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Disruption prediction with artificial intelligence techniques in tokamak plasmas

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In nuclear fusion reactors, plasmas are heated to very high temperatures of more than 100 million kelvin and, in so-called tokamaks, they are confined by magnetic fields in the shape of a torus. Light nuclei, such as deuterium and tritium, undergo a fusion reaction that releases energy, making fusion a promising option for a sustainable and clean energy source. Tokamak plasmas, however, are prone to disruptions as a result of a sudden collapse of the system terminating the fusion reactions. As disruptions lead to an abrupt loss of confinement, they can cause irreversible damage to present-day fusion devices and are expected to have a more devastating effect in future devices. Disruptions expected in the next-generation tokamak, ITER, for example, could cause electromagnetic forces larger than the weight of an Airbus A380. Furthermore, the thermal loads in such an event could exceed the melting threshold of the most resistant state-of-the-art materials by more than an order of magnitude. To prevent disruptions or at least mitigate their detrimental effects, empirical models obtained with artificial intelligence methods, of which an overview is given here, are commonly employed to predict their occurrence—and ideally give enough time to introduce counteracting measures.

Tokamaks are currently the most promising configuration for a commercial fusion reactor but—contrary to stellarators—they are prone to disruptions. Because they are also very complex devices, disruptions depend on many effects as well as on nonlinear interactions between them. Pulsed tokamak experiments consist of discharges of currents of the order of millions of amperes. The normal evolution of these discharges can be suddenly interrupted by various types of instability[1]. Particularly frequent and dangerous are instabilities related to excessive radiation (from the visible to the X-ray region of the spectrum), too high plasma density or anomalous current profiles.

Disruptions occur in two stages, namely the thermal quench and the current quench. During the thermal quench, most of the plasma's internal energy is lost on timescales of the order of 1 ms. This thermal quench is immediately followed by the current quench, during which the plasma current is extinguished in time intervals that can last from a few to hundreds of milliseconds in present-day tokamaks. The lead-up to a disruption is typically characterized by anomalies in several diagnostic signals, such as in the electron temperature (Fig. 1). These so-called precursor signals, however, can also be present in non-disruptive plasmas, making the prediction of disruptions a complex multi-objective problem. Because the mitigation of disruptions requires immediate termination of the discharge, false alarms are costly in terms of resources, as well as risking damage to the devices. For this reason, both false positives and false negatives need to be kept to a minimum.

The accurate prediction of disruptions will be even more important for next-generation tokamaks, which will operate with metallic plasma-facing components. Metal offers several advantages. First, it can stand the loads with acceptable erosion, meaning that it has a smaller impact on the lifetime of the components facing the plasma and thus on the efficiency of the tokamak. Second, retention of plasma fuel is comparatively low. High retention, that is, the accumulation of radioactive fuel within the wall, is a safety threat and would also affect the availability of the tokamak. However, recent experiments with metallic walls have shown that the challenge posed by disruptions is more severe for devices with metallic plasma-facing components than expected. ITER ('The Way' in Latin) requires there be less than 5% of pulses with disruptions at a maximum current of 15 MA (ref. [2]). Experiments on the Joint European Torus (JET) with the ITER-like wall (ILW) made of tungsten and beryllium have demonstrated that the rate of disruptions can be unacceptably high[3]. The rate in the so-called baseline reference scenario for ITER reached 80% on JET[4], but was excessive in all devices on which the scenario was tested under reactor relevant conditions. In the hybrid reference scenario that has been developed on JET, the rate of disruptions was ~20%, which also does not meet the requirements for ITER.

In light of these recent findings, abrupt termination of discharges is a major issue for current tokamaks and disruption prediction will be a crucial real-time requirement in even larger ones. Because theoretical models are often insufficient to reliably describe disruptions, empirical models based on machine learning are a common approach for understanding and predicting disruptions.

Models based on traditional machine learning

Disruption predictors based on machine learning are usually conceptualized as binary classifiers: the training process splits the operational space into two regions—disruptive and non-disruptive regions—and determines the boundary between. Ideally, classifications are meant to be carried out during discharges with a typical time resolution on the order of milliseconds. The signals are typically available in the form of time series, which are sequences of data points indexed in time (usually equally spaced). For disruption prediction, the signals have to be processed and then suitable predictors have to be developed. So far, the variety of existing real-time signal-processing methods implemented have explored practically all known data analysis techniques for time series in the time

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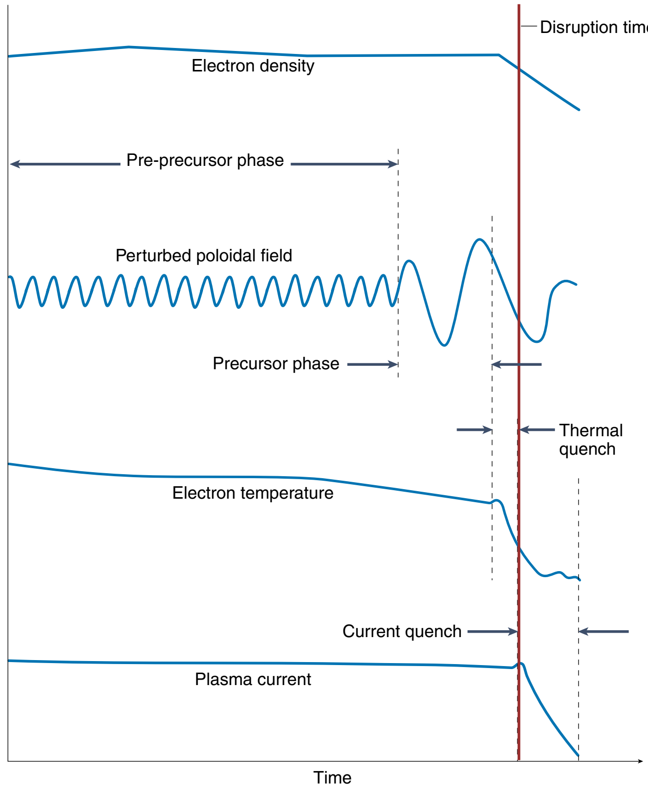

Fig. 1 | Disruption precursors. Time evolution of typical disruption precursors during normal operation and in the lead-up to a disruption. In agreement with the literature, the beginning of the current quench is considered the disruption time.

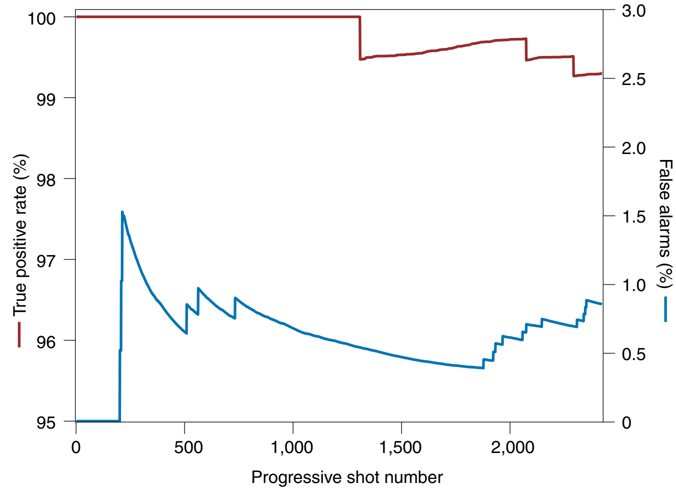

Fig. 2 | Performance of adaptive disruption predictors on JET with the ILW. The rate of correctly identified disruptions, the so-called true positive rate, is shown in red on the left vertical axis. The right vertical axis displays the false alarms rate. The *x* axis reports the sequential discharge number (the database consists of ~2,500 shots). The results are based on a purely adaptive approach, where the discharges in the figure had not been used in the training of the classifier, which was retrained only when errors occurred in the predictions.

domain[5–15]. These techniques have been complemented with tools in the frequency domain[16], based on Fourier transforms. Approaches relying on a mixture of time/frequency domains, including wavelet decompositions, have also been pursued[17–19]. With regard to classifier technologies, real-time compatible predictors have typically been based on artificial neural networks, support vector machines, fuzzy logic, generative topographic mapping and deep learning and have been studied on a broad range of tokamaks, including ADITYA (India)[20], ASDEX Upgrade (Germany)[21], DIII-D (United States)[22–24], J-TEXT (China)[25], NSTX (United States)[26], ALCATOR C-MOD (United States)[27], JT-60U (Japan)[28], EAST (China)[29–31], HL-2A (China)[32] and JET (United Kingdom)[33–35].

Of the three machine-learning-based predictors that were implemented in JET's real-time network, APODIS[17], SPAD[36] and Centroid[37], the former correctly identified disruptions in more than 98% of cases and had a false alarm rate (that is, wrongly classified non-disruptive data) in fewer than 2% of cases, with an average warning time of hundreds of milliseconds.

Despite encouraging results, this disruption predictor and others based on traditional machine-learning technologies suffer from inherent fundamental limitations. First, they are not derived from first principles but are empirical. This means that their results are difficult to interpret in terms of plasma dynamics, and whether they can be extrapolated to future, larger devices[38,39] remains unclear. Second, traditional machine-learning predictors require very large amounts of data for the training. Given the potential damage caused by disruptions, collecting many examples is not a viable option for large-scale devices such as ITER. Finally, the predictors lack generality. Even when large datasets are available, the performance of these predictors degrades quickly when a discharge presents characteristics different from those in the training data. Moreover, the use of predictors is typically restricted to the specific tokamak for which they were derived and it has proven challenging to transfer machine-learning classifiers from one device to another.

The classifiers employed in the studies on tokamaks mentioned above[20–35] were developed using real-time valid solutions, which guarantee response times within a specified time window. The predictors discussed in the remainder of this work have been tested offline with real-time compatible technologies and using only real-time available signals. After having been trained, these predictors can provide their output on a millisecond timescale, which is sufficiently fast not to affect the overall reaction time of the actuators for disruption mitigation and avoidance in tokamaks.

From closed- to open-world learning

The main drawbacks of traditional machine-learning predictors can be attributed to the assumptions adopted for their training. Most examples discussed above followed a closed-world approach to learning. This means that the information required for training the classifier has to be available before the first prediction. Moreover, the performance of traditional classifiers hinges on the assumption that the data are sampled independently from an identical distribution function. This assumption, however, implies that the plasmas are stationary in the sense that their data distribution function does not change substantially because the predictors have no capability of adapting to new regimes or new physics. In practice, these assumptions are systematically violated due to the rapid evolution of experimental programmes.

This situation is particularly unsatisfactory because humans can learn from few examples, can adapt to changing situations and can also transfer knowledge from one problem to similar ones.

In recent years, more attention has been devoted to providing deep learning and interpretable solutions for disruption prediction across tokamaks and in particular for the next generation of devices such as ITER[40]. Efforts towards implementing an open-world approach to learning have also become more popular, as evidenced by a series of adaptive strategies that have been developed to maximize the performance of disruption predictors in non-stationary conditions. The

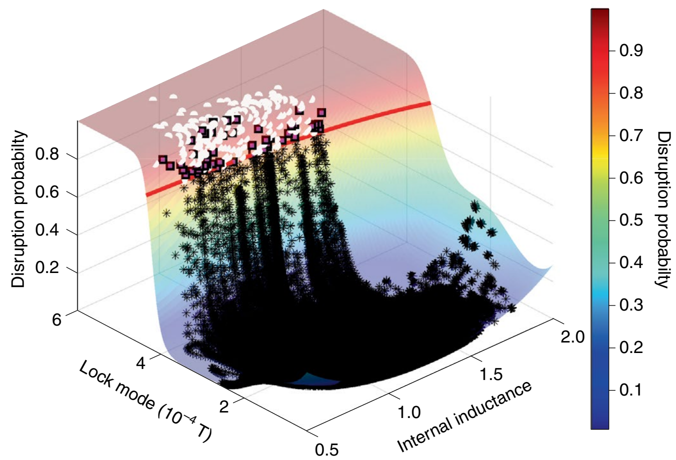

Fig. 3 | Non-disruptive and disruptive regions of the operational space in JET. In discharges with the ITER-like wall, non-disruptive and disruptive regions are identified. The vertical axis and the surface, depicted according to the colour code on the right, represent the posterior probability of disruption. The black asterisks show all the non-disruptive shots (ten random time slices for each shot). The white dots are the data of the disruptive shots, at the time when the predictor triggers the alarm. The black squares are the false alarms. The line separating the disruptive from the safe region of the operational space, whose equation was obtained from symbolic regression, is displayed in red. The lock mode measures the amplitude of macroscopic magnetic perturbations when they become stationary in the reference frame of the laboratory. The internal inductance refers to the plasma internal inductance as the plasma is a conductor. Figure adapted from ref. [49] under a Creative Commons license CC BY 4.0.

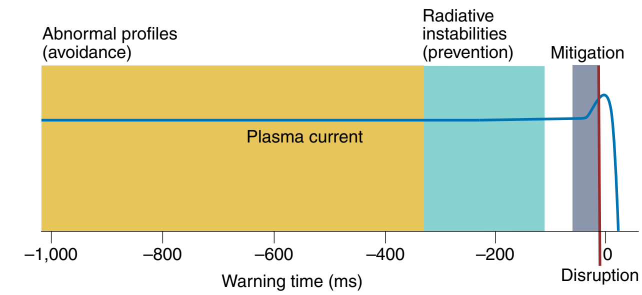

Fig. 4 | Warning time intervals for predictors. The predictors were optimized for avoidance, prevention and mitigation of disruptions. Avoidance actions keep the plasma within stability boundaries, prevention methods terminate the discharge in a controlled way, and mitigation techniques alleviate the consequences of unavoidable disruptions. More than 1,000 discharges of JET with the ILW were analysed. The warning times present negligible overlap, providing a clear estimate of the minimum intervals remaining to introduce remedial actions—from a minimum of 400 ms in the case of the avoidance predictor to tens of milliseconds in the case of the one for mitigation. The vertical red line indicates the disruption time, that is the beginning of the current quench, and the blue solid line represents the plasma current.

training of adaptive predictors is done from scratch, meaning that only a single example of each class (discharge with or without a disruption) is needed for a prediction[18,19,21,34]. The predictors are updated between discharges by refining the training sets and by implementing trajectory learning during the shots. The cases causing the predictors to err still contain a lot of useful information. Retraining them with these failed examples is an effective form of adaptive learning. Because fusion plasmas exhibit memory effects, taking into account the evolution of their properties (their trajectories as opposed to values at specific times) is beneficial for improvement of the predictor performance. The most advanced versions of open-world strategies also include various forms of de-learning that allow predictors to discard or reduce the effects of training data that no longer apply.

For the JET tokamak, fully general and automatic adaptive predictors have been developed. These are based on ensemble classifiers, which consist of a high number of specific predictors, each trained on slightly different datasets[41]. The outputs of the individual classifiers are then evaluated with a suitable decision function to determine whether a disruption is likely to occur. The overall performance of these adaptive predictors is promising: the rate of false alarms is less than 1% and the rate of correctly identified disruptions is higher than 99%. This is shown in Fig. 2, which reports the results for thousands of discharges at the beginning of the operation of JET with the ITER-like wall to simulate the initial operation of a new device[41]. In this case, the first prediction of the ensemble classifier was based on a single disruptive and four non-disruptive discharges[34,41]. Because adaptive predictors based on open-world learning have been successfully transferred from one device to another[42,43], they provide much better flexibility and generality than more traditional machine-learning techniques. Therefore, open-world learning is a very promising approach for implementation in next-generation tokamaks.

Interpretable models with symbolic regression

The classifiers discussed above provide mathematical models, which have no relation to the actual plasma dynamics and are difficult to interpret in terms of our understanding of plasma physics. For this reason, methodologies for steering the machine-learning process toward interpretable models, reflecting the actual physics and dynamics of the phenomena involved, are under development. This is more ambitious than 'traditional' explainable artificial intelligence[44], because the goal is to obtain mathematical equations describing the underlying physics[26,45,46].

Physics interpretability of models obtained with support vector machines was achieved by applying symbolic regression methods[47], which make use of genetic algorithms[48]. The deployment of symbolic regression allows the exploration of a large set of mathematical equations—hundreds of thousands of models—describing the boundary between non-disruptive and disruptive regions of the operational space. Each generation of models is evaluated based on a fitness function and those demonstrating better performance in terms of this metric are retained and used as starting point for the next iteration, from which new models are derived by using traditional genetic operators such as mutation, copy and cross-over.

The equation of the boundary between disruptive and non-disruptive regions in JET's operational space, with an ITER-like wall as displayed in Fig. 3, was obtained with symbolic regression and revealed information on factors that are likely to trigger disruptions[49].

Warning time prediction

Even predictors with a good performance in terms of success and false alarm rates suffer from a major limitation: on JET, the range of their warning times can be of the order of 1 s. Thus, the control system lacks the information about the time remaining before the beginning of the current quench— it could be in a few milliseconds or in a second. Given the importance of predicting the time remaining before the occurrence of a disruption[37] or at least providing a robust estimate of the minimum time still available to introduce remedial actions[50,51], accurate estimates of the warning time are indispensable. A recent study on JET combining support vector machines and genetic programming[52] allowed the integration of three classes of predictor, for the avoidance, prevention and mitigation of disruptions. As shown in Fig. 4, the warning times of the overall system obtained with the three predictors present negligible overlap, providing a clear lower bound of the time intervals available to introduce remedial actions.

Outlook

For the prediction of disruptions on next-generation tokamaks like ITER, these results need to be transferred to these devices. Achieving the same performance after adequate modifications of the algorithms would be a major breakthrough—even if the overall system requires large amounts of data for the training. In this regard, a coherent strategy is emerging for ITER, suggesting the deployment of adaptive predictors in the first operational stages, providing inputs to the genetic programming for the training of the integrated system that would provide accurate warning times for avoidance, prevention and mitigation of disruptions.

Apart from the prediction of disruptions in tokamaks, most of the discussed data-driven techniques are fully general and could be adapted for forecasting and understanding any form of collapse, crash and catastrophe in other fields of science. Indeed, some of these techniques are already being deployed in various disciplines ranging from earth science to epidemiology[53–55].

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