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Robustness and increased time resolution of JET Advanced Predictor of Disruptions

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Abstract
The impact of disruptions in JET is well-known not only with the carbon fiber composite (CFC) wall, but also with the metallic ITER-like wall (ILW). A disruption predictor, called APODIS, was developed and implemented for the JET real-time data network. This predictor uses seven plasma quantities (plasma current, mode lock amplitude, plasma internal inductance, plasma density, stored diamagnetic energy time derivative, radiated power and total input power) and it has been working during the ILW campaigns in JET. It has reached good results in terms of success rate, false alarm rate and prediction anticipation time. However, it is important to note that any signal could fail during any discharge. If an incorrect signal is used by APODIS, this can be an issue for the predictions. Therefore, the first purpose of this article is to determine the robustness of APODIS. Robustness is the predictor reliability when a signal fails. To determine the robustness, anomalous signals have been simulated and the quality of the APODIS predictions has been estimated. The results show that some signals, such as the mode lock and the plasma inductance, are essential for APODIS to provide a reasonable success rate. Under the failure of other signals, APODIS performance slightly decreases but remains acceptable. On the other hand, during the ILW campaigns, APODIS has missed some disruptions due to a lack of temporal resolution in the prediction. Owing to this reason, a second analysis has been carried out in this paper. The effect of increasing the prediction temporal resolution has been analyzed. The plasma signals are digitized at the same sampling frequency (1 ksample s^{-1}) but a sliding window mechanism has been implemented to modify the prediction period from 32 to 1 ms.

Keywords: APODIS, ILW, CFC, sliding window, robustness

(Some figures may appear in colour only in the online journal)

1. Introduction

Disruptions are one of the most critical events in nuclear fusion devices, which could produce fatal consequences for the integrity of future reactors. Due to this fact, disruption prediction with enough warning time is necessary in order to carry out mitigation actions. At present there are no reliable physics-driven predictors because disruptions are difficult to model from the point of view of the theory: event complexity, highly nonlinear interactions and diversity of causes. Focusing the attention on JET, it should be noted that the number of disruptions is different between campaigns [1]. JET with the ITER-like wall (ILW) has increased the number of disruptions, but it is expected disruptions to be reduced as experience is gained on how to operate JET with the new wall [2, 3].

[6] See the annex of Romanelli F *et al* 2012 *Proc. 24th IAEA Fusion Energy Conf. 2012 (San Diego, CA, 8–13 October 2012)* www.fec2012.com.

With regard to disruption prediction, several studies have been developed in the past. Typically, they have been based on support vector machines (SVMs) and neural networks [4–9]. The models developed in [4–9], are able to learn from the data in the so-called training process. To train a predictor, a large number of discharges (hundreds or thousands of them) is necessary (the larger the better). Disruption predictors are binary classification systems that allow distinguishing between disruptive and non-disruptive plasma behaviors. The training process obtains a decision function (or model) to split the feature space into two regions that correspond to the aforementioned plasma behaviors. After the training process, the model can be used to detect the presence of a forthcoming disruption. At any time instant, the plasma behavior is represented by a feature vector $\boldsymbol{x} \epsilon \boldsymbol{R}^m$ whose components are features of distinctive nature. The classification of the feature vector as disruptive or non-disruptive is based on the location of the vector in relation to the decision function.

Also, it is important to mention that only real-time implementations of predictors are useful for disruption prediction. In addition, the goals of any predictor are to show high success rates, low rate of false alarms and to trigger the alarm with enough anticipation time to carry out mitigation actions.

APODIS (Advanced Predictor Of DISruptions) is a disruption predictor that was installed in the JET real-time network [9, 11]. APODIS uses several plasma quantities under different representations (time domain and frequency domain) to form the feature vectors by means of which is possible the recognition of an incoming disruption.

APODIS has obtained good results during the ILW campaigns (success rate above 98% and false alarm rate below 1%) [9], but it is clear that any signal can fail during a discharge and, therefore, it is a potential source of errors that can cause wrong predictions, i.e. missed alarms and/or false alarms. The first part of this article analyzes the APODIS robustness to signal failures. On the other hand, it has also been shown that APODIS misses some disruptions due to the lack of time resolution. Therefore, the second part of this paper is devoted to analyzing the results of APODIS versions with different temporal resolutions (from 32 ms up to 1 ms). The several implementations have been carried out without modifying the signal sampling rate, which is 1 ksample s^{-1} for each signal. Instead, a sliding window mechanism has been implemented.

Section 2 presents a review of APODIS. Section 3 deals with the APODIS robustness. Simulations of signal failures are carried out and the prediction results are discussed. Section 4 describes the sliding window mechanism to increase the temporal resolution of the predictions and how the predictions are modified. Finally, section 5 summarizes the results.

2. APODIS review

APODIS was defined as a combination of SVMs classifiers that use features from different JET signals with the aim of recognizing forthcoming disruptions. APODIS was trained with more than 4000 JET discharges between 2006 and 2008 (4070 non-disruptive discharges and 246 unintentional disruptions) and the resulting model was installed in the JET real-time network [11]. At present, APODIS works with seven JET signals (table 1) that are used under two different representations: time and frequency. This means that the feature vectors that are analyzed by APODIS have 14 components (seven in the time domain and seven in the frequency domain), $\boldsymbol{x} \epsilon \boldsymbol{R}^{14}$. The features are determined every 32 ms and this is the time period to identify a disruptive behavior. In the time domain, the features correspond to the mean value of the signals during the preceding 32 ms. In the frequency domain, the Fourier spectrum of each signal in the previous 32 ms is computed. APODIS uses as feature the standard deviation of each signal power spectrum after removing the dc component [10].

APODIS shows a two-tier structure. The first tier consists of three independent SVM classifiers which operate in parallel on consecutive 32 ms time windows. As a discharge is in execution, the three most recent 32 ms temporal segments are classified as disruptive or non-disruptive (figure 1) by M1, M2 and M3. Of course, it should be noted that each classifier (M1, M2 and M3) can make a different prediction. Therefore,

Table 1. List of signals used by APODIS to characterize plasmas.

Signal name	Units
Plasma current	A
Mode lock amplitude	T
Plasma internal inductance	
Plasma density	m^{-3}
Stored diamagnetic energy time derivative	W
Radiated power	W
Total input power	W

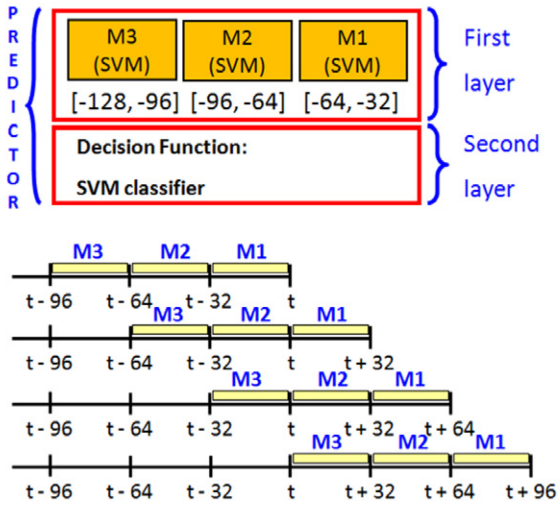

Figure 1. APODIS structure. The first tier, made up of three SVM classifiers, classifies the three most recent 32 ms temporal segments as disruptive or non-disruptive. Each classifier has been trained in a different temporal segment. Classifiers M1, M2 and M3 have been trained with disruptive examples in the intervals [−64, −32] ms, [−96, −64] ms and [−128, −96] ms respectively before the disruption. The outputs from the first tier are used as inputs to the second tier (another SVM classifier). This one decides whether to trigger an alarm. The APODIS temporal resolution is 32 ms.

it is necessary to combine the three outputs into a single one through the use of the second tier classifier. To this end, the M1, M2 and M3 outputs are used as inputs to the second tier, which is also a SVM classifier. This SVM classifier works as a decision function to decide whether or not to trigger an alarm.

The whole training and test process for APODIS is fully described in [9]. The APODIS predictor that is working in JET was trained with discharges produced during carbon fiber composite (CFC) campaigns and it has been working in real-time from the first ILW campaign [9, 11] without any retraining. After the three first JET ILW experimental campaigns (956 discharges, formed by 305 non intentional disruptions and 651 non-disruptive discharges), the success rate of the predictor is 98.36% (the average warning time (AWT) is 426 ms before the disruptions). The false alarm and missed alarm rates are 0.92% and 1.64% respectively [9].

3. Robustness analysis

This section explains the APODIS robustness analysis. Robustness is defined as the predictor reliability when a signal fails. The reliability has to be understood in terms of the success rate and the false alarm rate (fraction of non-disruptive discharges that are recognized as disruptive ones). In this article, the success rate is defined as the fraction of disruptive discharges that have been predicted with enough anticipation time. Enough anticipation time means to trigger an alarm well in advance to be able to put in operation mitigation actions. Usually, the minimum time in JET to activate the disruption mitigation valve is about 30 ms [1]. Therefore, only predictions whose anticipation times are greater than or equal to 30 ms will be considered a success. However, it is important to mention that disruptions predicted with less than 30 ms cannot be considered missed alarms. Therefore, disruptions with anticipation times between 1 and 30 ms have been considered tardy detections.

To accomplish the robustness analysis, simulations have been performed. These simulations replace one by one the signals of table 1 (except the plasma current) for a synthetic one. Two different scenarios have been considered. In the first one, a synthetic signal with mean value 0 and Gaussian noise is used during the whole discharge. This simulation can correspond to a situation in which some kind of instrumentation (power supplies, amplifiers, analog to digital converters, data transmission lines or so) fails without notice. In the second scenario, a different situation is generated. The test simulates the failure of a signal from a certain time of a discharge and the amplitude remains the same but with a Gaussian noise added.

This section is split in two subsections. Section 3.1 describes both the database and the simulations that have been performed. The robustness results are shown in section 3.2.

3.1. Database and simulations

The purpose of the reliability analysis is not to select the best signals for APODIS [12] but to determine the changes in the success and false alarm rates when a signal is in failure. As mentioned, the simulations replace each signal for a synthetic one. The plasma current was not substituted because it is the signal that switches on/off the APODIS predictor when it crosses a threshold of 750 kA.

Table 2. Database used for robustness analysis.

Campaign	Non int. disruption	Safe	Total
CFC campaigns 2008–2010			
C23	24	490	514
C24	14	36	376
C25	19	570	89
C26	58	1323	1381
C27a	43	320	363
C27b	70	513	583
C23–C27b	228	3578	3806
ILW campaigns 2011–2012			
	201	1036	1237

It should be noted that the feature vectors have dimension 14 and, therefore, the simulation of a signal in failure means to have two wrong features in each predictor input. This is a consequence of using both time and frequency domains for each signal.

To carry out the simulations, an off-line APODIS version and a huge database of discharges have been used (from both CFC and ILW campaigns). On the one hand, 3578 non-disruptive discharges and 228 unintentional disruptions between years 2008–2010 (CFC campaigns) have been considered. On the other hand, 1036 non-disruptive discharges and 201 unintentional disruptions from ILW campaigns (years 2011–2012) have been analyzed (table 2).

As mentioned, the robustness analysis performs two different simulations, where the difference resides on the different amplitudes that use the synthetic signals:

(a) The first simulation replaces the whole signal for a Gaussian noise distribution N (0, 1), where the notation $N(\mu, \sigma)$ is the usual one to represent a Gaussian distribution with mean μ and standard deviation σ (figure 2).
(b) The second simulation changes the latest 5 s of the signals by a Gaussian noise distribution N (0, 1). The latest 5 s are selected in different ways for non-disruptive and disruptive discharges. For non-disruptive discharges, they correspond to the latest 5 s before the plasma current crosses the 750 kA threshold in the ramp down. In the case of disruptive discharges, the 5 s interval coincides with the previous 5 s before the disruption (figure 3).

3.2. Robustness results

The results (table 3 for CFC campaigns and table 4 for ILW campaigns) show the same statistics in both simulations (figures 2 and 3), i.e., either replacing the whole signal for a Gaussian noise synthetic signal or replacing the signal at a certain time for a Gaussian noise synthetic signal. The worst results appear when the mode lock and the plasma inductance signals are in failure (figures 4 and 5). Therefore, these signals are absolutely necessary for APODIS. If either the mode lock or the plasma inductance signal is in failure, APODIS produces wrong predictions.

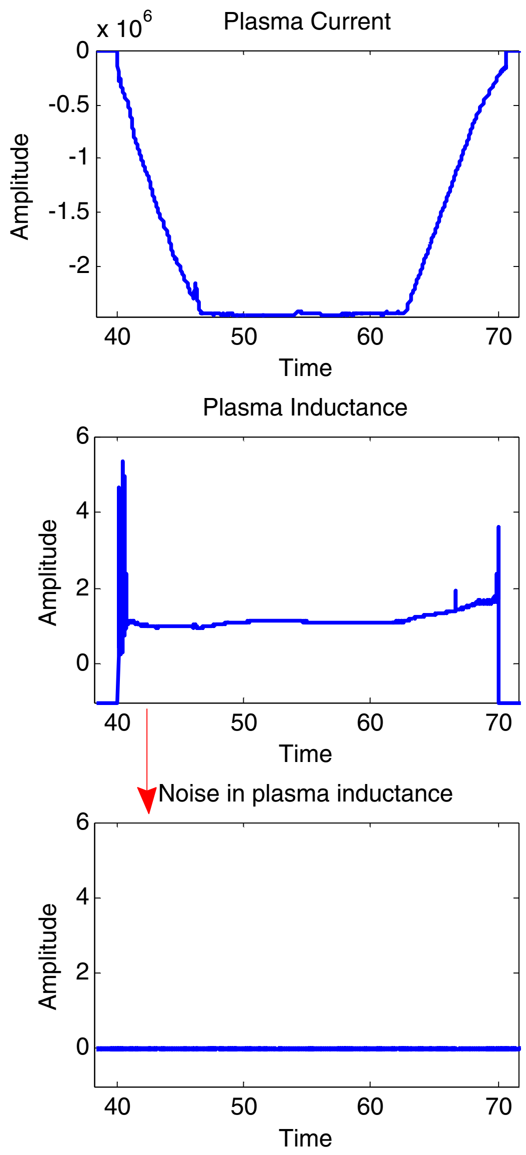

Figure 2. Replacement of the whole plasma inductance signal with a Gaussian noise distribution N (0,1) in a non-disruptive discharge.

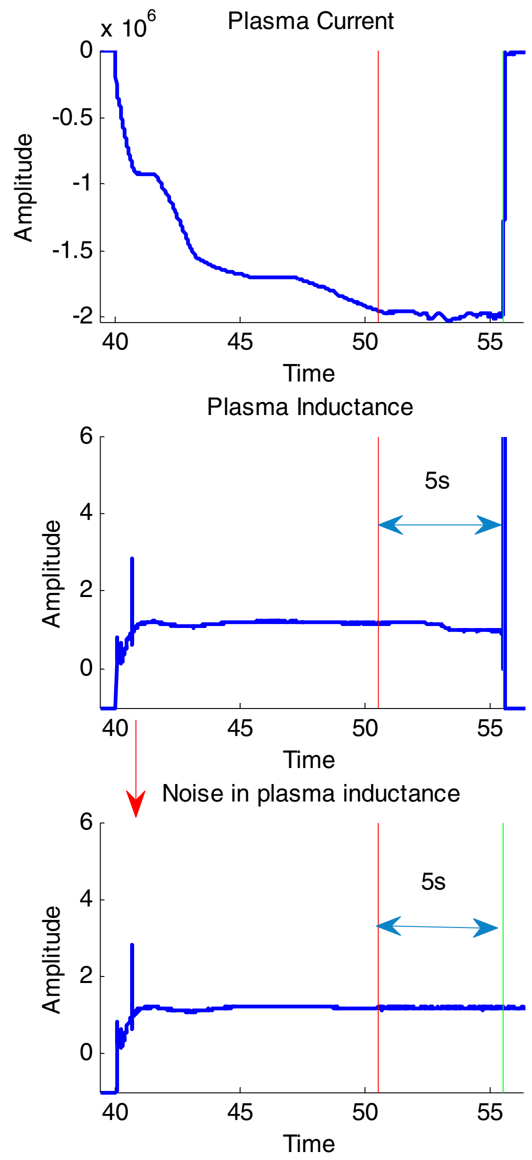

Figure 3. The latest 5 s of the plasma inductance signal are replaced with a Gaussian noise distribution N(0,1) in a disruptive discharge.

It should be emphasized that the results of tables 4 and 5 in relation to the simulations with all signals in the ILW discharges do not coincide with the rates given at the end of section 2. The APODIS real-time software is in execution in the JET real-time network from the discharge 82429. However, the off-line simulation starts in shot 81852.

On the other hand, the other signals, plasma density, diamagnetic energy time derivative, radiated power and total input power, are also important but have less impact in the prediction than the mode lock and the plasma inductance. Whereas the mode lock and the plasma inductance signals are essential, failures in the remaining signals slightly decrease the success rate. For example, figure 6 shows the case of the diamagnetic energy time derivative in which the success rate remains around 65% (instead of 69%) in the CFC campaigns and 73% (instead of 77%) in ILW discharges.

Also, the AWT has been analyzed. Table 5 shows the AWT obtained in CFC and ILW campaigns by simulating both the whole signal in failure and the latest 5 s of the signal in failure. It is important to note in this table that the off-line analysis with all the signals shows an AWT value of 491 ms (with a standard deviation of 1.320 s). The simulation of failure in the mode lock and in the plasma inductance gives very bad success rate and, therefore, in these cases the computation of the AWT does not make sense. Focusing the attention on the rest of the signals, the average AWT corresponding to failures in plasma density, FWDIA (stored diamagnetic energy time derivative) , radiated power and total input power in CFC campaigns is 489 ms (with a mean standard deviation of 1.093 s). With regard to the simulations corresponding to the ILW campaigns, the average AWT is 561 ms and the mean standard deviation is 1.695 s.

Table 3. CFC: C23–C27b robustness result. Both types of signal failure provide similar outcomes.

CFC campaigns 2008–2010				
Signals	Success rate	Tardy alarm rate	Missed alarm rate	False alarm rate
Replacement of the whole signal (figure 2)				
Offline analysis with all signals	69.3% (158/228)	11.4% (26/228)	19.3% (44/228)	7.5% (267/3578)
Mode lock failure	0% (0/228)	0% (0/228)	100%(228/228)	0% (0/3578)
Plasma inductance failure	1.3% (3/228)	1.3% (6/228)	97.4% (222/228)	0.3%(11/3578)
Plasma density failure	68.4% (156/228)	11.4% (26/228)	20.2%(46/228)	6.7% (239/3578)
FWDIA failure	64.9% (148/228)	8.8%(20/228)	26.3%(60/228)	4.1% (147/3578)
Radiated power failure	69.3% (158/228)	11.4% (26/228)	19.3% (44/228)	7.4% (266/3578)
Total input power failure	68.0% (155/228)	11.0% (25/228)	21.0% (48/228)	7.1% (254/3578)
Replacement of the last 5s of the signal (figure 3)				
Offline analysis with all signals	69.3% (158/228)	11.4% (26/228)	19.3% (44/228)	7.5% (267/3578)
Mode lock failure	0% (0/228)	0% (0/228)	100% (228/228)	0% (0/3578)
Plasma inductance failure	2.6% (6/228)	0.9% (2/228)	96.5% (220/228)	0.6%(20/3578)
Plasma density failure	68.4% (156/228)	11.4% (26/228)	20.2%(46/228)	6.7% (239/3578)
FWDIA failure	64.9% (148/228)	8.8%(20/228)	26.3%(60/228)	4.1% (147/3578)
Radiated power failure	69.3% (158/228)	11.4% (26/228)	19.3% (44/228)	7.4% (266/3578)
Total input power failure	68.0% (155/228)	11.0% (25/228)	21.0% (48/228)	7.1% (254/3578)

Table 4. ILW: C28–C30 robustness result. Again, similar results are obtained with the two simulations about the failures in signals that have been carried out.

ILW campaigns 2011–2012				
Signals	Success rate	Tardy alarm rate	Missed alarm rate	False alarm rate
Replacement of the whole signal (figure 2)				
Offline analysis with all signals	76.6% (154/201)	8.5% (17/201)	14.9% (30/201)	2.2% (23/1036)
Mode lock failure	0% (0/201)	0% (0/201)	100% (201/201)	0% (0/1036)
Plasma inductance failure	3.5% (7/201)	1.0% (2/201)	95.5% (192/201)	0% (0/1036)
Plasma density failure	72.6% (146/201)	9.5% (19/201)	17.9% (36/201)	1.5% (16/1036)
FWDIA failure	73.1% (147/201)	7.0% (14/201)	19.9% (40/201)	1.5% (15/1036)
Radiated power failure	75.6% (152/201)	9.0% (18/201)	15.4% (31/201)	2.0% (21/1036)
Total input power failure	78.1% (157/201)	8.5% (17/201)	13.4% (27/201)	3.0% (31/1036)
Replacement of the last 5s of the signal (figure 3)				
Offline analysis with all signals	76.6% (154/201)	8.5% (17/201)	14.9% (30/201)	2.2% (23/1036)
Mode lock failure	0% (0/201)	% (/201)	% (/201)	0% (0/1036)
Plasma inductance failure	8.5% (17/201)	0.5% (1/201)	91.0% (183/201)	6.3% (65/1036)
Plasma density failure	72.6% (146/201)	9.5% (19/201)	17.9% (36/201)	1.5% (16/1036)
FWDIA failure	73.1% (147/201)	7.0% (14/201)	19.9% (40/201)	1.5% (15/1036)
Radiated power failure	75.6% (152/201)	9.0% (18/201)	15.4% (31/201)	2.0% (21/1036)
Total input power failure	78.1% (157/201)	8.5% (17/201)	13.4% (27/201)	3.0% (31/1036)

4. Sliding window mechanism to increase the temporal resolution of the predictions

During the ILW campaigns, APODIS has missed some disruptions due to the lack of time resolution [9]. The predictor is enabled whenever the plasma current is above the threshold of 750 kA. Figure 7 shows a typical example of missed alarm as a consequence of a prediction period of 32 ms. Point A in figure 7 indicates the last prediction of APODIS for the given discharge. The prediction at that time is 'non-disruptive'. During the next 32 ms, a disruption takes place and the plasma current crosses the threshold of 750 kA. Therefore, APODIS is disabled and no more predictions are carried out. Consequently, the alarm is missed.

The effect of increasing the APODIS temporal resolution is analyzed in this section. Section 4.1 explains the database used for these purposes and describes the simulations performed to increase the time resolution by using a sliding window mechanism. Section 4.2 shows the results obtained from the simulations.

4.1. Database and simulation

As it was explained previously, APODIS makes a prediction every 32 ms. This prediction period should be shortened as much as possible in order to detect any disruption signature as soon as possible. Reference [11] shows that the computation time in the JET real-time network to form a feature vectors is hundreds of μs. Therefore, a time resolution of 1 ms can be achieved. The objective in the present analysis is not to change the sampling rate of the APODIS signals (which remain limited to 1 ksamples s^{-1}), but to change the time resolution of the prediction by implementing a sliding window mechanism. This mechanism allows APODIS implementing different time resolutions (16, 8, 4, 2 or 1 ms). In this way, APODIS is able to

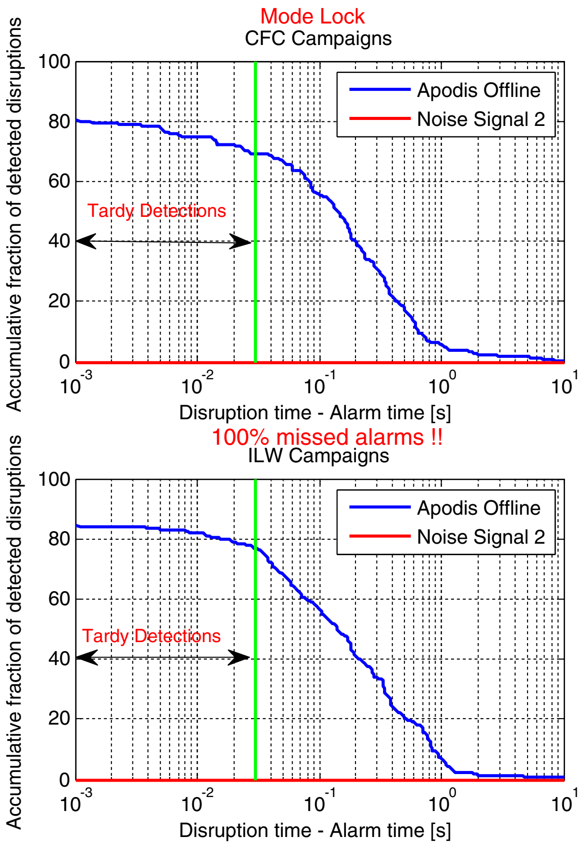

Figure 4. Results for CFC campaigns and ILW campaigns with mode lock signal in failure. The green line shows the time of 30 ms before the disruptions.

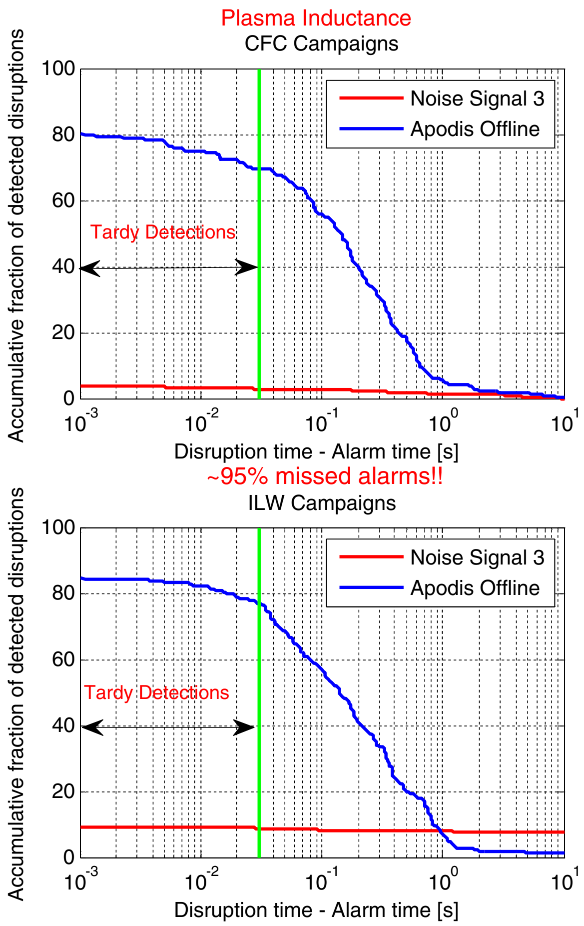

Figure 5. Results for CFC campaigns and ILW campaigns with plasma inductance signal failure. The green line shows the time of 30 ms before the disruption.

trigger an alarm every 16, 8, 4, 2 or 1 ms instead of the current temporal resolution of 32 ms (figure 8).

The database used in this analysis is made up of discharges from the three first ILW campaigns C28–C30. It is the same database used in section 3.1 for the ILW campaigns (table 2), which is made up of 1036 non-disruptive discharges and 201 unintentional disruptions.

4.2. Sliding window results

The results (table 6 and figure 9) show how the success rate increases for higher temporal resolutions, reaching a success rate of 83% for 1 ms of temporal resolution. Furthermore, higher temporal resolutions allow achieving better success rate and also reducing the missed alarm rates (table 6 and figure 9). On the other hand, while the success rate is increased for higher temporal resolutions, the false alarm rate also increases (table 6).

5. Conclusions

On the one hand, the robustness analysis shows that the mode lock and the plasma inductance signals are essential for APODIS. Any failure in these signals produces very low success rates, (0% for the mode lock signal failure and 5–10% for the plasma inductance signal failure). The other signals (plasma density, diamagnetic energy time derivative, radiated power and total input power) are also important but have a less impact. Failures in them produce success rates around 75%. The simulations that add Gaussian noise provide similar results. Focusing on the radiated power signal, it can be observed in tables 3 and 4 that its failure provides the same

Table 5. AWTs and standard deviation (STD) for CFC and ILW campaigns results.

Signals	AWT (ms)	STD (s)
Substitution for synthetic signal		
CFC campaigns 2008–2010		
Offline analysis with all signals	491	1.320
Mode lock failure	—	—
Plasma inductance failure	—	—
Plasma density failure	531	1.342
FWDIA failure	371	0.707
Radiated power failure	590	1.440
Total input power failure	463	0.884
ILW		
Offline analysis with all signals	573	1.667
Mode lock failure	—	—
Plasma inductance failure	—	—
Plasma density failure	515	1.703
FWDIA failure	561	1.700
Radiated power failure	561	1.678
Total input power failure	608	1.700

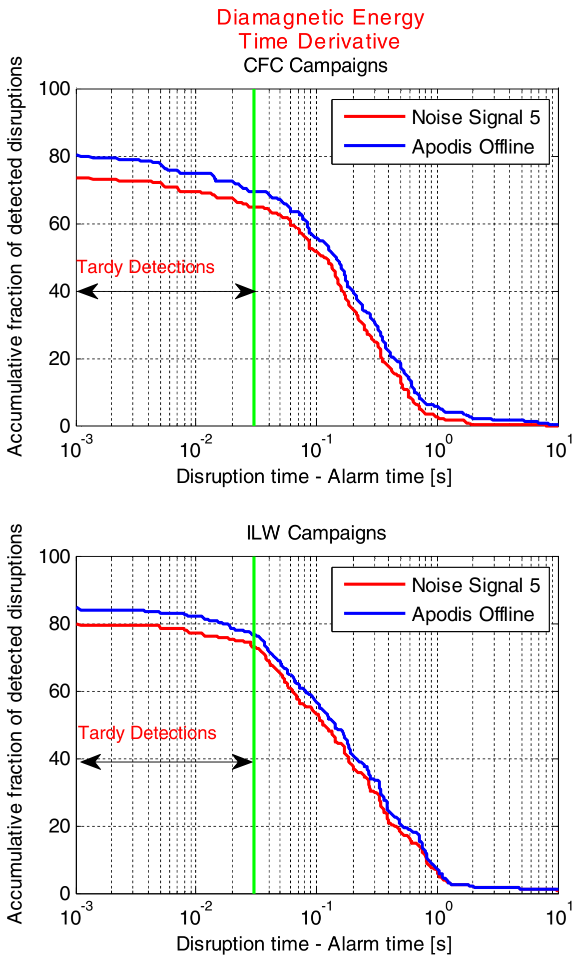

Figure 6. Results for CFC campaigns and ILW campaigns with diamagnetic energy time derivative signal failure. The green line shows a time of 30 ms before the disruption.

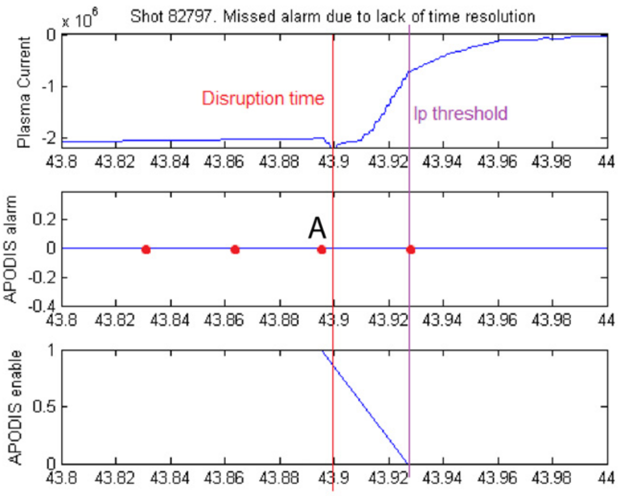

Figure 7. Example of missed alarm due to a lack of resolution. APODIS is disabled after the prediction in the point A because the plasma current becomes lower than 750 kA. This disruption would be predicted with a higher temporal resolution.

success rate and lower false alarm rate than the rest of the signals. It is interpreted as a specific result on the range of pulses used in the analysis, and more analysis with the

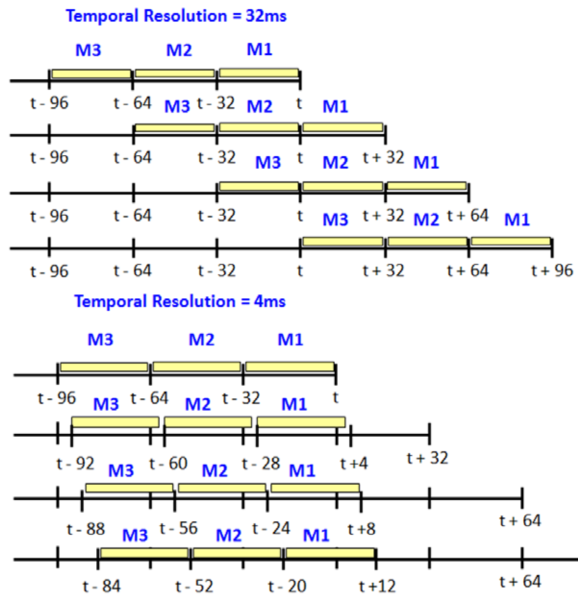

Figure 8. Example of temporal resolution of 32 ms (how APODIS works currently at JET) and temporal resolution of 4 ms.

Table 6. Sliding window rates: the first column shows the different time resolution, i.e. the frequency that APODIS will be able to trigger an alarm. The second and third column show success and false alarm rates.

Temporal resolution (ms)	Success rate	Tardy alarm rate	Missed alarm rate	False rate
32	76.6% (154/201)	8.0% (16/201)	15.4% (31/201)	2.9% (30/1036)
16	80.6% (162/201)	7.0% (14/201)	12.4% (25/201)	4.4% (46/1036)
8	81.6% (164/201)	7.5% (15/201)	10.9% (22/201)	5.0% (52/1036)
4	82.1% (165/201)	7.5% (15/201)	10.4% (21/201)	5.6% (58/1036)
2	82.5% (166/201)	8.5% (17/201)	9.0% (18/201)	6.0% (62/1036)
1	83.0% (167/201)	8.5% (17/201)	8.5% (17/201)	6.0% (62/1036)

incoming campaigns should be done to better understand this behavior.

A potential alternative to use the APODIS model with one signal in failure is to have trained different models with only six quantities (it is assumed that is in failure either the plasma density or the FWDIA or the radiated power or the total input power). This possibility has not yet been explored because the first objective was to know the limitations of the present APODIS predictor.

On the other hand, sliding window analysis shows that higher temporal resolutions can help to achieve better success rates, reaching 83% success rate and 8.5% tardy alarm rate for 1 ms resolutions. Despite of this, the false alarm rate slightly increases for higher temporal resolutions. Focusing on false alarm rate in table 6, 32 ms and 1 ms resolutions show 2.9% and 5.98% of false alarm rate respectively, which means an important difference. Higher time resolutions provide better

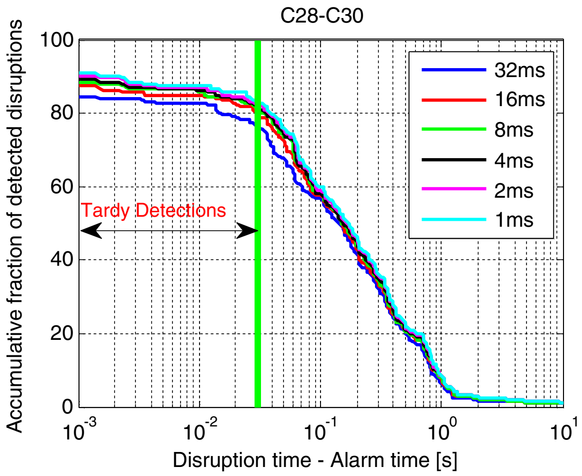

Figure 9. Sliding window results: higher temporal resolutions obtain better results, i.e. higher success rate and better predictions. The green line shows time of 30 ms before the disruption.

warning times, so if the main problem to overcome disruptions is to have enough time to carry out mitigation actions, we can conclude that increasing the temporal resolution of APODIS would be a good improvement in terms of both success rate and warning times.

Acknowledgments

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References

[1] De Vries P C *et al* 2009 Statistical analysis of disruptions in JET *Nucl. Fusion* **49** 055011
[2] De Vries P C *et al* 2012 The impact of the ITER-like wall at JET on disruptions *Plasma Phys. Control. Fusion* **54** 124032–40
[3] Matthews G on behalf of JET-EFDA Contributors 2013 Plasma operation with metallic walls: direct comparisons with the all carbon environment *J. Nucl. Mater.* **438** S2–S10
[4] Yoshino R 2005 Neural-net predictor for beta limit disruptions in JT-60U *Nucl. Fusion* **45** 1232–46
[5] Windsor C G *et al* 2005 A cross-tokamak neural network disruption predictor for the JET and ASDEX Upgrade tokamaks *Nucl. Fusion* **45** 337–50
[6] Cannas B *et al* 2007 A prediction tool for real-time application in the disruption protection system at JET *Nucl. Fusion* **47** 1559–69
[7] Murari A *et al* 2008 Prototype of an adaptive disruption predictor for JET based on fuzzy logic and regression trees *Nucl. Fusion* **48** 68–76
[8] Rattá G A, Vega J, Murari A, Vagliasindi G, Johnson M F, de Vries P C and JET-EFDA Contributors 2010 An advanced disruption predictor for JET tested in a simulated real-time environment *Nucl. Fusion* **50** 025005
[9] Vega J, Dormido-Canto S, López J M, Murari A, Ramírez J M, Moreno R, Ruiz M, Alves D, Felton R and JET-EFDA Contributors 2013 Results of the JET real-time disruption predictor in the ITER-like wall campaigns *Fusion Eng. Des.* **88** 1228–31
[10] Rattá G A, Vega J, Murari A, Johnson M and JET-EFDA Contributors 2008 Feature extraction for improved disruption prediction analysis at JET *Rev. Sci. Instrum.* **79** 10F328
[11] López J M, Vega J, Alves D, Dormido-Canto S, Murari A, Ramírez J M, Felton R, Ruiz M, de Arcas G and JET-EFDA Contributors 2014 Implementation of the disruption predictor APODIS in JET's Real-time network using the MARTe Framework *IEEE Trans. Nucl. Sci.* **61** 741–4
[12] Rattá G A, Vega J, Murari A and JET-EFDA Contributors 2012 Improved feature selection based on genetic algorithms for real time disruption prediction on JET *Fusion Eng. Des.* **87** 1670–8