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Abstract (Conference)

With the hundreds of signal measurements made in a nuclear power plant, the cost of sensor maintenance has become significant and the effects of sensor failures substantial, with lost power production and lost revenues for the operating utility. In this respect, continuous and effective monitoring of sensor performance reduces unnecessary maintenance by allowing the timely detection and identification of faulty sensors and the reconstruction of the incorrect signals before using them in the operation, control and protection of the plant [1].

In this paper, a signal reconstruction procedure based on the use of an ensemble of reconstruction models is adopted. The procedure is founded on the random subdivision of the set of sensor signals into small overlapping groups by the Random Feature Selection Ensemble (RFSE) technique [2], a Principal Components Analysis (PCA)-based reconstruction model [3] is developed for each group of signals and the outcomes of the individual models are aggregated to generate the reconstructed signal [4][5][6].

The issue of how to compute the ensemble-aggregated output is the focus of this work. The Simple Mean (SM), Globally weighted average (GWA) [4], Median (MD) and Trimmed Mean (TM) [5] aggregation methods are compared to a local fusion (LF) method [7] in which the aggregation is guided by the local performance of each model, i.e., its reconstruction accuracy on signal patterns of training similar to those to be reconstructed.

The comparison is made with respect to a real case study regarding the reconstruction of 215 signals measured at a Finnish nuclear Pressurized Water Reactor (PWR) located in Loviisa.

References (Conference)

[1] M. Hoffmann, “Signal Grouping Algorithm for an Improved On-line Calibration Monitoring System”, Proceedings of FLINS, Genova, Italy, Aug. 2006.

[2] R. Bryll, R. Gutierrez-Osuna, F. Quek, Attribute bagging: improving accuracy of classifiers ensembles by using random feature subsets, 2003, Pattern Recognition, Vol. 36, pp. 1291-1302.

[3] I.T. Jolliffe, “Principal Component Analysis”, Springer Eds., 2002.

[4] P. Baraldi, E. Zio, G. Gola, D. Roverso, M. Hoffmann, “Reconstruction of faulty signals by an ensemble of principal component analysis models optimized by a multi-objective genetic algorithm”, Proceedings of FLINS, Madrid, Spain, Sept. 2008.

[5] P. Baraldi, E. Zio, G. Gola, D. Roverso, M. Hoffmann, “Aggregation of randomized model ensemble outcomes for reconstructing nuclear signals from faulty sensors”, ESREL 2009, Sept 7-10.

[6] P.P. Bonissone et al., “Fast meta-models for local fusion of multiple predictive models”, Appl. Soft Comput. J. (2008), doi:10.1016/j.asoc.2008.03.006.

[7] P. Baraldi, A. Cammi, F. Mangili and E. Zio, “Local Fusion of an Ensemble of Models for the Reconstruction of Faulty Signals”, IEEE Transactions on Nuclear Science, submitted for publication.

Abstract

Sensors are placed at various locations in a production plant to monitor the state of the processes and components. For the plant state monitoring to be effective, the sensors themselves must be monitored for detecting anomalies in their functioning and for reconstructing the correct values of the signals measured. In this work, the task of sensor monitoring and signal reconstruction is tackled with an ensemble of Principal Component Analysis (PCA) models handling individual overlapping groups of sensor signals, randomly generated according to the Random Feature Selection Ensemble (RFSE) technique. The outcomes of these models are combined using a Local Fusion (LF) technique based on the evaluation of the models performance on set of training patterns similar to the test pattern under reconstruction. The performances obtained using the LF method are compared to those obtained using classical aggregation methods such as Simple Mean (SM) Globally weighted average (GWA), Median (MD) and Trimmed Mean (TM), on a real case study concerning 215 signals monitored at a Finnish Pressurized Water Reactor (PWR) nuclear power plant.

1 Introduction

For an effective contribution to the safe and productive operation of a nuclear power plant, sensors malfunctions must be promptly detected, since the effects of sensor failures can be substantial, with lost power production and lost revenues for the operating utility. With the hundreds of signals measurements made in a nuclear power plant, the cost of sensor maintenance has become significant. In this respect, continuous and effective monitoring of sensor performance reduces unnecessary sensor maintenance by allowing the timely detection and identification of faulty sensors and the reconstruction of the incorrect signals before using them in the operation, control and protection of the plant [1][2].

This work investigates the problem of reconstructing signals in real applications in which the number of measured signals is very large and cannot be handled effectively by a single auto-associative reconstruction model [3][4][5]. The problem is tackled by resorting to an ensemble-based signal reconstruction procedure [6][7]. Within an ensemble approach, signals are subdivided into small overlapping groups generated by the Random Feature Selection Ensemble (RFSE) technique [8][9]; for each group of signals a reconstruction models is built using the PCA method [10][11]; the outcomes of the different models are finally combined (Figure 1).

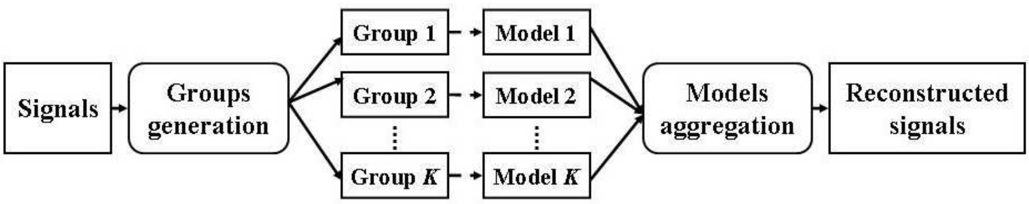

Figure 1: multi-group ensemble approach to signal reconstruction

The issue of how to aggregate the multiple signal reconstruction models outputs is the focus of this paper. Many techniques can be adopted, the most common being the Simple Mean (SM), the Globally weighted average (GWA), the Median (MD) and the Trimmed Mean (TM). In [13] and [14] a different solution called Local Fusion (LF) is investigated. This method assigns to each model of the ensemble a weight and a bias related to the error committed in the reconstruction of training patterns similar to the test pattern under reconstruction thus providing an evaluation of the models performance dynamically varying with the position of the test pattern in the signals space. Due to the promising results obtained in the simulated case study presented in [13], in this work the local fusion approach is applied to real

NPP data and the results obtained are compared to those resulting from the other techniques presented (SM, GWA, MD and TM).

In the LF approach, models performances are evaluated by considering a subset of training patterns selected on the base of their distance from the test pattern under reconstruction. Notice, however, that if the test pattern contains a faulty measurement, then the selected neighbouring patterns might not be the most similar to the true test pattern. In order to investigate this effect, two methods for the neighbourhood selection based on the Euclidean and geometric distances are compared.

The comparison is performed in the context of an application to the validation and reconstruction of the signals measured at a Finnish PWR nuclear power plant to which different faults are added to test the robustness of the different methods presented.

The paper is organized as follows. In Section 2, the randomized approach for generating diverse groups of signals is briefly summarized and in Section 3 the different methods applied for the aggregation of the models outcomes are described. In Section 4, the performance of the aggregation methods is analyzed with reference to a case study concerning the reconstruction of a data set of 215 signals measured at a Finnish nuclear Pressurized Water Reactor (PWR) located in Loviisa. Conclusions on the advantages and limitations of the proposed methods are drawn in the last Section.

2 The Random Feature Selection Ensemble approach

Figure 1 reports a sketch of the flow of modeling for signal reconstruction.

Usually, a typically large number n of signals f_i is available for building the signal validation and reconstruction model; thus, a single model cannot perform the reconstruction task with the desired accuracy and reliability and the signal set is partitioned into H subsets $\mathbf{F}_h$. Within the RFSE approach, the fast construction of diverse groups of signals is done by randomly sampling, with replacement, from the n available signals, the m signals which compose each subset $\mathbf{F}_h$ [8][9]. For each signals group a different PCA model is built [10][11]. The same signal f_i must be included in an adequate number H_i of subsets $\mathbf{F}_h$, so that the ensemble reconstruction $\hat{f}_i$ can be based on the aggregation of several diverse models outcomes $\hat{f}_i^h$, $h = 1,...,H_i$. The diversity of the outcomes $\hat{f}_i$ is guaranteed by the high signal diversity between the groups obtained through the RFSE technique.

3 Aggregation strategies

The reconstruction $\hat{f}_i$ of signal f_i is obtained by aggregating the H_i models outcomes $\hat{f}_i^h$. In general, the aggregation requires to associate a weight w_i^h and a bias correction b_i^h to the reconstruction $\hat{f}_i^h$ of each model h. The idea is to correct the values of $\hat{f}_i^h$ by subtracting the estimated bias b_i^h and to combine $\hat{f}_i^h$ with the other models estimates by means of a weighted average:

$$\hat{f}_i = \frac{\sum_{h|f_i \in \mathbf{F}_h} w_i^h \cdot \left(\hat{f}_i^h - b_i^h\right)}{\sum_{h|f_i \in \mathbf{F}_h} w_i^h} \tag{1}$$

Different techniques for the aggregation of the outcomes of multiple models have been applied in this work for comparison of their perform.

a. Simple Mean (SM)

All weights are assigned with the same value and the bias corrections are set to zero, i.e. $w_i^h = \overline{w}$ and $b_i^h = 0$, $\forall\ i = 1,..,n$ and $h = 1,...,H_i$.

b. Globally Weighted Average (GWA)

All bias corrections are set to zero, whereas the weights are inversely proportional to the performance of each model computed on the entire training dataset, i.e. $b_i^h = 0$, $\forall\ i = 1,..,n$ and $\forall\ \ h = 1,...,H_i$ and

$$w_i^h = \frac{1}{mae_{i,\mathbf{X}_{TRN}}^h} = \frac{1}{\sum_{\mathbf{X}_{TRN}} \left|\hat{f}_i^h - f_i\right|} \tag{2}$$

In [15] two alternative aggregation methods are devised based on the randomness of the models outcomes, which, if unbiased, are expected to distribute around the correct signal value.

c. Median (MD)

All bias corrections and weights are set equal to zero except for the weight $w_i^{h_C}$ corresponding to the reconstruction $\hat{f}_i^{h_C}$ which lies in the centre of the distribution of the outcomes $\hat{f}_i^h$ of the H_i models including signal f_i.

d. Trimmed Mean (TM)

All bias corrections are set equal to zero, whereas the weights are all assigned with the same value except for the weights $w_i^{h_{TM}}$ corresponding to the tails of the distribution of the outcomes $\hat{f}_i^h$ which are set to zero. In particular, being ϑ^{TM} the fraction of the model outcomes that are discarded, only the most central $H_i^{TM} = (1 - \vartheta^{TM})H_i$ reconstructions of f_i are associated to a constant weight.

e. Local fusion (LF)

In [13] it has been shown that the ensemble performance can be increased if both the bias corrections b_i^h and the weights w_i^h are computed locally, i.e., they vary as a function of the position in the signal space of the pattern under reconstruction. In this way the two parameters b_i^h and w_i^h can account for the variation of models performances in the different regions of the signal space.

Thus, according to [13] and [14], the local bias correction b_i^h and the local weight w_i^h to be assigned to model h in the reconstruction of signal f_i are set equal to:

$$b_i^h = me_{i,Q_{TRN}}^h = \sum_{Q_{TRN}} \left(\hat{f}_i^h - f_i \right) \tag{3}$$

$$w_i^h = \frac{1}{mae_{i,Q_{TRN}}^h} = \frac{1}{\sum_{Q_{TRN}} \left| \hat{f}_i^h - f_i \right|} \tag{4}$$

where $me_{i,Q_{TRN}}^h$ represents the local mean error, $mae_{i,Q_{TRN}}^h$ the local mean absolute error and $\mathbf{Q}_{TRN}$ is a set of neighbours of the pattern under reconstruction drawn from training dataset. According to the k -nn-based neighborhood approach here adopted [14], $\mathbf{Q}_{TRN}$ is formed by the k training patterns nearest to the test pattern. The choice of the nearest neighbours relies also on the way the distance of a training pattern $f^{TRN} = \left(f_1^{TRN}, ..., f_i^{TRN}, ..., f_n^{TRN} \right)$ from the test pattern $f^{TST} = \left(f_1^{TST}, ..., f_i^{TST}, ..., f_n^{TST} \right)$ is computed. Since the test pattern can contain the measurement of a faulty sensor, the choice of a distance metric which is robust in case of sensor fault is important. For this reason in this work the typical Euclidean definition of the distance (ED, eq.(5)) and the geometric distance (GD, eq.(6)) are considered for the identification of the nearest neighbours of the test pattern:

$$ED = \sqrt{\sum_{i=1}^{m} \left(f_i^{TRN} - f_i^{TST} \right)^2} \tag{5}$$

$$GD = \sqrt[m]{\prod_{i=1}^{m} \left| f_i^{TRN} - f_i^{TST} \right|} \tag{6}$$

4 Application

The ensemble approach here described has been applied to a real case study concerning the validation and reconstruction of 215 signals measured at the Pressurized Water Reactor (PWR) nuclear power plant located in Loviisa, Finland. A total number N=12713 of patterns $f_1(t),..., f_i(t),..., f_n(t)$, $t = 1,..., N$ made of $n = 215$ signals is available. Data signals have been sampled every hour from February 28, 2006 to November 1, 2007.

A training set $\mathbf{X}_{TRN}$ constituted by $N_{TRN} = 7000$ patterns is used for training the models; a validation set $\mathbf{X}_{VAL}$ of $N_{VAL} = 2000$ is used to determine the optimal number k of nearest neighbors to be used for the outcomes aggregation within the LF method. The optimal number m of signals to be included in each subset $\mathbf{F}_h$ has been taken from [11].

Table 1 presents the values assigned to the ensemble model parameters. The minimum redundancy is set for each signal to the value $H_i = 7$ in order to reduce the computational time, although a higher value may increase the ensemble performance.

Table 1
Ensemble parameters and settings

$m =$	38
$H_i \geq$	7
$H =$	40
$k =$	30
$\vartheta^{TM} =$	0.25
$H_i^{TM} \geq$	5

The set $\mathbf{X}_{TST}$ of the remaining $N_{TST} = 3713$ patterns is used to test the performance of the ensemble for different aggregation strategies.

4.1 Performance resulting from the different aggregation methods

In this Section several reconstructions of the faults-free test set and of faulty dataset derived from it are performed, with the objective of investigating the aggregation strategies.

Six reconstruction of the test set $\mathbf{X}_{TST}$ are obtained using different aggregation methods: SM, GWA, MD, TM and LF based on distances computed using the Euclidean (eq. (5), LF-ED) or geometric (eq. (6), LF-GD) definition. In these faults-free cases the performances of the ensemble aggregates are evaluated considering the average over all signals of the mean absolute value of the reconstruction error ($\overline{mae_i^M}$, M = SM, GWA, MD, TM, LF-ED, LF-GD).

In order to detect and reconstruct faults, it is important to produce a robust model, i.e. a model which can accurately reproduce the true signal value even in the presence of a fault. In this context, 100 datasets $\mathbf{X}_{TST,i_{CB}}$ and 50 datasets $\mathbf{X}_{TST,i_{NS}}$ are built from $\mathbf{X}_{TST}$, by adding respectively a positive and negative constant bias (CB) or a noise (NS) fault to a single signal f_{i_F} , $i_F = 1,...,50$, F = CB, NS, randomly selected among the 215 available signals. All faults start from the 50th pattern of the test dataset and have respectively a magnitude or a standard deviation equal to the standard deviation of signal f_{i_F} .

In the faults-free cases the performances of the ensemble aggregates are evaluated considering the average over all signal of the mean absolute value of the reconstruction error ($\overline{mae_i^M}$, M = SM, GWA, MD, TM, LF-ED, LF-GD), whereas in case of sensor fault the average value $\overline{mae_{i_F}^M}$ of the mean absolute errors $mae_{i_F}^M$, obtained in the reconstruction of the faulty signal f_{i_F} , is computed. The results are shown in Table 2.

Table 2
Mean absolute error (*mae*) obtained by using different combination strategies

Aggregation Strategy	mae^{M} (10^{-2})	$\overline{mae^{M}_{i_{CB}}}$ (10^{-2})	$\overline{mae^{M}_{i_{NS}}}$ (10^{-2})
1. SM	1.780	4.383	2.100
2. GWA	1.538(+13.6%)[a]	4.431(-1.1%	1.874 (+12.0%)[a]
3. MD	1.623(+8.8%)[a]	4.465(-1.9%)[a]	2.005 (+4.5%)[a]
4. TM	1.662(+6.6%)[a]	4.400(-0.4%)[a]	2.007 (+4.4%)[a]
5. LF-ED	1.400(+21.4%)[a]	4.419(-1.3%)[a]	1.689 (+19.5%)[a]
6. LF-GD	1.515(+14.9%)[a]	4.423(-0.9%)[a]	1.832 (+12.8%)[a]

[a]The reported percentages refer to the improvement of the performance with respect to the SM.

Considering the results obtained both in case of fault-free signals (mae^{M}), and in case of NS faults, the LF-ED method seems the best performing one. The LF-GD method does not increase the accuracy and the robustness of the reconstruction.

The local fusion strategy adopted in this example, assigns greater weights to the most accurate models without accounting for their robustness. The consequences of that are clearly visible in the case of constant bias fault where the LF strategy achieve poorer results than the SM. This could be avoid by computing the weights on the reconstruction of training data with added noise, as demonstrated in the previous Section.

Nevertheless, when the fault is corrected by iterating the reconstruction a number $N^{iter} = 5$ of times, upon detection and identification of the faulty sensor, the LF-ED aggregation method conveys the best results, also in case of CB fault, as shown in Table 3.

Table 3
Mean absolute error (*mae*) obtained by using different combination strategies, after 5 iterations of the reconstruction

Aggregation Strategy	$\overline{mae^{M}_{i_{CB}}}$ (10^{-2})	$\overline{mae^{M}_{i_{NS}}}$ (10^{-2})
1. SM	4.015	3.114
2. GWA	3.766(+6.2%)[a]	2.508(+19.5%)[a]
3. MD	3.956(+1.5%)[a]	2.763(+11.3%)[a]
4. TM	3.782(+5.8%)[a]	2.889(+7.2%)[a]
5. LF-ED	3.700(+7.8%)[a]	2.146(+31.1%)[a]
6. LF-GD	3.756(+6.4%)[a]	2.427(+22.1%)[a]

[a]The reported percentages refer to the improvement of the performance with respect to the SM.

Figure 2 compares the local fusion strategy using the Euclidean Distance with the other aggregation strategies by representing the percentage of success, i.e. the ratio between the number $n^{M>M'}$ of signals for which LF-ED outperforms strategy M' (= SM, GWA, MD, TM, LF-GD) over the total number n_{TST} of considered signals ($n_{TST} = 100$ in case of positive and negative CB faults and $n_{TST} =$ 50 in case of NS faults). Also, the average error reduction obtained by using the best performing method, i.e. the quantity $R^{M>M'} = \frac{1}{n^{M>M'}} \sum_{(i+,i_F+)}^{n^{M>M'}} (mae^{M'}_{(i+,i_F+)} - mae^{M}_{(i+,i_F+)})$ where $i+$ or $i_F +$ are such that $mae^{M}_{(i+,i_F+)} > mae^{M'}_{(i+,i_F+)}$, is shown.

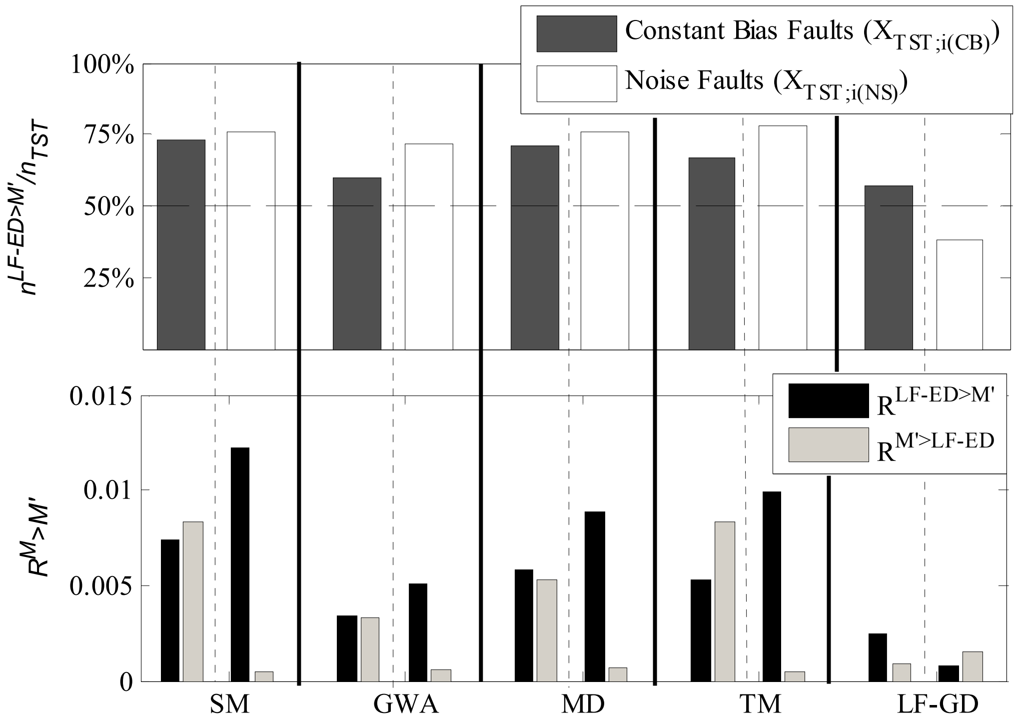

Figure 2: percentage of success of the LF-ED method (upper) and error reduction in using the best performing method (bottom) in the comparison of the LF-ED method with the other considered methods after 5 iteration of the reconstruction.

One can notice that the LF-ED method has a percentage of success almost always greater than 50%, i.e. it reconstructs more than half of the signals better than the compared method. Moreover, the mean error reduction $R^{LF-ED>M'}$ this method conveys when it performs better than the method under comparison (M') is usually greater than the error augmentation $R^{M'>LF-ED}$ produced when it performs worse.

To give a concrete example of how a faulty signal can be reconstructed by the proposed aggregation strategy, Figure 3 compares the reconstructions of the 41-th signal obtained by using the LF-ED and the SM aggregation strategies in the case of CB fault.

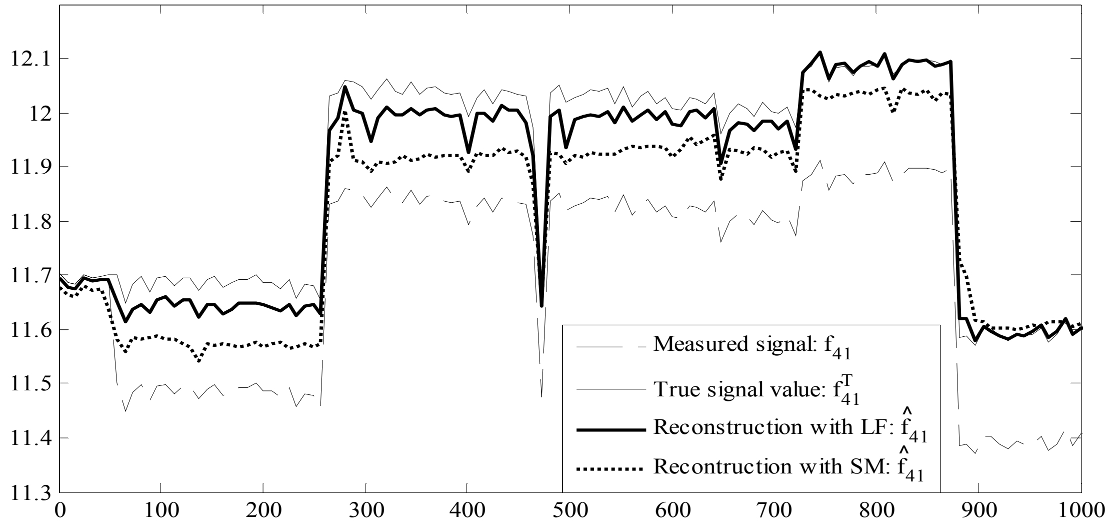

Figure 3: reconstruction $\hat{f}_{41}^{T}$ of true value f_{41}^{T} of the 164-th measured signal $\hat{f}_{41}$ using the SM and the LF-ED aggregation strategies.

************Riporto questo paragrafo, anche se alla fine lo elimineremo, per farti vedere, se ti interessano, i risultati corretti della group selection************

4.2 New procedure for the LF of models outcomes

In this Section the idea of totally excluding the most inaccurate models from the aggregation is integrated into the LF approach. The new procedure, hereafter called local fusion with group selection (LG-GS), consists in:

1. Determine the values the local bias corrections b_i^h and weights w_i^h as explained in Section 3, point c.
2. Set to zero the weights of a number $\vartheta^{GS} H_i$ of models assigned at step 1 with the lowest weights. The quantity $H_i^{GS} = (1-\vartheta^{GS}) \cdot H_i$ represents the number of selected groups; the fraction of excluded groups ϑ^{GS} is here set equal to 0.25.
3. Aggregate the outputs by using eq. (1).

In **Table 4** the results obtained with this new approach are reported and the LF-GS method is compared with the standard LF (since only the Euclidean definition of distance is considered the indication ED is here omitted).

Table 4
Results of the Local Fusion with Groups Selection

	Fault-free signals ($\mathbf{X}_{TST}$)	Signals with CB fault ($\mathbf{X}_{TST,i_{CB}}$)	Signals with NS fault ($\mathbf{X}_{TST,i_{NS}}$)
$\overline{mae_{(i,i_F)}^{LF-GS}}$ (10^{-2})	1.375 (+1.8%)[a]	4.441(-0.50%)[a]	1.675 (+0.81%)[a]
$n^{LF-GS>LF}/n_{TST}$	0.51	0.45	0.56
$R^{LF-GS>LF}$ (10^{-2})	8.88 10^{-4}	8.22 10^{-4}	5.45 10^{-4}
$R^{LF>LF-GS}$ (10^{-2})	4.17 10^{-4}	1.07 10^{-3}	3.84 10^{-4}

[a]The reported percentages refer to the improvement of the performance with respect to the LF.

Table 5
Results of the Local Fusion with Groups Selection iterating the reconstruction 5 times

	Signals with CB fault ($\mathbf{X}_{TST,i_{CB}}$)	Signals with NS fault ($\mathbf{X}_{TST,i_{NS}}$)
$\overline{mae_{(i,i_F)}^{LF-GS}}$ (10^{-2})	3.714(-2.0%)	2.098(+2.2%)

[a]The reported percentages refer to the improvement of the performance with respect to the LF.

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5 Conclusions

In this work the problem of reconstructing the correct value of faulty signals is tackled with an ensemble of PCA models. Signals are subdivided into diverse, overlapping groups using the RFSE procedure. A PCA reconstruction model is developed for each signals group and the multiple outcomes thus obtained are aggregated to provide the ensemble reconstruction using five different aggregation methods: SM, GWA, LF, MD and TM.

The LF is performed with two different settings, LF-ED and LF-GD, related to the way distances between the training and test patterns are computed. The second one does not introduce any significant change in the ensemble performance and it generally performs worst than the LF-ED method.

The aggregation methods have been evaluated in the reconstruction of fault-free and faulty signals. The comparison of the performance of different aggregation methods that in the signal validation task, and even more in the signal reconstruction one, the local fusion approach performs better than the other techniques considered.

Finally, the local performance identification and parameters computation have to be performed online; this could be a costly procedure. A procedure for the offline assignment of the local fusion parameters values is proposed in [14] and will be investigated in future research.

6 References

[1] M. Hoffmann, "On-line Monitoring for Calibration Reduction", HWR-784, OECD Halden Reactor Project, October 2005.

[2] M. Hoffmann, "Signal Grouping Algorithm for an Improved On-line Calibration Monitoring System", Proceedings of FLINS, Genova, Italy, Aug. 2006.

[3] D. Roverso, M. Hoffmann, E. Zio, P. Baraldi, G. Gola, "Solutions for plant-wide on-line calibration monitoring", 2007, *Proc. ESREL 2007*, Stavanger, Norway, Vol. 1, pp. 827-832.

[4] K. E. Holbert, B. R. Upadhyaya, "An Integrated Signal Validation for Nuclear Power Plants", 1990, *Nuclear Technology,* Vol. 92, No. 3, pp. 411-427.

[5] E. Zio, P. Baraldi, G. Gola, D. Roverso, M. Hoffmann, "Genetic Algoritms for Grouping of Signals for System Monitoring and Diagnostics", 2007, *Proc. ESREL 2007*, Stavanger, Norway, Vol. 1, pp. 833-840.

[6] P. Baraldi, E. Zio, G. Gola, D. Roverso, M. Hoffmann, "Genetic algorithms for signal grouping in sensor validation: a comparison of the filter and wrapper approaches", *Journal of Risk and Reliability (JRR)*, 2008, Proc. IMechE, Vol. 222, Part O, pp. 189-206. Monitoring and Diagnostics", 2007, *Proc. ESREL 2007*, Stavanger, Norway, Vol. 1, pp. 833-840.

[7] G. Gola, E. Zio, P. Baraldi, D. Roverso, M. Hoffmann, "Signal Grouping for Sensor Validation: a Multi-Objective Genetic Algorithm Approach", HWR-852, OECD Halden Reactor Project, Feb. 2007.

[8] R. Bryll, R. Gutierrez-Osuna, F. Quek, “Attribute bagging: improving accuracy of classifiers ensembles by using random feature subsets”, 2003, Pattern Recognition, Vol. 36, pp. 1291-1302.

[9] M. P. Perrone and L. N. Cooper, “When networks disagree: ensemble methods for hybrid neural networks”, 1992, National Science Fundation, USA.

[10] I.T. Jolliffe, “*Principal Component Analysis*”, Springer Eds., 2002.

[11] P. Baraldi, E. Zio, G. Gola, D. Roverso, M. Hoffmann, “A procedure for the reconstruction of faulty signals by means of an ensemble of regression models based on principal components analysis”, *NPIC-HMIT 2009 Topical Meeting*, April 5-9, 2009.

[12] P. Baraldi, E. Zio, G. Gola, D. Roverso, M. Hoffmann, “Reconstruction of faulty signals by an ensemble of principal component analysis models optimized by a multi-objective genetic algorithm”, *Proceedings of FLINS*, Madrid, Spain, Sept. 2008.

[13] P. Baraldi, A. Cammi, F. Mangili and E. Zio, “Local Fusion of an Ensemble of Models for the Reconstruction of Faulty Signals”, *IEEE Transactions on Nuclear Science*, submitted for publication.

[14] P.P. Bonissone et al., “Fast meta-models for local fusion of multiple predictive models”, *Appl. Soft Comput. J. (2008)*, doi:10.1016/j.asoc.2008.03.006.

[15] P. Baraldi, E. Zio, G. Gola, D. Roverso, M. Hoffmann, “Aggregation of randomized model ensemble outcomes for reconstructing nuclear signals from faulty sensors”, ESREL 2009, Sept 7-10.