SIGNAL GROUPING FOR CONDITION MONITORING OF NUCLEAR POWER PLANT COMPONENTS

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ABSTRACT

The present work investigates the possibility of building a condition monitoring model by splitting the usually very large number of signals measured by the sensors into subgroups and building a specialized model for each subgroup. Different criteria are considered for selecting the signal groups, such as the location of the measurements (i.e., signals measured in the same area of the plant belong to the same group) and their correlation (i.e., correlated signals are grouped together).

A real case study concerning 48 signals selected between those used to monitor the reactor coolant pump of a Pressurized Water Reactor (PWR) is considered in order to verify the monitoring performance of different grouping criteria. Performance metrics measuring accuracy, robustness and spill-over effect have been considered in the evaluation.

Key Words: Condition Monitoring, Empirical Modeling, Power Plants, Safety Critical Nuclear Instrumentation, Autoassociative models.

1 INTRODUCTION

For monitoring the condition of a component, a (typically empirical) model of its behavior in normal conditions is built; during operation, the behavior of the component actually observed is compared with that reconstructed by the model: a deviation between the observed and reconstructed behaviors reveals the presence of an abnormal condition [1].

In practical industrial implementations, the performance of a single model monitoring all the signals measured by the sensors, usually a very large number, may not be satisfactory [2]. At least two reasons call for a reduction in the number of input signals to an empirical model [3]. First of all, irrelevant, non informative signals for the reconstruction of a given signal result in a model which is not robust [3]–[6]. Second, when the model handles many signals, a large number of observation data is required to properly span the high-dimensional signal space for accurate multivariable interpolation [3].

The present work investigates the possibility of splitting the signals into subgroups and then building a specialized model for each subgroup. This involves two main ingredients: a base empirical model for reconstructing the signal values, and a procedure for grouping the signals. The empirical modeling technique adopted in the present work is the Auto-Associative Kernel Regression (AAKR) [7]. As for the grouping, different criteria can be considered to subdivide the set of signals into subgroups, e.g. the location of the measurement (i.e., signals measured in the same area of the plant are put in the same group), the correlation (i.e., the groups are formed by correlated signals), the time-dependency (i.e., signals showing different behaviors in time are grouped together), the physical homogeneity (i.e., groups are made only by temperature signals, only by pressure signals, etc.) and the functional homogeneity (i.e., groups are made of signals measured in different subsystems having the same function).

A preliminary analysis has identified:

1. the location of the measurements (i.e., signals measured in the same area of the plant belong to the same group) – “location”
2. signal correlation (i.e., correlated signals are grouped together) – “correlation”

as the two best performing criteria for grouping the signals [8].

In this paper, these two grouping criteria are tested on a real case study concerning 48 signals selected between those used to monitor the reactor coolant pump of a Pressurized Water Reactor (PWR). The monitoring performances obtained by the two different grouping criteria are compared against the performances obtained by developing a single model for monitoring all the signals. The comparison is made with respect to performance metrics that measure i) the accuracy, i.e. the ability of the overall model to correctly and accurately reconstruct the signal values when the plant is in normal operation; ii) the robustness, i.e. the overall model ability to reconstruct the signal values in case of abnormal operation and consequent anomalous behavior of some monitored signals [9], iii) the spill-over effect, i.e. the overall model ability to correctly reconstruct a signal in case of a process deviation that leads to anomalous behavior of other plant signals [9].

2 CONDITION MONITORING

Figure 1 shows a typical scheme of condition monitoring of a component. Sensor measurements $\vec{x}^{obs}$ are sent to an auto-associative empirical model of the component behavior in normal condition (nc). Thus, the model provides in output the values expected in case of normal condition, $\hat{\vec{x}}_{nc}$, of the input signals. A deviation between the measured $\vec{x}^{obs}$ and reconstructed $\hat{\vec{x}}_{nc}$ values in one or more signals reveals the presence of faults, in equipments or instruments [1].

In other words, in case of normal condition, the measured value $\vec{x}^{obs} = \vec{x}^{obs-nc}$ should be very similar to the model reconstructions $\hat{\vec{x}}_{nc}$, whereas in case of abnormal condition (ac) the model still reconstructs $\hat{\vec{x}}_{nc}$, which differs from the measured values $\vec{x}^{obs} = \vec{x}^{obs-ac}$. Notice that one usually does not know whether the component is working in normal or abnormal conditions, i.e. if $\vec{x}^{obs} = \vec{x}^{obs-nc}$ or $\vec{x}^{obs} = \vec{x}^{obs-ac}$, whereas, by observing the residuals $\vec{r} = \vec{x}^{obs} - \hat{\vec{x}}_{nc}$, it is possible to detect the component condition. In this respect, several methods of analysis of the residuals $\vec{r}$ for fault detection exist, e.g. the Sequential Probability Ratio Test (SPRT) [10].

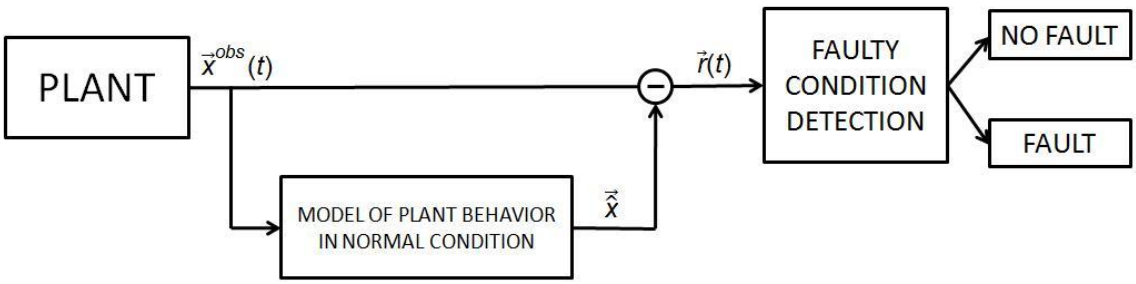

Figure 1. Condition monitoring scheme

2.1 Auto-Associative Kernel Regression (AAKR) method

The model considered in this work for reconstructing the component behavior in normal condition is based on the AAKR method [7]. AAKR is an empirical modeling technique that uses historical observations of the signals taken during normal plant operation. The basic idea of the method is to reconstruct the signal values in case of normal condition, $\hat{\vec{x}}_{nc}$, given a current signal measurement vector, $\vec{x}^{obs} = (x^{obs}(1),..., x^{obs}(q))$, as a weighted sum of the observations.

3 CONDITION MONITORING PERFORMANCE METRICS

In order to evaluate the performance of a condition monitoring model, the following criteria should be considered:

1. The accuracy, i.e. the ability of the model to correctly and accurately reconstruct the signal values when the plant is in normal operation. An accurate condition monitoring model allows to reduce the number of false alarms, i.e. detections of faulty behaviors when no faulty conditions are actually occurring.
2. The robustness, i.e. the model ability to reconstruct the values of the signals of interest in abnormal operation when some monitored signals behave anomalously. In abnormal plant conditions, a robust model reconstructs the value of a plant signal as if the plant were in normal operation: then, the differences between the measured and the reconstructed signal values can easily identify the abnormal condition.
3. The spillover effect; it measures the effect that the anomalous behavior of a monitored signal in abnormal operation has on the reconstruction of the other signals.

3.1 Accuracy

Under normal plant behavior, the accuracy metric is typically defined as the mean square error between the model reconstruction and the signal measured values. Let $X^{test-nc}$ be a matrix of signal measurements different from those in X^{obs-nc}, with $X^{test-nc}(k, j)$ indicating the true value of the *j*-th signal, *j*=1,…,*q*, of the *k*-th test pattern, *k*=1,…, N^{test} and $\hat{X}_{nc}^{test}(k, j)$ its reconstruction provided by the condition monitoring model; then, the mean square error with respect to signal *j* is [9]:

$$MSE(j) = \frac{\sum_{k=1}^{N^{test}} (\hat{X}_{nc}^{test-nc}(k, j) - X_{nc}^{test-nc}(k, j))^2}{N^{test}} \tag{1}$$

A global accuracy measure that takes into account all the monitored signals and test patterns is defined by:

$$MSE = \frac{\sum_{j=1}^{q} \sum_{k=1}^{N^{test}} \frac{(\hat{X}_{nc}^{test-nc}(k, j) - X_{nc}^{test-nc}(k, j))^2}{N^{test}}}{q} = \frac{\sum_{j=1}^{q} MSE(j)}{q} \tag{2}$$

Notice that, although the metric is named accuracy, it is actually a measure of error and, thus, a low value is desired.

3.2 Robustness

The purpose of condition monitoring is to identify abnormal conditions; performance metrics must then be introduced to quantify the ability of the model in reconstructing the signal values corresponding to normal plant operation for computing the residuals from the actual values, and enable fault detection. In this respect, real observed data measured by the sensors while abnormal plant conditions occur are usually not available; then simulation is used, where deviations are added on the signals measured during normal plant operation. Let $X^{test-ac(i)}$ be a matrix of test patterns whose values of the *i*-th signal have been disturbed with deviations, with $X^{test-ac(i)}(k, j)$ indicating the value of the *j*-th signal of the *k*-th test pattern, *k*=1,…, N^{test}, and $\hat{X}_{nc}^{test-ac(i)}(k, j)$ its reconstruction provided by the condition monitoring model which is expected to be the signal value in normal condition $X^{test-nc}(k, j)$.

Two performance metrics measuring the model robustness are here considered:

1) the auto-sensitivity of the model to a disturbance applied on signal *i* [9]:

$$S_{ac(i)}^{auto}(i) = \frac{1}{N^{test}} \sum_{k=1}^{N^{test}} \left| \frac{\hat{X}_{nc}^{test-ac(i)}(k,i) - \hat{X}_{nc}^{test-nc}(k,i)}{X^{test-ac(i)}(k,i) - X^{test-nc}(k,i)} \right| \tag{3}$$

This metric measures the ability of the model to provide the same reconstructions in the two cases of disturbed or undisturbed signal *i*. In this respect, notice that a model characterized by a very low accuracy (high *MSE*) and very high robustness (small $S_{ac(i)}^{auto}(i)$) is not satisfactory for condition monitoring since it still provides signal reconstruction very different from signal values in normal plant operation.

2) the accuracy in the reconstruction of the disturbed signal *i*:

$$A_{ac(i)}^{auto}(i) = \frac{1}{N^{test}} \sum_{k=1}^{N^{test}} (\hat{X}_{nc}^{test-ac(i)}(k,i) - X^{test-nc}(k,i))^2 \quad (4)$$

This metric measures the mismatch between signal reconstructions and signal values in normal plant operation. However, since it does not consider neither the difference between the reconstructions in the cases of disturbed and undisturbed signals, nor the magnitude of the signal deviation ($X^{test-ac(i)}(k,i) - X^{test-nc}(k,i)$), it cannot be directly interpreted as a measure of model robustness.

Again, these two metrics actually measure errors and, thus, low values are desired.

The global robustness measures $\overline{S_{ac}^{auto}}$ and $\overline{A_{ac}^{auto}}$ have been obtained by applying a disturbance to all the signals, computing the robustness $S_{ac(i)}^{auto}(i)$ and $A_{ac(i)}^{auto}(i)$ and taking, respectively, the mean values:

$$\overline{S_{ac}^{auto}} = \frac{\sum_{i=1}^{q} S_{ac(i)}^{auto}(i)}{q} \quad (5)$$

$$\overline{A_{ac}^{auto}} = \frac{\sum_{i=1}^{q} A_{ac(i)}^{auto}(i)}{q} \quad (6)$$

3.3 Spill-over effect

In case of anomalous behavior of some monitored signals because of some plant faults, the spill-over effect can lead to incorrect model reconstructions of other plant signals. In order to quantify this effect, two metrics which consider the model reconstruction $\hat{X}_{nc}^{test-ac(i)}$ of the artificially disturbed dataset $X^{test-ac(i)}$ are considered:

1) the cross-sensitivity of signal j to a disturbance on signal i [9]:

$$S_{ac(i)}^{cross}(j) = \frac{1}{N^{test}} \sum_{k=1}^{N^{test}} \left| \frac{\hat{X}_{nc}^{test-ac(i)}(k,j) - \hat{X}_{nc}^{test-nc}(k,j)}{X^{test-ac(i)}(k,i) - X^{test-nc}(k,i)} \right| \quad (7)$$

2) the accuracy in the reconstruction of an undisturbed signal j when the i-th signal is disturbed:

$$A_{ac(i)}^{auto}(j) = \frac{1}{N^{test}} \sum_{k=1}^{N^{test}} (\hat{X}_{nc}^{test-ac(i)}(k,j) - X^{test-nc}(k,j))^2 \tag{8}$$

Also these metrics actually measure errors and, thus, low values are desired.

Global performance measures of the spill-over effect are:

i) The mean spill-over effect of a disturbance applied on signal i over all the other undisturbed signals:

$$\overline{S}_{ac(i)}^{cross} = \frac{\sum_{j=1;\, j\neq i}^{q} \frac{1}{N^{test}} \sum_{k=1}^{N^{test}} \left| \frac{\hat{X}_{nc}^{test-ac(i)}(k,j) - \hat{X}_{nc}^{test-nc}(k,j)}{X^{test-ac(i)}(k,i) - X^{test-nc}(k,i)} \right|}{q-1} \tag{9}$$

$$\overline{A}_{ac(i)}^{cross} = \frac{\sum_{j=1;\, j\neq i}^{q} \frac{1}{N^{test}} \sum_{k=1}^{N^{test}} (\hat{X}_{nc}^{test-ac(i)}(k,j) - X^{test-nc}(k,j))^2}{q-1} \tag{10}$$

ii) The mean values of $\overline{S}_{ac(i)}^{cross}$ and $\overline{A}_{ac(i)}^{cross}$ considering disturbances applied on all the signals:

$$\overline{\overline{S}^{cross}} = \frac{\sum_{i=1}^{q} \overline{S}_{ac(i)}^{cross}}{q} \tag{11}$$

$$\overline{\overline{A}^{cross}} = \frac{\sum_{i=1}^{q} \overline{A}_{ac(i)}^{cross}}{q} \tag{12}$$

3.4 Cross-validation procedure for the estimation of the performance metrics

In order to accurately estimate the values of the performance metrics on test sets of signals values not previously used in the model development, a cross-validation procedure can be adopted [11-13]. In particular, in the application that follows the so called "*K*-fold" cross-validation error estimate is used to compare the performances [14]. The original dataset is randomly partitioned into $K = 10$ blocks of equal size. One of these blocks is used as validation data subset for the evaluation of the performance metrics of interest, and the remaining 9 blocks are combined together to constitute the training data subset. The cross-validation process is then repeated 10 times (the 10-folds), each time using a different block as validation set.

4 APPLICATION

A real case study concerning 48 signals used to monitor the Reactor Coolant Pump (RCP) of a French Pressurized Water Reactor (PWR) is considered. The signals values have been measured every hour for a period of 11 consecutive months and concern four RCPs, each one on a line of a primary circuit.

All observed measures containing at least a signal value outside the interval $\mu \pm 3\sigma$, with μ indicating the signal mean and σ the signal standard deviation, have been eliminated from the dataset as outliers. This has been done because empirical models have been proven to achieve superior performances if patterns characterized by abnormal values (outliers) are eliminated from the training dataset.

4.1 Groupings

The 48 signals have been re-organized in groups on the basis of the two following criteria:

1. location of the measurement (i.e., signals measured in the same area of the plant belong to the same group): this group has led to the identification of 5 groups;
2. correlation (i.e., groups containing correlated signals together). Signals with an absolute value of the correlation coefficient larger than 0.8 are put in the same group: in other words, each signal in a group has at least a correlation larger than 0.8 with one of the other signals in the group (notice that this means that in a group there can be pairs of signals with correlation lower than 0.8); applying this procedure, 5 groups have been identified, whereas the remaining signals, characterized by a correlation coefficient lower than 0.8 with all other signals, have been put together in a sixth group of uncorrelated signals.

For each group of signals, an AAKR model has been developed.

The performances obtained by the models based on the two different grouping criteria have been compared among them and against the performance obtained by a single model built on all 48 signals.

The optimal value of the bandwidth h in the AAKR has been identified following a trial and error procedure. In particular, at each cross validation, the training set has been divided into two subsets, one used to train the AAKR model, the other to identify the optimal value of h on a dataset different from that used for the performance evaluation.

4.2 Condition monitoring performance

4.2.1 Accuracy

The global accuracies achieved by the different grouping criteria in terms of *MSE* (Eq. 1) are reported in Table I.

Table I. Mean and standard deviation of the overall grouping criteria performance in a 10-folds cross-validation (first row) and ranking of the grouping criteria (second row)

	All	**Location**	**Correlation**
MSE	0.0659±0.0033	0.0227±0.0018	0.0169±0.008
Ranking	3rd	2nd	1st

First of all, notice that a single-group model formed by all signals is remarkably less accurate than the models based on groups formed by the two considered grouping criteria, as expected. The overall best grouping criteria is correlation, although the 10 signals of the correlation group formed by the uncorrelated signals are individually better reconstructed by the location grouping criterion (Table II).

Table II. Ranking in the reconstruction of the individual signals. The number of times in which the grouping criterion results the best (1st), the second best (2nd), the worst (3rd) in the reconstruction of a signal is reported

	All	Location	Correlation
1st	0	10	38
2nd	5	33	10
3rd	43	5	0

The results confirm that accurate groups are formed by highly correlated signals.

4.2.2 Robustness

In order to measure the model robustness according to the two metrics $\overline{S_{ac}^{auto}}$ and $\overline{A_{ac}^{auto}}$ introduced in Section 3.2, plant transients characterized by abnormal plant behavior have been simulated by adding a random noise to the signal measurements. In particular, it has been assumed that during a plant transient only one signal is altered with respect to its value in normal operation, and the related deviation has been taken proportional to a Gaussian noise with mean zero and standard deviation:

$$\sigma_{noise}(i) = 0.1 \cdot \sigma(i) \tag{13}$$

with σ(i) indicating the standard deviation of the signal under normal plant behavior.

Table III reports the two metrics $\overline{S_{ac}^{auto}}$ and $\overline{A_{ac}^{auto}}$ measuring the model robustness.

Table III. Mean and standard deviation of the robustness performance metrics $\overline{S_{ac}^{auto}}$ and $\overline{A_{ac}^{auto}}$ in a 10-folds cross-validation (first row) and ranking of the grouping criteria (second row)

	All	Location	Correlation
$\overline{S_{ac}^{auto}}$	0.1001 ± 0.0014	0.3493 ± 0.0026	0.3787 ± 0.0029
Ranking	1st	2nd	3rd
$\overline{A_{ac}^{auto}}$	0.0663 ± 0.0032	0.0251 ± 0.0017	0.0195 ± 0.0008
Ranking	3rd	2nd	1st

The single group containing all 48 signals permits to achieve the best performance according to the $\overline{S_{ac}^{auto}}$ metric, since it gives very similar reconstructions of signals independently of the application of noise to the signals. Furthermore, the single group containing all the signals gives the best performance in the reconstruction of 43 of the 48 signals according to $\overline{S_{ac}^{auto}}$ (Table IV). This is due to the fact that AAKR reconstruction is based on the distance of the test patterns from the training ones, computed in a high-dimensional space. Thus, the variation of one signal value leads to a small variation of the multidimensional distances, and consequently to very similar reconstructions in the cases of disturbed and undisturbed signals.

Table IV. Ranking in the $S_{ac(i)}^{auto}(i)$. The number of times in which the grouping criterion results the best (1st), the second best (2nd), the worst (3rd) in the $S_{ac(i)}^{auto}(i)$ is reported

	All	Location	Correlation
1st	43	1	4
2nd	5	23	20
3rd	0	24	24

However, since the high value of MSE indicates that the single group is not accurate in the signal reconstruction, the low value of $\overline{S_{ac}^{auto}}$ is more related to the non satisfactory reconstruction of the signals than to its ability in monitoring the plant in case of anomalies.

In Tables 4 and 5, the ranking of $S_{ac(i)}^{auto}(i)$ and $A_{ac(i)}^{auto}(i)$ for each grouping criterion is reported. Notice that the values of $\overline{A_{ac}^{auto}}$ are very similar to the values of *MSE* reported in Table 1. This can be interpreted by observing that the difference between the reconstructions in the cases of disturbed and undisturbed signals $\hat{X}_{nc}^{test-ac(i)}(k,i)$ and $\hat{X}^{test-nc}(k,i)$ tends to be small leading to similar values in Eq. 5 and 8 defining the two metrics.

Although the correlation grouping seems globally more robust than the location grouping, there are 14 signals for which $A_{ac(i)}^{auto}(i)$ is more satisfactory for the location grouping (Table V). It is interesting to observe that 8 of these 14 signals belong to groups of the correlation grouping formed by only 4 signals. These results show that two important factors to obtain robust reconstructions are the correlation of the signals in the group and the group size: the best performance are obtained by large groups of highly correlated signals.

Table V. Ranking in the $A_{ac(i)}^{auto}(i)$ of the individual signals. The number of times in which the grouping criterion results the best (1st), the second best (2nd), the worst (3rd) in the $A_{ac(i)}^{auto}(i)$ is reported

	All	Location	Correlation
1st	0	14	34
2nd	10	29	9
3rd	38	5	5

4.2.3 Spill-over effect

The two performance metrics $\overline{S_{ac}^{cross}}$ and $\overline{A_{ac}^{cross}}$ have been evaluated in order to verify the spill-over effect for the different grouping criteria. Table VI reports the performance metrics with respect to a noise applied to each signal, and considering its effect on all the other signals.

Table VI. Mean and standard deviation of the spill-over performance metrics $\overline{S_{ac}^{cross}}$, $\overline{A_{ac}^{cross}}$ in a 10-folds cross-validation (first row) and ranking of the grouping criteria (second row)

	All	Location	Correlation
$\overline{S_{ac}^{cross}}$	0.0208 ± 0.0005	0.0154 ± 0.0003	0.0183 ± 0.0003
Ranking	3rd	1st	2nd
$\overline{A_{ac}^{cross}}$	0.0659 ± 0.0033	0.0227 ± 0.0018	0.0170 ± 0.0008
Ranking	3rd	2nd	1st

In Tables VII and VIII the ranking of $\overline{S}_{ac(i)}^{cross}(j)$ and $\overline{A}_{ac(i)}^{cross}(j)$ for each grouping criterion is reported.

Table VII. Ranking in the $\overline{S}_{ac(i)}^{cross}(j)$ of the individual signals. The number of times in which the grouping criterion results the best (1st), the second best (2nd), the worst (3rd) in the $\overline{S}_{ac(i)}^{cross}(j)$ is reported

	All	Location	Correlation
1st	16	21	11
2nd	8	23	17
3rd	24	4	20

Table VIII. Ranking in the $\overline{A}_{ac(i)}^{cross}(j)$ of the individual signals. The number of times in which the grouping criterion results the best (1st), the second best (2nd), the worst (3rd) in the $\overline{A}_{ac(i)}^{cross}(j)$ is reported

	All	Location	Correlation
1st	0	10	38
2nd	0	38	10
3rd	48	0	0

Considering the $\overline{S_{ac}^{cross}}$ metric, the group formed by all 48 signals is the worst performing since it contains in the same group the disturbed signal and the remaining signals on which the effects of the disturbance are evaluated. On the other side, if a grouping criterion is applied, the signals belong to different groups and thus a deviation applied to a signal influences only the reconstruction of the signals in the same group and not of those in other groups. For example, a noise applied to a generic signal influences the reconstruction of all the 47 signals considered for the evaluation of the two metrics when the group formed by all 48 signals is considered, whereas it influences the reconstruction of only the signals in the same group in the cases of the correlation and location groups.

It can be also noticed that the biggest group, after that with all signals, comes out from correlation grouping, and its performance in terms of $\overline{\overline{S}_{ac}^{cross}}$ results to be the worst. In fact, since the value of $\overline{S}_{ac(i)}^{cross}(j)$ is equal to 0 for all those signals which do not belong to the group where the i-th abnormal signal is, the smaller is a group, the smaller is the value of $\overline{\overline{S}_{ac}^{cross}}$. Furthermore, the presence of a big group formed by many signals (22) in the correlation grouping renders its $\overline{\overline{S}_{ac}^{cross}}$ performance lower than that of the location grouping, which is formed by smaller groups.

With respect to the $\overline{\overline{A}_{ac}^{cross}}$, notice that it follows the behavior of the accuracy metric *MSE*. In the case of big groups, since the AAKR reconstruction is based on the distance between the test pattern and the training ones, the variation of one signal value in a high dimensional space leads to a small variation of the multidimensional distances, and consequently to very similar reconstructions in the cases of disturbed and undisturbed signals:

$$\hat{X}_{nc}^{test-ac(i)}(k,j) \approx \hat{X}_{nc}^{test}(k,j), \forall k,j \qquad (14)$$

leading to:

$$MSE(j) = \frac{\sum_{k=1}^{N^{test}} (\hat{X}_{nc}^{test-nc}(k,j) - X^{test-nc}(k,j))^2}{N^{test}} \approx \frac{\sum_{k=1}^{N^{test}} (\hat{X}_{nc}^{test-ac(i)}(k,j) - X^{test-nc}(k,j))^2}{N^{test}} = A_{ac(i)}^{cross}(j) \qquad (15)$$

Considering groups formed by few signals, the reconstruction of signals not belonging to the group of the disturbed signal *i* is exactly equal to the reconstruction of the signals when no anomaly is applied:

$$\hat{X}_{nc}^{test-ac(i)}(k,j) \equiv \hat{X}_{nc}^{test}(k,j) \qquad (16)$$

and thus:

$$A_{ac(i)}^{cross}(j) \equiv MSE(j) \qquad (17)$$

while there are differences in the reconstruction only for those signals belonging to the group of the abnormal signal i:

$$\hat{X}_{nc}^{test-ac(i)}(k,j) \neq \hat{X}_{nc}^{test}(k,j) \qquad (18)$$

and thus

$$A_{ac(i)}^{cross}(j) \neq MSE(j) \tag{19}$$

Nevertheless, since $\overline{A_{ac}^{cross}}$ is the mean value of $A_{ac(i)}^{cross}(j)$, the contribution of the few signals belonging to the group of signal *i* is hidden by the contribution of the many signals not belonging to the same group of signal *i*, and thus:

$$\overline{A_{ac}^{cross}} \cong MSE \tag{20}$$

The expected conclusion from the analysis of cross-sensitivity is that there is a clear advantage in using small groups, since the presence of an anomaly affecting a signal of a group tends to influence only the reconstruction of the few signals in the same group.

5 CONCLUSIONS

Two different signal grouping criteria for the condition monitoring of a Reactor Coolant Pump have been considered in this work. The comparison of the performances of the models built on the groups thereby identified has been made with respect to performance metrics measuring the accuracy, i.e. the ability of the model to correctly and accurately reconstruct the signal values when the plant is under normal operation, and the robustness, i.e. the model ability to reconstruct the signal values in case of abnormal operation and consequent anomalous behavior of some monitored signals.

The most accurate reconstructions have been obtained by grouping the signals according to their correlation, i.e. by considering groups formed by highly correlated signals. The main drawback of this grouping criterion is the presence of a group of signals with low correlation among each other, which results in low accuracy on these signals.

With respect to the robustness of the condition monitoring model, the results have shown that the larger is the number of signals in a group, the more similar are the model reconstructions in case of disturbed and undisturbed signals. However, it has been shown that groups formed by many signals, as the group formed by all 48 signals, tend to be less accurate in the reconstruction of the undisturbed signals.

Finally, the evaluation of the spill-over effect leads to the conclusion that there is an advantage in using small groups, since the presence of an anomaly affecting a signal of a group tends to influence only the reconstruction of the few signals in the same group.

The results obtained in this work have shown that although the correlation grouping criterion permits to globally achieve the most satisfactory results in terms of accuracy, robustness and spill-over effect, there are few plant signals better reconstructed by other grouping criteria. This stimulates the research on other grouping techniques.

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