Pipe leaks detection under varying environmental conditions by using a data driven approach

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Abstract

Structural damage diagnosis under varying environmental conditions is one of the main challenges for developing reliable condition monitoring systems. If damage detection systems are implemented without taking into account environmental influences, false alarms can be produced. Thus, in this work a data driven approach, which considers augmented baseline models, is used to treat different temperature and moisture scenarios in a pipe leak detection algorithm based on principal component analysis (PCA). First, guided waves are induced along the pipe surface structure by means of an active piezoelectric system, where piezoelectric records from the pristine structure are processed through PCA, in order to build a baseline model. Then, statistical indexes allow stablishing several temperature and moisture levels as different cluster states. Thus, common strategies can be adapted to environmental conditions by using robust features. The effectiveness of the methodology is demonstrated by analyzing experimental measurements obtained from a carbon steel pipe section. The results show that the methodology can be used to detect leaks under different environmental conditions, suitable for noninvasive structural damage detection.

Keywords: Piezo-diagnostics, Principal Component Analysis (PCA), pipe leaks detection, guided waves.

1 Introduction

In most of SHM proposed methodologies which consider varying environmental conditions, they can be confused with changes caused by structural damages. Thus, reliable methodologies for damage detection should take into account the effect of these environmental conditions (humidity, wind, temperature gradients, etc.) in order to avoid false-positive or negative damage diagnosis. In this sense, in last years, several approaches in the field of damage diagnosis have paid attention to the effect of variable environmental conditions [1], [2], [3], [4], [5], [6].

One of the methods used to deal this effect is to perform correlation between the measured vibration characteristics and the corresponding environmental conditions [2]. Other approaches separate different environmental conditions into different clusters by means of Self Organizing Maps [3] or by using NullSpace method [4], which facilitates optimal based selection techniques [5]. Also, principal component analysis (PCA) [6] have been proposed as statistical tool to distinguish structural damages under environmental conditions, where environmental effects are treated as embedded features.

However, to discern changes resulting from environmental influences respect to changes due to actual damages is still a challenging task. One of the drawbacks is the high sensitivity of measured responses from a structure to damage and environmental variables, therefore it is difficult to define robust features insensitive to environmental variations. Other issues regarding practical situations is the requirement of environmental variable sensors installed in the host structure permanently, which is highly dependent of a proper location.

In this paper, PCA is used as alternative to deal environmental conditions regarding to temperature and humidity variations. It is proposed to build an augmented baseline model in order to include the environmental influences into the data variability, where environmental variables are measured only once. Structural damages are identified by means of piezo-diagnostics principle and statistical indexes. The effectiveness of the implemented data driven approach is validated using experimental measurements from a carbon steel pipe loop. It is demonstrated that pipe leaks detection is achieved considering several temperature/humidity scenarios at laboratory scale.

2 Pipe leaks detection methodology

The methodology for pipe leaks detection described in this article consist of first inducing guided waves along the surface pipe structure by means of piezoelectric devices, taking advantage of piezo-diagnostics principle. Then, piezoelectric measurements of the pristine structure are used to build a baseline model by means of principal component analysis (PCA) [7]. Finally, new measurements are analyzed with statistical indexes in order to detect abnormal conditions in the pipe structure. The effectiveness of this methodology has been experimentally validated on previous works. Thus, by using piezo-diagnostics and PCA it is possible to detect damages in aluminum and composite plates [8], to localize masses in aircraft sections [9], to distinguish between several pipe leaks scenarios [10], and to recognize cut saw elements in a laboratory tower.

2.1 Piezo-diagnostics

Piezo-diagnostics refers to structural health monitoring techniques based on the analysis of measurements from piezo electrical devices bonded along the surface structure. Thus, guided waves are generated by applying an electrical voltage to one of the PZT mounted on the structure. Then, the response to elastic waves propagation along the target structure can be measured by the remaining PZT in a pitch–catch mode.

The guided waves traveling through structural discontinuities produce scattering, reflection, and mode conversion, which makes possible to identify structural damages. Many applications for SHM, which take advantage of piezo-diagnostic principle to examine the structural signature, can be found in the literature. For instance, a methodological Review of Piezoelectric based acoustic wave generation and detection techniques for SHM is reported by Zhigang et. Al [11]. In addition, an overview of piezoelectric impedance-based health monitoring are discussed by Baptista et. Al. [12].

2.2 Cross-correlation of piezoelectric signals

The first processing stage of the methodology for pipe leak detection consist of computing the cross correlation between actuating and sensed signals, which is intended to exclude external signals common to actuation and sensing elements, and to eliminate noisy data trends. Thus, bias and noise are minimized. The cross-correlation function between two signals $X(t)$ and $Y(t)$ is defined by eq. (1).

$$R_{XY}(t,t+\tau) = \lim_{N\to\infty} \frac{1}{N} \sum_{k=1}^{N} X_k(t) Y_k(t+\tau) \tag{1}$$

Where N is the number of signal samples and τ is the lag time interval used to compute the cross-correlation function.

2.3 Minimal representation of cross-correlated piezoelectric signals

The second processing stage of the methodology for pipe leak detection consist of representing the cross-correlated piezoelectric signals, regarding to nominal state of the pipe structure, in a new reduced space of coordinates with minimal redundancy, by applying PCA. The central idea of PCA is to reduce the dimensionality of a data set $\boldsymbol{x}$, which consists of a large number of interrelated variables, while the data variation is retained as much as possible. The objective of PCA is to find a set of $\boldsymbol{r}$ basis vectors that satisfies the extreme value problem stablished by eq. (2) [13].

$$\begin{aligned} &\min_{P_i} \varepsilon^2(r) = \mathrm{E}\{\|x - x(r)\|^2\} \\ &s.t.\ \ {P_i}^T P_j = \delta_{i,j} \quad i,j = 1,2,\dots,r \end{aligned} \tag{2}$$

The basis vector $\boldsymbol{P}$ can be estimated by computing the singular value decomposition of the covariance matrix $\boldsymbol{C_x}$ established by eq. (3), which can be solved by using NIPALS, POD or QR procedures [14].

$$C_x P = P\lambda, \quad where\ \mathrm{C}_X = \frac{1}{\mathrm{m}-1} X^{\mathrm{T}}\mathrm{X} \tag{3}$$

Where, $\boldsymbol{m}$ is the number of trial records used to estimate the covariance matrix, and λ the respective eigenvalues. If cross-correlated piezoelectric signals of the pristine structure are arranged in an unfolded matrix (**X**), a baseline model is obtained by means of the basis vectors, according to PCA procedure in eq. (4).

$$X = TP^T + E = model + noise \tag{4}$$

Where, **P** is a linear transformation matrix that relates the data matrix $\boldsymbol{X}$ in the new coordinates and it is known as the principal components. **T** are the projected matrix to the reduced space and the noise E-matrix describe the residual variance neglected by the statistical model. The singular values ($\boldsymbol{\lambda}$) are the respective variances of this new coordinates reduced-space. Scaling normalization procedures can be included in order to eliminate bias and scale variance trends.

2.4 Pipe leaks detection

The last stage of the methodology for pipe leak detection consist of determining the existence or absence of pipe leaks. It consists of analyzing new PZT measurements representing the current state of the pipe structure. The cross-correlated piezoelectric signals are organized in a row vector, which is standardized by applying the respective scaling normalization procedure and considering mean values and standard deviations of the undamaged baseline matrix $\boldsymbol{X}$. Then, the normalized row vector of new measurements is projected onto the reduced space by using eq. (4). Finally, Q and T^2 statistical indexes are used to pipe leaks recognition [7], where differences between statistical indexes regarding to baseline and current state are attributed to leak presence.

The Q-statistic, defined by Eq. (5), is a lack of fit measure between the analyzed experiment and the baseline records.

$$Q = \sum_j \left(e_j\right)^2 \tag{5}$$

Where, e_j is the residual error for each $j-th$ principal component used to reconstruct the trial experiment.

The Hotelling T^2 statistic, defined by Eq. (6), indicates how far each trial is from the center (T = 0) of the reduced space of coordinates.

$$T^2 = \sum_{j=1}^{r} \frac{t_{sij}^2}{\lambda_j} = T'\lambda^{-1}T \tag{6}$$

2.5. Robust baseline model building

SHM methods based on guided waves are adversely influenced by variable environmental and operational conditions of the monitored structure, where false alarms are the main issue reported in the literature. Thus, in this approach temperature and humidity changes effects are considered by augmenting the baseline model, in order to become robust the pipe leak detection.

2.5.1. Temperature and humidity changes effects

Several researches (see [15], [16] and [17]) in the field of damage detection based on guided waves summarize the next adverse effects produced by temperature changes:

- Change in the properties of PZT transducer such as piezoelectric constants.
- Degradation in properties of adhesive used to bond transducers to the host structures.
- Thermal expansion, such as change in plate thickness, piezo dimensions and distances traveled by the guided wave along the structure.
- Change in elastic properties, including density and Young modulus, which cause changes in wave velocity.

In addition, high temperatures in metallic materials cause thermal creep and stress conditions, which reduce its useful life with a higher effect when it is subjected to fatigue.

On the other hand, the mechanical and piezoelectric properties of the PZT are fewer influenced by humidity absorption. However, in the literature is reported a remarkable large impact of humidity changes over amplitudes measured from PZT systems [18]. Additionally, high relative humidity produces corrosion degradation in pipe structures.

2.5.2. Augmented baseline model

Since a pipeline operates under several temperature and humidity scenarios, it is proposed to consider these conditions by building an augmented baseline model including measurements at the expected temperature/humidity real operation scenarios. Thus, experimental records of undamaged state at different temperature/humidity levels should be unfolded in a two-way matrix as is shown in Figure 1.

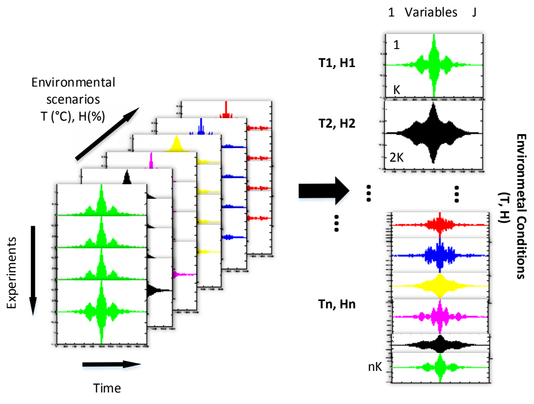

Figure 1 Undamaged-augmented experimental data matrix.

In this sense, by processing the augmented experimental data in Figure 1, the variation for different temperature/humidity levels are taken into account in the PCA model building procedure. It means that the PCA baseline model established by eq. (4) is built after computing cross-correlated piezoelectric signals of the undamaged-augmented data matrix.

3. Experiment design

The methodology described in the above section was experimentally validated in a carbon-steel pipe loop by considering leaks at different temperature and humidity conditions. Thus, this section presents the experimental setup to produce different temperature/humidity scenarios.

3.1.Humidity and Temperature Conditioning

Figure 2 describes the conceptual design established to obtain experimental records considering several temperature/humidity scenarios. High power lamps, located at the top of the pipe structure, mimic the sun influence by radiating heat waves on the pipe. The heating is focused in the area where the PZT devices are installed, which is intended to affect mainly the piezo-devices couplant properties. On the other hand, a trough-shaped vessel was conditioned between the floor and pipe zone to produce humidity changes. Temperature levels were feedback controlled by an adjustable power source, while the humidity was treated as a disturbance since the high interrelation between these two environmental variables. However, in order to achieve homogenized conditions in the moisture levels, the through-shaped vessel was filled with water, which is then regulated by using coolers and heating resistors. Thus, moist air and steam flow affects the humidity conditions near to the pipe structure.

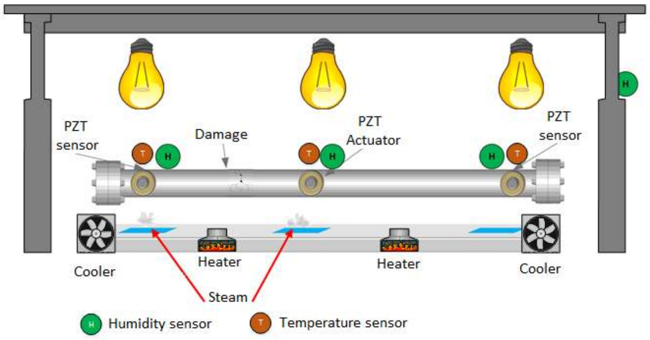

Figure 2 Experiment design to produce temperature and humidity variations.

Temperature and humidity measurements were obtained by using the HSM20G and LM35 sensor devices, which operate at [10% to 90%] and [55° C to 150°C] ranges respectively. In addition, a PI algorithm was implemented (phase controlled) in the Arduino hardware platform in order to regulate the average temperature in the pipe structure. The scenarios studied in this paper are detailed in Figure 3, where a combination of heating lamps, heating resistors (steam) and cooler elements (moist air) are specified.

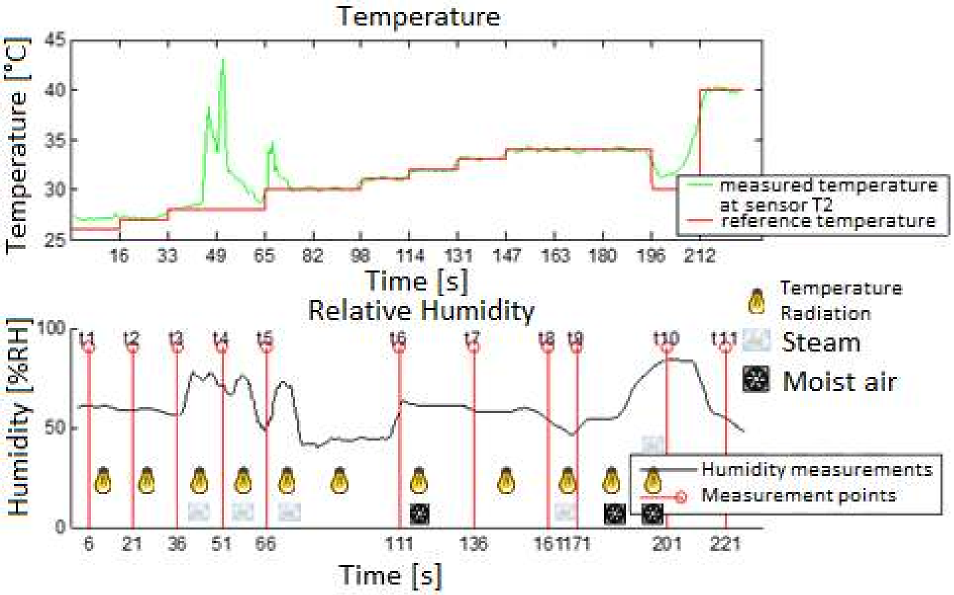

Figure 3 Temperature and humidity scenarios.

According to Figure 3, the first record (t_0) correspond to uncontrolled environmental conditions, and then eleven temperature set-points (t_1, …, t_{11}) were produced each 10 minutes for a total of 11 humidity/temperature scenarios.

3.2.Pipe loop description

The test structure used to validate the leaks detection methodology is a carbon-steel pipe loop, which consists of five 100x2.54x0.3 cm (length, diameter, thickness) sections (see Figure 4. Each pipe section contains bridles at its ends and three piezoelectric devices (PZT) bonded along the surface structure. The PZT devices located at the middle of each section operated as actuators and the remaining ones as sensors. A burst type signal, generated by means of an AWG PicoScope series 2000, was used to excite the PZT actuator around its resonance frequency (~100 KHz) and then it is amplified to ±10 V. In addition, a valve that controls the airflow from a compressor at 80 psi is installed in the pipe loop, while a manometer is used to indicate the operation pressure.

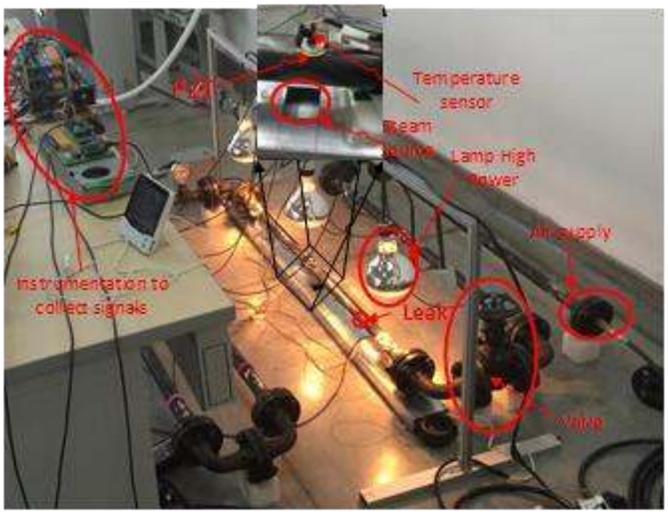

Figure 4 Pipe loop experiment.

According to Figure 4, changes in the temperature/humidity conditions mainly affects the third section of the pipe loop, where three lamps and two coolers are used for these purposes. In order to evaluate the effectiveness of the leaks detection methodology, 100 experimental repetitions were recorded for scenarios corresponding to undamaged and leak states under different temperature/humidity conditions (t_0, …, t_{11}). The leak was induced by a full opening of a hole between the PZT devices (Actuator-Sensor) in the third section of the pipe loop structure. The baseline model is built by using measurements from the ten PZT sensors.

4. Experimental results

A preliminary test was conducted by using only the 100 experiments at uncontrolled environmental conditions, in order to build the PCA baseline model. Figure 5a presents the T^2 and Q statistical indexes for the undamaged (UND_1, …, UND_{11}) scenarios under different temperature/humidity conditions, while Figure 5b depicts results for one leak at the respective humidity/temperature scenarios (T_0, …, T_{11}), where clusters for each environmental condition are observed.

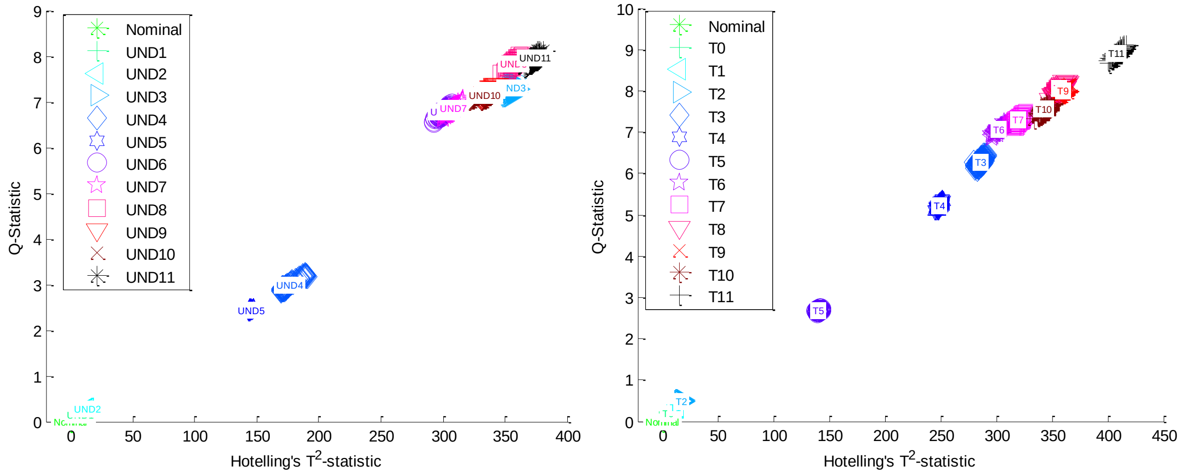

Figure 5 Q vs T^2 statistical indexes at different humidity/temperature conditions computed by using a non-controlled temperature signals baseline model. A.) Undamaged states. B.) Leak condition

According to Figure 5, the leak and undamaged states are treated as different conditions for each temperature/humidity scenario. Even, for small environmental changes is difficult to differentiate between the undamaged and leak states. Also, the dispersion for different temperature/humidity conditions at undamaged state is large and comparable to the leak measurements. Therefore, humidity/temperature changes could be confused with leak states, which is an undesirable characteristic for detection purposes.

In order to build the robust baseline model, 1200 undamaged experiments under different environmental conditions (UND_0,…, UND_{11}) were achieved. The Q and T^2 statistical indexes for undamaged and leak scenarios at different humidity/temperature conditions, computed by using this augmented baseline model, are depicted in Figure 6.

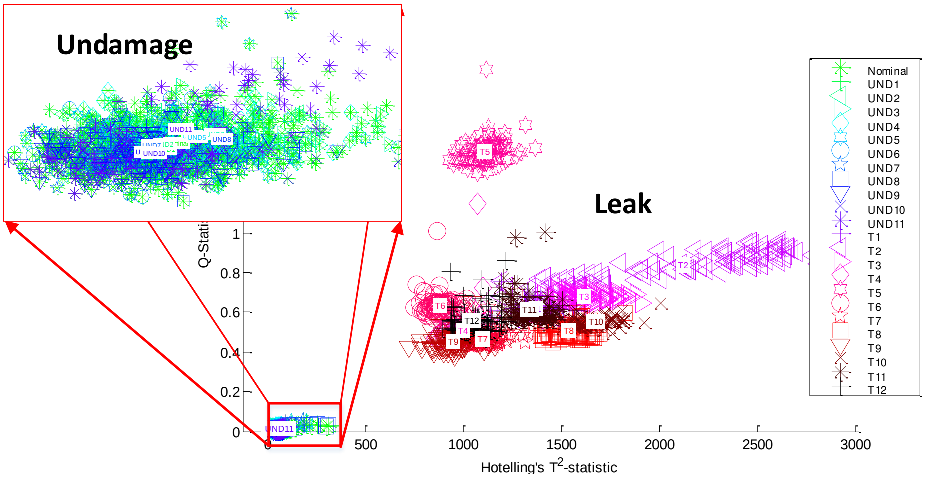

Figure 6 Damage indexes for leaks at different environmental conditions by using an augmented baseline model.

According to the results in Figure 6, a better differentiation between the undamaged and leak states is observed, and they are grouped in separated clusters. For undamaged cases it is observed low Q-values $[0{,}3x10^{-3}$ $-2x10^{-3}]$ and T^2 indexes with lower dispersion respect to the initial indexes (Figure 5a). In addition, Q statistic has a lower sensitivity to variations in environmental conditions than T^2 index.

The time piezo-electrical signals recorded in one of the PZT sensors for the undamaged state under different temperature conditions are plotted in Figure 7. The relative humidity for these cases can be considered constant (~60%).

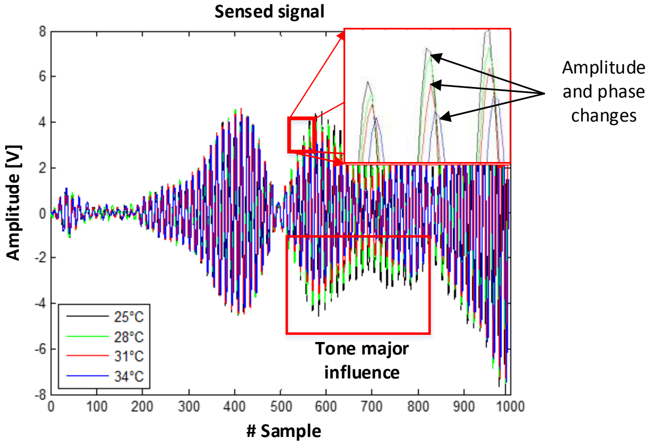

Figure 7 Time records of PZT responses at different temperature conditions

According to Figure 7, temperature changes produce phase shift and amplitude attenuation in the guided waves response, which has been reported in the literature.

Since temperature and moisture environmental variables are highly correlated, a second test was conducted in order to emphasize the humidity influence. Thus, the lamps were power off and the humidity conditions were modified by means of coolers and heating resistors (Figure 2). The six (t_1, …, t_6) studied scenarios are detailed in Figure 8.

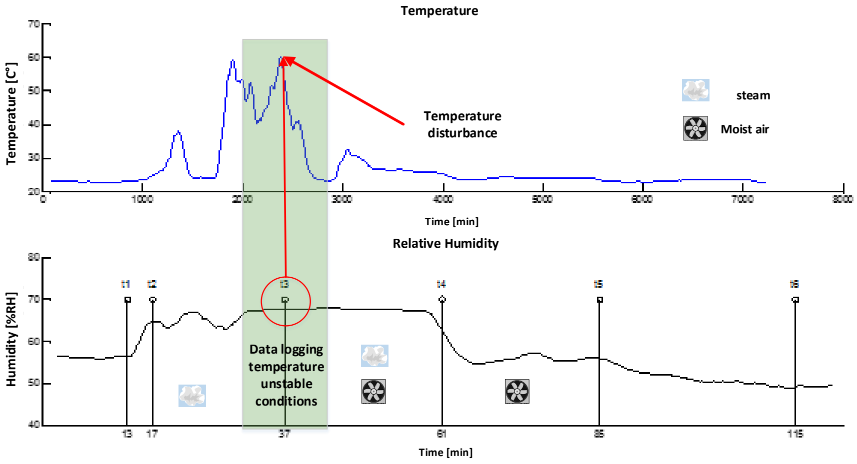

Figure 8 Scenarios to evaluate humidity influence

According to Figure 8, if steam is used to change the humidity conditions, a temperature disturbance is induced (scenario t_3). The respective time piezoelectric signals are illustrated in Figure 9, where no meaning differences can be observed, except for scenario t_3. In this case, similar to the above case, the temperature affects the signal amplitude.

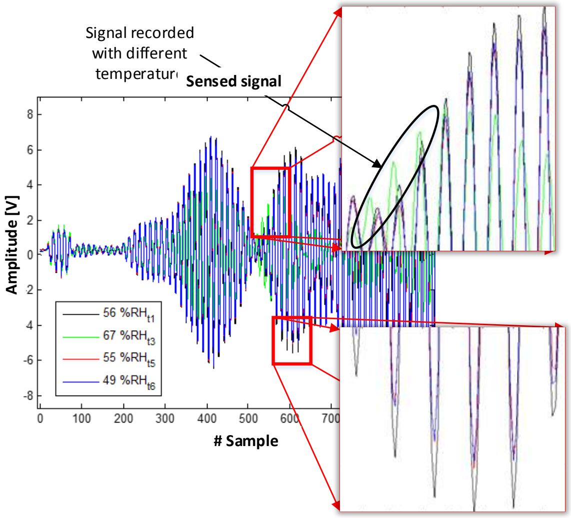

Figure 9 Time records of PZT responses at different humidity conditions

5. Conclusion

In this paper, a leak detection methodology was modified in order to consider humidity/temperature effects, by including cross correlated signals and an augmented baseline model. Experimental results of applying the modified methodology on a pipe loop, shown that a robustness to detect leaks under temperature/humidity variations is achieved, by using the T^2 and Q statistical indexes computed by means of the augmented model. Thus, the squared prediction error (Q-statistic) values for undamaged cases keep low for different humidity/temperature conditions, which means that the pristine structure state is properly represented. In addition, it can be concluded that piezoelectric records are mostly affected by temperature changes than by humidity variations. Finally, one advantage of the proposed methodology is that only one experiment for undamaged state should be conducted in order to build the robust baseline model and no optimal location of sensors was required, however, additional studies are necessary to evaluate couplant effects as well as real operational conditions.

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