A modified Auto Associative Kernel Regression method for robust signal reconstruction in nuclear power plant components

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ABSTRACT:

The application of the Auto Associative Kernel Regression (AAKR) method to the reconstruction of correlated plant signals is not satisfactory from the point of view of the robustness, i.e. the capability of reconstructing abnormal signals to the values expected in normal conditions. To overtake this limitation, we propose to modify the traditional AAKR method by defining a novel measure of the similarity between the current measurement and the historical patterns. An application of the proposed modified AAKR method to the condition monitoring of a pressurizer of a Pressurized Water Reactor (PWR) Nuclear Power Plant (NPP) shows benefits with respect to the traditional AAKR method, in terms of earlier detection of abnormal conditions and correct identification of the signals responsible for triggering the detection.

1 INTRODUCTION

The objective of condition monitoring is to assess the health state of industrial components and to identify possible incipient faults (Venkatasubramanian et al. 2003a, 2003b, 2003c, Hines et al. 2007). To this aim, a model is usually built to reconstruct the values of the monitored signals expected in normal conditions (Hameed et al. 2009). During operation, observed signal measurements are compared with the reconstructions provided by the model: abnormal conditions are detected when the reconstructions are remarkably different from the measurements.

Several empirical reconstruction modeling technique have been applied for condition monitoring of industrial components (Guglielmi et al. 1995, Nabeshima et al. 1998, Jack et al. 2002, Harkat et al. 2007, Chevalier et al. 2009, Baraldi et al. 2013a). These methods provide accurate reconstructions of the measured signals under normal operations, but they often tend to be not robust, i.e. in case of abnormal conditions the reconstructions of the signals are not properly estimating the values of the signals expected in normal conditions (Baraldi et al. 2012). In particular, it has been shown that the reconstruction provided by the AutoAssociative Kernel Regression (AAKR) method (Baraldi et al. 2011a, Di Maio et al. 2013) of an anomalous transient characterized by a drift of one signal can be not satisfactory for two reasons: 1) the reconstruction of the signal affected by the drift tends to assume values in the middle between the drifted values and the expected values of the signal in normal conditions; 2) the reconstructions of other signals not affected by the drift tend, erroneously, to be different from the signal measurements. The consequence of 1) is a delay in the detection of abnormal conditions, whereas the consequence of 2) is that the condition monitoring system, although it correctly triggers an abnormal condition alarm, is not able to correctly identify the signal that triggers the alarm.

The objective of the present work is to propose a robust signal reconstruction method capable of early detecting abnormal conditions and providing accurate reconstructions of the values of the signals subject to the abnormal conditions.

The proposed method is based on the modification of the measure of similarity used by the AAKR method: instead of using the Euclidean distance, the proposed method introduces a penalty vector which reduces the contribution provided by those signals which are expected to be subject to the abnormal conditions. The rationale behind this modification is the attempt to privilege those abnormal conditions caused by the most frequently expected malfunctions and failures. The performance of the proposed method has been tested on simulated data describing the behaviors of a pressurizer of a Pressurized Water Reactor (PWR) Nuclear Power Plant (NPP)

(Baraldi et al. 2010, Baraldi et al. 2013b). The remainder of the paper is organized as follows. In Section 2, the fault detection problem is introduced. In Section 3, the AAKR method is briefly recalled. Section 4 shows the limitation of the traditional AAKR approach to condition monitoring and states the objectives of the present work. In Section 5, the proposed modification of the traditional AAKR is described and discussed. In Section 6, the application of the proposed method to a case study concerning the monitoring of 6 signals in the pressurizer of a Nuclear Power Plant is presented. Finally, in Section 7 some conclusions are drawn.

2 FAULT DETECTION

The condition monitoring adopted in this work is based on an empirical model reproducing the plant behavior in normal conditions. The model receives in input the vector, $\boldsymbol{x}^{obs}(t)$, containing the actual observations of the J signals monitored at the present time, *t*, and produces in output the reconstructions, $\hat{\boldsymbol{x}}_{nc}(t)$, i.e. the values that the signals are expected to have in normal conditions (Baraldi et al., 2012) (Fig. 1). If the actual conditions at time *t* are abnormal instead, the residuals $\Delta\boldsymbol{x} = \boldsymbol{x}^{obs}(t) - \hat{\boldsymbol{x}}_{nc}(t)$, i.e. the variations between the observations and the reconstructions, are large and can be detected by observing the exceedance of a prefixed thresholds by at least one signal.

3 AUTOASSOCIATIVE KERNEL REGRESSION (AAKR)

The basic idea behind AAKR is to reconstruct at time *t* the values of the signals expected in normal conditions, $\hat{\boldsymbol{x}}_{nc}(t)$, on the basis of a comparison of the currently observed signals measurements (also referred to as test pattern), $\boldsymbol{x}^{obs}(t) = [x^{obs}(t,1), \dots, x^{obs}(t,J)\,]$, and of a set of historical signals measurements collected during normal condition of operation. In practice, AAKR performs a mapping from the space of the measurements of the signals $\boldsymbol{x}^{obs}(t)$ to the space of the values of the signals expected in normal conditions, $\hat{\boldsymbol{x}}_{nc}(t)$:

$$\hat{\boldsymbol{x}}_{nc}(t) = \varphi\left(\boldsymbol{x}^{obs}(t)|\bar{\bar{X}}^{obs-nc}\right) : \mathbb{R}^J \rightarrow \mathbb{R}^J \qquad (1)$$

where $\bar{\bar{X}}^{obs-nc}$ indicates a $N \times J$ matrix containing *N* historical observations of the J signals performed in normal conditions. Since the mapping is independent from the present time, *t*, at which the signals observations are performed, the present time *t* will be omitted from the notations. Thus, $x^{obs}(j)$, $j = 1, \dots, J$, indicates the value of signal j at the present time. The reconstruction of the expected values of the signals in normal conditions, $\hat{\boldsymbol{x}}_{nc} = [\hat{x}_{nc}(1), \dots, \hat{x}_{nc}(J)\,]$, is performed as a weighted sum of the available historical observations; for the generic j-th element of $\hat{\boldsymbol{x}}_{nc}$,:

$$\hat{x}_{nc}(j) = \frac{\sum_{k=1}^{N} w(k) \cdot x^{obs-nc}(k,\ j)}{\sum_{k=1}^{N} w(k)} \qquad (2)$$

The weights, $w(k)$, measure the similarity between the test pattern, $\boldsymbol{x}^{obs}$, and the k-th historical observation vector, $\boldsymbol{x}^{obs-nc}(k)$. They are evaluated through a kernel, Ker, i. e. a scalar function which can be written as a dot product (Burges, 1998, Müller et al. 2001, Widodo et al. 2007).
Traditional AAKR adopts as Ker function the Gaussian Radial Basis Function (RBF) with bandwidth parameter h, i.e.:

$$w(k) = \frac{1}{\sqrt{2\pi h^2}} e^{-\frac{\left\|x^{obs} - x^{obs-nc}(k)\right\|^2}{2h^2}} \qquad (3)$$

In fault detection applications, Euclidean and Mahalanobis distances are typically used to compute the distance in the Gaussian RBF (Baraldi et al. 2011b). In this work, in order to account for differences in the scale and variability of the different signals, a Mahalanobis distance is used, defined by the covariance matrix, *S*, such that:

$$\begin{aligned}&\left\|\boldsymbol{x}^{obs} - \boldsymbol{x}^{obs-nc}(k)\right\|^2_{mahal} = \\ &\left(\boldsymbol{x}^{obs} - \boldsymbol{x}^{obs-nc}(k)\right) S^{-1} \left(\boldsymbol{x}^{obs} - \boldsymbol{x}^{obs-nc}(k)\right)\end{aligned} \qquad (4)$$

Assuming independence between the signals, S is given by:

$$S = \begin{bmatrix} \sigma_1^2 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma_J^2 \end{bmatrix} \qquad (5)$$

where σ_j^2 indicates the estimated variance of signal j in the historical observations.

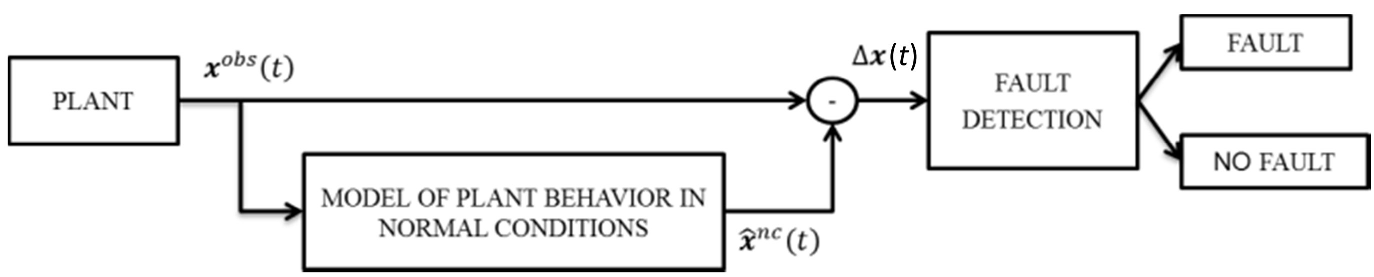

Figure 1 Scheme of condition monitoring for fault detection.

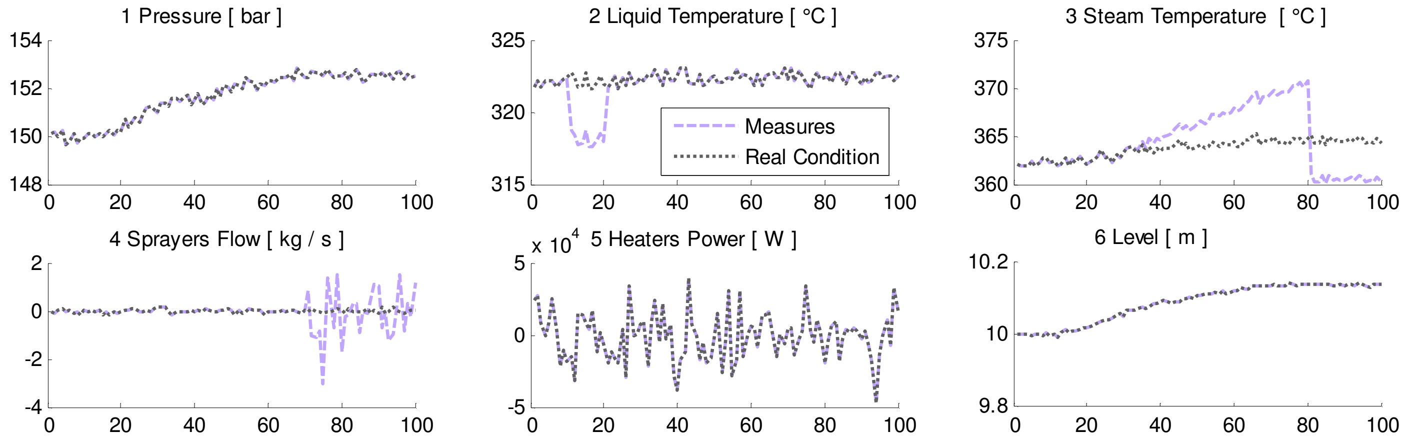

Figure 2 Measured abnormal value (light-dashed line) and corresponding normal condition value (dark-dotted line) of a test transient.

4 LIMITATIONS IN THE USE OF AAKR FOR SIGNAL RECONSTRUCTION

The low robustness of the traditional AAKR method is well illustrated by the following case study concerning the monitoring of the pressurizer of a Pressurized Water Reactor (PWR) Nuclear Power Plant (NPP) (Baraldi et al. 2010, Baraldi et al. 2013b). The dataset is composed of 37 simulated transients in normal conditions. Each transient is monitored for 100 time steps by 6 sensors measuring pressure, liquid temperature, steam temperature, spray flow, heaters power and liquid level. Table 1 reports the high degree of correlation between the signals.

Table 1. Degree of correlation between monitored signals. S1: pressure, S2: liquid temperature, S3: steam temperature, S4: spray flows, S5: heaters power, S6: liquid level.

	S1	**S2**	**S3**	**S4**	**S5**	**S6**
S1	1.00	-0.07	0.98	-0.46	-0.23	0.98
S2	-0.07	1.00	-0.08	0.01	0.18	-0.22
S3	0.98	-0.08	1.00	-0.46	-0.23	0.97
S4	-0.46	0.01	-0.46	1.00	-0.14	-0.45
S5	-0.23	0.18	-0.23	-0.14	1.00	-0.26
S6	0.98	-0.22	0.97	-0.45	-0.26	1.00

A traditional AAKR reconstruction model has been developed using the 37 transients. Then, an abnormal condition transient has been simulated by assuming sensor failures leading to a jump of the liquid temperature from time 10 to 20, a linear drift on the steam temperature signal from time 30 followed by a step at time 80 and an additive noise impacting the spray flow sensor from time 70 till the end of the observation period. Figure 2 shows the measured (dashed-light) and the real value (dotted-dark) of the 6 signals in the test transient, whereas Figure 3 shows the reconstructions of the signals provided by the AAKR method (dashed-light) and the signals expected in normal condition (dotted-dark). Notice that the reconstructions are not robust: 1) pressure, steam temperature and level reconstruction do not reflect the expected normal conditions after time step 30; 2) sprayers flow and heaters power reconstruction are far from the correct reconstruction during the time window 10-20.

A low robustness in the reconstruction leads to two practical problems: 1) delay in the detection of abnormal conditions; 2) identification of abnormal conditions on signals different from those which are actually affected by the abnormal behaviors.

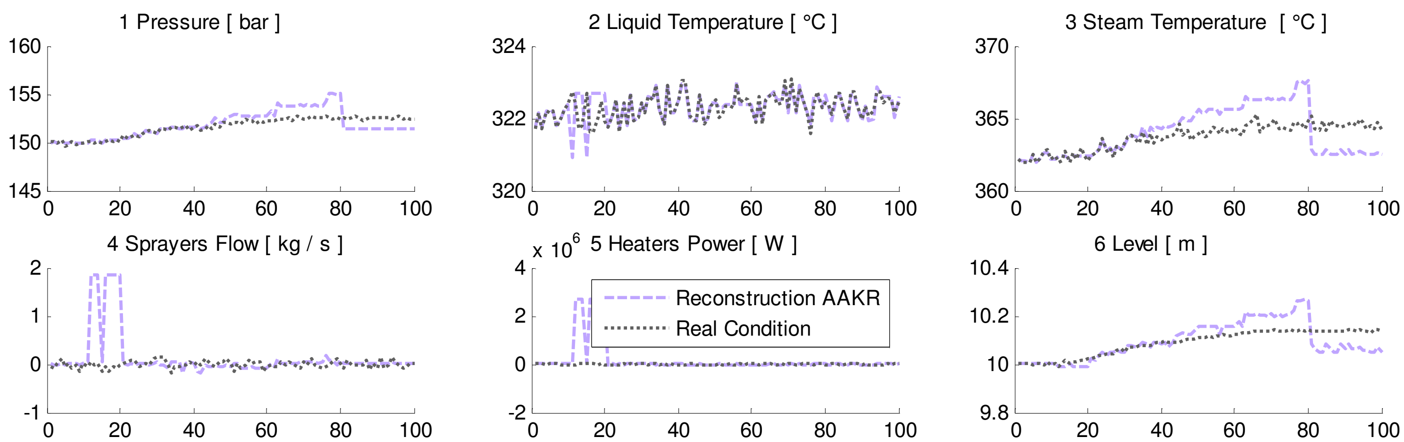

Figure 3 Reconstruction (light-dashed line) of the expected normal values (dark-dotted line) of a transient affected by abnormal conditions.

5 MODIFIED AAKR

In order to enhance the AAKR robustness, we propose to modify the computation of the weights w performed by the traditional AAKR (Eq. 2). The basic ideas underling the proposed modification are (a) to identify the signals affected by abnormal behaviors and (b) to reduce their importance in the computation of the similarity between the test pattern and the historical observations.

With respect to (a), we assume that the probability of occurrence of a fault causing variations on a large number of signals is lower than that of a fault causing variations on a small number of signals:

$$P(S_{fault\,1}) \leq P(S_{fault\,2}) \text{ if } |S_{fault\,2}| \leq |S_{fault\,1}| \quad (6)$$

where $S_{fault\,1}$ and $S_{fault\,2}$ indicate the sets of signals affected by variations due to the abnormal (faulty) conditions, and $|S_{fault1}|$ and $|S_{fault\,2}|$ their cardinality. If we consider, for example, the problem of sensor failures, it is reasonable to assume that the probability of having N_1 faulty sensors at the same time is lower than that of having a lower number of faulty sensors, $N_2 \leq N_1$, at the same time.

The proposed procedure computes the similarity measure between the observation, $\boldsymbol{x}^{obs}$, and the generic *k-th* historical observation, $\boldsymbol{x}^{obs-nc}(k)$, in two steps: (a) a pre-processing step consisting in the projection of $\boldsymbol{x}^{obs}$ and $\boldsymbol{x}^{obs-nc}(k)$ in a new space defined by a penalty vector, $\boldsymbol{p} = [p(1), \dots, p(J)]$, with increasing entries, i.e. $p(1) \leq \dots \leq p(J)$ and (b) the application of the Gaussian RBF kernel in the new space.

Step (a) is based on:

- computing the vector of the absolute values of the normalized differences between $\boldsymbol{x}^{obs}$ and $\boldsymbol{x}^{obs-nc}(k)$:

$$|\boldsymbol{x}^{obs} - \boldsymbol{x}^{obs-nc}(k)|_{\sigma} = \left(\left| \frac{\boldsymbol{x}^{obs}(1) - \boldsymbol{x}^{obs-nc}(k,1)}{\sigma_1} \right| \dots \left| \frac{\boldsymbol{x}^{obs}(J) - \boldsymbol{x}^{obs-nc}(k,J)}{\sigma_J} \right| \right) \quad (7)$$

- defining a permutation matrix, P_{perm}, i.e. a matrix which, when multiplied to a vector, only modifies the order of the vector components; in our procedure, we define a matrix, P_{perm}, such that when it is applied to the vector $|\boldsymbol{x}^{obs} - \boldsymbol{x}^{obs-nc}(k)|_{\sigma}$, the components of the obtained vector are the same of that of $|\boldsymbol{x}^{obs} - \boldsymbol{x}^{obs-nc}(k)|_{\sigma}$, but they appear in a decreasing order, i.e. the first component is the one with the largest difference in $|\boldsymbol{x}^{obs} - \boldsymbol{x}^{obs-nc}(k)|_{\sigma}$;
- defining a diagonal matrix with decreasing entries on its diagonal:

$$D_{\boldsymbol{p}} = \begin{bmatrix} \sqrt{p(1)} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \sqrt{p(J)} \end{bmatrix} \quad (8)$$

  where the vector $\boldsymbol{p} = [p(1), \dots, p(J)] = tr(D_{\boldsymbol{p}})$ will be referred to as penalty vector;
- projecting $\boldsymbol{x}^{obs}$ and $\boldsymbol{x}^{obs-nc}(k)$ in a new space defined by the transformation:

$$\begin{aligned} &\boldsymbol{\psi} : \mathbb{R}^J \to \mathbb{R}^J \\ &\boldsymbol{\psi}(\boldsymbol{x}^{obs}) = D_{\boldsymbol{p}}\, P_{perm}\, \boldsymbol{x}^{obs} \\ &\boldsymbol{\psi}(\boldsymbol{x}^{obs-nc}) = D_{\boldsymbol{p}}\, P_{perm}\, \boldsymbol{x}^{obs-nc} \end{aligned} \quad (9)$$

In step (b), we apply to $\boldsymbol{\psi}(\boldsymbol{x}^{obs})$ and $\boldsymbol{\psi}(\boldsymbol{x}^{obs-nc})$ the Gaussian kernel with Euclidean distance:

$$w(k) = \frac{1}{\sqrt{2\pi h^2}} e^{-\frac{\|\boldsymbol{\psi}(\boldsymbol{x}^{obs}) - \boldsymbol{\psi}(\boldsymbol{x}^{obs-nc})\|^2}{2h^2}} \quad (10)$$

6 APPLICATION OF THE METHOD TO THE CASE STUDY

The data previously introduced in Section 4 are used to develop the modified AAKR reconstruction method. In particular, the 37 transients have been divided into 3 subsets:

- Training set $\bar{\bar{X}}_{train}^{obs-nc} \in \mathbb{R}^{2700 \times 6}$, which is used as historical dataset to train the model;
- Validation set $\bar{\bar{X}}_{val}^{obs-nc} \in \mathbb{R}^{1000 \times 6}$, which is used to set the optimal parameter values;
- Test set, $\bar{\bar{X}}_{test}^{obs-nc} \in \mathbb{R}^{400 \times 6}$, which is used to test the performance of the method.

For both the traditional and modified AAKR methods, the optimal bandwidth parameter, h, has been identified by minimizing the Mean Square Error (MSE) of the reconstructions on the validation set, $\bar{\bar{X}}_{val}^{obs-nc}$:

$$MSE_h = \frac{\sum_{k=1}^{N_{val}} \sum_{s=1}^{J} \left(\hat{\boldsymbol{x}}_{val}(k,s) - \boldsymbol{x}_{val}^{obs-nc}(k,s) \right)^2}{N_{val}} \quad (11)$$

The transients in the test set are used to set the alarm thresholds (see Table 2), which have been taken equal to 3 times the standard deviation of the obtained residuals. Notice that for signals 2 and 3 the traditional AAKR provides lower thresholds; on the contrary, the modified AAKR provides lower thresholds for signals 4 and 5. This is due to the fact that the traditional AAKR provides more accurate reconstructions of signals 2 and 3, whereas the modified AAKR of signals 4 and 5.

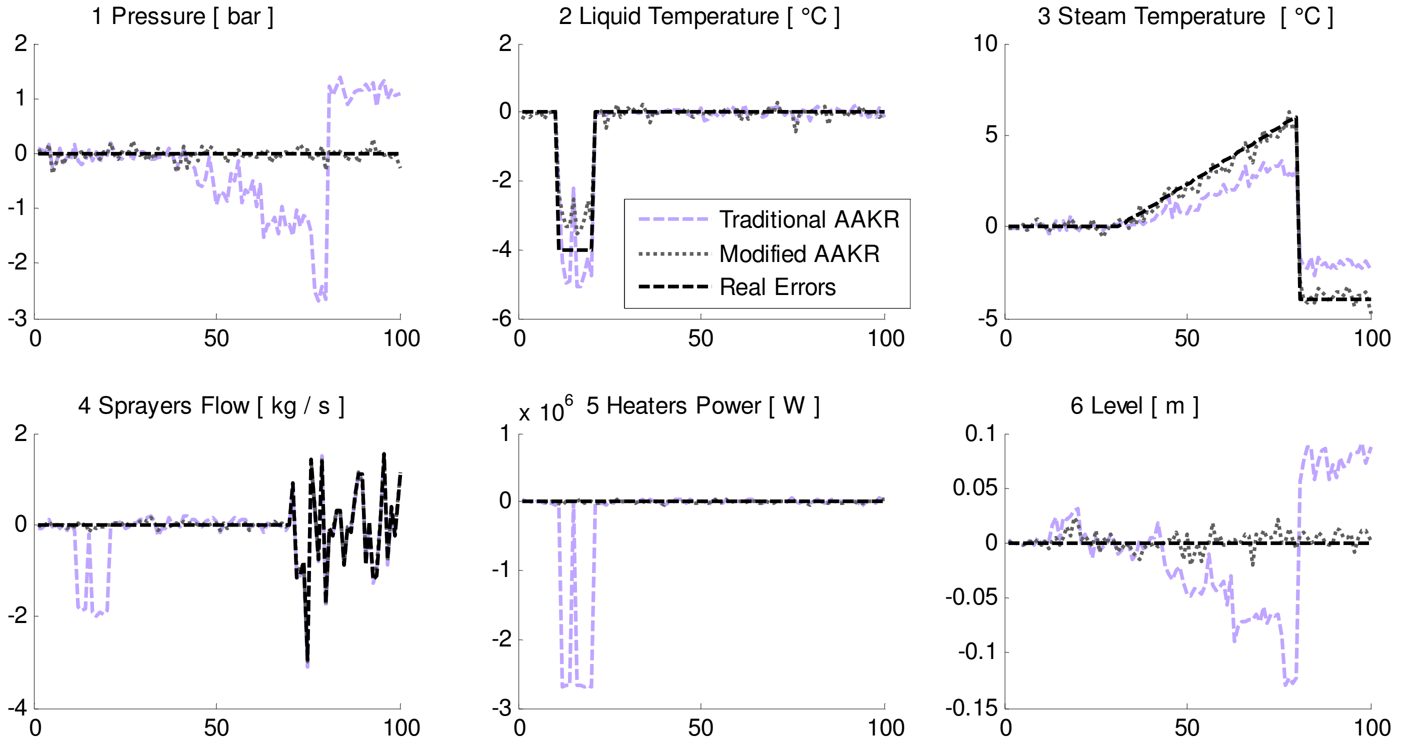

Figure 4 Residuals obtain by the traditional AAKR (light-dashed line) and by the modified AAKR (dark-dotted line); the synthetic error added to the signal is also reported (black-dashed line).

Table 2. Alarm thresholds for traditional and modified AAKR.

AAKR	S1	S2	S3	S4	S5	S6
TRADITIONAL	0.37	0.10	0.32	0.23	5.74E+04	0.02
MODIFIED	0.40	0.53	0.68	0.15	3.96E+04	0.02

We have then tested the performance of the modified AAKR on the same abnormal condition transient introduced in Section 4. Figure 4 shows that the modified AAKR provides residuals that tend to reflect the simulated abnormal condition. For example, considering the time window 10-20, the modified AAKR identifies the wrong calibration of the liquid temperature sensor, whereas the traditional AAKR identifies, erroneously, an abnormal condition also on sprayer flow and heaters power sensors. Furthermore, the modified AAKR provides a more robust reconstruction of the steam temperature when the corresponding sensor is subject to a linear drift followed by a step change.

7 CONCLUSIONS

In this work, we have considered condition monitoring via Auto Associative Kernel Regression (AAKR) for fault detection in a pressurizer of a Pressurized Water Reactor (PWR) Nuclear Power Plant (NPP). A modification of the traditional AAKR has been proposed to achieved a more robust reconstruction of the signal expected in normal condition. By projecting the data in a new signal space according to a penalty vector, the modification aims at reducing the contribution of the signals affected by malfunctioning to the evaluation of the similarity.

The application of the modified AAKR to the monitoring of 6 signals in a pressurizer of a Nuclear Power Plant has shown that it provides a more robust reconstructions of the signals than the traditional AAKR method.

8 REFERENCES

Baraldi P., Cammi A., Mangili F., Zio E., 2010, *"Local fusion of an ensemble of models for the reconstruction of faulty signals"*, IEEE Transactions on Nuclear Science, Vol. 57, No. 2 part 2, pp. 793-806.

Baraldi P., Canesi R., Zio E., Seraoui R., Chevalier R., 2011a, *"Genetic algorithm-based wrapper approach for grouping conditional monitoring signals of nuclear power plant system"*, Integrated computer-Aided engineering, vol. 18,pp. 221-234.

Baraldi P., Gola G., Zio E., Roverso D., Hoffman M., 2011b, *"A randomized model ensemble approach for reconstructing signals from faulty sensors"*, Expert systems with application, vol. 38, No. 8.

Baraldi P., Di Maio F., Pappaglione L., Zio E. and Seraoui R., 2012, *"Condition Monitoring of Power Plant Components During Operational Transients"*, Proceedings of the Institution of Mechanical Engineers, Part O, Journal of Risk and Reliability, 226(6) 568–583, 2012.

Baraldi P., Di Maio F., Genini D., Zio E., 2013a, "*A fuzzy similarity based method for signal reconstruction during plant transients*", Chemical Engineering Transactions, 33, pp. 889-894, 2013.

Baraldi P., Di Maio F., Zio E., 2013b, *"Unsupervised Clustering for Fault Diagnosis in Nuclear Power Plant Compo-*

nents", International Journal of Computational Intelligence Systems, Vol. 6, No. 4, pp. 764-777.

Burges C. J.C., 1998, *"A Tutorial on Support Vector Machines for Pattern Recognition",* Data Mining and Knowledge Discovery, vol. 2., pp. 121-167

Chevalier R., Provost D., and Seraoui R., 2009, *"Assessment of Statistical and Classification Models For Monitoring EDF's Assets"*, Sixth American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation.

Di Maio, F.; Baraldi, P.; Zio, E.; Seraoui, R., 2013, *"Fault Detection in Nuclear Power Plants Components by a Combination of Statistical Methods"*, IEEE Transaction on Reliability, 62 (4) , pp. 833-845, 2013.

Guglielmi G., Parisini T., Rossi G., 1995, *"Fault Diagnosis And Neural Networks: A Power Plant Application"*, Control Engineering Practice, vol. 3, No. 5, pp. 601-620.

Hameed, Z., Hong, Y. S., Cho, Y. M., Ahn, S. H., & Song, C. K., 2009. "*Condition monitoring and fault detection of wind turbines and related algorithms: A review"*, Renewable and Sustainable Energy Reviews,vol. 13, No. 1, pp. 1-39.

Harkat M.F., Djelel S., Doghmane N., Benouaret M., 2007, *"Sensor Fault Detection, Isolation and Reconstruction Using Nonlinear Principal Component Analysis"*, International Journal of Automation and Computing, vol. 4, No. 2, pp. 149-155.

Hines J. W., Garvey D., 2007, *"Process and Equipment Monitoring Methodologies Applied to Sensor Calibration Monitoring"*, Quality and Reliability Interantional, vol. 23, No. 1, pp. 123-135.

Jack L.B., Nandi A.K., 2002, *"Fault detection using support vector machines and artificial neural networks, augmented by genetic algorithms"*, Mechanical Systems and Signal Processing, vol. 16, No. 2-3, pp. 373-390.

Müller, K.-S, Mika, S., Rätsch, G., Tsuda, K., Schölkopf, B., 2001, "*An introduction to kernel-based learning algorithms",* IEEE Transactions on Neural Networks, vol. 12,No. 2, pp. 181-201.

Nabeshima K., Suzudo T., Suzuki K., Turcan E., 1998, *"Real-time Nuclear Power Plant Monitoring with Neural Network"*, Journal of Nuclear Science and Technology,vol. 35, No. 2, pp. 93-100.

Venkatasubramanian V., R. Rengaswamy, K. Yin, S. N. Kavuri, 2003a, "*A review of process fault detection and diagnosis Part I: Quantitative model-based methods*", Computers and Chemical Engineering, vol. 27, pp. 293-311.

Venkatasubramanian V., R. Rengaswamy, S. N. Kavuri, 2003b, "*A review of process fault detection and diagnosis Part II: Qualitative models and search strategies*", Computers and Chemical Engineering, vol. 27, pp. 313-326.

Venkatasubramanian V., R. Rengaswamy, S. N. Kavuri, K. Yin, 2003c, "*A review of process fault detection and diagnosis Part III: Process history based methods*", Computers and Chemical Engineering, vol. 27,pp. 327-346.

Widodo A., Yang B., 2007, *"Support vector machine in machine condition monitoring and fault diagnosis"*, Mechanical Systems and Signal Processing, vol. 21, No. 6, pp. 2560-2574.