

Detecting Aging of Process Sensors With Noise Signal Measurement

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Abstract – In this paper, methods for detecting failures in process sensors from the noise measurement due to aging issues are examined. The data are acquired from the water level and pressure measurement transmitters in the Olkiluoto nuclear power plant in Finland: units Olkiluoto 1 and Olkiluoto 2. Methods found from the literature about the failure indicators are presented. Changes in the sensor response time as well as in the resonance peaks in the signal are identified from the power spectrum of the signal.

In addition, a new method for fingerprinting the sensors using the Principal Component Analysis (PCA) of the signal spectra is presented. By following the changes in these fingerprints and the variations between parallel measurements of the redundant sensors, symptoms of sensor failures can be detected. In the experiments we were able to produce stable fingerprints for the differential pressure transmitters used in the water level measurement. Potential failure in one differential pressure sensor in unit Olkiluoto 2 is found with the fingerprint method and by analyzing the changes in the spectrum.

Keywords – process sensors; aging; data analysis

I. INTRODUCTION

Aging of components is an important research issue especially for process industry. Mechanical tearing and other forms of erosion have influence in secure operation of processes. It is not easy to predict how long various components can be used safely without any effects of degradation in their use.

This paper deals with condition monitoring with noise signal. Information needs are mostly related to concrete renewal needs on process operation. The aim is to improve the usability on the plant, which includes also aspects of economic value. Partly theoretical study includes also an assessment of operability.

Our test case uses the reactor tank water level control in Olkiluoto nuclear power plant (NPP) in Finland. The pressure and differential pressure transmitters are used for pressure and water level measurements in the Olkiluoto plant. The aim is to develop a procedure to improve the condition monitoring of sensors.

The Olkiluoto NPP has a need for on-line calibration and monitoring. We try to find out what can be learned from equipment aging-related noise measurement. It helps to determine for how long an old component can still be used, and in planning of maintenance intervals.

The methods for detecting and predicting failures in process sensors are examined based on the features and the changes in the response signal of sensors. Four parallel signals from four redundant sensors are measured for each measurable quantity in critical monitoring system. Simultaneous failure of two sensors may lead to a shutdown of the plant. Even single failure already requires corrective actions.

Our study includes both literature review and an experimental part. In this paper we present physical background of the process sensors and their measurement setup in this operation environment. Then, after a glance to the related work in the literature, we present the methodology used in the experiments and the realization. After the experiments and results, discussion concludes the paper. A master's thesis has been published from this project [1].

II. PHYSICAL BACKGROUND

The water level is one of the most important measurables in a nuclear reactor pressure vessel (RPV). The technological possibilities for the water level measurements are however quite limited. Due to the extreme radiation environment inside the RPV, technology utilized in conventional pressure vessels is not readily usable. This challenge can be overcome by using the principle of merging containers. The RPV is equipped with small pipes, sensing lines, that connect the RPV to a differential pressure sensor as depicted in Fig. 1 Thus the measurement of water level (in the RPV) becomes the measurement of pressure difference between the sensing lines (to the RPV). As an additional advantage, the sensor can be mounted to an environmentally-friendly location.

The lines sense the pressure in the RPV. The lower line is typically connected to RPV at a level below the normal water level, i.e. to the water volume. On the other hand, the upper line is connected at a level above the normal water level, i.e. to the steam volume. The absolute pressure inside the RPV can be assumed to be constant. Thus, pressure difference seen by these lines originates from the weight of the water column between the lines connection points in the RPV, i.e. the water level.

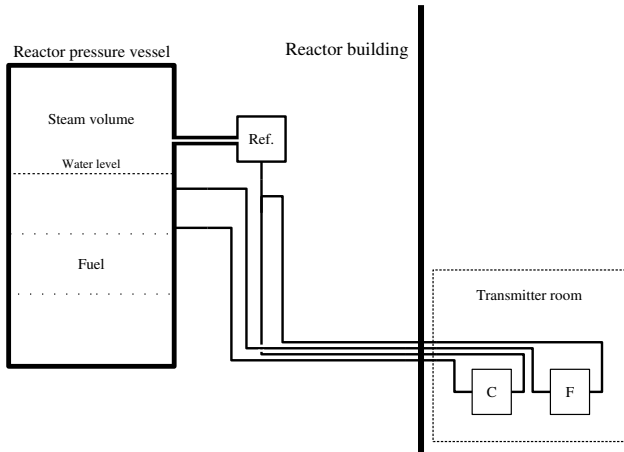


Figure 1. Illustration of the sensing lines of the differential pressure sensors used in RPV water level measurement at Olkiluoto NPP. Fine and coarse pressure sensors are denoted by F and C respectively. Ref denotes the reference vessel of the sensing lines.

III. LITERATURE REVIEW

In addition to an outright failure of the sensor, the two most common modes of aging related failures in pressure sensors are changes in the sensor calibration and response time [2]. Calibration shifts can be caused either by various mechanical problems in the sensor, by leakages or degradation of the fill fluid in the sensor itself or in the sensing lines or by the aging of the electronic components of the sensor [2]. Response time problems, on the other hand, are not usually related to problems in the sensor electronics [2].

On-line detection of calibration changes is possible either by using measurements of redundant sensors or by examining the values of interdependent measurable variables of the process [3]. These variables include the measurements of other sensors and the values of process actuators. By modeling these interdependent relationships by either analytical [3] or by machine-learning models [4]–[6], one can detect abnormal values in different variables.

The response time of a sensor can be estimated from the sensor output signal using a noise analysis method described by Hashemian et al. [7]. The method is based on monitoring the natural fluctuations in the sensor output signal. The assumption is that the fluctuations in the input signal of the sensor consist of white noise, with constant power spectral density (PSD) across all the frequencies of the spectrum. Therefore the PSD of the output signal will be proportional to the transfer function of the sensor [7].

The PSD is the discrete-time Fourier transform of the autocorrelation sequence ϕ_{XX} of a wide-sense stationary (WSS) random signal $X[n]$ [8].

$$S_{XX}(\omega) = \sum_{l=-\infty}^{\infty} \phi_{XX}[l]e^{-j\omega l}, \text{ where } |\omega| < \pi \quad (1)$$

The autocorrelation function of a WSS signal satisfies a following symmetry property:

$$\phi_{XX}[-l] = \phi_{XX}^*[l] \quad (2)$$

Where ϕ_{XX}^* denotes the complex conjugate. By using this symmetry property it can be shown that the PSD is a real-valued function of ω [8].

If there exist a suitably accurate analytical model of the sensor transfer function one can fit the PSD of the observed output noise signal to that model and obtain an estimate of the sensor response time from the model parameters [9].

In practice the PSD can be calculated from the observed time series signal via Fast Fourier Transform (FFT). Alternatively one can analyze the output noise signal in time domain using autoregressive (AR) modeling and calculate the response time using the parameters of the AR model [10]. Estimating the sensor response time accurately using noise analysis procedures, however, requires special expertise and experience as the procedures have to be manually adjusted to each individual sensor type [9].

Additionally, by fitting of the PSD of the sensor output signal to analytical models of the sensor transfer function one can detect problems in the sensing lines. These include voids, blockages and leaks [11]. It is also possible to distinguish between specific modes of sensor failure by using quaternion numbers based on the shape of the PSD [12]. Again, this approach requires an analytical model of the transfer function specific to the type of sensor in question.

A second approach to the on-line detection of faulty sensors is to compare the PSDs of healthy and failing sensors. A real time monitoring system for detection of anomalies in the behavior of equipment has been developed by Ortiz-Villafuerte et al. and tested at the Laguna Verde NPP [13]. The monitoring system is based on storing *patterns*. In this context a pattern is a vector representation of a PSD, sampled at discrete frequencies.

During the training period, a set of reference patterns is created for each sensor. These reference patterns correspond to different operational states of the plant. Then, during plant operation new observations are compared against the stored reference pattern. If a new observation is similar enough to an existing reference pattern it modifies the value of that pattern, so the reference patterns evolve over time. Anomalies are detected when an observation does not match any reference pattern in memory.

The method presented in this paper has goals similar to the one used at the Laguna Verde plant. However we do not try detect anomalies in real-time but instead

improve the prediction accuracy by concentrating on the most strongly differing frequencies by using Principal Component Analysis (PCA).

IV. METHODOLOGY

Generally the occurrence of failures of pressure sensors in NPPs is very rare and the time between the successive failures in a single NPP might be years [2]. In Olkiluoto the last failure of a differential pressure sensor of the reactor tank monitoring system happened in 2013. On the other hand high frequency signal data are stored generally only for few weeks. Therefore no high frequency data from known failing sensors are currently available. As such supervised methods for classification between good and failing sensors cannot be implemented. On the other hand no continuous online monitoring system for quality of signal noise is currently implemented.

In this context our aim is to develop a method for detection of abnormalities and changes indicative of imminent sensor failure in the PSD of the sensor signal. The method should be possible to implement by performing few regular high frequency signal noise measurements during each fuel cycle of the plant.

Our approach is to improve the failure detection accuracy by concentrating on the most strongly differing frequencies. These frequencies are found by using PCA as a dimensionality reduction method on the data consisting of the PSDs of redundant sensors at different points in time.

PCA also provides a two dimensional visualization of data in which the relative differences between samples can be estimated. This is especially useful in the early years of acquisition of signal noise data when there are not yet enough data points for statistical analysis.

Later, when more data are acquired, PCA transformed data can be used as a basis for automated clustering approach to anomaly detection and finally to classification between good and failing sensors.

PCA transform is an unsupervised method which is used to find principal components – the directions of the largest variance - in the original dataset [14].

The transformation matrix of the PCA, \mathbf{W} can be calculated by using the covariance matrix $\mathbf{\Sigma} = Cov(\mathbf{X})$, where \mathbf{X} is a normalized zero mean matrix of the original dataset [14].

$$\mathbf{\Sigma}\mathbf{W} = \mathbf{\Lambda}\mathbf{W} \quad (3)$$

Here $\mathbf{\Lambda}$ is a diagonal matrix whose diagonal elements are the eigenvalues of \mathbf{W} . The PCA transform from the point \mathbf{x} in the original space to the point \mathbf{z} in the PCA space is then calculated as

$$\mathbf{z} = \mathbf{W}\mathbf{x} \quad (4)$$

When selecting only the first, most important, principal components, the PCA can be used as a dimensionality

reduction method which preserves as much as possible of the variance of the original data.

Assume we have \mathbf{n} different PSD samples. We then sample from each sample the value of the PSD at \mathbf{m} different frequencies yielding a \mathbf{m} -dimensional dataset of \mathbf{n} samples. This dataset is used as an input of the PCA dimensionality reduction algorithm. By selecting two most significant principal components we form a 2-dimensional dataset of \mathbf{n} samples.

The coordinates of the PSD of a single sensor sample in these two new dimensions form a *fingerprint*. These fingerprints are used to compare and visualize the differences and the similarities of the PSD samples and also to monitor the changes in these differences over time. Our hypothesis is that in normal conditions the fingerprint for the PSD of a single sensor remains the same across samples taken at different points in time.

We can identify which frequencies contain most of the variance by examining the contributions of the different frequencies in the original dataset to the primary components.

By concentrating on the two strongest principal components we are concentrating on the directions which are the most interesting when looking for linear differences between the samples. The property of concentrating to the strongest differences is well suited to the problem of aging related failure detection where there are various possible failure modes and basically any of the anomalies in the data are of interest.

A major challenge with the application of this method is that the PSD contains noise and artifacts which are not related to the sensor itself. These stem from the dynamic nature of the process itself but also from other sources such as the differences between the sensing lines of the different sensors. It might be advisable to exclude some frequencies from the PSD samples if they are known to contain excessive noise.

Another problem is the linearity of the PCA transformation. Non-linear similarities and differences between the PSD samples are not preserved in the fingerprints.

V. REALIZATION AND EXPERIMENTS

The power spectral densities are calculated using the method presented by Welch [15]. In this method the signal is divided into smaller segments. The segments are filtered with some suitable window function to avoid the distortion caused by the limited length of the segments. A periodogram is calculated for each segment via discrete Fourier transform and the final PSD is formed as the mean of these periodograms.

The implementation used in this project is the *pwelch*-function in the Matlab Signal Processing Toolbox [16] and the window function is the Matlab implementation of a four-term Blackman-Harris window. The segment length is 2048 samples and the overlap between segments is 1945 samples.

Primary components are calculated with the *pca* -function in the Matlab Statistics and Machine Learning Toolbox [16]. The contributions of the different frequencies to the principal components are calculated as the absolute values of the component coefficient matrix produced by the *pca* -function.

We examine four different types of sensors. Two of these types are differential pressure sensors used to measure water level in the reactor tank. The types differ by the sensitivity of measurement, which is based on the vertical location of the nozzles of the sensing lines in the tank as depicted in Fig. 1. Also there are two types of pressure sensors used to measure the steam pressure in the tank. These also differ by their sensitivity which is based on the sensor itself.

We examine the PSD samples of the sensors of both units Olkiluoto 1 and Olkiluoto 2 together, as the internal structure of both units is similar, except for few minor differences.

The measurements of the sensor signals are taken at the following dates: 26th May 2015, 11th November 2015 and 29th February 2016. Each measurement is taken during the normal operation of the plant. The 26th May samples are taken only from sensors of Olkiluoto 1. Samples taken at the other two dates include measurements from the sensors of both units. The measurement of the fourth sensor of Olkiluoto 2 are however missing from 11th November samples due to technical difficulties in the data collection system. The different samples are listed in the Table I.

Table I. LISTING OF SENSOR NUMBERS AND DATES OF THE SAMPLES USED IN THE EXPERIMENT

Date	Sensors	
	Olkiluoto 1	Olkiluoto 2
26th May 2015	1, 2, 3 and 4	
11th November 2015	1, 2, 3 and 4	1, 2 and 3
29th February 2016	1, 2, 3 and 4	1, 2, 3 and 4

The original sampling frequency of the data is $100Hz$. The frequencies below $0.5Hz$ and above $45Hz$ are discarded to avoid unwanted noise from the actual process and from the electric power grid respectively.

Altogether, there are 19 PSD samples used in the analysis for each type of sensor. From each sample the value of the PSD is picked at 130 unique frequencies sampled approximately logarithmically. The total input dataset of the PCA is then a 19×130 matrix.

VI. VERIFICATION

Due to the scarcity of the available data a rigorous quantitative estimation of the efficiency of the proposed method is not possible. However it is possible to evaluate the fingerprinting properties of the PCA method by examining how the different samples of the same sensor cluster together. We compare the clustering properties of

PCA transformed samples versus samples obtained by logarithmically sampling frequencies from a PSD graph.

The comparison is performed using *k*-means clustering [17], which partitions the dataset into *k* clusters with each sample belonging to the cluster with the nearest mean. The algorithm works in two-step iterations by first updating the cluster means and then the members of the clusters.

After clustering we calculate the number of clusters to which the samples from single sensor belong to. The average of these values over all the sensors is used to measure the efficiency of the fingerprinting. Ideally all the samples from the same sensor would cluster together in the same cluster.

The *k*-means clustering is performed using the Matlab implementation [16], which employs *k*-means++ algorithm [18]. *K*-means++ uses a proportional randomization in each iteration for improved running time and quality of results [18].

The number of clusters *k* is set to 8 which is the number of different sensors in the dataset. The distance measure used is the squared euclidean distance. As *k*-means++ is a random algorithm which converges to some local optima each clustering is repeated 5000 times to correct for random errors.

VII. RESULTS

The experiments for the differential pressure sensors show that the samples of the same sensor are generally clustered together in the principal component space. The hypothesis that the coordinates of the PSD of a sensor sample in the principal component space could act as a fingerprint that characterizes the sensor is supported by these results. The clusters of the different sensors, however, overlap each other so these sensor fingerprints are not unique to one sensor.

Additionally, the corresponding sensors from the two different units seem to generally cluster near each other. This indicates that the structural differences in the placement of each sensor inside the plant affect the spectra of the sensors. Also, samples of the same sensor models were clustered together. This would indicate that internal structure of the sensors affect the PSD of the sensors. On the other hand, the results of the non-differential pressure sensors show clustering based on the date of the measurement and the reactor unit. For these sensors the hypothesis of the stable fingerprint for each sensor does not hold.

An example of a representation of the fingerprints of PSD samples in principal component space is shown in the Fig. 2. The samples are taken from the differential pressure sensors of the fine sensitivity water level measurement. In the figure, it can be seen that the fingerprint for 29th February sample the sensor OL2-4 differs from all the other fingerprints in the directions of both principal components. The PSDs of all the fine sensitivity water

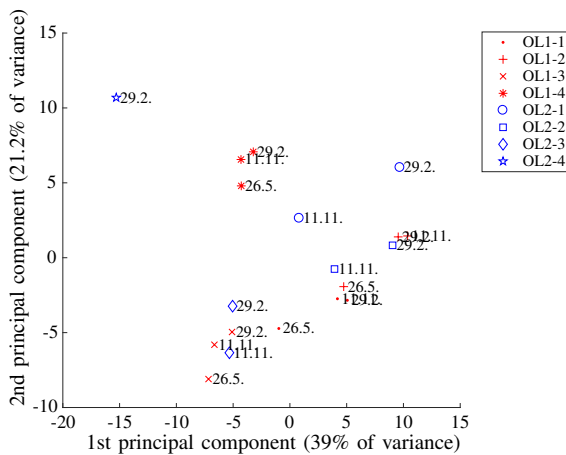


Figure 2. Coordinates of the PSD samples of the differential pressure sensors of fine sensitivity water level measurement, plotted in the space of two first principal components.

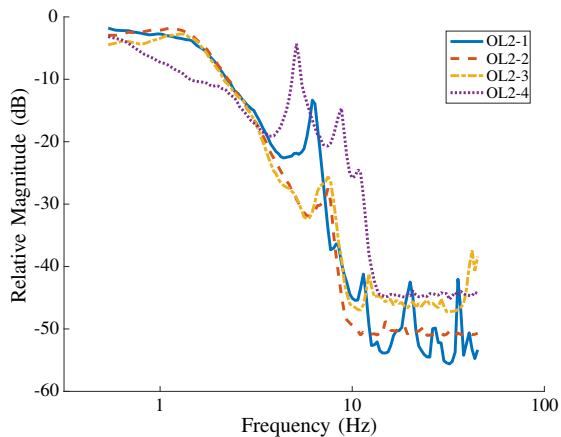


Figure 3. PSD of the signal noise of the differential pressure sensor of fine sensitivity water level measurement sensor of Olkiluoto 2 unit taken on 29th February 2016. Sensor-4 exhibits lower spectral magnitude in the $1Hz-3Hz$ range and stronger resonance peaks around $5Hz-10Hz$ range than other sensors.

level measurement sensors of Olkiluoto 2 unit for the 29th February are presented in Fig. 3. The PSD for sensor OL2-4 exhibits lower magnitude in the peak near $1Hz$ frequency. This peak can be associated with the real pole of the transfer function and its weakening usually indicates an increase in the sensor response time [7], [19]. Additionally the resonance peaks around $5Hz-10Hz$ range appear stronger in the sensor OL2-4 PSD.

The contributions of the different frequencies to the primary components of fine sensitivity water level sensors are presented in Fig. 4. These show that the main components of the two principal components are the $1Hz$ region and the $5Hz-10Hz$ resonance peaks mentioned above. The PCA method successfully captures the strongest

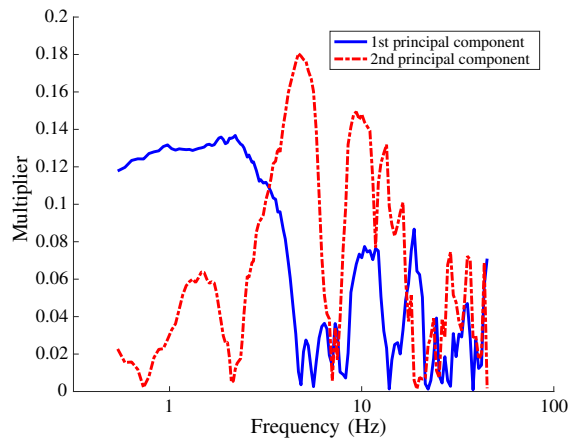


Figure 4. Contributions of the different frequencies to the first two principal components of the all PSD samples of the differential pressure sensors of the fine sensitivity water level measurement.

linear differences in the sample space.

The 29th February is the only sample available for the sensor OL2-4. Therefore, no definitive conclusions can yet be made regarding the reasons for the above mentioned anomalies in its spectrum. Also it is worth noting that the sensor in question has been replaced in 2001 and is of a different model than other sensors of fine sensitivity water level measurement. Other fingerprints show no evidence of noticeable changes in the sensor PSDs during the duration of this project.

The results of clustering performance comparison for fine sensitivity water level sensors are presented in Fig. 5. The figure shows the average number of clusters versus the different number of sampling dimensions used. The sampling dimensions are either the primary components in the PCA transformed data or discrete frequencies in the logarithmically sampled data.

The results show the PCA transformed samples generally clustering to fewer clusters than samples sampled logarithmically from PSD when using low number of sampling dimensions. Also the results indicate that the clustering performance of using only two PCA dimensions is suboptimal with best clustering performance being achieved with five primary components.

VIII. DISCUSSION

The method presented here is only a first step in the process of detecting and predicting aging related faults. Testing if the changes in the fingerprints over time correspond to or indicate actual failures of the sensors naturally requires data from sensors which are known to be failing. Considering the relative infrequency of the sensor failures in nuclear power plants gathering this data at Olkiluoto will probably take years.

The fingerprinting method presented here seems to generate reasonably stable fingerprints for differential

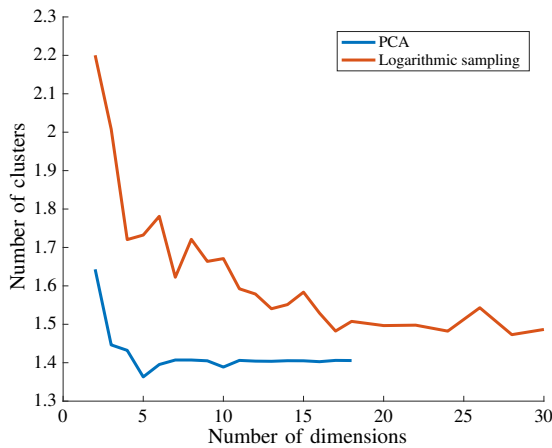


Figure 5. Average number of clusters for the samples of a single sensor using k -means clustering ($k = 8$). X -axis denotes the number of dimensions present in the samples. The dataset used is from the PSD samples of the fine sensitivity water level measurement.

pressure sensors. The clustering performance estimation however suggests that if these fingerprints are to be used as the basis of an automated clustering system then more than two primary components should be used.

For non-differential pressure sensors however the fingerprints are not stable over time. This might be due to differing operational conditions in the different phases of the fuel cycle of the plant. Repeated measurements over multiple fuel cycles are required to confirm if fingerprinting non-differential pressure sensors is at all possible with this method.

The fingerprinting method presented here is also applicable to other types of sensors, provided that input data of the sensor contain enough white noise so that the differences in the sensor transfer function are visible in the output PSD of the sensor.

IX. CONCLUSIONS

We have presented a method of generating fingerprints of the PSDs of pressure and differential pressure sensors used in nuclear power plants. The method uses PCA transform to enhance the fingerprint resolution by concentrating on the most strongly differing frequencies in the dataset. Changes in these fingerprints over time could be used to detect anomalies in these PSDs and discover possible faults related to the aging of the sensors.

Applying the method on operational pressure sensor data produces stable fingerprints for differential pressure sensors. However for non-differential pressure sensors the fingerprints are not stable over time. By analyzing the fingerprints and spectral properties one anomalous PSD of a differential pressure sensor at Olkiluoto 2 nuclear power plant is recognized. However the application of

the method to the proper fault recognition will need measurements over longer time period.

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