

AN INNOVATIVE INTELLIGENT SYSTEM FOR FAULT DETECTION IN TOKAMAK MACHINES

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Abstract

In this paper¹ a new fault detection strategy, based on soft computing techniques, to isolate and classify some faults occurring in a tokamak fusion plant is described. In particular, attention is focused on measurements of vertical stresses during plasma disruptions. The strategy is based on a neural model which estimates suitable features of the expected sensor response, allowing to isolate the most frequently occurring faults, together with a fuzzy inference system able to classify the detected faults. A comparison with traditional fault detection techniques implemented at JET² has shown a great improvement, because of the great precision in detecting sensor faults, the ability in discriminating among different faults, and the high degree of automation achieved.

1 INTRODUCTION

The Joint European Torus (JET) is the most important project in the coordinated fusion programme of the EURATOM, whose long term objective is the creation of a prototype of a fusion reactor. In this tokamak, plasma disruptions produce fast *Vertical Displacement Events* (VDE) of its centroid, inducing significant mechanical loads on the vessel structure, with radial and vertical components of several MN, during typical time intervals ranging from 20ms to 50ms [1]. Recently, the new MDS (Machine Diagnostic System) system, dedicated to the mechanical measurements on the vacuum vessel has been installed. Many mechanical sensors have been installed, especially strain gauges and linear variable resistors (LVR), and a diagnostic system is being developed. Usually, signals provided by MDS are used by scientists to perform further computations, which are strongly affected by the inclusion of a faulty measurement into the signal set. So far, a coarse validation has been performed on line by MDS machines, applying threshold checks, and physical redundancy based algorithms. The final, finer validation is instead left to experts, who perform a visual analysis of the signals. The need for automatic tools for fault detection is therefore strongly felt by experts, considered for example that MDS alone is constituted by 256 signals, and a further expansion to 512 is in

progress.

In this work, vertical stress fast measurements (2.5 kHz), taken at disruptions, are considered. The proposed approach is to detect faults occurring in mechanical measurements by means of a cascade of a neural model and a fuzzy inference engine. In order to get a neural network design with reasonable dimensions, and to train the network with reliable, non noisy data, it has been preferred to design a neural model able to estimate some significant features of the expected dynamical sensor response, able to reveal the most frequently occurring faults. The model residuals are then evaluated by a fuzzy inference system, in order to classify the encountered faults. Related results are shown, together with a comparison with previous traditional fault detection methodologies used at JET.

2 JET MEASUREMENT MONITORING

Vacuum vessel vertical stresses are mainly supported by pairs of angled struts (called legs) connected to both the top and the bottom Main Vertical Ports (MVP), located on each octant of the vessel. Vertical stresses on each leg are measured by means of a couple of strain gauges, whose outputs are stored in the JPF (Jet Pulse File) at different sampling rates. For disruption data analysis, strain gauges data are sampled at 2.5 kHz and stored for about 800 ms around the disruption time [2]. After disruptions, total vertical stresses are computed on the basis of the 32 measurements produced by bottom strain gauges, taking into account only a manually validated subset of them. Traditional fault detection techniques used so far in MDS system, are based on thresholds, traditional modeling, and on an algorithm exploiting the physical redundancy of the sensors. These approaches are not satisfactory because of the pulsating nature of JET: each experiment differs from the past ones, and scientific interest is mainly focused on transient phases and a high or low value for a sensor measurement does not provide a good information on its own. The dynamics of the experiment is dramatically relevant, and a faulty sensor might perfectly stay within the expected bound without following the proper dynamics.

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3 THE NEURAL APPROACH

A classical neural pattern recognition approach constituted the first attempt to solve this problem, although this approach was not satisfactory. All the trained neural classifiers denoted a sufficient capability in distinguishing good measurements from faulty ones, but they were incapable of discriminating among different kind of faults. Thus, the idea of taking into account the causes of the physical phenomena took place [3].

The main dynamical events during an upwards VDE are a large downwards swing, followed by a slow decay with oscillations at about 14Hz, called rocking motion [2]. The downwards swing is the most relevant concerning the fatigue life of MVP. This swing is estimated by computing the so called F-Number [4]. This is a simple nonlinear function of seven typical currents, that are part of the settings of the experiments. They are:

1. The plasma current I_p ;
2. The current in the inner poloidal coil I_{pfx} ;
3. The current in the plasma shaping circuit, multiplied by the effective number of turns in the shaping circuit, $N_{sh} * I_{sh}$;
4. The four divertor currents, I_{D1} , I_{D2} , I_{D3} , I_{D4} .

A good estimate for the swing is obtained by evaluating the F-number formula at a time named *STIME*, that is 200 ms before the actual disruption time. This is to avoid considering corrective actions performed on the relevant currents by PPCC (Plasma Position Control Circuit), that actually modifies the “natural” trend of the experiment.

Thus, we conjectured that, as vertical stresses are mainly supported by the octant legs, and the same damped oscillating behaviour can be observed on the actual strain gauge response trend, the above currents could constitute a good set of possible causes to model the strain gauge response. A Multilayer Perceptron (MLP) has then been trained to estimate the strain gauge response on the basis of the *STIME* instantaneous values of the seven currents described above. The input vector is therefore constituted by seven inputs. The choice of what getting from the output of the network is maybe the most delicate within the whole design process, because of the need of getting the most of information with the smallest net dimension. A prior investigation on strain gauge signals has shown the following main categories of faults:

- **gain faults**, signals denoting the same shape of the other components of the group, scaled by a factor;
- **bias faults**, signals denoting the same shape of the others, broken in several parts separated by steps;
- **spike faults**, signals with large and occasional spikes;
- **noise faults**, in which a high frequency noise (about 115 Hz) induced by FRFA (Fast Radial Field Amplifier) is too relevant with respect to the signal.

Hence, analysing the waveforms of typical sensor responses, four significant features have been reckoned to be sufficient to isolate the faults described above. Denoting with $x_i(k)$ the sensor discrete outputs, with $i = 1 \dots 32$,

and k being the discrete time index, they can be listed as:

- Maximum peak of the oscillations, that is, together with the next feature, a good indicator for gain and step faults;

$$M_i = \max_k x_i(k)$$

- Average value of the sensor response (N_s being the number of samples of the sensor output);

$$A_i = \frac{1}{N_s} \sum_{k=1}^{N_s} x_i(k)$$

- Maximum of the absolute value of the prime difference function, that is an indicator for detecting spikes;

$$P_i = \max_k |x_i(k) - x_i(k-1)|$$

- Sum of FFT samples between 100 and 130 Hz, that is an indicator for the FRFA induced noise. Being $X_i(f_j) = \text{abs}(\text{FFT}\{x_i(k)\})$, it is

$$N_i = \sum_{f_j=100\text{Hz}}^{130\text{Hz}} X_i(f_j)$$

The designed MLP has therefore seven inputs and four outputs. After a trial and error process, a suitable size for the hidden layer has been fixed to two neurons. The above features have been calculated after having stripped off the initial offset, because it depends on the sensor calibration. The MLP has been trained on 60 JET disruption data, representative of several kind of disruptions in the three adopted divertor configurations. A very large testing set, constituted by 200 disruptions, guarantees the validity of the proposed approach for a wide range of situations. A representative figure to test the model performance has been chosen as the maximum error committed considering 95% of the cases. The related error figures are reported in table 1.

Feature	Max. Err. 95%	Range
M_i	16kN	0–200 kN
A_i	8kN	0–200 kN
P_i	3kN	0–80 kN
N_i	1000	0–10000

Table 1: Maximum estimate error committed by MLP in 95% of the cases and corresponding measurement ranges

As it can be observed in Table 1, the error committed are very small with respect to the corresponding ranges. The fault classification can then be performed by analysing the combinations of feature errors. This task is accomplished by the inferential fuzzy logic based engine described in the next section.

4 THE FUZZY FAULT CLASSIFIER

In this section, the fuzzy inference system (FIS) for fault classification is presented. It is meant to analyse the errors between actual signal features, and expected ones, that are those provided by the ANN described in section 3. Fault can occur either solely or concurrently, on the basis of the various combinations of the residuals computed on the neural model output. A Sugeno fuzzy system has been chosen [5]. The inputs of the inference engine, **PKe**, **AVe**, **SPe**, and **NOe** are the differences between actual and estimated features. Each input has three associated *membership functions*, defining the concepts of positive, negative, or null error. Shapes and overlaps of membership functions have been established by a trial and error process, considering heuristics, performance, and sensor and model accuracy. This FIS is able to provide information about three qualities of the signals. They are **Amplification**, **Bias**, and **Disturbances**. These qualities are the actual outputs of the fuzzy system. Each of the outputs can assume three crisp values, as follows:

- **Ampl. and Bias:** high (1), low (-1), and ok (0);
- **Disturbances:** noise (-1), spikes (1), and ok (0).

The adopted fuzzy rules, inspired by expert knowledge, are:

1. if PKe is pos and AVe is zero then Amp is hi and Bias is ok
2. if PKe is neg and AVe is zero then Amp is lo and Bias is ok
3. if PKe isnot neg and AVe is pos then Amp is ok and Bias is hi
4. if PKe isnot pos and AVe is neg then Amp is ok and Bias is lo
5. if PKe is zero and AVe is zero then Amp is ok and Bias is ok
6. if SPe isnot pos and NOe is notpos then Dis is ok
7. if SPe is zero and NOe is pos then Dis is noise
8. if SPe is pos and NOe is pos then Dis is spikes

Rules from 1 to 4 set up the qualities about amplification and bias, anylising both the error on the maximum peak and on the temporal average. As an example, rule 1 says that if the error on the peak is positive and the error on the average is zero, the signal is just magnified but not translated, that is what has been previously called *gain error*. As it has been remarked by experts, high frequency noise and spikes do not occur simultaneously, so the fuzzy output **Disturb** is used to detect both kind of faults on the basis of the two features related with disturbances (noise and spikes).

A statistical parameter to validate our approach has been chosen as the average number of faulty sensor per pulse (AFSP). It has been worked out both for the previous validation algorithm and the one proposed in this work.

Apart from random checks performed through the whole disruption set, in which the AI-based method has always shown better results, we checked that during the operational campaign in which evaluation has been performed, exactly four sensors were faulty.

Method	Total (sens X pulses)	Faults	AFSP
Traditional	3072	51	0.5
AI-based	3072	375	3.90

Table 2: A comparison between an AI-based method and a traditional one

5 CONCLUSION

In this work, after preliminary studies, we have implemented a fault detection tool for fast disruption data coming from a set of strain gauges in JET fusion plant. This activity is currently performed by experts who manually examined hundred of signals a day. Joining artificial neural network and fuzzy logic, exploiting human experience and past data, we succeeded in accomplishing this task. The validity of results is confirmed both by comparison with the classic technique used for validation, and by JET experts who thoroughly examined validation results.

6 REFERENCES

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