and reaches conclusions applying specific inference rules. The ability to represent sets with fuzzy boundaries allows this logic to represent also linguistic variables and it is therefore a very good tool to take into account the very valuable but often not easily quantifiable opinion of the experts. A fuzzy identifier for the identification of the plasma confinement regime was therefore developed with the help of the Matlab® Fuzzy Logic Toolbox [11] using a Mamdani-type Fuzzy Inference System (FIS) [12]. The main difficulty consisted in representing in a suitable way the information contained in the signals, in order to select the best inference rules for the discernment between the L or H mode.

At JET the D± signal is sampled at two different frequencies during the pulse, 10kHz for the first 115000 samples and 5kHz for the remaining samples. It was chosen to take into consideration only the part of the signal with the higher sampling frequency. In order to obtain a parameter from the D_α radiation signals (S3AD/AD34-35) that could be a suitable input for the fuzzy logic identifier, the chosen approach was trying to extrapolate the information about the frequency spectrum of the signal and its time evolution during the discharge. To achieve such a result, an overlapping sliding window Fast Fourier Transform (FFT) analysis was performed. The window used for the computation of the FFT comprises 1000 samples, obtaining a frequency resolution of 10Hz. The window is moved along the samples, using a step size of 100 samples, so that the result obtained has a sampling period of 10ms. Most of the other main signals reported in Table 2 have, in fact, a sampling frequency of 100Hz. At this stage the signal obtained by this elaboration of the experimental data consists therefore of the D± frequency spectrum, calculated every 10ms on a window sliding over the signal itself. The time assigned to each frequency spectrum is the right extreme of the window used to calculate the FFT. This result is, then, a tri-dimensional signal. In order to reduce it to a bi-dimensional one, the frequency spectrum is integrated over frequency up to 600Hz, from which the amplitude of the lowest frequency components is subtracted. Indeed, for the scope of the present analysis, it is not important to obtain the single harmonic components and their amplitude but just to determine how big is the contribution of the higher harmonic terms. The resulting signal, which is directly proportional to the ELMs frequency content, is provided as first input to the fuzzy network and is called "Dα Spectrum Integral".

The first component of each FFT calculation, that represent the DC component of D_α, constitutes another signal, which is time derived in order to estimate the step in the D_α signal, the most evident symptom of the transition from L to H mode or vice versa. This signal is provided as the second input and is called "D_α DC derivative".

The third input is the time derivative of the plasma β normalized with respect to the diamagnetic energy (Bndiam). As already mentioned, both the L-H and the H-L transitions are accompanied by a change in the slope of this quantity. The derivative allows identifying this change quite accurately. It also turns out to be useful to include in the set of inputs the plasma regime, L or H, as determined by the algorithm at the previous step.

In perfect agreement with the philosophy of the fuzzy logic, the output of the network, the confinement mode of the plasma, is not represented by a crisp indicator but by a continuos quantity, a number comprised between 0 and 1, 0 indicating the L mode and 1 the H mode.

The fuzzy sets for the input signals were devised manually after a careful observation of the various input signals during the transitions and steady state. In particular in **Table 4** the membership functions (mfs) for the signals involved are reported:

A total of 12 if-then rules, involving all or part of the input signals, were elaborated (Table 5). The resulting algorithm was tested on the shots from the previously described database, a total of 25, and then compared with the estimated transition times from the experts.

The performances of the identifier are of about 95.3% of success at steady state. The LH transition time was determined with a time error less than 0.1s in 19 shots, while the HL one with an error less than 0.2s in 18 shots. On some shots it resulted quite difficult to identify correctly the transition. For the L-H transition the maximum error is of about half a second, observed in 5 shots, while for the inverse transition the maximum error was of 0.63s observed in three shots. It is worth mentioning that the shots for which the identifier is less accurate are those deemed more difficult to interpret also by the experts, who estimate that the error bars in the determination of the transition time are comparable to the uncertainties in the identifier output.

4. CLASSIFICATION BASED ON VECTOR MACHINES

A Support Vector Machine (SVM) is a supervised algorithm developed by Vapnik and others [13] over the past decade. The algorithm addresses the general problem of learning to discriminate between two classes (positive and negative class) of n-dimensional vectors. During the so-called learning phase a set of input-output patterns (training set) has to be suitable chosen by the designer in order to set the design parameters.

The SVM algorithm operates by mapping the training set into a possibly high-dimensional feature space and attempting to locate in that space a plane that separates the positive from the negative examples. During the test phase, the SVM can then predict the classification of an unlabeled example by mapping it into feature space and asking on which side of the separating plane the example lies. Much of the SVM's power comes from its criterion for selecting the best plane when many candidate planes exist. Statistical learning theory suggests that, for some classes of well-behaved data, the choice of the optimal separating hyper-plane, which maximizes the margin between itself and the closest data point, will lead to maximal generalization when predicting the classification of previously unseen examples.

The optimal hyper-plane can be obtained by solving the following optimisation problem:

$$E\,(\underline{w}) = \frac{1}{2}\,\underline{w}\underline{w}^T + C\sum_{i=1}^{N}\xi_i$$

subject to

$$\begin{aligned} & y^i \text{¥} (\underline{w}^T \Phi_i (x^i) + b) \text{‡} 1 - \xi_i \\ & \xi_i \text{‡} 0 \end{aligned} \qquad i = 1,\ldots,N$$

where $\underline{w}$ and b are coefficients of the optimal hyper-plane equation, C is the error penalty, and ξ_i are parameters for handling no separable inputs. The index i labels the N training cases, x^i is the ith training pattern and i^{th} is the corresponding class label. The kernel Φ is used to transform data from the input to the higher dimensional feature space.

There are different kernels that can be used in SVM models:

- polynomial $\Phi_i\,(\underline{x}^i, \underline{x}^j) = (\gamma \underline{x}^i \yen \underline{x}^j + \vartheta)^p$
- radial basis $\Phi_i\,(\underline{x}^i, \underline{x}^j)\; e^{-\|x^i - x^i\|^2/2\sigma^2}$

The dominant feature, which makes SVMs very attractive, is that classes that are nonlinearly separable in the original space can be linearly separated in the higher dimensional feature space. Thus, SVM is capable of solving complex nonlinear classification problems.

4. RESULTS

The non-linear SVM classifiers have been trained using the OSU SVM Classifier Matlab Toolbox (ver. 3.00) based on the version 2.33 of LIBSVM [13]; LIBSVM is a software library for classification and regression by means of Support Vector Machines, that implements the training algorithms developed by Vapnik [15].

In this case, the available 27 pulses have been divided in two sets: the 30% of the pulses (8 pulses, 9128 samples) have been used for setting the parameters of the SVM (training set), and the remaining 70% (19 pulses, 21679 samples) have been used as test set.

As input to the SVMs three signals were selected, almost the same used by the Fuzzy Logic identifier:

- high frequency components of the Dα radiation
- derivative of the continue component of the Dα radiation
- the time derivative of the plasma β normalized with respect to the diamagnetic energy (Bndiam)

In table 7, the performance of the best SVM classifier are reported in terms of the samples correctly classified:

Improvements of these results (table 8) have been obtained adding to the previous signals the absolute value (not only the derivative) of the β normalized with respect to the diamagnetic energy (Bndiam).

The reported results were obtained with the radial basis kernel and it was also double-checked that adopting the polynomial did not cause any significant difference in the success rate.

SUMMARY AND CONCLUSIONS

The traditional approach of Discriminant Analysis was tried to identify JET confinement regime but its performances were not completely satisfactory. The accuracy was not particularly high even when five different signals were used as inputs. Moreover the use of the absolute value of so many signals is believed to limit the generalisation capability of the technique, requiring significant fine tuning, when the main parameters of the discharges are significantly varied. These drawbacks motivated the investigation of different solutions. First of all a systematic analysis of the best way to include the information of the D_α signal was performed. Second a fuzzy logic approach was implemented, to handle the vagueness aspects of the problem in hand. With this method, a success rate of 95 % was achieved using only the D_α and the Bndiam as inputs. Moreover, since mainly the derivatives of the inputs are exploited, this identifier is less dependant on the engineering parameters of the discharge and can potentially be successfully applied to a larger set of configurations. To compare the results of the fuzzy identifier with another distance based method, the alternative of Support vector machines was also implemented. The results are slightly inferior (91%) when almost the same input signals are used. On the other hand the success rate increases to 95% when also the absolute value of Bndiam is included.

The series of tests reported in this paper constitute a good staring point for the identification of the best regime identifier for JET. In the near future, in addition to assessing the generalisation capability of the fuzzy logic and the SVM approaches on a wider data base, these techniques will also be tested during JET next campaigns in a variety of new plasma configurations. Since the main goal of JET is now to develop ITER relevant scenarios, this activity should naturally provide some interesting information in the perspective of the next step machines.

REFERENCES

1]. R.Felton et al, "*Real-time measurement and control at JET - experiment control*" presented at SOFT 2004, Venice, September 2004 to be published in Fusion Engineering and Design.

[2]. A.Murari et al., "*Real-time measurement and control at JET - signal processing and physics analysis for diagnostics*" presented at SOFT 2004, Venice, September 2004 to be published in Fusion Engineering and Design.

[3]. P. Arena et al. "*Real time monitoring of radiation instabilities in TOKAMAK machines via CNNs*", IEEE Transaction on Plasma Science, Vol. 33, Issue 3, June 2005, pp. 1-9.

[4]. E Joffrin, et al., "*Integrated Scenario in JET Using Real Time Profile Control*" Plasma Phys. Control. Fusion 45 No 12A (December 2003) A367-A383.

[5]. P.Franzen et al. "*On-line confinement regime identification for the discharge control system at ASDEX Upgrade*", Fusion Technology, **33**, Jan. 1998.

[6]. D Moreau et al., "*Real-time control of the q-profile in JET for steady state advanced tokamak operation*", Nuclear Fusion, **43** (9), September 2003, 870-882.

[7]. O. Barana, A. Murari et al,"*Neural networks for real time determination of radiated power in JET*" Rev. Sci. Instrum. **73**(5) May 2002.

[8]. Martin et al. "*Statistical analysis of the ohmic H-mode accessibility in TCV*", Plasma Phys. Control. Fusion **40** (1998) 697-701.

[9]. L.Giannone et al."*Regime identification in ASDEX Upgrade*", Plasma Phys. Control. Fusion **46** (2004) 835-856.

[10]. Zohm, H., "Edge localized modes (ELMs)", Plasma Physics Control Fusion, vol. 38, pp. 105-128, 1996.

[11]. Fuzzy Logic Toolbox User's Guide, Version 2, The Mathworks, Inc., 2002.

[12]. Mamdani, E.H. ans S. Assilian, "An experimenti in linguistic synthesis with a fuzzy logic controller", *International Journal of Man-Machine Studies*, vol. 7, no. 1, pp. 1-13, 1975.

[13]. Vapnik V. , "Statistical Learning Theory Wiley-Interscience", New York 1998.

[14]. Chang c.c., Lin c.j., *"LIBSVM a library for support vector machines"*, Sofware: http://www.csie.ntu.edu.tw/~cjlin/libsvm, 2001.

[15]. Vapnik V., "*The nature of Statistical Learning Theory* ", Springer, New York, 1995.

TABLES

JPN	Ip(MA)	TF (T)	N_e $(10^{18}/m^2)$	NB(MW)	RF(MW)	Neutrons(n·s/m^2)?	W_{dia}(MJ)
58569	2.5	2.5	140	15.3	–	2.5e+16	5.0
58730	2.5	2.4	250	13.7	3.8	1.9e+16	6.3
58810	2.1	3.0	132	15.4	–	3.2e+16	5.3
58816	2.5	2.4	107	8.7	–	8.3e+15	2.0
58819	2.5	2.4	123	8.6	–	6.8e+15	1.9
58844	2.5	2.4	172	13.4	–	2.4e+16	5.4
58853	2.5	2.4	215	13.1	–	3.0e+16	5.9
58858	2.5	2.5	146	15.4	–	1.6e+16	5.0
58886	2.8	2.7	138	9.4	6.3	1.5e+16	5.2
58906	2.0	2.6	97	15.2	–	2.1e+16	4.0
58907	2.0	2.6	100	12.5	–	1.8e+16	3.8
58909	2.0	2.6	173	15.2	–	2.5e+16	4.6
58971	2.0	2.3	84	5.2	–	2.3e+15	1.7
59051	2.5	2.7	171	12.8	3.9	1.7e+16	4.5
59055	2.5	2.7	196	12.8	3.2	9.8e+15	4.0
59083	2.0	2.6	159	14.9	3.6	2.5e+16	4.8
59085	2.0	2.6	179	15.2	3.7	2.5e+16	4.8
59151	2.7	2.7	134	15.6	9.2	3.3e+16	6.7
59293	2.0	2.4	135	14.2	–	3.8e+15	3.1
59355	2.5	2.6	256	15.0	4.8	2.6e+16	7.3
59375	3.1	2.6	277	13.9	4.4	2.1e+16	7.6
59423	2.5	2.4	310	13.8	4.4	2.7e+16	6.7
59424	2.5	2.4	339	15.3	4.5	3.0e+16	7.0

Table 1: list of pulses used in the paper including main plasma parameters

1. Engineering parameters

Description	Name
Total heating power	P_{tot}
Plasma current	I_{pab}
Toroidal magnetic field	B_t

2. Plasma response parameters

Description	Name
Beta normalised with respect to the diamagnetic energy.	Bndiam
Beta normalised with respect to the Magneto-hydrodynamic energy	Bndia
Magneto-hydrodynamic energy	W_{mhd}
Time derivative of diamagnetic. Energy	FDWDT
Area averaged electron temperature	T_{eav}
Maximum electron temperature	T_{max}
Line integrated density	Ne1
Plasma inductance	LI
Safety factor	Q_{95}

3. Plasma shape parameters

Description	Name
Elongation	ELO

Table 2: list of tested parameters

Size of feature space	Best combination	Success rate
1	β_N	0.80
2	B_t β_N	0.85
3	B_t β_N l_i	0.90
4	I_{pab} Bt β_N l_i	0.90
4	I_{pab} β_N l_i	0.90
4	B_t β_N l_i q_{95}	0.90
5	I_{pab} β_N l_i q_{95} κ	0.90

Table 3: Combinations of plasma parameters yielding the highest success rates

Signals	Type	# of mf	Mf name	Mf type	Mf Parameters
Dα Spectrum integral (Dα-SI)	Input	4	Low	Zmf	[0.01 0.07]
			Medium	Gauss2mf	[0.02 0.06 0.064 0.21]
			High	Gauss2mf	[0.06 0.39 0.4 1.04]
			Very High	sigmf	[9 1.15]
Dα DC derivative (Dα-der)	Input	3	Negative	Trapmf	[-30 -24.4 -0.28 -0.005]
			Null	Trimf	[-0.5 0 1.5]
			Positive	trapmf	[0.5 2 26.5 61.7]
Bndiam derivative (Bn-der)	Input	3	Negative	Trapmf	[-20 -20 -1.7 -0.17]
			Nul	Trimf	[-1.5 0 1.5]
			Positive	Trapmf	[0.31 1.0 20 20]
Mode previous cycle (Mode-pc)	Input	3	L	Trapm	[-1 -1 -0.3 0.5]
			LH	Trimf	[0.3 0.5 0.7]
			H	Trapmf	[0.5 0.7 2 2]
Mode (Mode)	Output	3	L	Trapmf	[-1 -1 -0.3 0.5]
			LH	Trimf	[0.3 0.5 0.7]
			H	trapmf	[0.5 0.7 2 2]

Table 4 : Membership functions. For details about the Mf type please consult [2]

Rule #	**Linguistic terms**
1	If Dα is low and Dα-der is neg and Bn-der is pos and Mode-pc is L then Mode is H
2	If Dα-SI is medium and Dα-der is neg and Bn.der is pos and Mode-pc is L then Mode is H
3	If Dα-SI is high them Mode is H
4	If Dα-SI is very high the Mode is H
5	If Dα-SI is medium and Bn-der is neg and Mode-pc is H then Mode is L
6	If Dα-SI is low and Bn-der is neg and Mode-pc is H them Mode is L
7	If Dα-SI is low and Bn-der is not pos and Mode-pc is L then Mode is L
8	If Dα-SI is medium and Bn-der is not pos and Mode-pc is L then Mode is L
9	If Dα-SI is low and Dα-der is not neg and Bn-der is pos and Mode-pc is L then Mode is L
10	If Dα-SI is medium and Dα-der is not neg and Bn-der is pos and Mode-pc is L then Mode is L
11	If Dα-SI is low and Dα-der is null and Bn-der is null and Mode-pc is H then Mode is H
12	If Dα-SI is low and Dα-der is null and Bn-der is null and Mode-pc is L then Mode is L

Table 5: Linguistic rules.

Signals	Percentage of success
Dα-SI, Dα-der, Bn-der, Mode-pc	95.3 %
Dα-SI, Dα-der, Bn-der, Mode-pc, Bndiam	95.7 %

Table 6: Performances of the Fuzzy Logic identifier

Set	Percentage of success
Training	96.83%
Test	90.96%

Table 7: Performances of the SVM classifier using Dα-SI, Dα-der, Bn-der

Set	Percentage of success
Training	99.39%
Test	95.77%

Table 8: Performances of the SVM classifier adding Bndiam to the precious signals

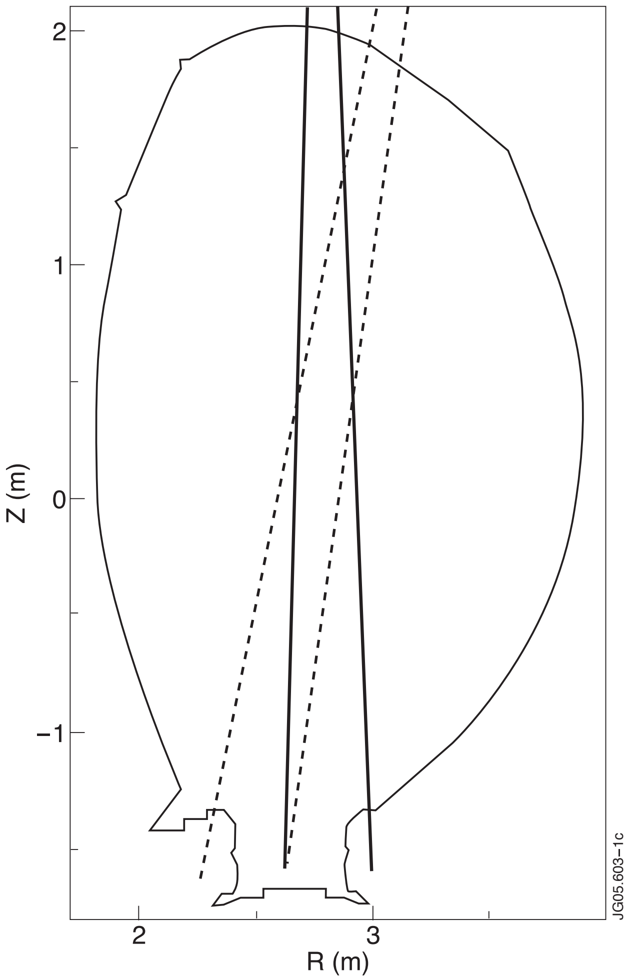

Figure 1: Field of view for the calculation of the Dα signal

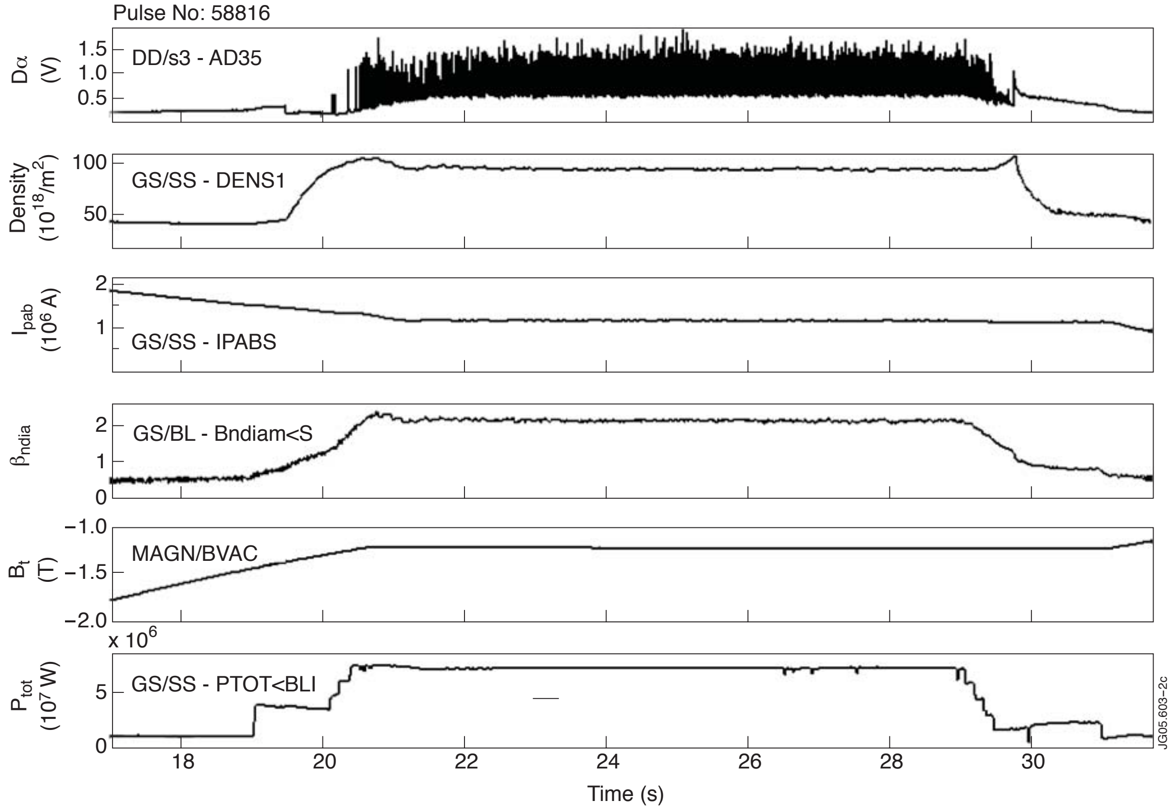

Figure 2: trend of some of the observed signals during a plasma discharge (Pulse No: 58816). It is possible to observe the drop in the Dα signal during a L-H transition and a little step up of the signal itself during the transition back to the L-mode.

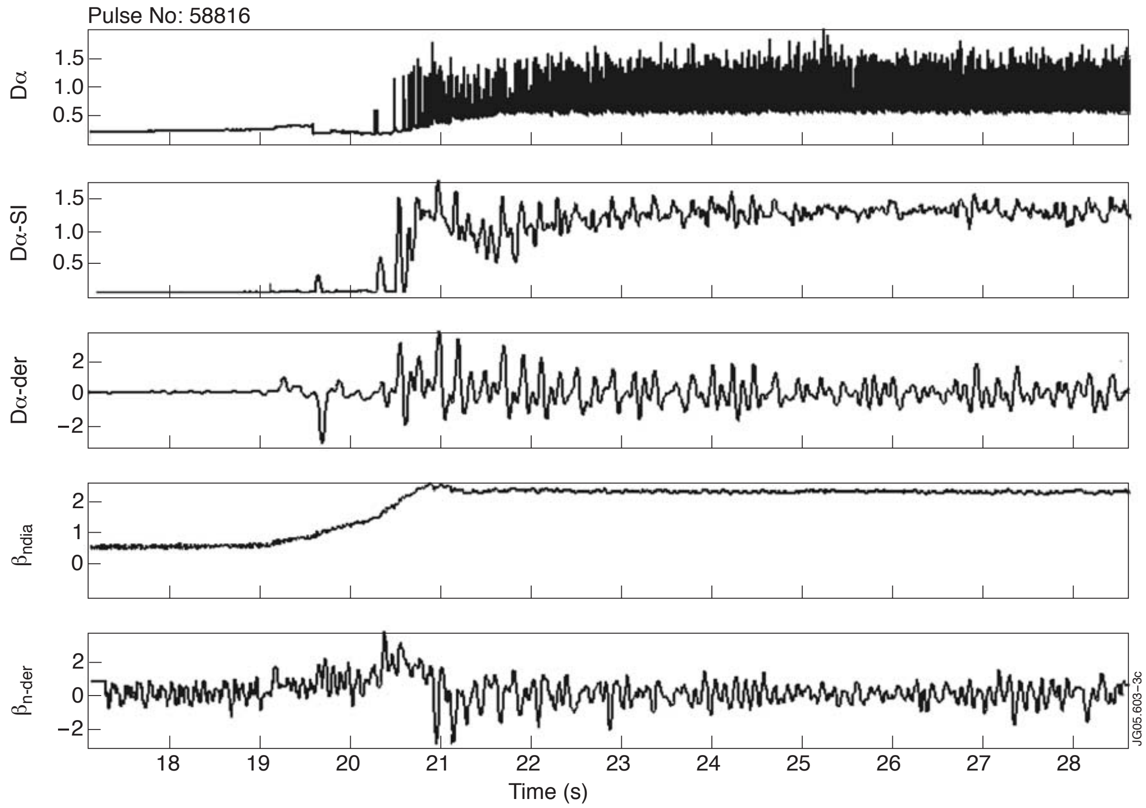

Figure 3: Trend of signals used in the fuzzy logic identifier