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Transients Analysis of a Nuclear Power Plant Component for Fault Diagnosis

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We analyze signal data collected during 148 shut-down transients of a nuclear power plant (NPP) turbine for fault diagnosis. The aim is to identify groups of transients with similar characteristics, under the conjecture that faults and malfunctioning of the same type lead to a similar behavior of the measured signal transients. The fault diagnosis method is based on the combined use of an original fuzzy-based slope and similarity analysis with spectral clustering.

1. Introduction

Fault diagnosis can be seen as a classification problem in which specific classes of fault are associated to specific values of measured signals (Zio et al., 2006). In general terms, fault diagnosis methods can be divided into two categories: model-based and data-driven (Venkatasubramian et al., 2003, Sheng et al., 2004). Model-based methods need expert specific domain knowledge for model building while not guaranteeing the timely detection of faults (Tian et al., 2007), whereas data driven methods can satisfy a number of practical requirements, such as short calculation time and high accuracy (Zio, 2012; Baraldi, 2012a). We develop a new data driven method for identifying specific signal transient behaviors associated to different types of fault. A first task to be done is the extraction of signal features relevant for the transients classification. Several techniques of feature extraction can be used, such as pointwise difference (Baraldi et al., 2012b), correlation (Guyon et al., 2003), Principal Component Analysis (PCA) (Baraldi et al., 2010). Problems may arise when dealing with misaligned signals (Secchi et al., 2008), i.e., amplified and/or delayed transients data. To overcome this, we develop an effective feature extraction technique for misaligned data, which we call Fuzzy-based slope analysis. For the clustering, we then propose to compute the similarity between signal trajectories by measuring the fuzzy similarity of the extracted features (Zio et al., 2010). A similarity graph (von Luxburg, 2007) is built, in which each vertex represents a trajectory and the weight associated to the edge connecting two vertices is the value of (fuzzy) similarity between the two corresponding trajectories. Spectral clustering is finally applied in order to find an optimal partition of the graph (von Luxburg, 2007). The developed framework of analysis has been tested on a real industrial case regarding the shut-down transients of a turbine of a NPP.
The rest of the paper is organized as follows: Section 2 states the problem and describes the available NPP turbine data; in Section 3 the proposed framework of analysis is described in details along with the application to the case study; in Section 4 the obtained results are shown and discussed in detail; finally, in Section 5, some conclusions and remarks are drawn.

2. NPP turbine shut-down transients

We consider the measured values of 70 signals taken at T=4500 time steps with a fixed sampling frequency during N=148 NPP turbine shut-down transients. The generic i-th transient, i=1,...,148, can be seen as a multidimensional trajectory into the 70-dimensional signal space, and represented by the matrix

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of values $\overline{\overline{X^i}}$ whose component x^i_{lk} represents the value of signal k taken at time t_l. For fault diagnosis, we want to partition the 148 multidimensional trajectories into an a priori unknown number of clusters, C, each one containing trajectories of similar functional behavior, with the assumption that they have been originated by the same physical setting (nominal or faulty).

2.1 Data pre-treatment: reduction of the dimensionality of the signals space

Each *i*-th transient entails a very large amount of data (4500 simultaneous measurements of 70 signals) that challenge the identification of similarities between the transients in a signal space characterized by such a high dimensionality (Baraldi et al., 2012d). To overcome this problem, we have calculated the correlation among the signals and retained those with large correlation values, i.e., containing relevant information for clustering the transients. A spectral clustering algorithm applied to a correlation matrix of size [70, 70] has allowed identifying six groups of signals characterized by a high degree of correlation among them and a low degree with the signals of other groups. The largest group is composed by 27 signals and includes the active power signal, two vibration signals and twenty four temperature signals. For limitation of paper length, the analyses described in Sections 3 and 4 will take into account only this group of signals.

3. The framework for unsupervised clustering

In this Section, we introduce the basic method for fault diagnosis developed and applied to the shut-down transients of NPP turbines. In Section 3.1, the fuzzy-based slope analysis feature extraction technique is applied to the raw signal data; Section 3.2 describes the calculation of the fuzzy-similarity measure between transients represented by the extracted features; finally, Section 3.3 describes the application of the spectral clustering method to the obtained similarity matrix.

3.1 Feature extraction: Fuzzy-based slope analysis

The developed feature extraction technique is properly devised to overcome problems of misaligned transients. It consists of five steps, applied separately to each *k*-th signal, k=1,...,27:

1. **Signal slope computation:** divide the *i*-th transient of the *k*-th signal in R=9 intervals of length L= T/R=4500/9=500. The number of intervals has been found by trial-and-error. For each *r*-th interval, r=1,..,9, the slope ${}^{r}\Delta^i_k$ of the signal is computed using the least squares regression method on the signal values in the considered interval (Frank, 1987).
2. **Signal slope distribution:** collect the slope values of the *k*-th signal in all the 148 transients and build separately the signal slope empirical distributions for the positive and the negative values.
3. **Percentiles computation:** calculate the 1st and the 50th percentiles of the negative slopes distribution (N_1 and N_{50}), and the 50th and the 99th percentiles of the positive slopes distribution (P_{50} and P_{99}).
4. **Fuzzy sets and membership functions creation**: consider the signal slope, Δ, as a linguistic variable that can be approximated within a fuzzy framework defined by the fuzzy sets (terms) high negative, low negative, low positive and high positive. In this case, the membership functions μ which define the fuzzy sets are *S*=5 asymmetric, unevenly spaced triangular functions centered on the percentile values computed at step (3) and on the zero value (V_0): we chose asymmetric, unevenly spaced triangular fuzzy sets, based on the computed percentiles values, because they only depend on the distribution of the available signal slope values, and allow to describe the signals slope behavior better than symmetric triangular fuzzy sets, which are centered on a priori established values and may lead to the creation of empty fuzzy sets (Baldwin et al., 2003).

Once the membership functions have been defined, each computed signal slope can be characterized by its degrees of membership to the fuzzy sets which represent the level to which the slope verifies the extent properties of the set, as shown in Figure 2.

5. **Feature extraction**: for each *i*-th transient compute the mean membership ${}_{s}\overline{\mu}^i_k$ of the *k*-th signal to each of the *s* fuzzy sets:

$$
{}_{s}\overline{\mu}^i_k = \frac{1}{R}\sum_{r=1}^{R} {}^{r}_{s}\mu^i_k \qquad \begin{array}{l} s=1,..,5 \\ i=1,..,148 \\ k=1,..,27 \\ r=1,..,9 \end{array} \tag{1}
$$

In this way, since five different membership values are obtained for each signal, the matrix $\overline{\overline{X^i}}$ of size [*4500*, 27] describing a transient is transformed into a vector $\overline{Y^i}$ of size [135] which constitutes the new representation of trajectory *i,* as shown in Figure 1.

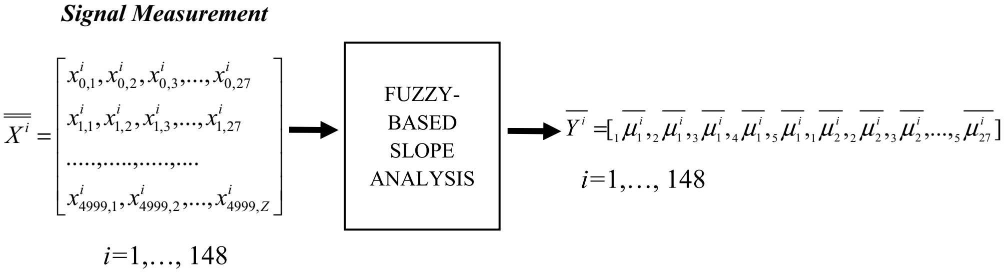

Figure 1: Sketch of the proposed technique for the fuzzy-based slope analysis for the feature extraction

3.2 Pattern matching by fuzzy-similarity

The similarity between transients *i* and *j* can be computed by considering the corresponding vectors of extracted features $\overline{Y^i}$ and $\overline{Y^j}$. To this aim, a fuzzy similarity measure is considered to determine the degree of closeness of the two trajectories with reference to the pointwise difference between the corresponding feature values (Zio et al., 2010; Baraldi et al., 2012b). Without loss of generality, let us define the pointwise difference δ_{ij} between the trajectories $\overline{Y^i}$ and $\overline{Y^j}$:

$$\delta_{ij} = \sqrt{\sum_{f=1}^{135}\left(y^i_f - y^j_f\right)^2} \tag{2}$$

The pointwise difference of the two trajectories is then evaluated with reference to an “approximately zero” fuzzy set (FS) specified by a function which maps δ_{ij} into a value μ_{ij} of membership to the condition of “approximately zero”: values of μ_{ij} close to 0 indicate that the signal evolutions in the two transients *i* and *j* are very different, whereas values close to 1 indicate high similarity.
In this work, the following bell-shaped function is used:

$$\mu_{ij} = e^{-\frac{\delta_{ij}^2}{\sigma^2}} \tag{3}$$

The arbitrary parameter *σ* can be set by the analyst to shape the desired interpretation of similarity into the fuzzy set: the larger the value of *σ*, the narrower the fuzzy set and the stronger the definition of similarity (Zio et al., 2010). Applying eq. (2) and eq. (3) with an optimized value of the bell-shaped function parameter σ= 0.55, we have built the similarity matrix $\overline{\overline{W}}$ of size [148,148], whose values represent the functional similarity between transients.

3.3 Transient clustering by spectral clustering

From the matrix $\overline{\overline{W}}$ of size [148,148] a similarity graph *G* = (*V*,*E*) is constructed, where each vertex v_i represents the *i*-th trajectory and the weight associated to the edge p_{ij} connecting the two vertices *i* and *j* is the similarity value μ_{ij} (Alpert et al., 1999). The original problem of identifying groups of similar trajectories can then be reformulated as that of finding a partition of the similarity graph such that the edges connecting elements of different groups have small weights and the edges connecting elements within a group have large weights. Figure 3 shows the 148 eigenvalues of the Random walk Laplacian matrix $\overline{\overline{L_{rw}}}$ obtained by applying the spectral analysis method to matrix $\overline{\overline{W}}$ (Baraldi et al., 2012b). Since the first four eigenvalues are closer to zero and the gap between the fourth and the fifth is larger, the number of clusters C is set equal to 4, according to the eigengap theory (von Luxburg, 2007).

The relevant information to be used for partitioning the graph (i.e., clustering the transients) consists into the eigenvectors $\overline{u}_1, \overline{u}_2, \ldots, \overline{u}_4$ associated to the 4 smallest eigenvalues (Baraldi et al., 2013). The problem of clustering the 148 trajectories $\overline{\overline{X^i}}$ is now reduced to the problem of finding four clusters among the 148 4-dimensional vectors, where for each *i*-th transient $\overline{u}^i = \{u_1^i, u_2^i, ..., u_4^i\}$ constitutes a reduced representation of $\overline{\overline{X^i}}$. The Fuzzy C-Means (FCM) clustering algorithm fed with $\overline{u}^i$ provides the memberships μ_{ic} of the *i*-th transient to the *c*-th cluster, c=1,2,3,4 (Baraldi et al., 2012c). The transient with the largest value of membership to a cluster is named prototypical trajectory, and its functional behavior can be taken as most characteristic of the cluster.

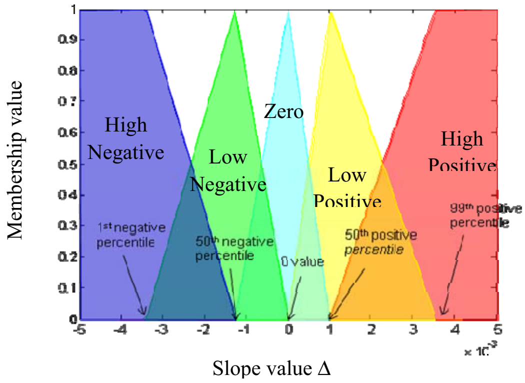

Figure 2: Membership functions of the linguistic variable slope

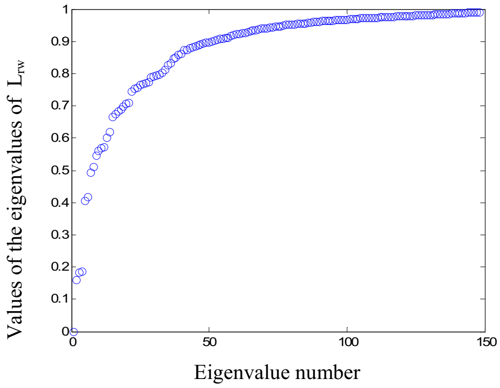

Figure 3: The 148 eigenvalues of L_{rw}

4. Clustering Results

With respect to the matrix of values μ_{ic}, two categories of transients have been distinguished:

- Transients assigned to a cluster with high confidence (the largest membership value is larger than 0.7) are hereafter labelled “assigned”.
- Transients not assigned to any cluster with enough confidence are hereafter labelled “not assigned”.

As an example, Figure 4 shows the evolution of the signal 3 in the “assigned” transients of the four identified clusters. Clusters 1 and 4 mainly differ in the rate of decrease of the signals: those belonging to cluster 1 are characterized by a sharper, less smooth decrease than those of cluster 4. Although the distinction between these two groups depends on the rate of decrease of the signals, their functional behaviour is almost the same. Furthermore, it is possible to note that, even if the distinction between the more characteristic transients belonging to cluster 1 and cluster 4 is clearly marked, there are several transients at the border between the two clusters for which the signal behavior seems to be very similar. On the contrary, clusters 2 and 3 show peculiar functional behaviors which allow distinguishing them from other transients: those belonging to cluster 2 exhibit a smooth rise followed by a decrease of the signal, whereas those belonging to cluster 3 show a short and more marked decrease followed by a rise.

The low degrees of membership of the “not assigned” transients can be due to two different causes:

- the “border-line” transients could belong to more than one cluster, i.e., being at the border of two clusters they share some characteristics with both.
- The “outliers” transients are very different to those of the four identified clusters, i.e. their signal behaviours are not similar to those of the transients of any of the identified clusters.

In order to identify if the “not assigned” transients are “border-line” or “outliers”, we have used an auto-associative method, previously developed in the context of fault detection (Baraldi et al., 2012d). The idea is to develop an auto-associative model using a training set formed by the patterns of the “assigned” transient (Figure 5). When the “not assigned” transients are fed to the developed auto-associative model AAKR (Baraldi et al., 2012d) two cases may arise: the signal reconstructions (output of the AAKR model) are similar to the signal behaviour of the “not assigned” transient (input to the AAKR model) or they are different. In the former case, we can conclude that the “not assigned” transient is similar to those used for the model training, i.e. the transients of the four clusters, and, thus, the transient is at the border of two clusters. Contrarily, in case of remarkable difference between the reconstruction and the “not assigned” transient, we can conclude that the transient is atypical with respect to the training transients and, thus, it is an outlier characterized by anomalous signal behaviors. According to this analysis, 6 out of the 15 transients are “outliers”, whereas the remaining 9 transients are “border-line”.

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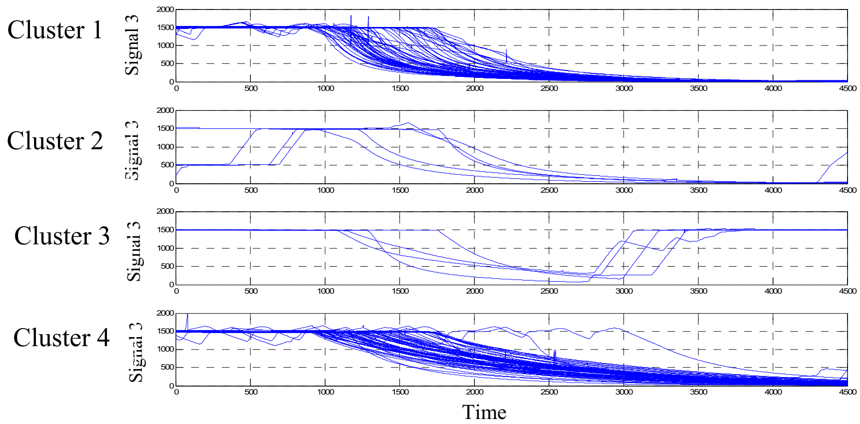

Figure 4: Evolutions of the signal 3 in the transients assigned to the four clusters

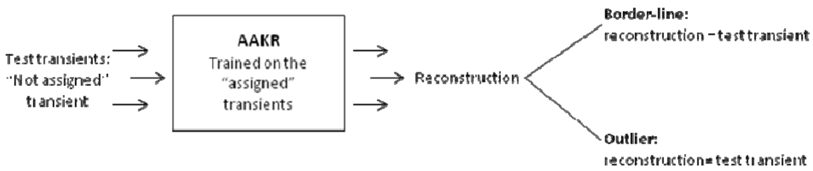

Figure 5: Sketch of the proposed fault detection auto-associative method

The majority of the border-line transients belongs to cluster 4: they show a rate of the decreasing part of the signal which cannot be univocally defined as "sharp" or "smooth". Figures 6 (left) shows signals 3, 24 and 32 for a "border-line" transient (dashed line) and compare it with the evolution of the signals in the prototypical transients of clusters 1 and 4. Notice that the signal evolution of the "border-line" transient is in the middle of the signal evolution of the prototypical transients. Figure 6 (right) shows the signal behaviors in the "outlier" transient 100. Notice that the difference between the functional behavior of the signals in this transient and in the prototypical transient of the most similar cluster is remarkable.

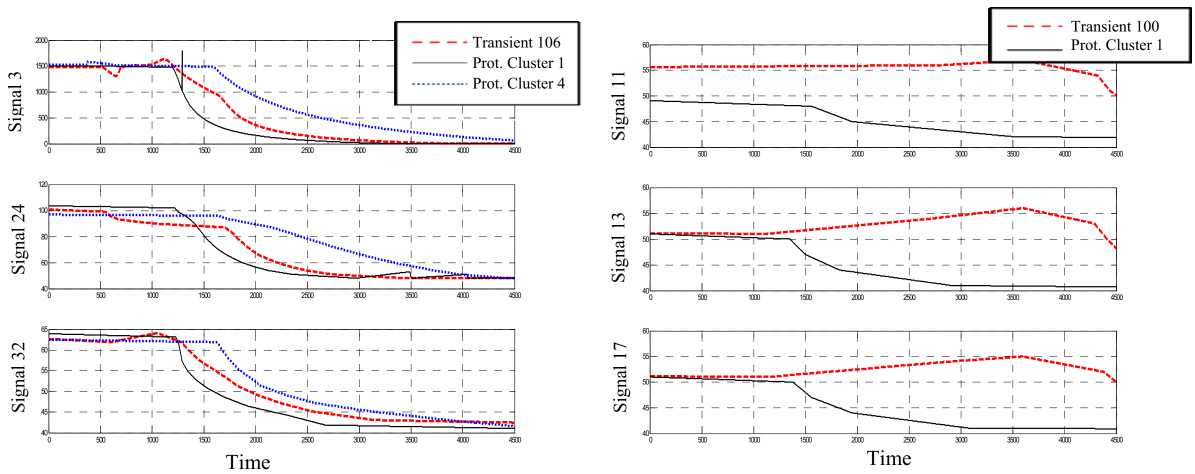

Figure 6; Left: evolution of signals 3, 24 and 32 in transient 106 and in the prototypical transients of clusters 1 and 4. Right: evolution of signals 11, 13 and 17 in transient 100 and in the prototypical transient of cluster 1

5. Conclusions

In this work, we have developed a framework of unsupervised classification of transients for identifying different behaviours associated to different faults. We have preceded the clustering task with a feature extraction capable of treating misaligned data. The proposed fuzzy-based slope analysis for feature extraction is able to capture functional shapes in case of misaligned transients and seems to be a general and reliable technique. We have then computed the similarity between the trajectories by considering the fuzzy similarity of the extracted features, obtaining a squared similarity matrix. The transients clustering is then obtained by the application of the spectral analysis and the following FCM algorithm to the similarity matrix. The application of the proposed framework to a real industrial case study concerning 148 shut-down transients of a NPP turbine has demonstrated the feasibility of the approach. Four different groups of transients have been identified: two groups mainly differ for the rate of decrease of signals correlated to the turbine speed, whereas the other two groups are characterized by transients with anomalous behaviors of some signals, which should be analyzed by NPPs experts to understand whether they are associated to malfunctioning, faults or peculiar working conditions. The applied methodology has also identified the presence of 6 atypical transients (outliers) which have not been associated to any group with enough confidence, which can be considered also as a symptom of malfunctionings or faults.

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