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Preprint of Paper to be submitted for publication in Plasma Physics and Controlled Fusion

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Robustness and Increased Time Resolution of JET Advanced Predictor of Disruptions (APODIS)

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** See annex of F. Romanelli et al, "Overview of JET Results",*
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ABSTRACT
The impact of disruptions in JET is well-known not only with the CFC (Carbon Fiber Composite) 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 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 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. Because of 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 (1ksample/s) but a sliding window mechanism has been implemented to modify the prediction period from 32ms to 1ms.

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. Because of this reason, 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 number of disruptions is different between campaigns [1]. Currently the number of disruptions has increased with the ILW, but it is expected to reduce with increasing experience on how to operate with the new wall [2, 3].

Several studies have been developed mainly based on support vector machines (SVM) and neural networks to overcome the disruption prediction [4-9].

The models made in [4-9], are able to learn from data in the training process, using hundreds and thousands discharges from the databases of the respective fusion devices. After the training process, models could be used to detect disruptions, but it is not enough to overcome this issue, a disruption predictor has to be able to work in real time. Moreover a disruption predictor should provide high success rates and warning times to carry out mitigation actions. Previous works do not show the possibility to be implemented in real time or they have not been used in real time.

APODIS (Advanced Predictor of Disruptions) is a data-driven system that was installed in the JET real time network [9]. This predictor uses several plasma quantities under different representations (time domain and frequency domain) to recognize incoming disruptions.

Looking to the future that lays ahead, ITER will need a disruption predictor able to learn from scratch due to the fact that there will be no database to start. Recent studies have been developed with good results [12, 13].

Although APODIS has obtained good results during the ILW campaigns, it is clear that any signal could fail during a discharge. If one of the signals used by APODIS fails, it can cause errors in the predictions: missed alarms and/or false alarms. The first part of this article shows the APODIS robustness analysis when any of its input signals fail.

On the other hand, it has also been seen that APODIS misses some disruptions due to the lack of time resolution. The second part of this paper is devoted to showing the results of an APODIS version with different temporal resolutions (up to 1 ms) by implementing a sliding window mechanism. 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 conclusions.

2. APODIS REVIEW

APODIS was defined as a combination of Support Vector Machines (SVM) classifiers which use features from different JET signals with the aim of predicting disruptions [8, 10]. 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 [9]. At present, APODIS works with 7 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 (7 in the time domain and 7 in the frequency domain). 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 [9].

The whole training and test process for APODIS is fully described at [8]. APODIS algorithm that is working in JET was trained with discharges produced during the CFC campaigns and it has been working in real time from the first ILW campaign [9, 11]. After the first 3 JET ILW campaigns (991 discharges, formed by 305 non intentional disruptions, 35 intentional disruptions and 651 non disruptive discharges), the success rate of the predictor is 98.36% (alarms are triggered in average 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 explain the robustness analysis consisting of different simulations replacing the real signal that APODIS uses, with a Gaussian noise distribution in two different ways. The Gaussian noise simulates the failure of a signal, typically the unavailability of a measurement. Two different scenarios are considered: firstly the signal is assumed to be missing during the whole discharge; secondly it is assumed that only a part of the discharge is affected by the problem with the signal. Subsection 3.1 shows the database and simulations which have been performed. Then the robustness results are shown in subsection 3.2.

3.1 DATABASE AND SIMULATIONS

Robustness could be defined as the sensitivity and effectiveness of the predictor reliability when a signal fails. The purpose of this study is not to select the best signals for APODIS [14] but to determine the APODIS reliability depending on the failed signal. The simulations have been carried out for every signal APODIS uses, except the plasma current, which enables or disables APODIS when it crosses the 750kA threshold.

To carry out this analysis, an offline version of APODIS has been used and a huge database formed by 3578 non disruptive discharges and 228 non intentional disruptions from CFC campaigns (years 2008-2010) and 1036 non disruptive discharges and 201 non intentional disruptions from ILW campaigns (years 2011-2012)(Table 2). This database is processed replacing the real signal by a Gaussian noise distribution and then these new discharges with signal failures are tested using an offline APODIS version.

The robustness analysis performs two different simulations by using Gaussian noise instead of the real signals. The whole database is generated replacing the real signal in two ways (mentioned below) and then a whole test is carried out to obtain the reliability of APODIS with the failed signal:

a) First simulation replaces the whole signal by Gaussian noise distributions with $\mu = 0$ and $\sigma = 1$, N (0, 1). (Figure 2).
b) Second simulation replaces the latest 5s of the signals by Gaussian noise distributions with $\mu = 0$ and $\sigma = 1$, N (0, 1). The latest 5s are selected in different ways for non disruptive and disruptive discharges. For non disruptive discharges, the previous 5s before plasma current crosses the 750kA threshold in ramp down; and disruptive discharges, the previous 5s before disruption time (Figure 3).

3.2. ROBUSTNESS RESULTS.

The results (*Table 3* for CFC campaigns and *Table 4* for ILW campaigns) show similar statistics in both simulations, the main difference is the time to disruption. If the mode lock and plasma inductance signals fail (Figures 4 and 5), 100% and 95% of missed alarms are respectively obtained. Therefore, these signals are absolutely necessary for APODIS. If the mode lock or the plasma inductance signals fail, very low success rate is obtained.

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, which remains around 80-90% (Figure 6).

4. SLIDING WINDOW MECHANISM TO INCREASE THE TEMPORAL RESOLUTION OF THE PREDICTIONS

During ILW campaigns, APODIS has missed some disruptions due to a lack of resolution [4]. This section is divided in two subsections. Subsection 4.1 explains the database formed by discharges from ILW campaigns during the years 2011-2012 and the simulation based on different temporal resolution sliding windows. Then subsection 4.2 shows the sliding window results obtained from the simulations.

4.1. DATABASE AND SIMULATION

APODIS analyzes windows every 32ms. Hence, it cannot trigger an alarm during the 32 ms in which it is analyzing the new data and APODIS disables before trigger an alarm (Figure 7). If the temporal resolution is higher than 32ms, these alarms would be triggered. The idea in this analysis is not to change the sampling rate of APODIS (which remains limited by the 1 ms sampling rate of the measurements), but to change the temporal resolution by implementing a mechanism of sliding windows. This mechanism allows APODIS to implement different time resolutions (16, 8, 4, 2 or 1ms). This way, APODIS could trigger an alarm every 16ms, 8ms, 4ms, 2ms or 1ms instead of the present temporal resolution of 32ms (Figure 8).

The database used in this analysis is made up of discharges from ILW campaigns C28-C30. It is the same database used in 3.1 for the ILW campaigns (Table 2), formed by 1036 non disruptive discharges and 201 non intentional disruptions. Although an offline version of APODIS has been used in this study, it is important to mention that APODIS online (APODIS working in real time at JET) started at shot 82429; however, this database starts at shot 81852, when every signal was available as raw signal. In addition, every shot has been preprocessed with the sliding window mechanism, that is, the mean value of the signals during the preceding 32 ms and the Fourier spectrum of each signal in the previous 32 ms, are computed every 16, 8, 4, 2 and 1ms. Once the whole campaign is preprocessed for each temporal resolution, a test of the whole campaign is carried out.

4.2. SLIDING WINDOW RESULTS

The results (Table 5 and Figure 9) show how the success rate increases for higher temporal resolutions, reaching a success rate of 98% for 1ms and 2ms temporal resolution. Furthermore, higher temporal resolutions allow achieving better predictions (Figure 9). Temporal resolution of 1 ms and 2 ms provides the same success and false rates, but better predictions are obtained by temporal resolution of 1ms. On the other hand, while the success rate is increasing for higher temporal resolutions, the false alarm rate also increases (Table 5).

CONCLUSIONS

In the one hand, robustness analysis shows that mode lock and plasma inductance signals are essential for APODIS. Any failure in these signals produces very low success rates, 0% for mode lock signal failure and 5-10% for plasma inductance signal failure, so these signals are essential for APODIS. The other signals (plasma density, diamagnetic energy time derivative, radiated power and total input power) are also important but have a less impact decreasing the success rate around 80-90% when they fail, as it is clear from table 3 and 4 where the best results (in terms of success and false alarm rate) are obtained. Both simulations, Gaussian noise distribution in the whole signal and Gaussian noise distribution at a certain time (5s before plasma current crosses 750kA threshold for non disruptive discharges, disruption time for disruptive discharges), provide similar results. The main difference between both simulations is the time to the disruption. Focusing in radiated power signal, it can be observed in table 3 and 4 that radiated power signal failure provides the same success rate and lower false alarm rate than all the signals. It is interpreted as a specific result on the range of pulses used in the analysis, and more analysis with the incoming campaigns should be done to understand better this behavior. Nevertheless, this signal cannot be removed from the predictor because this study show how APODIS works when a signal fails, but if we remove this signal, the predictor should be trained with the remaining signals.

On the other hand, sliding window analysis shows that higher temporal resolutions can help achieve better success rates, reaching 98% success rate for 1ms and 2ms resolutions. Despite of this, false alarm rates slightly increases for higher temporal resolutions. Focusing on false alarm rate in table 5, 32ms and 1ms resolutions show 2.9% and 5.98% of false alarm rate respectively, which means an important difference. Despite of this, higher time resolutions provides better warning times, so if the main problem to overcome disruptions is to have enough time to carry out a mitigation action, we can conclude that increasing the temporal resolution of APODIS would be a good improvement in terms of both success rate and warning time.

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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

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

CFC campaigns 2008-2010				
Campaign	**Non Intentional Disruption**	**Intentional Disruption**	**Safe**	**Total**
C23	24	8	490	522
C24	14	12	361	387
C25	19	22	570	611
C26	58	49	1323	1430
C27a	43	10	320	373
C27b	70	59	513	642
C23-C27b	228	160	3578	3966
ILW campaigns 2011-2012				
Non Intentional Disruption	**Intentional Disruption**	**Safe**	**Total**	
201	56	1036	1293	

Table 2: Database used for Robustness Analysis.

CFC: C23-C27b		
Simulation 1		
Signals	**Success Rate**	**False Rate**
Offline Analysis with all signals	82.89% (189/228)	7.46% (267/3578)
Mode Lock Failure	0% (0/228)	0% (0/3578)
Plasma Inductance Failure	4.38% (10/228)	0.31%(11/3578)
Plasma Density Failure	82.02% (187/228)	6.68% (239/3578)
FWDIA Failure	75.44% (172/228)	4.11% (147/3578)
Radiated Power Failure	82.89% (189/228)	7.43% (266/3578)
Total Input Power Failure	80.7% (184/228)	7.1% (254/3578)
Simulation 2		
Signals	**Success Rate**	**False Rate**
Offline Analysis with all signals	82.89% (189/228)	7.46% (267/3578)
Mode Lock Failure	0% (0/228)	0% (0/3578)
Plasma Inductance Failure	3.95% (9/228)	0.56% (20/3578)
Plasma Density Failure	82.02% (187/228)	6.68% (239/3578)
FWDIA Failure	75.44% (172/228)	4.11% (147/3578)
Radiated Power Failure	82.89% (189/228)	7.43% (266/3578)
Total Input Power Failure	80.7% (184/228)	7.1% (254/3578)

Table 3: CFC: C23-C27b Robustness Result. Simulation 1 refers to the whole signal replaced by Gaussian noise distribution, and Simulation 2 refers to latest 5s of the signal replaced with Gaussian noise distribution.

ILW: C28-C30		
Simulation 1		
Signals	**Success Rate**	**False Rate**
Offline Analysis with all signals	96.02% (193/201)	2.22% (23/1036)
Mode Lock Failure	0% (0/201)	0% (0/1036)
Plasma Inductance Failure	29.35% (59/201)	0% (0/1036)
Plasma Density Failure	95.52% (192/201)	1.54% (16/1036)
FWDIA Failure	95.02% (191/201)	1.45% (15/1036)
Radiated Power Failure	96.02% (193/201)	2.02% (21/1036)
Total Input Power Failure	96.02% (193/201)	2.99% (31/1036)
Simulation 2		
Signals	**Success Rate**	**False Rate**
Offline Analysis with all signals	96.02% (193/201)	2.22% (23/1036)
Mode Lock Failure	0% (0/201)	0% (0/1036)
Plasma Inductance Failure	9.95% (20/201)	6.27% (65/1036)
Plasma Density Failure	95.52% (192/201)	1.54% (16/1036)
FWDIA Failure	95.02% (191/201)	1.45% (15/1036)
Radiated Power Failure	96.02% (193/201)	2.02% (21/1036)
Total Input Power Failure	96.02% (193/201)	2.99% (31/1036)

Table 4: ILW: C28-C30 Robustness Result. Simulation 1 refers to the whole signal replaced by Gaussian noise distribution, and Simulation 2 refers to latest 5s of the signal replaced with Gaussian noise distribution.

Temporal Resolution (ms)	Success Rate	False Rate
32	95.52% (192/201)	2.9% (30/1036)
16	96.52% (194/201)	4.44% (46/1036)
8	97.51% (196/201)	5.02% (52/1036)
4	97.51% (196/201)	5.60% (58/1036)
2	98.01% (197/201)	5.98% (62/1036)
1	98.01% (197/201)	5.98% (62/1036)

Table 5: 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.

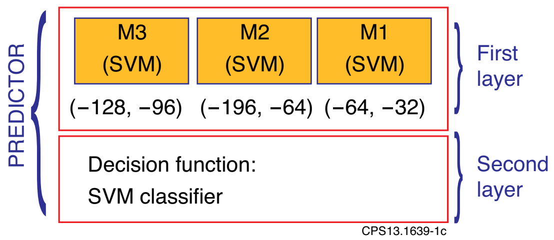

Figure 1: APODIS structure. The first tier, made up of 3 SVM classifiers, classifies the three most recent 32 ms temporal segments as disruptive or non-disruptive. Each classifier has been trained in a different temporal segment. Classifier M1 has been trained in the interval [-64, -32]ms before the disruption; M2 is trained in the interval [-96, -64]ms before the disruption; and M3 is trained in the interval [-128, -96]ms before the disruption. The outputs from the first tier are used as inputs to the second tier (another SVM classifier). This one decides to trigger or not an alarm.

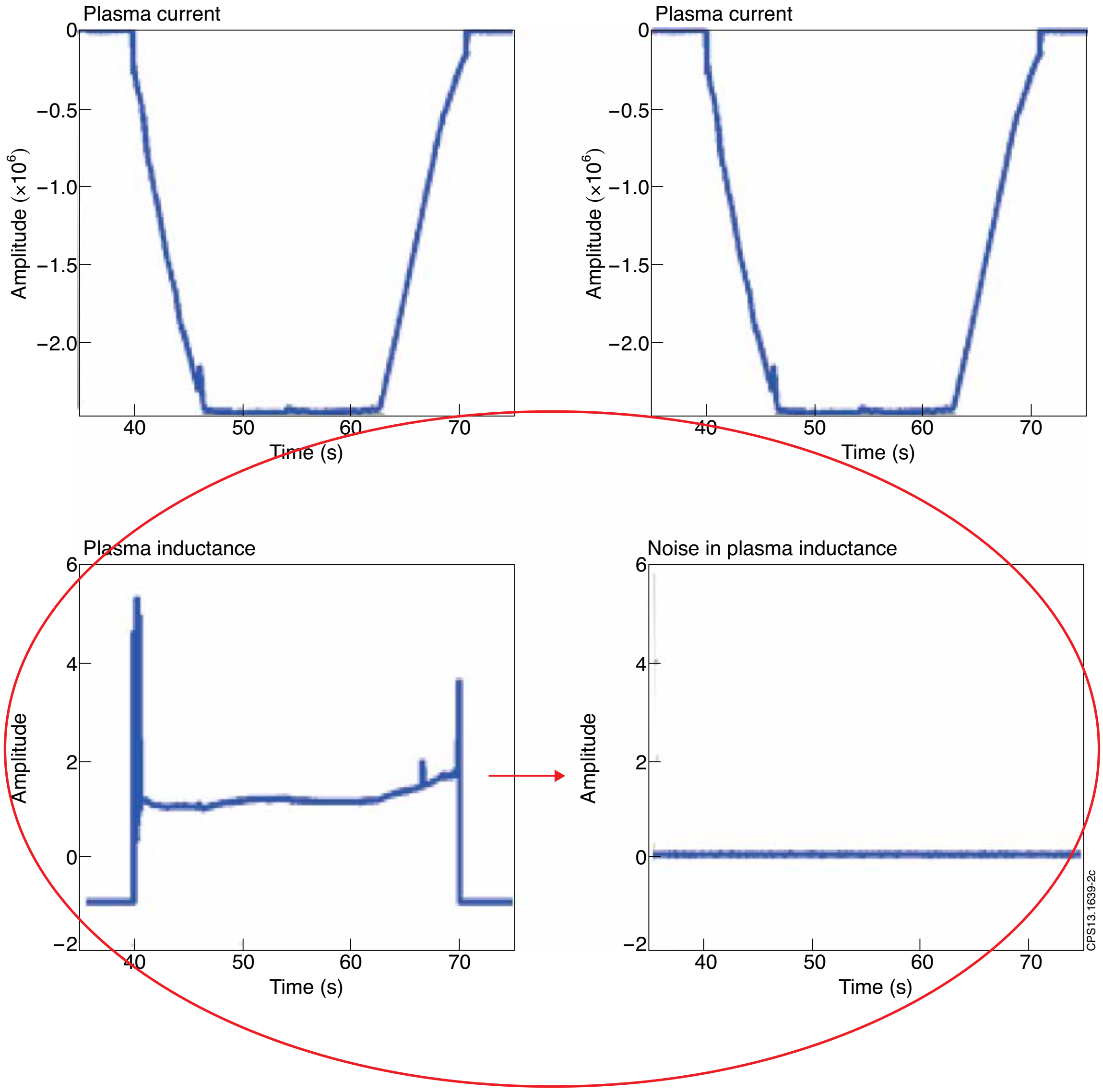

Figure 2: Replacement of the whole plasma inductance signal with Gaussian noise distribution N (0,1) in a non disruptive discharge.

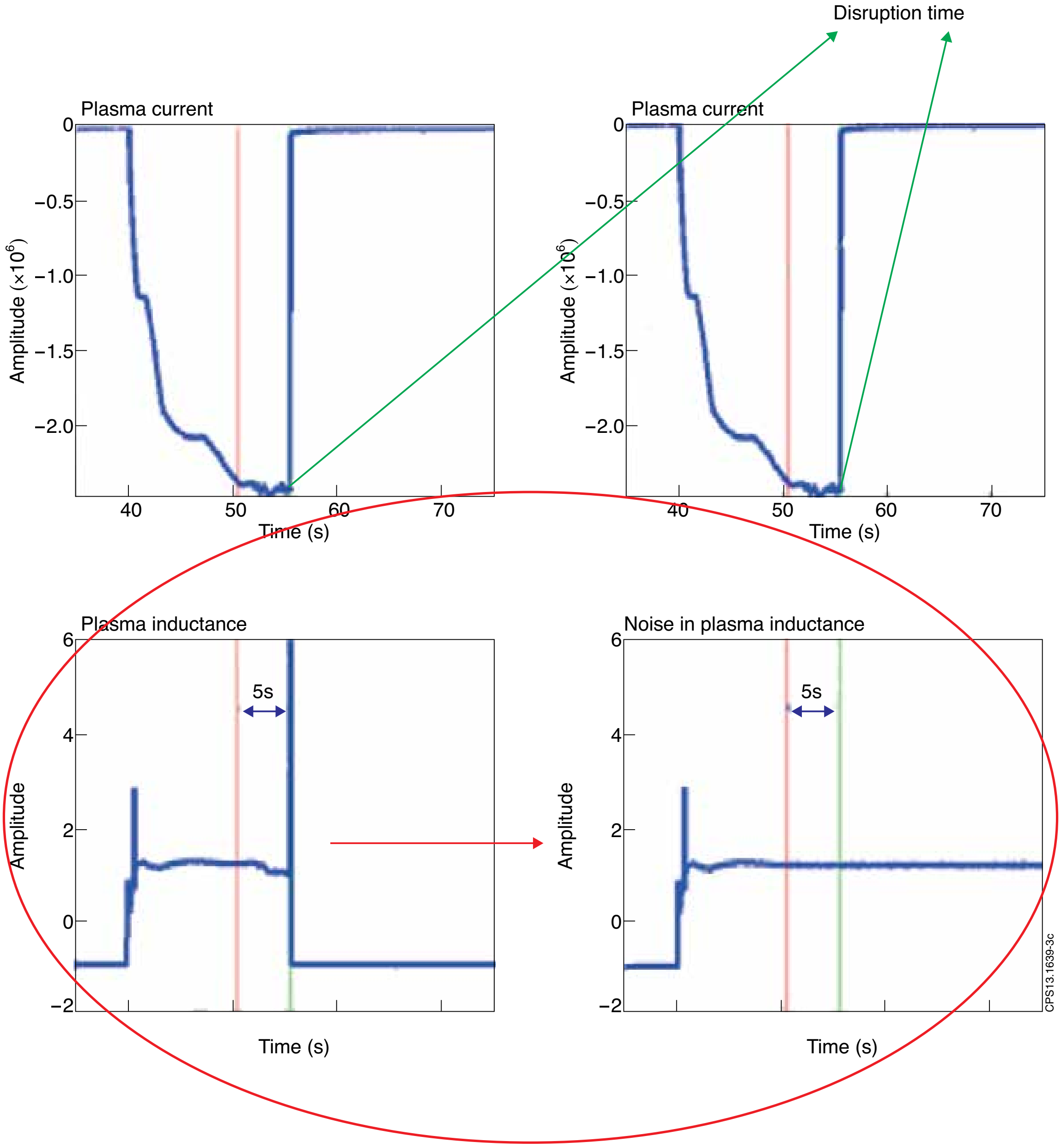

Figure 3: The latest 5s of the plasma inductance signal are replaced with a Gaussian noise distribution N(0,1)in a disruptive discharge.

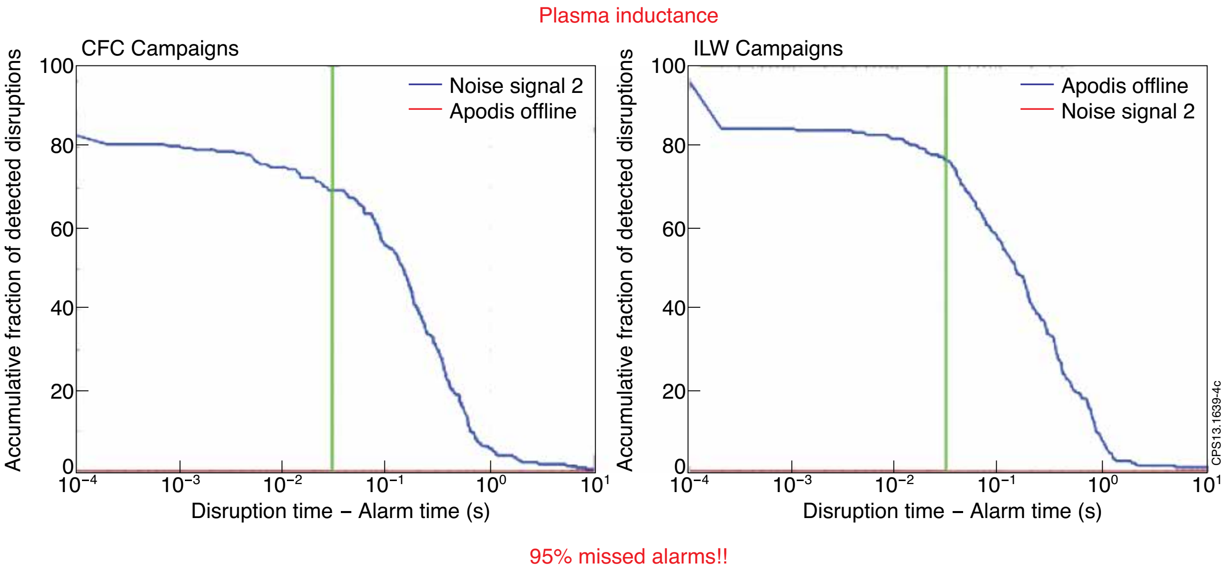

Figure 4: Results for CFC campaigns and ILW campaigns with mode lock signal failure.

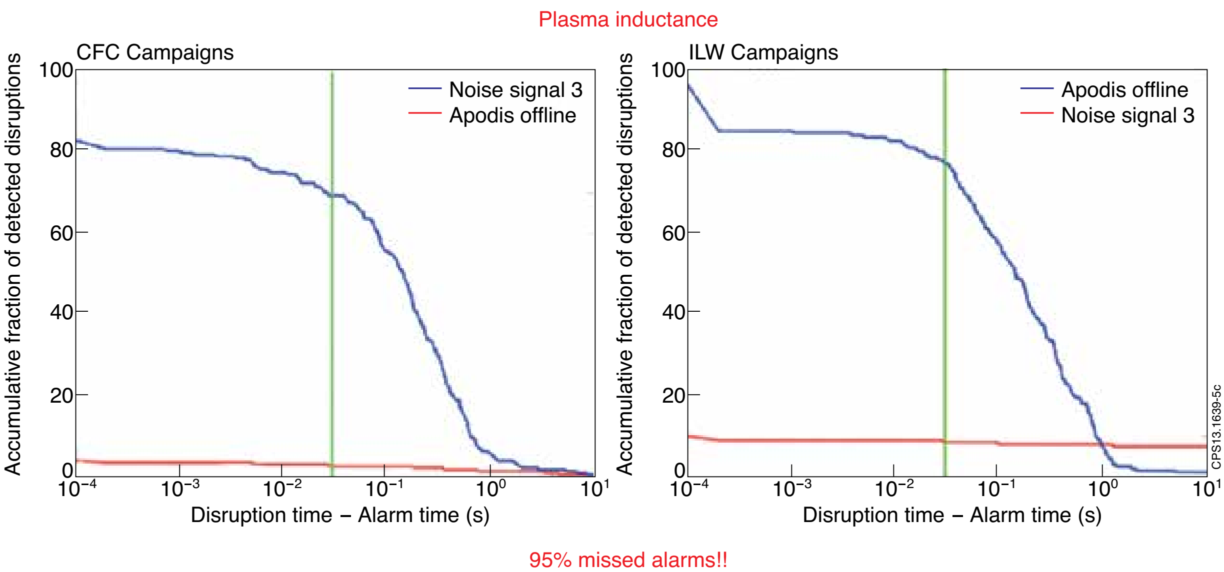

Figure 5: Results for CFC campaigns and ILW campaigns with plasma inductance signal failure.

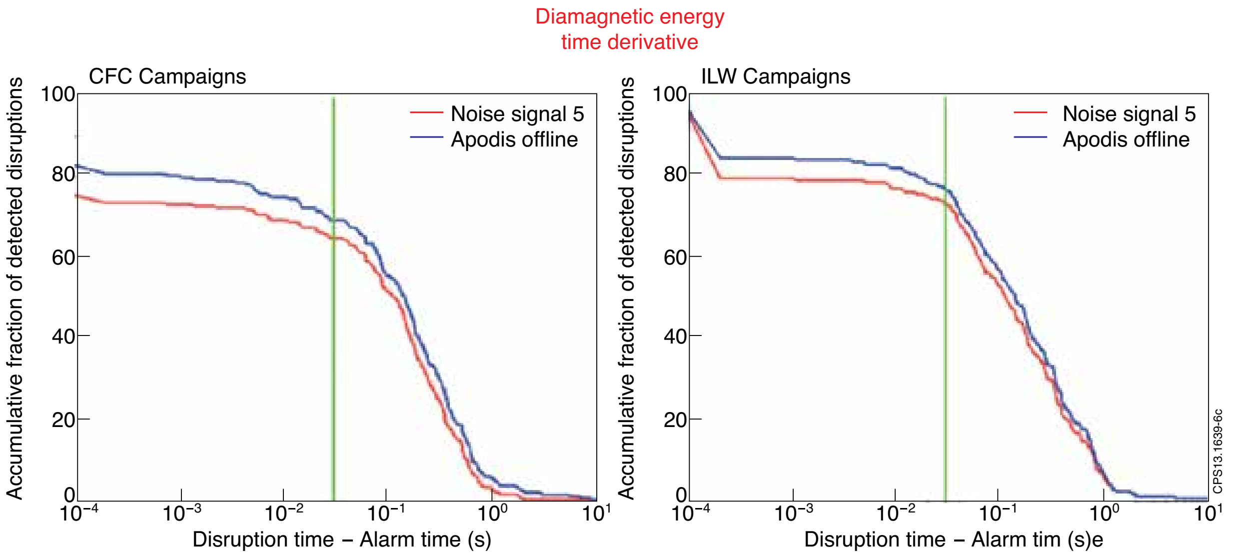

Figure 6: Results for CFC campaigns and ILW campaigns with diamagnetic energy time derivative signal failure. The remaining signals (plasma density, radiated power, total input power) have similar results; success rate slightly decreases around 80-90%.

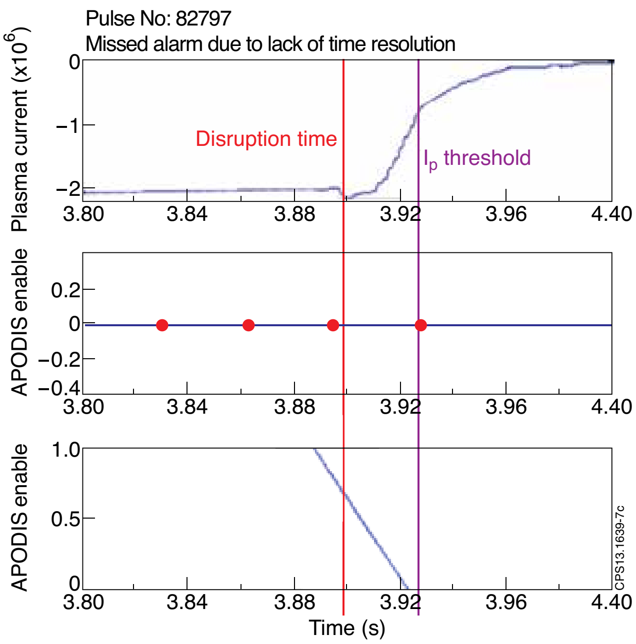

Figure 7: Example of missed alarm due to a lack of resolution. APODIS disables in the last 32ms window when disruption occurs. This disruption would be predicted with a higher temporal resolution.

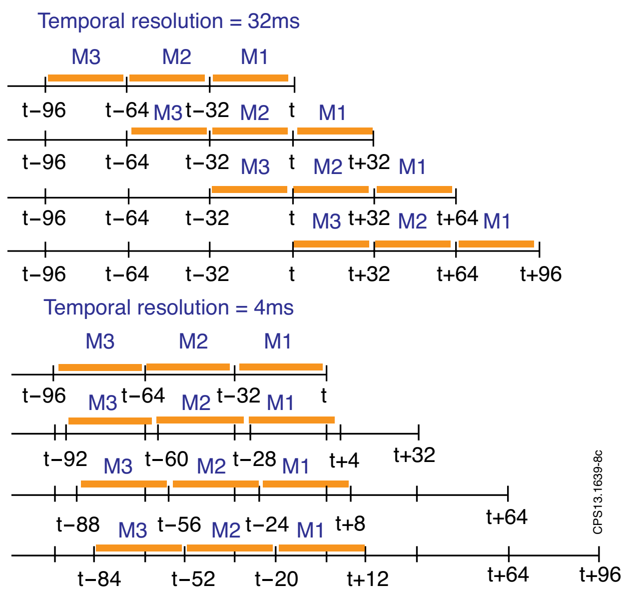

Figure 8: Example of temporal resolution of 32ms (how APODIS works currently at JET) and temporal resolution of 4ms.

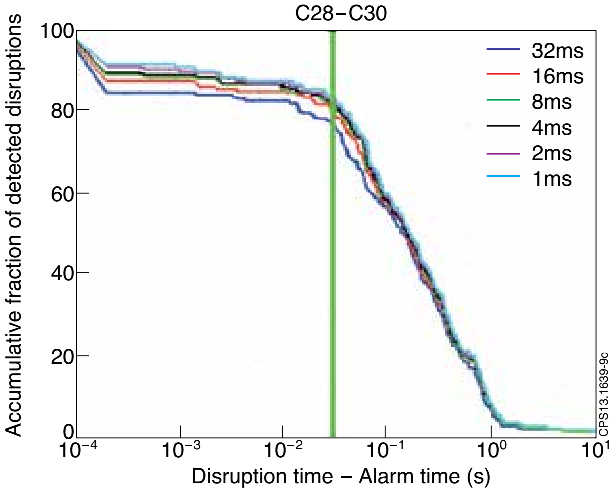

Figure 9: Sliding window results: higher temporal resolutions obtain better results, i.e. higher success rate and better predictions. The green line shows time of 30ms before the disruption.