Non-stationary signal analysis in water pipes monitoring

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Abstract— In order to develop early failure detection tools for hydro-power plants, “Electricité de France” (EDF) has equipped its high pressure pipes with sensors which monitor the pressure surge transients, the position of the intake and overpressure valves. The control valves are constructed so that the pressure will not exceed a maximum threshold called the Maximum Guaranteed Pressure (MGP). Modifications in the normal behavior of these control valves can generate high pressure surges over passing the MGP. In this paper, several methods which allow predicting the anomalies in the normal behavior of the hydro-power plant system will be presented.

Keywords: Transient analysis, water-hammer, dynamic time warping, recurrence plot analysis.

I. INTRODUCTION

EDF is a French company in charge of the production and distribution of electricity. These last years, it has started research programs whose objectives are the developing and the implementing of algorithmic tools for monitoring the production hydro-power plants. The goal is to improve their planning of maintenance and safety. In this context, EDF has equipped the pressure pipes with sensors monitoring the pressure surge transients generated by the rapid shut-down of water intake valves and also the position of these control valves.

In hydro-power plants the water present in the reservoir is brought close to the power-plant by a system of pipes following a slow slope. From here to the turbines the water is brought down by a steep slope pipe called the high pressure pipe. The high pressure pipe communicates with a surge tank which protects the duct system against the water-hammer phenomenon appearing in the hydraulic network.

During the normal exploitation of the hydro-power plant the water intake valve could be operated by the control system. These operations can generate more or less violent pressure surge waves. During the normal shut-down or whenever a fault affecting the plant is detected, the water intake valves are rapidly closed generating transient pressure variations in the pipe(s). As so, we can observe a succession of periodic oscillation with decreasing amplitude which characterise the free hydraulic response of the system formed between the closed valve and the surge tank. The shape and frequency of these oscillations depend on the length between the intake valve and the surge tank and on the elastic properties of the steel pipe. The valves closing time is tuned so that the maximal pressure reached in the pipe does not exceed a given value, called the MGP. The closing time is tuned at regular times, during planned maintenance operations.

However, due to faults occurring in the control system or because of the drifts in the tuning parameters, the shut-down operation may be slightly modified, which may cause the pressure in the pipe to increase above the MGP.

In order to be able to detect drifts or faults occurring during the power production process and thus to decide an early maintenance operation, the solution of treating the signals recorded by the monitoring system during the shut down process was proposed. The goal is to develop a method able to detect modifications in the law of interdependence between these signals, which may be an indicator of a fault affecting one of the power plant components. The only information available for each power plant is a set of recordings obtained when the hydraulic system was operating normally. Based on these recordings a number of interdependence laws can be computed which will form a learning set. Whenever a new set of signals is recorded, it must be compared to the learning set in order to decide whether or not it is similar. This is a typical problem of monitoring based on historical data which can be solved by novelty detection. The objective of these methods is to build a decision system whose output could be for example the value 0 if the signals are similar with the learning set and 1 otherwise.

It can be used in any fault detection systems whenever the normal behaviour of the processes is the only information available. As in any classification problem, the first step will be the extraction of specific numeric values from each law of interdependence. These numeric values will be used to represent each set of signals by a scalar or vector. The learning set forms a scatter of points in the representation space. The choice of the features that form the representation space depends on the method used. In the following, two methods which could extract the numerical values will be presented: the dynamic time warping (DTW) and recurrence plot analysis (RPA).

II. DYNAMIC TIME WARPING

The Dynamic Time Warping algorithm is a well-known method used in many areas. It was extensively used in the 70s by application to the speech recognition [1] and it is currently used in areas like: handwriting and online signature matching [2], sign language and gestures recogntion [3], data mining and time series clustering [4], protein sequence alignment and
chemical engineering, music and signal processing [5]. The DTW algorithm is extremely efficient in finding the similarities between two time series. It minimizes also the effect of phase shifts between the signals, the algorithm being able to find similarities even if the phase shift is important. The following figure represents the difference between a simple Euclidian distance and the DTW:

![Figure 1. Comparison between the Euclidian distance and DTW](image)

In order to compare two time series $A = (x_1, x_2, ..., x_N) \in \mathbb{N}$ and $B = (y_1, y_2, ..., y_M) \in \mathbb{M}$, with values in some space $\Phi$, we define a function $d : \Phi \times \Phi \rightarrow \mathbb{R} \geq 0$ called the local distance:

$$d(x_i, y_j) = \sqrt{(x_i - y_j)^2}, \quad (\forall)i \in [1, N], \quad j \in [1, M];$$

(1)

Intuitively we can say that $d$ has small values if the time series are very similar and large values if they are different. The algorithm starts by building the distance matrix $D$ of dimension $(N \times M)$ representing all pairwise distances between $A$ and $B$. This matrix is called the local distance matrix. Once the matrix built, the algorithm finds the optimal path in this matrix by minimizing the sum of the local distances encountered going from an initial point $(1,1)$, which corresponds to the beginning of the sequences, towards the final point $(N,M)$ which corresponds to the end of the sequences.

Consequently, we can show that the optimal warp path is obtained by computing for each entrance $(i,j)$ the accumulated distance $D(i,j)$ by adding the distance between the current pair of points to the smallest value contained in the matrix at $D(i-1, j)$, $D(i, j-1)$ and $D(i-1, j-1)$. By applying the principle of Dynamic Programming we can show that this distance can be computed with the following recurrence:

$$D(i, j) = d(x_i, y_j) + \min\{D(i-1, j-1), D(i-1, j), D(i, j-1)\}$$

(2)

Formally speaking, the alignment path built by DTW is a sequence of points $P = (p_1, ..., p_k)$ with $p_i = (x_i, y_i) \in [1 : N] \times [1 : M]$ for $i \in [1 : k]$ which must satisfy the following criteria:

- **Boundary condition**: $p_1 = (1,1)$ and $p_k = (N,M)$. The starting and ending points of the warping path must be the first and the last points of aligned sequences.

- **Monotonic condition**: $x_1 \leq x_2 \leq ... \leq x_k$ and $y_1 \leq y_2 \leq ... \leq y_k$. This condition preserves the time-ordering points.

- **Step size condition**: this criterion limits the long jumps (shifts in time) in the warping path while aligning the sequences. The basic step size condition is formulated as: $p_i - p_j \in \{(1,1),(0,0),(0,1)\}$.

The cost function associated with a warping path computed with respect to the local cost matrix (which represents all pair wise distances) will be:

$$D(A, B) = \sum_{i=1}^{K} d(x_{\bar{i}}, y_{\bar{j}})$$

(3)

The warping path which has a minimal cost associated with alignment is called the **optimal warping path**.

Finally, the matching cost will be normalized by the length $K$ of the warping path because otherwise longest signals will have a bigger matching cost than the shorter ones:

$$MatchingCost = D(A, B) / K;$$

(4)

### III. Recurrence Plot Analysis

#### III.1 Phase space and Recurrence Plots

Recurrence is a fundamental property of dynamical systems which can be exploited to characterize the system’s behavior in a phase space. In 1987, Eckmann et al. [6] introduced the method of recurrence plots (RP) to visualize the recurrences of dynamical systems.

The RP algorithm start by computing the phase space trajectories of a discrete time series $u_i = u(i \Delta t)$, where $i = 1, ..., N$, and $\Delta t$ is the sampling rate of the measurement. A frequently used method for constructing the phase space is the time delay method:

$$\tilde{x}_i = (u(i), u(i + \tau), ..., u(i + \tau(m - 1)))$$

(5)

where $m$ is the embedding dimension and $\tau$ is the time delay. An example of the phase space trajectory of the Rossler system is given in Figure 3.

Supposing a trajectory $\{\tilde{x}_i\}_{i=1}^{W}$ of a system in its phase space then the corresponding RP is based of the following recurrence matrix:

![Figure 2. Optimal warping path $P = (p_1, ..., p_k)$](image)
where \( N \) is the number of measured points \( \tilde{x}_i \), \( \varepsilon \) is a threshold distance, \( \Theta(\cdot) \) the Heaviside function and \( \| \| \) is a norm. For states which are in an \( \varepsilon \) -neighborhood the following notation will be introduced:

\[
x_i \equiv x_j \iff R_{i,j} \equiv 1.
\]

(7)

The recurrence plot is obtained by plotting the matrix defined by Eq.(6). Two different colors for plotting the recurrence states will be used e.g., a black dot at the coordinates \((i,j)\) if \( R_{i,j} \equiv 1 \) or a white dot if \( R_{i,j} \equiv 0 \). Since \( R_{i,i} \equiv 1 \), \( i = [1,N] \) by definition, we will always find in the RP a black main diagonal called the line of identity (LOI).

III.2 Structures in RPs

The main purpose of the RP is to visualize the trajectories of a time series in a phase space. This method yields important insights into the time evolution of these trajectories, because typical patterns in RPs are linked to a specific behavior of the system. The RPs can be roughly classified into the following categories:

- **Homogeneous RPs**: are typical for the stationary systems
- **Periodic or quasi-period RPs**: for the periodic and quasi-periodic systems
- **Drift and disrupted RPs**: generated by non-stationary systems

The disruptions in the RPs correspond, for example, to events occurring in the analyzed time series. With this in mind, we can say the RPs allow finding extreme and rare events using the frequency of their recurrence.

III.3 Cross Recurrence Plots (CRPs) and Joint Recurrence Plots (JRP)

CRP method is an extension of the RPs and it was introduced as a method to analyze the interdependencies between two different systems by comparing their recurrence states. On the other hand it makes no sense analyzing two systems with different physical meaning in the same phase space, as so one can say that the CRP will be most appropriate in investigating the relationship between the outcomes of the same system. For example different outcomes will be obtained by subjecting the system to different physical or mechanical processes.

Analogously to the RPs the CRPs are obtained by plotting the cross recurrence matrix:

\[
CR_{i,j}(\varepsilon) = \Theta(\varepsilon - \| \tilde{x}_i - \tilde{y}_j \|), \quad i = 1,\ldots,N \quad j = 1,\ldots,M
\]

(8)

The JRP method allows comparing two physically different time series by considering the recurrences of their trajectories in their respective phase spaces. In order to find a joint recurrence, one has to look for the times when the two series recur simultaneously. This approach preserves the individual phase spaces, furthermore, two different thresholds for each system could be considered. Thus the joint recurrence matrix was introduced:

\[
JR_{i,j}(\varepsilon_x, \varepsilon_y) = \Theta(\varepsilon - \| \tilde{x}_i - \tilde{y}_j \|)\Theta(\varepsilon - \| \tilde{y}_j - \tilde{y}_i \|), \quad i, j = 1,\ldots,N
\]

(9)

More generally the multivariate joint recurrence matrix can be defined:

\[
JR^{(k)}(\varepsilon) = \prod_{k=1}^m R^{(k)}_{i,j}(\varepsilon), \quad i, j = 1,\ldots,N
\]

(10)

The corresponding CRPs and JRP s are obtained by plotting Eq.(8) and Eq.(9) respectively.

III.4 Recurrence Quantification Analysis (RQA)

RQA groups several measures of complexity which quantify the small scale structures in the RP [10]. These measures are based on the recurrence point density and on the diagonal and vertical line structures of the RP. A computation of these measures in small windows (sub-matrices) of the RP
moving along the LOI yields the time dependent behavior of these variables. In is important to emphasize that the RQA can also be applied to CRPs and JRPs. In the following, some of the measures proposed for using in our case of non-stationary signals will be presented:

1) Measures based on the recurrence density:

- **Recurrence Rate (RR):** is a measure of density of recurrence points
  \[ RR(\varepsilon) = 1/N^2 \sum_{i,j=1}^{N} R_{ij}(\varepsilon) \]  
  (11)

2) Measures based on the diagonal lines:

- **Determinism (DET):** is measure of systems predictability
  \[ DET = \sum_{i=1}^{N} P(i) / \sum_{i=1}^{N} P(i) \]  
  (12)

- **Average diagonal line length:**
  \[ L = \sum_{i=1}^{N} P(i) / \sum_{i=1}^{N} P(i) \]  
  (13)

- **Divergence:**
  \[ DIV = 1/L_{\text{max}}; \quad L_{\text{max}} = \max(|l_i|) \]  
  (14)

- **Entropy:** reflects the complexity of the RP with respect to the diagonal lines structure
  \[ ENTR = -\sum_{i=1}^{N} p(i) \ln p(i) \]  
  (15)

3) Measures based on the vertical lines:

- **Laminarity:**
  \[ LAM = \sum_{v=1}^{N} vP(v) / \sum_{v=1}^{N} vP(v) \]  
  (16)

- **Trapping Time:**
  \[ TT = \sum_{v=1}^{N} vP(v) / \sum_{v=1}^{N} vP(v) \]  
  (17)

IV. Results

In the following some results of the methods described previously will be presented. The signals being tested are issued from sensors installed by EDF in their hydro-power plants. The discrete time series are sampled at a rate of 40Hz. An example of these signals is showed in figure5. The original signals are truncated between the point where the intake water valve starts to close and the point where the overpressure valve closes. The movement of the intake valve influences the shape of the pressure signal which in term governs the movement of the overpressure valve.

![Figure 5. Pressure signal, Intake water valve and Overpressure Valve positions](image)

These 3 signals will be used in the DTW algorithm as follows: first a sum of the movements of the two valves will be computed and then a law of interdependence between this sum and the pressure signal will be constructed. This set of 3 signals will be represented by a 2 element vector containing the Matching Cost (Eq.4) (whose value depends on the interdependence law) and the Maximal Pressure value.

![Figure 6. Examples of interdependence laws with DTW algorithm](image)

In figure6 are presented the laws of interdependence computed using the normal signals and laws of interdependence computed using the derivatives of the signals. These signals are obtained by the sensors of one power-plant during the normal shut-down sequence. Based on these curves, one can define the normal behavior of the hydraulic system which will form the learning set of the classification algorithm. Another approach will involve the associated two element vector which will be used in specialized classification software.

Another approach for constructing the representation vector of the 3 signal set will be the use of RP, in particular the JRP method. The representation vector will contain the values of RR, DET, L, DIV, ENTR, LAM and TT (Eq.11-17). In figure7 some results of the JRP method are showed.
V. CONCLUSIONS AND FUTURE WORK

In this paper 2 methods for novelty detection in water pipes monitoring were proposed. Both methods used are powerful tools in examining and classifying time series. The methods were employed to extract numerical values and construct some sort of law of interdependence from the available signals. Until now the results are encouraging but the drawback is the lack of real signals to be tested. For this purpose a simple model of the hydro-power plant hydraulic system will be used for generating a signal database. By applying the methods to the generated database a learning set could be constructed. Further work will be done in generating faulty signals in order to validate the ability of these methods to detect abnormal events.

REFERENCES