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TOWARD ACOUSTIC NOISE TYPE DETECTION BASED ON QQ PLOT STATISTICS *

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Abstract. *Fault detection and state estimation using acoustic signals is a procedure highly affected by ambient noise. This is particularly pronounced in an industrial environment where noise pollution is especially strong. In this paper a noise detection algorithm is proposed and implemented. This algorithm can identify the times in which the recorded acoustic signal is influenced by different types of noise in the form of unwanted impulse disturbance or speech contamination. The algorithm compares statistical parameters of the recordings by generating a series of QQ plots and then using an appropriate stochastic signal analysis tools like hypothesis testing. The main purpose of this algorithm is to eliminate noisy signals and to collect a set of noise free recordings which can then be used for state estimation. The application of these techniques in a real industrial environment is extremely complex because sound contamination usually tends to be intense and nonstationary. The solution described in this paper has been tested on a specific problem of acoustic signal isolation and noise detection of a coal grinding fan mill in thermal power plant in the presence of intense contaminating sound disturbances, mainly impulse disturbance and speech contamination.*

Key words: *Acoustic signal, QQ plot, noise detection, predictive maintenance*

1. INTRODUCTION

It is well known that the largest financial loss for modern industrial plants is due to inefficient or untimely maintenance [2]. This is especially true for power plants which are designed to be in function for many decades after their construction. Therefore, it is only logical that there is a significant amount of research done in an attempt to prolong the working life of the plant, improve the quality of its operation [3] and reduce unnecessary losses [4]. With this in mind, the fact that predictive maintenance has become a very

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popular area of research is not so surprising. Crucial aspects of predictive maintenance are fault detection and state estimation, i.e. the estimate of whether the fault has occurred somewhere within the system or whether certain components are worn and the maintenance needs to be done in order to replace them.

The accelerometers are the sensors most commonly used for implementing predictive maintenance algorithms on rotating machinery. The logic behind this is sound: as the fault occurs within the rotating element or as the wear of some components becomes pronounced, the vibration of the machine is sure to change accordingly [5]. The sensors can measure this vibration and algorithms can be constructed which can, based on the change in vibration signal, detect the amount of wear of certain components. These techniques are widely used in the industry with much success [6]; however, an alternative has been presented in the early 90s. This alternative proposes the use of acoustic signals for the same purpose. It has been shown that sound recordings can be as informative as vibration signals when it comes to state estimation of components [7], but acoustic sensors (microphones) are cheaper to obtain and are contactless, which is a very important feature for certain types of processes. One major drawback of using microphones for predictive maintenance is the fact that they are very sensitive to ambient noise. This makes them less than ideal for the use in an industrial environment which is usually very polluted with contaminating noise. For this reason microphones are still rarely used for predictive maintenance in real industrial environments.

One way to significantly increase the applicability of acoustic signals for this purpose is developing an algorithm capable of filtering out the acoustic noise caused by the surrounding events. There are many preprocessing algorithms developed in recent years for purpose of fault detection and state estimation. Using one of the standard frequency filters is usually not applicable because it is very difficult (if not impossible) to determine the frequencies on which the noise is dominant. Even if that can be established, usually the useful part of the signal exists on the same frequencies as well, so filtering out the noise would significantly damage the informative part of the signal. Impulse disturbance in time domain, for example, is equally pronounced on all frequencies, so it cannot be filtered using traditional algorithms.

Taking this into consideration one can easily conclude that standard frequency domain analysis is not reliable enough for noise detection in acoustic signals. Therefore advanced procedures should be used for this purpose, such as statistical analysis of the signal. Statistical parameters of the recorded signal can be very informative in this case because different statistical behavior is expected when the noise occurs and when the signal is in its nominal form. One of the standard tools used for statistical comparison and analysis are QQ plots and they are shown to be quite effective in this case [8].

The purpose of the algorithm proposed in this research is not removal, but rather detection of noise. The entire recording is separated into windowed signals, and each windowed segment is tested for noise. This is done by comparing the statistical distribution of the recorded signal against the statistical distribution of the signal in nominal working condition. The comparison is conducted using QQ plots and Neyman-Pearson hypothesis test. The noisy sequences are discarded and those which are classified as nominal are saved for the purpose of state estimation or some other predictive maintenance procedure.

The algorithm developed in this research is seen as a part of a larger system of state estimation and fault detection mechanism of rotating elements in thermal power plants based on acoustic signals. It has been tested on real recordings taken in thermal power plant Kostolac A1 in Serbia, on a specific fan mill which is a part of coal grinding subsystem. It has been shown that state estimation of impact pates within a mill is possible only by using recordings from a microphone placed in the vicinity of the mill [9]. However, it has also been shown that noise can significantly influence the classification results. The purpose of this algorithm is to conduct signal preprocessing, so that the noise-free samples of the acoustic signals can be used for state estimation of impact plates of the mill.

This paper is structured as follows. Section 2 contains theoretical description of the algorithm used, mainly QQ plots and Neyman-Pearson method of hypothesis testing. Section 3 contains the description of the real industrial coal grinding subsystem in thermal power plants on which this algorithm has been tested. In Section 4 the detailed results of the algorithm are given. Here, the algorithm has been tested on nominal and noisy signals. Furthermore, the effect of the change of certain parameters of the algorithm has been examined, as well as upgrade of the algorithm which enables it to be used for classification and not just noise detection. Finally, the conclusions are presented in Section 5.

2. QQ Plot as a Tool for Noise Detection

In nominal, stationary operation of the system it is assumed that the statistical parameters of the measured signals will remain constant. If, on the other hand, an event occurs that causes a deviation from nominal state (e.g. nonstationary ambient noise), statistical parameters of the recorded signals are expected to change in a certain way. Therefore, the probability distribution of the recorded signal in nominal regime is going to be different from the distribution of the signal which is polluted with noise. This change is going to depend on the duration and the type of noise, so the statistical parameters can be used not only for noise detection, but for noise classification as well.

2.1. QQ plot

A very efficient graphical tool which is used to compare the expected and obtained probability distribution is a QQ plot method [10]. This graph is obtained by plotting quantiles of the measured signal against the quantiles of the expected probability distribution. If the two distributions are similar, all the points in QQ plot will approximately lie on the line $x = y$. Figure 1 shows a QQ plot of an experimentally obtained zero mean unit variance Gaussian distribution against its theoretical expectation.

The application of this type of data inspection allows not only the comparison of two probability distributions, but also the identification of the distribution of recorded model. For example, if outliers occur at the end of the $x = y$ line, this means that the measured distribution has lager (or smaller) tails than the expected distribution. If all dots lie on the line, but the angle is not 45^o, then the variance of the expected distribution is not the same as in the measured signal.

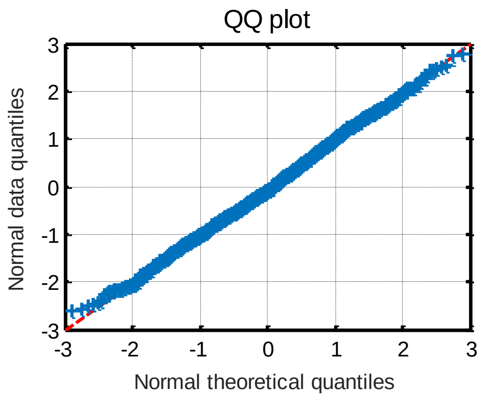

Fig. 1 Experimentally obtained Gaussian samples plotted against the theoretical distribution.

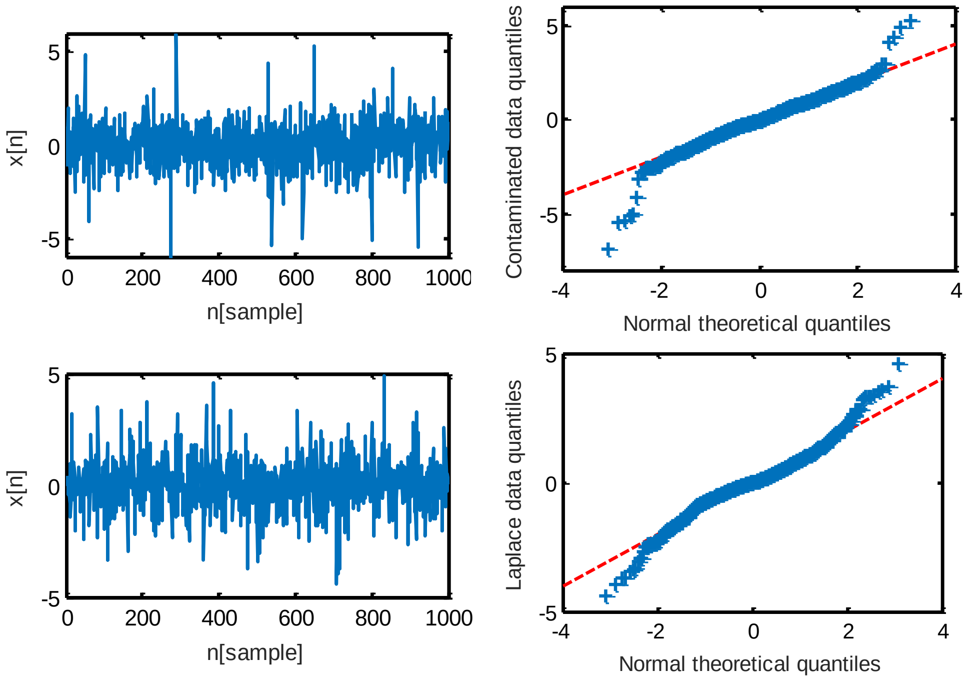

Fig. 2 Contaminated Gaussian distribution in time domain (upper left) with the appropriate QQ plot (upper right) and Laplace distributed sample data in time domain (lower left) with its QQ plot (lower right).

Using these rules one can easily infer the shape of the probability distribution as a function of the expected distribution. For example, a Gaussian signal polluted with noise is expected to contain large tails on the QQ plot, as in Fig. 2 (up). On the other hand, if the distribution of experimentally obtained signal is significantly different in nature than the expected distribution, one will expect the deviation from $x = y$ axis for both lower and higher values of quantiles. This is shown in Fig. 2 (down) where Laplacian distributed experimental samples are plotted against the Gussian distribution. The graph indicates that the obtained samples have higher values than the Gaussian distribution will indicate and there is a curve for lower values as well.

If the measured samples $x_i,\ i = 1, \ldots, n$ form a distribution $F(x)$, an ordered non-decreasing sequence y_i can be obtained, where $y_i \leq y_j$ for $i < j$. Here, n represents the number of samples taken. By observing the ordered sequence y_i, the formula for conditional probability can be obtained [8] which calculates the probability that measurement y will have the rank i in the said sequence:

$$P(i|y) = \binom{n-1}{i-1} F^{i-1}(y)\big(1 - F(y)\big)^{n-i}. \tag{1}$$

2.2. Hypothesis testing

QQ plots in this research are used to represent the relationship between the measured signal distribution and the distribution of the signal in nominal working conditions. For this reason hypothesis testing is implemented in order to decide, based on the available data, whether the assumption of nominal working conditions is correct. If not, then the signal is considered polluted by noise and is discarded.

The noise detection algorithm developed in this research relies heavily on Eq. (1). In order to successfully implement it several initial calculations need to be performed. First the expected probability distribution in nominal regime (when there is no noise) needs to be established. Then, after calculating nominal probability density function f_n, the discriminant boundaries should be determined. If all the samples of the QQ plot lie within these boundaries, then the recorded signal is in nominal working condition, i.e. there is no noise. If, on the other hand, points on the QQ plot find themselves beyond the calculated boundaries, the fault has occurred, and the recorded samples are dismissed.

There are two objectives which must be taken into account when establishing valid bounds on the QQ plot. The first objective is maximization of the probability that the noise-free recordings will be classified as valid. The second objective is minimization of the probability that faulty recordings will be falsely classified as valid. Therefore, a tradeoff needs to be made, and as a solution a variation of Neyman-Pearson method [11,12] for hypothesis testing has been chosen. This means that the probability p for the desired efficiency under nominal conditions has been fixed. In the literature this value is usually adopted in the range between 0.9 and 0.99. In this paper the value $p = 0.95$ has been taken. Therefore, lower and upper bounderies (α and β) are calculated so that the following condition is satisfied:

$$\int_{\alpha_i}^{\beta_i} f(y_i|i)dy_i = F(\beta_i|i) - F(\alpha_i|i) = p, \tag{2}$$

where the probability density function $f(y_i|i)$ can be expressed using the Bayesian formula:

$$f(y_i|i) = \frac{P(i|y_i)f_n(y_i)}{P(j)}. \tag{3}$$

3. CASE STUDY

Coal fueled thermal power plants play a very important role in energy production worldwide and are the number one energy provider in Serbia. For that reason an increase of productivity and work life of an entire plant, as well as its subsystems, is of great economical importance. Coal grinding subsystem is one of the key parts of thermal power plant and is responsible for pulverization of coal, so it can be used in a burner system.

In thermal power plant Kostilac A1 in Serbia fan mills used for coal pulverization have ten impact plates which rotate around the center. Pulverization occurs as a result of friction between the plates and the chunks of coal within the mill. When the coal is grinded into a fine powder it is transported into a burner system where it is used as a fuel. The particles which are not small enough return back into the mill where they are additionally pulverized.

After several weeks the impact plates within the mill get worn due to constant impact with coal chunks and rock and the efficiency of the mill starts to decrease. This is when the maintenance needs to be performed or other more serious problems and malfunctions will occur. The algorithms which can detect the moment the maintenance is needed based on the recorded acoustic signals have already been developed. They, however, are unable to perform their function when the noisy measurements are provided, which often happens with acoustic signals in a real industrial environment.

Mills in thermal power plants produce high intensity noise and they are located in the vicinity of other mills of the coal grinding subsystem. Therefore, the acoustic environment in which the recordings are measured is extremely complex. Even with all this in mind, the frequency features of this noise are very informative for state estimation of impact plates within the mills. However, given that the area around the mill consists of a large number of other actuators, valves, pipes, pumps, additional works such as welding, repairs, maintenance and the like, are quite common. At the same time, the sound recording is being enriched by sporadic impact of larger chunks of coal. These occurrences contaminate acoustic recording and, considering that their statistics are not included in the training sets used for impeller state estimation algorithms, they can cause the algorithm to make a wrong decision or, at the very least, cause a large time delay in making a correct decision. For this reason it is of great importance to develop techniques for detection and, if possible, classification of contamination in the acoustic recording.

Acoustic signals used to demonstrate the results of the proposed algorithm are recorded in different acoustic surroundings of the mill. One part of these recordings is taken in nominal working conditions in which, other than the noise from the mills and other rotating elements, there are no other sources of contamination. The second group of recordings consists of nominal sound sources as well as the sound of people talking in the vicinity of the microphone. The third group of signals contains nominal sound as well as the sound produced during welding and repair of the steam lines near the mill.

The noise detection algorithm developed in this research has been tested on real acoustic signals recorded in thermal power plant Kostolac A1 in Serbia. There are 10 impact plates within the mill for which the noise detection algorithm has been tested and the recorded signal has the sampling frequency of 48kHz. The length of the obtained recording is approximately 20 minutes. This recording consists of intervals in which the system is in nominal regime, as well as intervals when the artificially created noise has been used to pollute the recording.

4. RESULTS

The proposed algorithm is tested in several steps. First the learning part of the algorithm is conducted in which the recordings in nominal regime are analyzed. In this way the nominal probability density function f_n, as well as the discriminant boundary for nominal recordings are obtained. After that, the algorithm is tested on both contaminated and nominal samples in order to determine how prone it is to false classification. The effect of window length on proposed algorithm is analyzed as well. Finally, an attempt has been made to classify the obtained noise and to determine whether the impulse disturbance or speech contamination has occurred.

4.1. Nominal recordings

As it is stated earlier, the initial part of the algorithm is a learning process in which sufficiently long signal in nominal regime is used to approximate the nominal probability density function. After that the Hilbert transform of the signal is performed in order to obtain an envelope of the signal.

There are several ways to approximate the probability density function (pdf) of the obtained sequence. One is by observing the scaled histogram of the signal, and the other is using the method of kernel functions. The latter method is chosen in order to obtain a smoother version of the estimate without a significant increase in computational complexity. For pdf estimation an Epichenkov kernel function is used due to the fact that it is most commonly applied in the literature because it minimizes the mean square error. As expected, the pdf estimate obtained in this way roughly resembles the shape inferred from the histogram.

After estimating pdf of a noise-free signal, the next step is to determine the boundaries of a QQ plot from Eq. (2). Seeing how all the samples of a Hilbert transform of the signal are positive and the expected behavior of a noisy signal would be a larger variance and a greater mean value (with respect to noise-free parameters) a slight simplification of (2) can be implemented, for the sake of easier numerical calculations:

$$\int_0^{\alpha_i} f(y_i|i)dy_i = p. \tag{4}$$

The lower classification boundary does not need to be determined because when the noise occurs, the points on the QQ plot are expected to drift above the $x = y$ line. Therefore, Eq. (4) is used for the purpose of noise detection and boundary α calculation. The resulting QQ plot of the samples in nominal regime and the calculated boundary are shown in Fig. 3.

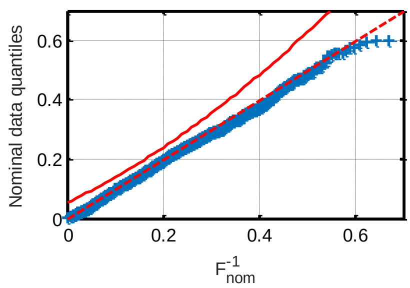

Fig. 3 QQ plot of nominal recorded quantiles with respect to nominal expected quantiles, with boundary α.

4.2. Noisy recordings

Testing the algorithm as a tool for noise detection is conducted on the part of the signal which is 12 seconds long and whose Hilbert transform is shown in Fig. 4. This signal contains dominant sections of nominal regime (blue), sections contaminated with speech (green) and samples which contain impulse disturbance (red). In this way all the aspects of noise detection algorithm are tested. The Hilbert transform is applied in order to obtain an envelope of the signal.

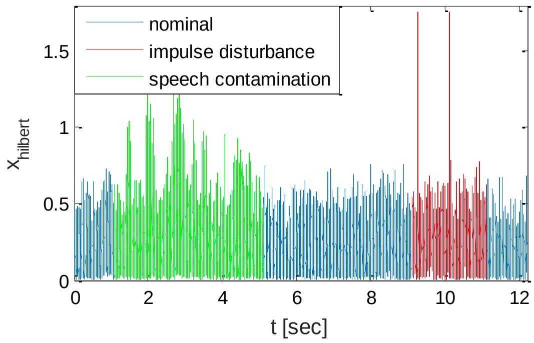

Fig. 4 Part of the recording on which the algorithm has been preliminary tested. Blue represents the nominal regime, green represents the part of the signal contaminated with speech, and red represents the part of the signal contaminated by impulse disturbance.

The testing recording has been separated into smaller pieces obtained using window the size of 1sec, with overlap of 50%. Each window has been tested for noise, and the noisy recordings have been dismissed. All the windows which include only the nominal behavior without the noise have QQ plots which resemble the shape shown in Fig. 3. All the points of the plot are below the discriminant boundary and are therefore classified as noise-free samples.

The effect of speech contamination on the QQ plot depends heavily on the percentage of contaminated signal which is enveloped within the window, as shown in Fig. 5. In case when the windowed signal consists exclusively of speech contaminated samples (Fig. 5 down), its QQ plot has quantiles which lie on an approximately straight line with angle larger than 45°. This indicates that the variance of the recorded signal, as well as its mean value, is larger than expected. Also, most of the samples lie above the discriminant line which means that the algorithm has detected the noise. The situation is not so clear when only part of the window which is examined contains speech contaminated samples. In that case the angle of the plot is lower and, depending on the amount of speech included in the window, sometimes all the quantiles lie below the discriminant line. This means that the contamination has not been detected (Fig. 5 up).

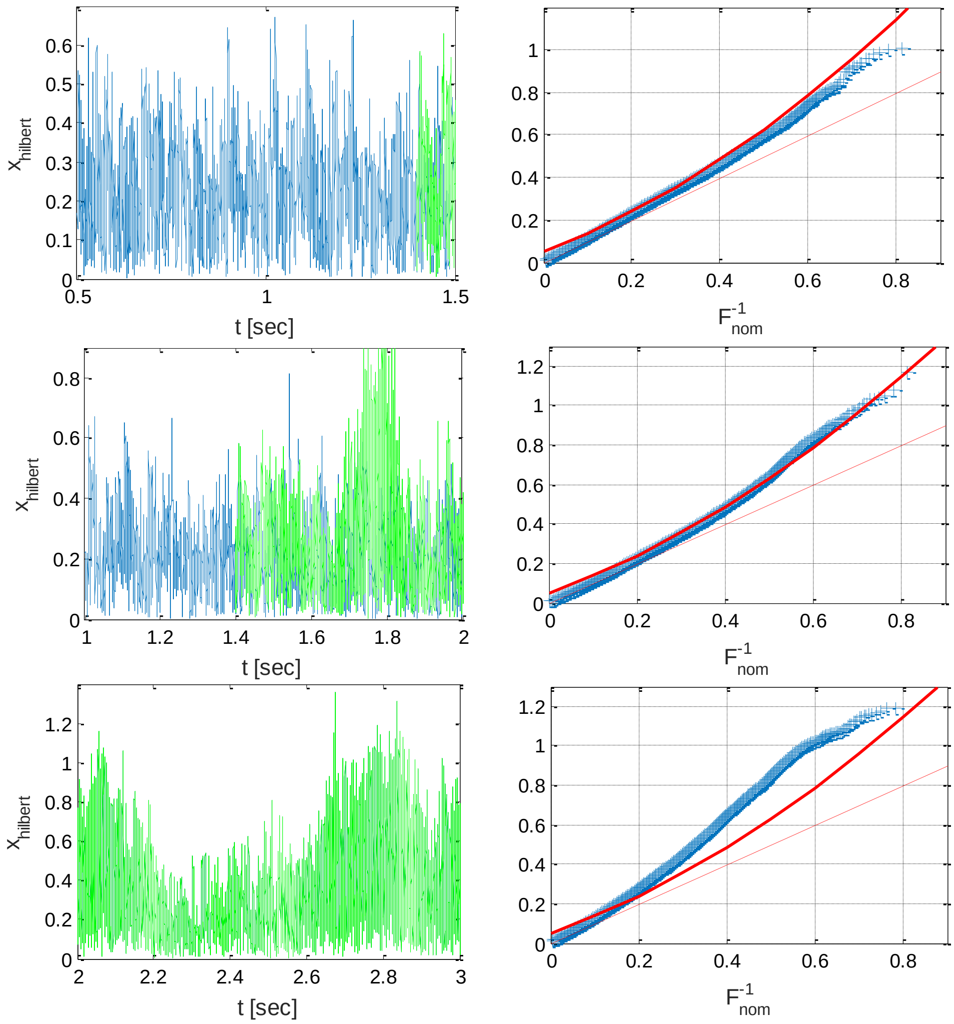

Fig. 5 Speech contaminated samples in time domain (left) and the appropriate QQ plot (right). Upper figures show the behavior of the plot when only small part of the speech contamination is encompassed in the window. Central figures show the behavior when about 50% of the window contains contamination, while lower figures show what happens when the contamination is present in the entire windowed signal.

With impulse disturbance the problem becomes much simpler and the algorithm manages to detect the contamination regardless of the percentage of noisy samples in the window. The nature of impulse disturbance is so abrupt that even a small number of samples encompassed within a window is enough to significantly change the statistical parameters. The appropriate QQ plot of this is shown in Fig. 6.

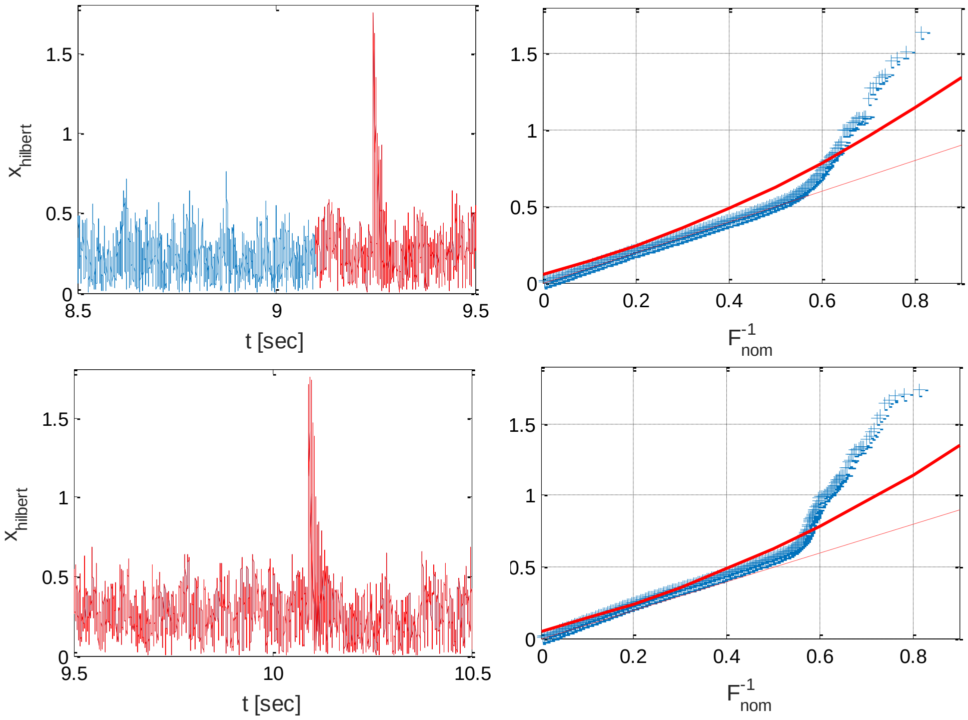

Fig. 6 Samples which contain impulse disturbance in time domain (left) and the appropriate QQ plot (right).

The classification results of the algorithm are presented in Table 1. While classifying the nominal samples and samples which contained impulse disturbance the algorithm has achieved accuracy of 100%, while speech contamination has a lesser percentage of detection. This is due to the fact that the statistical parameters of the windowed signal do not vary considerably with respect to the nominal regime when only a small part of the window contains speech contamination. This is precisely what happened in those 2 windowed parts of the signal which were wrongly classified.

Table 1 Results of the noise detection algorithm

	Nominal recordings	Speech contamination	Impulse disturbance
Classified as nominal	13 (100%)	2 (25%)	0
Classified as noisy	0	6 (75%)	4 (100%)

4.3. Length of the window adjustment

The previous analysis suggests that the proposed algorithm easily detects impulse disturbances, but speech contamination can be somewhat more elusive. In the given example, out of 8 windowed signals contaminated with speech, the algorithm cannot correctly classify two of them. The problematic windowed signals are at the beginning and the ending of the speech sequence and incorrect classification is due to the fact that there is a small percentage of contaminated samples inside the window. One way to correct this error is by changing the length of the window. The noise detection results as the length of the window is changed are given in Table 2.

Table 2 Changeable length of the window tested on speech contaminated signals

Window length	Classified as nominal	Classified as noisy	Total number of windowed signals
$w = 1.5s$	1 (17%)	5 (83%)	6
$w = 1s$	2 (25%)	6 (75%)	8
$w = 0.5s$	2 (13%)	13 (87%)	15
$w = 0.1s$	31 (37%)	52 (63%)	83

One thing which is obvious from the results is the fact that the number of speech contaminated windowed signals increases as the length of the window decreases. This is important for statistical significance of the experiment. However, with smaller number of samples inside the window, the QQ plots are not as representative as they are for larger number of samples. The table shows that for window sizes between 1.5s and 0.5s only one or two windowed signals are wrongly classified as nominal, and those correspond to the beginning or the end of the sequence, as discussed previously. Therefore smaller length of the widow will yield statistically better results because higher percentage of signals will be correctly classified as noisy.

By continuing to decrease the length of the window, however, the algorithm starts to behave inconsistently. For window length of 0.1s the percentage of misclassified signals drastically increases. This is due to several factors. First of all, QQ plots have fewer samples and are therefore less accurate. Secondly, the dynamics of speech is such that usually the gaps between the words, and sometimes even within a single word, are larger than 0.1s. Therefore there are a significant number of windowed signals which do not contain any information about the speech. Furthermore, while other window lengths correctly classify all nominal recordings and all impulse disturbance recordings, for $w = 0.1s$ misclassification occurres not only for speech contaminated signals, but for nominal signals as well.

4.4. Noise detection and classification

From Fig. 5 and 6 it is clear that two different types of noise present themselves quite differently on the QQ plot. With this in mind it might be possible to classify which type of noise has occurred when the algorithm detects the presence of contamination. The way in which this can be done is by determining another classification line, as in Eq. (4), but this time with respect to speech contaminated signals, rather than nominal recordings. In this way two classification lines are obtained, one which classifies nominal recording from the contaminated ones, and the other which detects whether contaminated recordings have impulse or speech disturbance, as shown in Fig. 7. In the upper graph it can be seen that nominal recordings do not trigger any errors. Speech contaminated recordings can be seen in the lower left part of the figure, and they fit ideally between two classification lines. Impulse disturbance, on the other hand, has the quantiles above both discrimination lines, as can be seen in the lower right part of the figure.

This upgraded algorithm for noise detection and classification has been tested on the recording from Fig. 4 and the results are shown in Table 3. As can be seen, the impulse disturbance has been impeccably classified as such. Nominal recordings have a high percentage of nominal classification as well. Speech still has the lowest detection and classification percentage due to the facts discussed earlier.

Table 3 Results of the noise detection algorithm

	Nominal recordings	Speech contamination	Impulse disturbance
Classified as nominal	100%	25%	0
Classified as noisy	0%	55%	0
Classified as impulse noise	0%	20%	100%

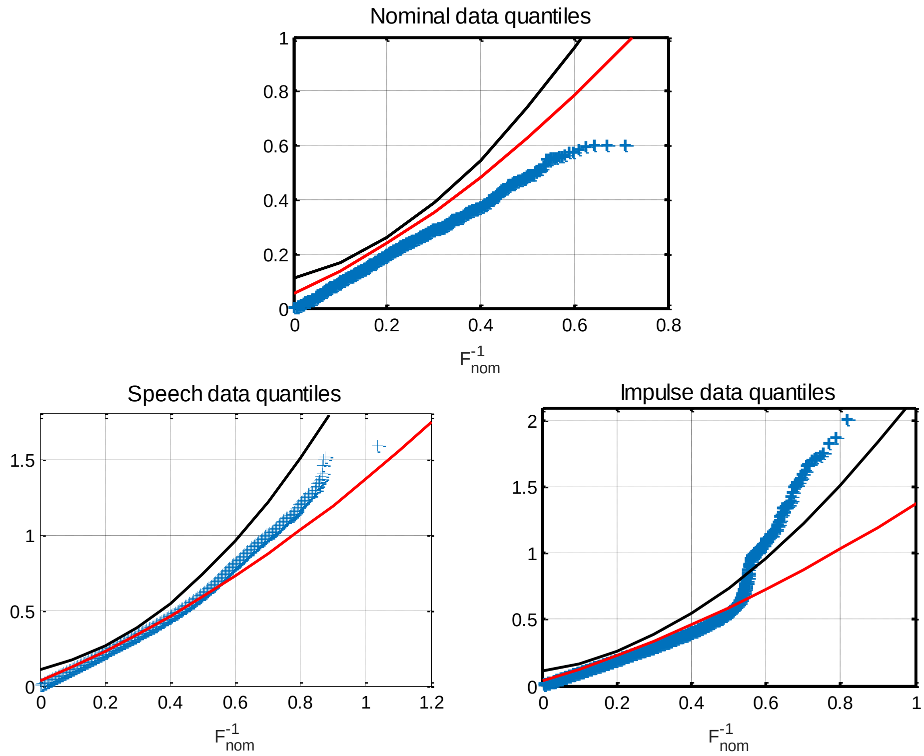

Fig. 7 QQ plot with 2 classification lines. When the samples of a QQ plot go above the red line, the noise has been detected. However, if samples are above the black line, this means that impulse disturbance has occurred, and when they are between the red and blue classification lines the speech contamination has occurred.

5. CONCLUSION

In this paper an algorithm was presented which is capable of detecting the occurrence of noise in acoustic signals and is able to classify this noise with high percentage of accuracy. The main tool used for this purpose is a QQ plot with probability density function estimates and hypothesis testing algorithms. This research has been conducted with a purpose of making acoustic signals more broadly usable in the industry as a tool for predictive maintenance and state estimation of machines.

The algorithm has been tested in a real industrial environment in thermal power plant Kostolac A1 in Serbia, and is shown to be capable of detecting whether the noise has occurred, and to classify whether the impulse disturbance or speech contamination is in question. Furthermore, the influence of the length of the window used on the efficiency of the algorithm is tested as well.

Successful detection and classification is much lower on speech signals than on impulse disturbance due to the fact that the intensity of the speech, as well as words that are spoken directly influence the amount of contamination of the nominal signal. Therefore, if someone speaks quietly or makes long pauses while speaking, the chances are that the proposed algorithm will not manage to detect all the polluted parts of the signal. Also the percentage of contamination which is included in the analyzed window affects the detectability of the contamination, so the beginning and an ending of a speech contaminated sequence may not always be detectable. This can be improved by increasing the overlap between the windows and decreasing the size of the window, but only up to a point.

The algorithm proposed in this paper is an introductory research of a preprocessing tool that should be capable of detecting and isolating acoustic noise in an industrial environment with a purpose of making acoustic recordings more compelling for usage in industrial predictive maintenance algorithms. Further research is going to contain robustification of the algorithm and improvement of speech detection possibly by using correlation analysis or some similar tools. Also, a pdf estimation of noisy signals based on their QQ plots is something that might yield more robust results as well.

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