

G.A. Rattá, J. Vega, A. Murari, G. Vagliasindi, M.F. Johnson, P.C. de Vries
and JET EFDA contributors

An Advanced Disruption Predictor for JET Tested in a Simulated Real Time Environment

“This document is intended for publication in the open literature. It is made available on the understanding that it may not be further circulated and extracts or references may not be published prior to publication of the original when applicable, or without the consent of the Publications Officer, EFDA, Culham Science Centre, Abingdon, Oxon, OX14 3DB, UK.”

“Enquiries about Copyright and reproduction should be addressed to the Publications Officer, EFDA, Culham Science Centre, Abingdon, Oxon, OX14 3DB, UK.”

An Advanced Disruption Predictor for JET Tested in a Simulated Real Time Environment

G.A. Rattá¹, J. Vega¹, A. Murari², G. Vagliasindi³, M.F. Johnson⁴, P.C. de Vries⁴
and JET EFDA contributors*

JET-EFDA, Culham Science Centre, OX14 3DB, Abingdon, UK

¹*Asociación EURATOM/CIEMAT para Fusión. Avda. Complutense, 22. 28040 Madrid, Spain.*

²*Associazione EURATOM-ENEA per la Fusione, Consorzio RFX, 4-35127 Padova, Italy*

³*Dipartimento di Ingegneria Elettrica Elettronica e dei Sistemi-Università degli Studi di Catania, 95125 Catania, Italy*

⁴*EURATOM-UKAEA Fusion Association, Culham Science Centre, OX14 3DB, Abingdon, OXON, UK*

** See annex of F. Romanelli et al, "Overview of JET Results",
(Proc. 22nd IAEA Fusion Energy Conference, Geneva, Switzerland (2008)).*

ABSTRACT.

Disruptions are sudden and unavoidable losses of confinement that may put at risk the integrity of a Tokamak. However, the physical phenomena leading to disruptions are very complex and nonlinear and therefore no satisfactory model has been devised so far neither for their avoidance nor their prediction. For this reason, machine learning techniques have been extensively pursued in the last years. In this paper a real time predictor specifically developed for JET and based on Support Vector Machines is presented. The main aim of the present investigation is to obtain high recognition rates in a real time simulated environment. To this end the predictor has been tested on the time slices of entire discharges exactly as in real world operation.

Since the year 2000, the experiments at JET have been organised in campaigns named sequentially beginning with the campaign C1. In this article results from the campaign C1 (year 2000) and up to C19 (year 2007) are reported. The predictor has been trained with data from JET's campaigns up to C7 with particular attention to reducing the number of missed alarms, which are less than 1%, for a test set of discharges from the same campaigns used for the training. The false alarms plus premature alarms are of the order of 6.4%, for a total success rate of more than 92%. The robustness of the predictor has been proven by testing it with a wide subset of shots of more recent campaigns (from C8 to C19) without any retraining. The success rate over the period between C8 to C14 is on average 88% and never falls below 82%, confirming the good generalisation capabilities of the developed technique. After C14, significant modifications were implemented on JET and its diagnostics and consequently the success rates of the predictor between C15 to C19 decays to an average of 79%. Finally, the performance of the developed detection system has been compared with the predictions of the JET Protection System (JPS) The new predictor clearly outperforms JPS up to about 180 ms before the disruptions.

1. INTRODUCTION AND PREVIOUS STUDIES.

Disruptions are major instabilities that can take place during a Tokamak operation. They consist of sudden losses of confinement which cause the abrupt termination of the discharge. In addition to affecting the execution of the research programme, they can constitute a risk for the structural integrity of the machine [1]. Disruptions can be triggered by various instabilities which, on time scales even of the order of milliseconds, can force the plasma out of its safe operational limits with the resulting loss of energy and termination of the plasma current. The first phase of the disruption, the so called thermal quench, can cause extremely high thermal loads on the plasma facing components and more in general on the first wall. As a consequence of the subsequent plasma abrupt current quench, large eddy currents can be induced in the vacuum vessel and surrounding structures creating forces potentially capable of producing severe damage to the device. Up to now, their occurrence has proven to be an unavoidable aspect of Tokamak operation particularly in high performance configurations.

The physical characterisation of disruptions for prediction and control is an extremely complex

task. The amount of available signals in each pulse and the non-linear relationship between them have rendered impossible up to now the development of a physical model to reliably recognize and predict the occurrence of this hazardous plasma behaviour. Therefore in the last decade, various machine learning techniques, mainly Artificial Neural Networks and Support Vector Machines, have been used as an alternative approach to disruption prediction [2-7]. These computational systems are capable of building general models, by “learning” from the data in the so-called “training process”. Once the systems have been trained, they can be applied to detect the specific behaviour they were designed to identify.

Unfortunately, and notwithstanding the considerable amount and quality of previous investigations, the obtained results have not been completely satisfactory. The most relevant deficiency, in most of the previous works [2-5], is that the complete evolution of the discharges is not analyzed in its full length but only certain selected parts of the shots are considered. The models developed in this way are therefore useful to study the physics of the phenomenon but they cannot be applied in real-time environments, where the need of predicting disruptions extends to the whole evolution of the pulse. Moreover in some of the mentioned works, databases with less than 300 shots have been considered [2, 6, 7]. Also, the determination of the predictor performance was usually limited to the period in which the actuators can undertake mitigation actions. Some disruptions cannot be identified by any algorithm, trained system or formula, even few ms before the sudden loss of confinement takes place. Those types of disruptions were normally discarded from the databases. On the contrary, to assess the performance of the present predictor in a fully general way, those problematic discharges have been included both in the training and test sets for all the cases discussed in this paper.

One of the most advanced published study performed so far at JET is the one by [7]. However, it was performed with a medium-size database (172 disruptive pulses and 102 non disruptive pulses). Also, the premature alarms were not defined and the overall results are encouraging but still could be improved. In the cited work, the false alarms are minimized and the missed alarms are considered a secondary concern issue, prioritizing the continuity of the research programme over the protection of the device’s integrity.

Another relevant work at JET that must be mentioned [8] is a neural network trained with 360 discharges which achieved 90% of successful detections with 5% of missed alarms. However, the testing shots were from the same period of experiments used for the training and therefore the robustness of the predictor for newer campaigns was not assessed.

Even if it refers to a different device (ASDEX-Upgrade) and therefore its applicability in JET has not been verified, it is worth mentioning the predictor developed by [9]. It is based on the training of a neural network using 8 plasma parameters and their time derivatives extracted from 99 disruptive discharges. Once trained, the system was tested firstly off-line with 500 shots attaining 85% of successful recognitions with 1% of missed alarms. Secondly the test was performed on-line during 128 pulses with 79% of correct identifications. In this last case, the fast types of disruptions were considered unrecognizable and discarded to calculate the statistics.

In the present research the complete evolution of the considered discharges is followed from the beginning to the end to determine whether a disruption is forthcoming or not. The applied database is the biggest used so far at JET for studying real-time disruption recognition with learning systems. The database contains all types of disruptions in the considered campaigns. No type of disruption has been excluded and no bias has been introduced in the selection of the training and testing sets (they have been selected completely randomly). The final database consists on 2124 discharges (for which all the needed signals are available) and have been properly validated by the experts.

Significant pre-processing of each signal, according to a procedure fully described in a previous work [3] and summarized in section 3, has been applied to every shot to extract the main features every 30ms. This feature extraction procedure is performed to achieve high recognition rates with a minimum of missed alarms. This is motivated by the consideration that, in the perspective of ITER, particular attention will have to be devoted to disruption avoidance given the potential damage to the machine.

From a methodological point of view, two main innovative developments have been implemented to obtain the results described in this paper. First of all, a series of different predictors based on Support Vector Machines (SVM) and trained during specific time intervals before the disruption, have been deployed in parallel. The determination whether to trigger an alarm or not is obtained by a decision function, again based on SVM, on the basis of the outputs of the individual predictors. This second layer of SVM, which is the second original aspect of the technique, is adaptive in the sense that it can be retrained automatically with the signals of each new discharge. Finally, the model has been trained with shots of the campaigns up to C7 (discharges numbers from 42815 to 57346). It has been tested with discharges up to the campaign C14 with very positive performances (practically no degradation in the success rates). After C14, JET has been subjected to structural modifications, in particular the replacement of the divertor and the bolometric diagnostic, and therefore the success rates from C15 to C19 are lower.

With regard to the structure of the paper, section 2 is devoted to a brief introduction to the SVM and their conceptual basis. Section 3 describes the databases used and outlines the feature extraction method. Section 4 is focused on the training method, whereas the subject of section 5 is the development of the final decision function, the step leading to the triggering of an alarm or not. Section 6 reports the results obtained during the campaigns on which the predictor has been trained. Section 7 demonstrates the system generalisation capability by testing the predictor with pulses of campaigns from C8 to C19. In section 8, a comparison between the developed predictor and JET Protection System (JPS) is performed. A final discussion with the prospects for further investigations is the subject of the final section.

2. INTRODUCTION TO SUPPORT VECTOR MACHINES AND MACHINE LEARNING CONCEPTS.

Artificial intelligence is a branch of science based on programming computers to solve complex

problems in an intelligent way. Machine learning is the name given to a set of artificial intelligent techniques aimed at making computers ‘learn’. By detecting significant patterns in the available data, a computational system based on these techniques can take decisions or make predictions about new data coming from the same physical object or source. In this sense, the system is able to acquire a generalisation capability by ‘learning’ about the source generating the data.

Supervised methods are a category of machine learning techniques which can be applied to automatic classification. They usually work in two stages. In the first one, called training, a set of known examples and the class they belong to, are provided to the system. Once the training has been completed, a classifier is created. That classifier is used in the second stage, called testing. In this second phase, new examples are provided to the classifier, which determines the class each one belongs to.

For the present work, the inputs are feature vectors corresponding to JET discharges and the possible classes are two: disruptive and non disruptive. After the training, in the testing phase, the rate of successful classifications can be assessed in terms of percentages.

The supervised learning system utilized in this study is based on Support Vector Machines [8] because of their simplicity, good performance and generalisation capability. SVM calculates a separating hyper-plane using a quadratic optimization algorithm that maximizes the margin in a two-class classification problem (see figure 1.a.). These margins are the distances from the separating hyper-plane to the closest training examples. In this way, the learnt solution is based only on those examples (support vectors) closest to the hyper-plane. SVM is also applicable to non linearly separable problems (figure 1.b). In those cases, the original space is transformed into a higher dimensional feature space with functions called kernels. In that transformed space, the objects can be again separated by a hyper-plane.

Once this separating hyper-plane has been calculated, it is used to determine the class of the new tested objects. The hyper-plane splits the space in two and the objects are classified depending on in which of the two regions of the space they belong to. Besides, extra information can be derived from this classification method: the distance between the objects and the hyper-plane can be calculated and it can be considered an indicator of the classification confidence. If the distance between the new tested object and the hyper-plane is large, this means that the classification is more reliable. If instead the distance is small, the new object is near the hyper-plane and therefore closer to the boundary with the other class. A small distance, then, indicates a low reliability of classification.

The implemented software [9, 10] used to obtain the results reported in this paper is included in public licensed environments for MATLAB® and C++.

3. THE DATABASE.

A large dataset extracted from the JET database (Pulse No’s in the range from 42815 to 70722) has been utilized in this study. It contains the highest number of discharges ever considered for real-time disruption prediction studies using learning systems. A subset of the database has been used to

build the predictor and to test it. The shadowed part of table 1 indicates the portion of the database used for this purpose (training and testing datasets) with randomly selected shots of campaigns up to C7. Once the system has been trained and tested (sections 4, 5 and 6), its robustness has been proved with a wide number of shots from C1 (year 2000) to C19 (year 2007). The quality of the predictions is finally compared with the ones provided by JPS (shots from C1 to C19). The number of disruptive and non disruptive pulses used in the testing stages is detailed in the rest of table 1.

At JET, thousands of signals are acquired in every pulse. The selection of the most informative physical quantities is fundamental to properly identify an incoming disruption. On the one hand, too many signals could overload the learning capacity of an automatic system. On the other hand, too few could not provide enough information to perform reliable prediction. Thirteen signals to study disruptions have been chosen for training and testing the classifier (see table 2). The majority or all of this set (that includes some time derivatives of the signals which can improve the recognition of the phenomenon) have also been used in previous researches on the subject [3, 5, 7].

Because each measurement has been acquired by a different diagnostic, their sampling rates are not necessarily the same. Therefore a simple interpolation algorithm has been applied to standardise the sampling rate to 1 kHz. It is necessary to highlight that every one of the 13 signals are required and consequently the shots, for which any of these measurements is not available, have not been considered. The percentage of discarded shots has been about 8.5% mainly due to the lack of reliable total radiated power estimates.

Another potential issue is the extreme amplitude difference between some signals, in many cases of several orders of magnitude. This aspect is a complicating factor for any classification system. The system could automatically assign higher weights to certain signals because of their absolute values and not because of their relevance for the prediction. Consequently, a standard normalization formula has been applied:

$$\text{Normalizes Signal} = \frac{\text{Signal}-\text{Min}}{\text{Max}-\text{Min}}$$

where Min and Max, respectively, represent the minimum and maximum values of each signal in the training set. This normalization rescales the signal values to the interval between 0 and 1 preserving the information about their relative magnitudes. To demonstrate that a predictor provides sufficient and reliable performances, it is necessary to train and test it using a considerable number of discharges from a large database of stored signals. To properly assess the potential of the predictor for control applications, it has been designed to use the data sequentially as if they became progressively available during an actual experiment. For that, time windows of 30ms are considered. The techniques used to extract the disruptive-related features for these intervals of 30ms are described in [3]. In that paper it is explained that a simple visual inspection reveals the presence of high frequency components in the signals as the discharges approach the disruption. For each time interval, the standard deviation of the fast Fourier transform is calculated and then the thirteen values (one

per signal) are finally concatenated creating the feature vector. This feature extraction procedure has been chosen since it provides the best performance as reported in detail in [3].

Using these feature vectors, the ultimate action of taking a decision (to trigger or not an alarm) is performed as if they were being acquired and processed in real time.

4. TRAINING PROCESS

Various classifiers based on SVM have been trained to identify forthcoming disruptions. The training has been performed by providing the learning systems with two classes of inputs: features belonging to disruptive discharges and features of non disruptive discharges.

Particular attention has been devoted to avoiding any form of bias in the selection of the training set. A balanced number of disruptive and non disruptive shots (263 and 175 respectively) of the database have been chosen randomly for the training process.

The notation used to identify the models can be summarized as follows:

$M(i)$ is the model trained for an specific time interval i before the disruption.

where $i = 1, 2, 3, \dots, 8$

$M(1)$ corresponds to the period $[-60, -30]$ ms before the disruption.

The others $M(i)$ refer to the intervals $[-30(i+1), -30i]$ ms before the disruption

The training inputs, for each model have been:

As **disruptive features**: time windows $[-30(i+1), -30i]$ ms before the disruption for all shots in the disruptive training dataset.

As **non disruptive features**:

- All the time windows from the beginning of the shot to 1 second before the time of the disruption for all the pulses in the disruptive training dataset. In this interval, even disruptive shots do not show any abnormal behaviour and they can be considered non-disruptive.
- All the time windows of the non disruptive discharges available in the non disruptive training dataset.

To optimise the success rates, different combinations of the trained classifiers have been considered. The choice to implement more than one classifier is due to the need of taking into account the temporal evolution of the discharge. To this end, sequences of consecutive classifiers, optimised for various time intervals of 30ms before the disruptions, have proved to achieve higher performance than a single model trained over a longer period. The classifiers are meant to operate in parallel on consecutive time windows as shown in figure 2. The number of predictions provided by this concatenation of n models (with $n = 3$ in the example of figure 2) is n .

At this point the pending issue is the determination of the optimal number of classifiers to be used in parallel. Because of the novelty of this approach, this number n was unknown and consequently different combinations have been tested. To this end 8 classifiers have been developed

(models trained with earlier time intervals have very poor performance due to the fact that not enough information is contained in the signals too far away from the disruption). With these models, 7 sequences that include consecutive classifiers have been created concatenating them as follows:

Sequence 1: M2, M1.

Sequence 2: M3, M2, M1.

Sequence 3: M4, M3, M2, M1.

Sequence 4: M5, M4, M3, M2, M1.

Sequence 5: M6, M5, M4, M3, M2, M1.

Sequence 6: M7, M6, M5, M4, M3, M2, M1.

Sequence 7: M8, M7, M6, M5, M4, M3, M2, M1.

For clarity sake, the whole training procedure, as implemented for sequence two, is summarised in the following pseudo code:

WHILE (end condition, detailed in section 6, is not satisfied)

FOR (the whole training database)

1. The first classifier of the sequence (M3) analyzes the first 30ms of each shot, the second classifier, the seconds 30ms and the third the third 30ms (see again figure 2).
2. The 3 outputs of the sequence (one per classifier included in the sequence) are analyzed with a Decision Function (DF), consisting of another SVM classifier (described in detailed in section 5). This decision function determines whether the combination of outputs provided by the sequence indicates a forthcoming disruption or not.

IF (a disruptive behaviour is recognized)

An alarm is immediately triggered and the relevant data is stored for future analysis in an archive similar to table 3 (Fig.3).

ELSE (no disruptive behaviour is recognized)

No alarm is triggered, no data is stored and the next 30ms of discharge are analyzed. Then, model 3 will analyze the time windows previously analyzed by model 2, model 2 will analyze the time windows previously analyzed by model 1, and model 1 will analyze the next incoming 30ms of the shot, (returning to 2).

END IF

END FOR

END WHILE

5. THE DECISION FUNCTION

The n output values of the classifiers not always coincide, i.e. some models predict an incoming disruption and others do not. Then, a decision function has to be implemented to determine automatically whether an alarm has to be triggered or not. The development of this function is crucial to attain the best possible recognition rates for the global predictor. The accurate determination of what relationship of the n results provides the best performances can be performed automatically by a classification system. Consequently, again SVM was applied for this purpose.

In the adopted procedure, the outputs provided by the individual classifiers described in section 4 are used to train the classification system that implements the actual decision function. This final decision function is obtained through an iterative process. First, a set of conditions has been empirically formulated to determine the Initial Decision Rule (IDR), which allows performing the first discrimination of the discharges in disruptive and non disruptive (see later). The IDR is just applied in the first step. Then an iterative procedure has been implemented to converge on an optimised decision function DF. This procedure performs the analysis of the shots to obtain refined results to train the next DF. The process continues till an ending condition is activated.

The IDR has been formulated empirically. A considerable time consuming analysis has been performed to interpret the results of the n classifiers and to set the empirical conditions that decide the triggering of an alarm. It is also worth mentioning that a different IDR for each sequence of classifiers. For sequence 2 (M_3, M_2, M_1) the IDR is described in the following, where the V_i are the distances of the M_i outputs to the separating hyper-planes.

If ($V_3 > 0$ & $V_2 > -0.4$ & $V_1 > -0.8$)

The alarm must be triggered.

Instead, for sequence 1 (M_2, M_1) the conditions are:

If ($V_1 + V_2 > 0$)

OR

If ($V_2 > 0.3$)

The alarm must be triggered.

Obviously, this combination of empirical rules is not the most accurate procedure to achieve the highest recognition rates (applying the IDR to sequence 2, a success rate of 80% is obtained).

At the end of the first iteration the stored results are employed to train the next DF (Fig.3). The criterion consists of saving the relevant data every time an alarm is triggered. The results fill a table that contains a number of rows equal to the number of analyzed discharges.

In table 3 the six possible types of results that can occur in practice are summarized. The first column represents an index, the second the shot number, the third the time when the system has detected a disruptive behaviour, the fourth the real disruption time (0 if the pulse is non disruptive), the fifth is the difference between column three and four and the last three columns report the

values provided by each model of the sequence.

These results are just examples obtained from one iteration of the optimization process that leads to the development of the final decision function. The rows represent:

1. An incoming disruption correctly recognized 110ms before it occurs.
2. Two possible cases of missed alarms:
 - a) A disruptive behaviour not recognized in a disruptive shot.
 - b) A disruption that is recognized after the occurrence of the disruption
3. A premature alarm: a disruptive behaviour is detected in a disruptive shot too much in advance (more than 1 second). In the example 4339ms before the disruption occurs.
4. A non disruptive pulse where, correctly, no disruptive behaviour has been recognized.
5. A false alarm: a non disruptive discharge where, incorrectly, a disruptive behaviour has been recognized.

The outputs of each classifier (three last columns of the example table 3) of the sequence are given to the SVM learning system to create the DF. The outputs for training the DF can be divided in two groups or classes. **The first class** (alarm activation) contains all the models output values of case 1 (table 3), i.e. all the cases where the system has correctly determined an incoming disruption. With these examples the system learns when an alarm must be triggered. **The second class** (NO alarm activation) contains all the model output values of the cases 3 (premature alarms) and 5 (false alarms) of table 3. With these examples the system is trained to neither activate an alarm too early in disruptive shots nor in non disruptive shots.

After each iteration a new DF is trained. Then this new DF replaces the previous one. Also a new table, similar to table 3, is obtained and added to the previous ones. This new data is used for training the next DF. In this way, at every new iteration, more data is entered to refine the previous DF. Its optimization continues till the ending condition (the success rates obtained with the DF do not improve after 5 iterations of the complete training process) is activated (see figure 4).

6. TESTING.

The testing phase was performed with a different subset of discharges belonging to the same period the predictor was trained with. As in the training case, the shots have been divided in time slices of 30ms from the start of the shot. All the 7 sequences of section 4 have been tested. For each of these sequences, the most performing decision function is utilized to identify disruptive behaviours in the testing stage. Finally, the obtained results are employed to compute statistics for each sequence.

During the training phase a clear tendency has been noticed: sequences that concatenate more than 3 models do not provide the best classification. The best performance is not achieved using shorter sequences either. The higher success rates are obtained with the sequence 2 which seems to strike the proper trade-off between complexity and simplicity.

However, the performances of the classifiers can only be evaluated reliably in the testing phase.

When the predictor is given new cases to classify, the results show again that the best sequence remains number 2 (see table 4). In the table, from left to right, each column represents the classifiers and the rates of Missed Alarms (MA), False Alarms (FA), Total Errors (TE) and Success Rates (SR) expressed in percentage. The average recognition time (AVG) represents the mean time, expressed in ms, between the triggering of the alarms and the occurrence of the actual disruptions for the whole testing set. The typical warning times required at JET to perform mitigation actions are between 30ms and 200ms [14].

7. TESTING THE SYSTEM WITH SHOTS OF MORE RECENT CAMPAIGNS

In section 2 it was mentioned that SVM has generalization capabilities. To confirm the potential of the developed predictor in this respect, it has been tested with pulses of the campaigns C8-C19. It is worth mentioning that after C14, significant changes have been implemented on the device, including the MKII GB LBSRP (Mark II Gas Box Load Bearing Septum RePlacement) installation and the substitution of the previous bolometer system with a new one, which provides signals different from the ones the predictor was initially trained with. Also, the Error Field Correction Coils (EFCC) [15], that can affect the Mode Lock signal have been installed to change the error field level and to measure the beta limit.

The final results have been summarized in figure 5. The light shadowed rectangle indicates the campaigns in which the model has been previously trained and validated. The non shadowed middle part of the figure displays the percentages that have been computed over 376 shots (50% of them disruptives). The variation the success rate is below 11.6% (between 94.12% and 82.35%). In that interval (C8 to C14) the minimum success rate has been obtained in C11, the Trace Tritium Experiment Campaign at JET. Because of the restrictions in the use of tritium, stringent operation rules were followed in C11. Due to the operational constraints, considerably fewer disruptions were made. Typical disruptions that usually take place during other campaigns have not happened. Many of the disruptions during this campaign were fast and difficult to classify.

Finally, the dark shadowed portion of figure 5 illustrates the results of the campaigns C15-C19 (246 discharges, half of them disruptives). The cause of many of the false alarms after C14 can easily be found, such as the use of EFCCs affecting the Mode Lock signal and thus confusing the SVM detection system. If action is taken to prevent such false alarms the performance would look considerably better. But we have decided to leave these in to give a realistic trend of the performance for a working device to which often new components are added. Besides, since C15 till the beginning of C16 the machine was subjected to an unusual increment of operational problems. UFOs, dirty plasmas and even leaks in the vacuum vessel interrupted the research program. The worst rates have been attained in C19 mainly due to the noticeable increment of false alarms. About 47% of those alarms are caused by anomalies detected by the predictor. In those experiments the EFCC were used and probably affected the Locked Mode signal. Other ~44% of the false alarms are triggered by the detection of large radiation spikes, that can be measured by the new bolometer diagnostic but not by

the previous one the system was trained with. Therefore, the SVM detection system wrongly identified those sudden and unlearned increments of the radiation as disruption precursors.

It is worth emphasizing that the stability of the performance over different campaigns, mainly from C8 to C14, not used in the training of the predictor, is an indeed positive and new result. After C14 the results are still encouraging because the causes of the increment in the false alarms have been recognized and therefore they can be corrected in a future predictor.

8. COMPARISON WITH THE SYSTEM AVAILABLE IN JET

The performances of the predictor have been compared with the results of the JET Protection System [16], which is the system used in real time on JET for the generation of alarms for incoming disruptions. Most of the alarms triggered by the JPS are due to largMode Lock signals [14]. This system has been implemented in JET for avoidance strategies in all discharges and therefore is the main reference tool.

For the proper comparison of both systems some issues must be taken into account. JPS intervenes during the execution of an experiment every time it considers that a disruptive activity has been detected [14]. Due to this direct intervention on the plasma evolution, it is impossible to calculate statistics of false alarms and therefore only disruptive pulses have been taken into account for the comparison. Also for comparison purposes, the premature alarms have not been measured as previously but in the same manner they are computed by JPS. The rates are calculated in relationship to the “warning times”. The warning times (the difference between the disruption time and the alarm time) are relevant because they represent the temporal margin the actuator have to perform avoidance or mitigation actions during the execution of a pulse. Each point in the curves plotted in figure 6 is the accumulated percentage of recognized disruptions with a warning time equal or higher than the specified in the corresponding x-axis.

Using JET disruptive database, it has been possible to test the SVM system over all the disruptive shots included in the period between the beginning of campaign C8 till the end of JET’s campaign C19 (483 disruptions, 347 of them unintentional).

To improve the comprehensibility of the attained results, separated and combined statistics over unintentional disruptions (the ones which occur during normal operation) and intentional disruptions (the ones explicitly triggered during sessions devoted to studying their physics) have been calculated. The results depicted in figure 6 show that notable higher recognition percentages are achieved with the SVM predictor for both unintentional and intentional disruptions. The SVM system provides significant higher rates than the JPS in the time interval up to ~180ms before the disruption. In the interval between ~180ms and ~0.9 seconds the JPS shows a better accuracy. This behaviour is coherent with the training of the system, based on examples covering the interval up to 200 ms before the disruptions. On the other hand some of the JPS’s missed alarms may have been due bad acquisitions of the Mode Lock signal, one of the main reference measurement analyzed by the JPS [14]. The JPS system statistics have been computed over all the discharges from C1-C19, even with

possible corrupted data, whereas the SVM predictor discarded an 8.5% of the shots due to the lack of some required signals of the analyzed pulses.

DISCUSSION

To summarise, several sequences of learning systems that analyze the complete evolution of each pulse have been developed to achieve the highest possible disruption prediction rates. The final predictor has been trained and tested on all types of disruptions from the campaigns up to C7. Subsequently it has been tested over a wide range of shots from more recent campaigns not used for the training. Finally the performance of the SVM predictor has been compared with the JPS.

In the testing stage, that included the campaigns C7 and earlier ones, with the best performing classifier, the overall success rate is 92.73%, with a 0.91% percent of missed alarms. This percentage of missed alarms is the result of 1 error over 110 shots (66 disruptives and 44 non disruptives). The same rate computed only over the disruptive experiments for the same campaigns would be 1.52 % (1 missed alarm over 66 disruptive shots). The missed alarms are minimized and the sum of false and premature alarms is reduced to less than the 6.4%.

The robustness of the predictor has been proven by testing it with a significant number of pulses belonging to more recent campaigns than the ones it was trained with. The relevance of this aspect is significant because the lack of generalisation capability across campaigns was one of the main weaknesses of previous predictors. The results show clearly that the high performances remain fairly constant until a major modification of the device has been implemented. After that, the success is still high but the percentage of errors increases to 9%.

Finally, the developed method has been compared with the JPS used at JET for many years. Considerable higher performances have been attained in the interval up to ~150ms before the disruption. These are especially relevant results due to the fact that the typical time required by the actuators to perform effective mitigation actions at JET is about 30ms.

To conclude, it is worth mentioning that in this work the highest priority has been assigned to reducing the number of missed alarms in order to preserve the integrity of the device. A different balance between these requirements could be reconsidered and the classifier optimised for different operational constraints.

With regard to future developments, it is planned to upgrade the SVM predictor by training it with signals of time interval earlier than 200 ms before the disruptions. So early in the discharges, the main indicator of forthcoming disruptions is the locked mode. By properly increasing the weight of this signal, a significant improvement of the success rate is expected.

ACKNOWLEDGEMENTS

This work was partially funded by the Spanish Ministry of Science and Innovation under the Project No. ENE2008-02894/FTN. This work, supported by the European Communities under the contract of Association between EURATOM/CIEMAT, was carried out within the framework of the European

Fusion Development Agreement. The views and opinions expressed herein do not necessarily reflect those of the European Commission.

REFERENCES:

- [1]. F.C. Schuller 1995. "Disruption in tokamaks". *Plasma Physics Controlled Fusion*. **37** A135–62.
- [2]. B. Cannas, et al. 2006. "Disruption prediction at ASDEX Upgrade using neural Networks". 33rd EPS Conference on Plasma Physics. Contributed Papers, (Eds.) F. De Marco, G. Flad. ECA 30 I. European Physical Society, Geneva, P-2.143.
- [3]. G.A. Rattá, J. Vega, A. Murari and M. Johnson. "Feature extraction for improved disruption prediction analysis at JET". *Review Scientific Instruments* **79**, 10F328 (2008).
- [4]. B. Cannas, et al. 2004. "Disruptions forecasting at JET using Neural Networks". *Nuclear Fusion* **44** 68-76.
- [5]. A. Murari, et al. 2008. "Prototype of an adaptive disruption predictor for JET based on fuzzy logic and regression trees". *Nuclear Fusion* **48** 035010.
- [6]. B. Cannas, R.S. Delogu, A. Fanni, P. Sonato and M.K. Zedda: "Support vector machines for disruption prediction and novelty detection at JET", *Fusion Engineering and Design*, **82**, Issues 5-14 (2007) 1124-1130.
- [7]. B. Cannas, et al. "A prediction tool for real-time application in the disruption protection system at JET". *Nuclear Fusion* **47** No 11 (November 2007) 1559-1569.
- [8]. F. Milani, "Disruption Prediction in JET". PhD Thesis. Univ. of Aston, Birmingham.(1998)
- [9]. G. Pautasso, et al., "On-line prediction and mitigation of disruptions in Asdex. Upgrade", *Nuclear Fusion*, vol. **42**, no.100, 2002.
- [10]. C. Cortes and V. Vapnik, "Support-Vector Networks", *Machine Learning*, **20**, 1995.
- [12]. "The Spider - A machine learning in Matlab". <http://www.kyb.tuebingen.mpg.de/bs/people/spider/main.html> Max-Planck Institute for biological Cybernetics, Tuebingen, Germany.
- [13]. T. Briggs. 2005. MATLAB/MEX Interface to SVMlight. www document, <http://www.ship.edu/~thb/mexsvm/>.
- [14]. P.C. de Vries, M.F. Johnson and I. Segui. "Statistical Analysis of Disruptions in JET". *Nuclear Fusion* **49** (2009) 055011
- [15]. I. Barlow, M. Bigi, J. Bird, G. Bonizzoni, R. Buttery and R. Clay *et al.*, The error field correction coils on the JET machine, *Fusion Engineering and Design* **58–59** (2001), pp. 189–193.
- [16]. A. Santagiustina, S.A. Arshad, G. Bosia, M. Browne, D.J. Campbell, Dapos, G. Antona, G. Fishpool, G.F Neill. "Design of the $m = 2$, $n = 1$ tearing mode control system for JET". *Fusion Engineering - Supplement*, 1993., 15th IEEE/NPSS Symposium on Volume, Issue , 11-15 Oct 1993 Page(s):58 – 61.

Shots (Campaigns)	Number of discharges
Disruptive-train (C7 and earlier ones)	263
Non disruptive-train (C7 and earlier ones)	175
Disruptive-test (C7 and earlier ones)	66
Non disruptive-test (C7 and earlier ones)	44
Disruptive test (C1 to C19)	1245
Non disruptive test (C8 to C19)	331
Total disruptive (C1 to C19)	1574
Total non disruptive (C1 to C19)	550
Total discharges (C1 to C19)	2124

Table 1. List of the databases and total number of discharges used for the analysis.

Signal name	Units
1. Plasma current.	A
2. Poloidal beta.	
3. Poloidal beta time derivative.	s^{-1}
4. Mode lock amplitude.	T
5. Safety factor at 95% of minor radius.	
6. Safety factor at 95% of minor radius time derivative.	s^{-1}
7. Total input power.	W
8. Plasma internal inductance.	
9. Plasma internal inductance time derivative.	s^{-1}
10. Plasma vertical centroid position.	m
11. Plasma density.	m^{-3}
12. Stored diamagnetic energy time derivative.	W
13. Net power (total input power <i>minus</i> total radiated power).	W

Table 2. List of the signals analyzed in each shot.

N°	Shot	Detection Time[s]	Disruption Time[s]	Margin [ms]	Output of M3	Output of M2	Output of M1
1	56658	23.911	24.021	110	-0.910	0.448	0.0852
2a	54827	0	13.866	0	0	0	0
2b	55253	23.101	22.979	-122	-1.800	-1.391	-1.154
3	53740	5.881	10.22	4339	-0.896	-1	0.445
4	56782	0	0	0	0	0	0
5	52641	0.916	0	-916	-1.176	-1.202	-1.008

Table 3. Examples of the six possible cases of correct and incorrect classifications that can occur in practice.

	MA	FA	PA	TE	SR	AVG
Predictor 1 [Sequence 1, DF1]	0	5.4545	5.4545	10.909	89.091	128.01
Predictor 2 [Sequence 2, DF2]	0.909	4.5455	1.8182	7.2727	92.727	146.23
Predictor 3 [Sequence 3, DF3]	0	4.5455	5.4545	10	90	132.23
Predictor 4 [Sequence 4, DF4]	0	5.4545	9.0909	14.545	85.455	128.84
Predictor 5 [Sequence 5, DF5]	0	4.5455	7.2727	11.818	88.182	136.45
Predictor 6 [Sequence 6, DF6]	0	5.4545	5.4545	10.909	89.091	136.23
Predictor 7 [Sequence 7, DF7]	0	5.4545	6.3636	11.818	88.182	121.01

Table 4. Overall test results.

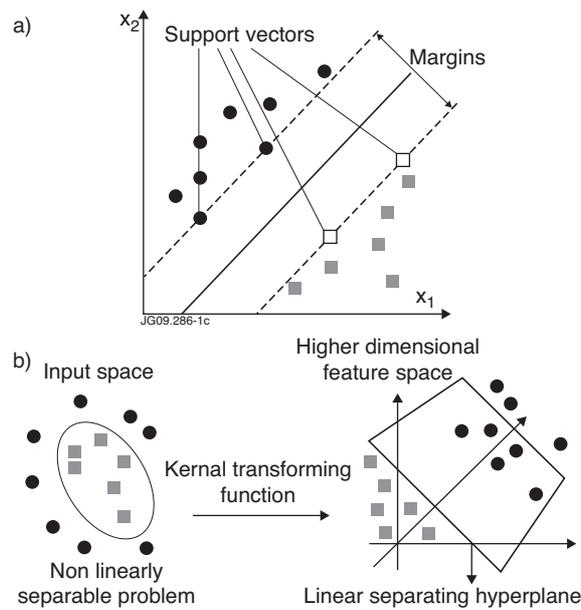


Figure 1: (a) Support vectors providing maximal separation margins in a linearly separable problem. (b) A non linearly separable case solved with a linear separating hyper-plane in a higher dimensional space.

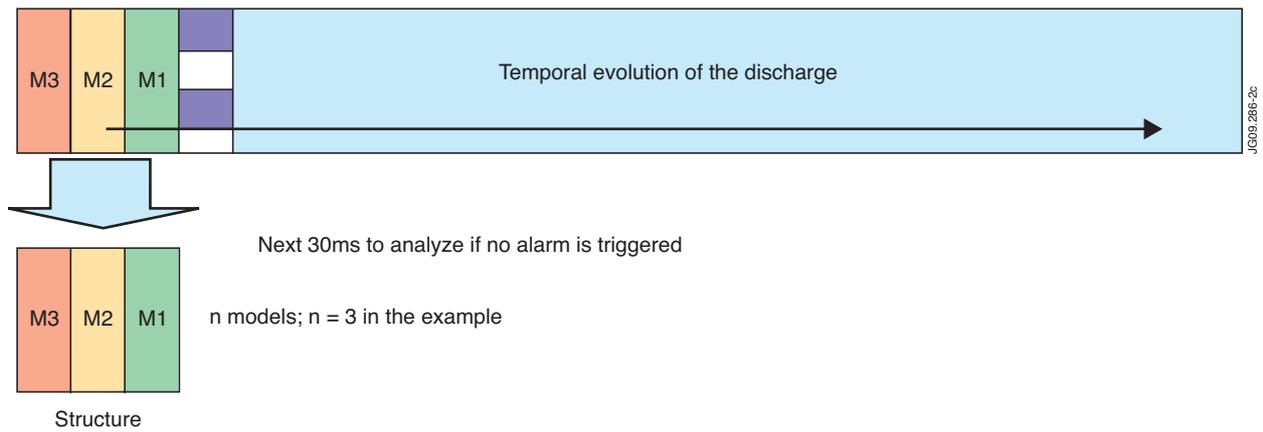


Figure 2: Scheme of the real time analysis of a discharge using a series of classifiers analysing in parallel consecutive time windows.

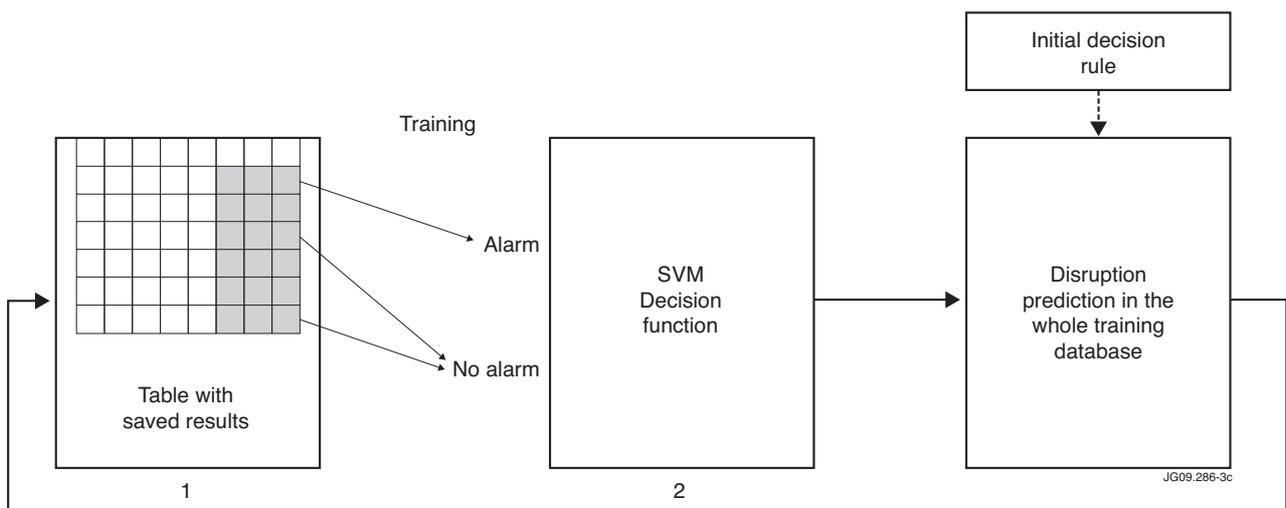


Figure 3: General decision function training scheme.
 (i) The relevant data is stored.
 (ii) A new DF that replaces the previous one is trained.

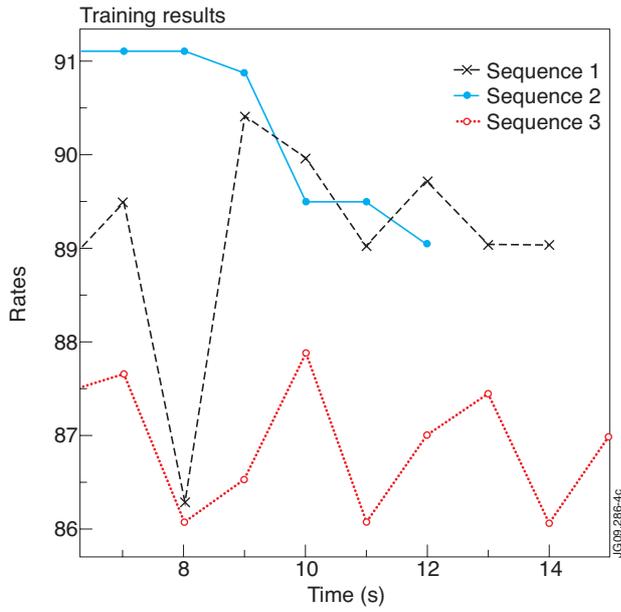


Figure 4: Training results of three sequences. The training procedure is stopped after five iterations

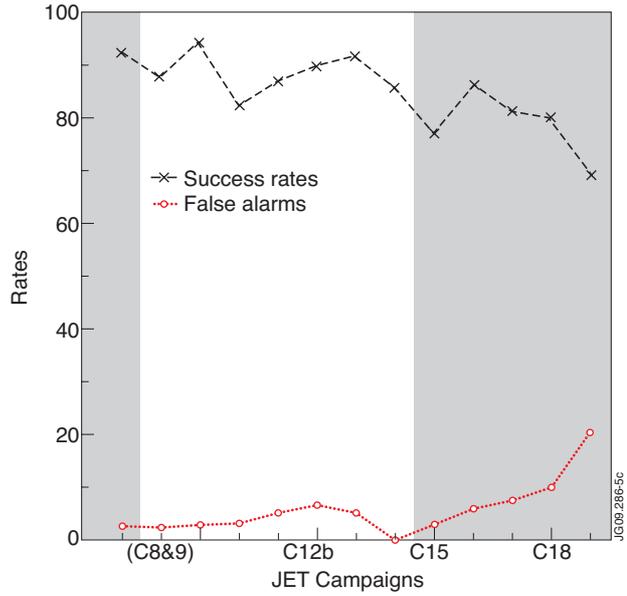


Figure 5: Success and false alarms rates of the previously trained model in posterior campaigns. Three different periods have been independently analyzed. First (left), the training and validation period that includes campaign C7 and earlier ones (light shadowed). Second, the testing period between the campaigns C8 to C14 (middle, not shadowed), Third (right), after structural changes of the device, the period between C15 to C19 (dark shadowed part of the graph).

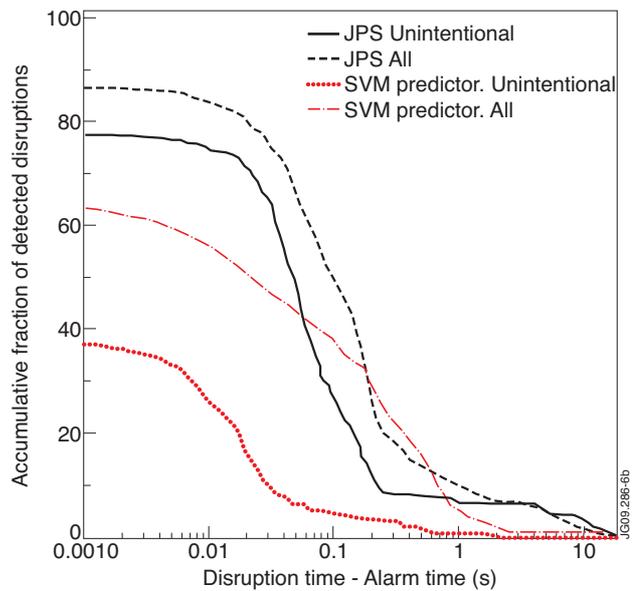
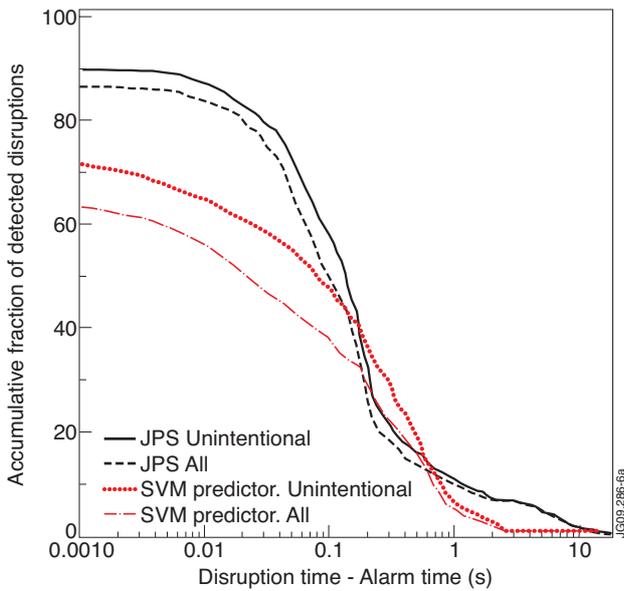


Figure 6: Warning times (disruption time minus alarm time) for all the disruptive pulses from campaign C1 till campaign C19. Top figure: The cumulative percentages of unintentional and all detected disruptions for the SVM method are compared with the JPS results. Bottom figure: The cumulative percentages of intentional and all detected disruptions for the SVM method are compared with the JPS results.