Large-scale signal reconstruction for sensor monitoring and diagnostics in nuclear power plants

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ABSTRACT

On-line sensor monitoring and diagnostics systems aim at detecting anomalies in sensors and reconstructing their correct signals during operation. Since 1994, research at the OECD Halden Reactor Project has focused on the problem of sensor monitoring and diagnostics, eventually leading to the development of the PEANO system for signal validation and reconstruction. PEANO combines empirical techniques like Fuzzy Clustering and Auto-Associative Neural Networks and has proved to be successful in a variety of practical applications. Nevertheless, using one single empirical model sets a limit to the number of signals that can be handled at a time. Recently, efforts have been made to extend the applicability of PEANO to the whole plant, which requires the validation and reconstruction of thousands of signals. This has entailed moving from a single-model to an ensemble-of-model approach which has involved the investigation of new issues. This paper presents the method hereby developed for on-line, large scale sensor monitoring and signal reconstruction and a practical application of the method to the reconstruction of signals measured at nuclear power plants.

1 INTRODUCTION

Accurate health monitoring and prompt fault detection of systems, structures and components are fundamental issues for safe and efficient management and operation of modern plants.

Signals collected by sensors placed at various locations in the plant convey information about the system's operation conditions to the automated controls and to the operators, providing the current representation of the plant state. Based on such information, control systems can be tuned during operation, corrective or emergency actions can be taken for safely handling critical situations and preventing accidents in case system malfunctions or anomalies are detected and prognostic assessments can be drawn regarding the components' remaining useful life, allowing a more cost-efficient planning for their repair or replacement. Furthermore, such efforts eventually lead to reducing unexpected production downtime and shortening maintenance, thus increasing the overall plant efficiency.

For these reasons, sensors have a fundamental role within the plant operation. Nevertheless, before using the collected signals to act on the plant, it is of primary importance to monitor the sensors' performance and health state for increasing the confidence in the recorded values, promptly detecting eventual sensor failures or malfunctions and possibly reconstructing the incorrect signals in order to avoid to convey misleading information which may lead to unsafe and/or inefficient actions. Finally, monitoring the sensors' performance during operation allows identifying amongst the large number of sensors present in the plant those which are failed and thus require maintenance, bearing the benefit of reducing unnecessary human action on sensors which is often the cause of sensors' malfunctions or de-calibrations (Hoffmann, 2005; Hoffmann, 2006).

The problem of monitoring sensors and correctly reconstructing the corresponding signals can be tackled with empirical models such as fuzzy logic (Heger *et al.*, 1996; Holbert *et al.*, 1995) and neural networks (Wang and Holbert, 1995; Holbert, 1992). In particular, auto-associative models are suitable to the task and have been applied in nuclear case studies (Holbert and Upadhyaya, 1990; Fantoni *et al.*, 2003; Fantoni and Mazzola, 1996).

Since 1994, research at the Halden Reactor Project (HRP) has focussed on the problem of sensor monitoring and diagnostics and has led to the development of the PEANO system for signal validation. PEANO is based on a combination of fuzzy clustering and Auto-Associative Neural Networks (AANNs) and has proven successful in a variety of applications (Fantoni *et al.*, 2003; Fantoni and Mazzola, 1996; Moffmann *et al.*, 2001; Hoffmann and Kirschner, 2004; Kirschner and Hoffmann, 2004; Fantoni, 2005). Nevertheless, a limitation of PEANO is that it can handle limited amounts of signals (typically less than 70). In fact, AANNs are very powerful, accurate and robust tools for signal reconstruction, but they require a long, iterative training process to tune their parameters which hardly reaches convergence as the amount of information to handle grows. Therefore, in realistic applications such as nuclear power plants, a single reconstruction model cannot handle effectively the reconstruction of the large number of signals involved. Lately, efforts have been made for extending the applicability of PEANO to the whole plant (Roverso *et al.*, 2007; Zio *et al.*, 2007; Baraldi *et al.*, 2008a; Gola *et al.*, 2007; Gola *et al.*, 2008; Baraldi *et al.*, 2008b), which have eventually led to establish a procedure for handling large-scale sensor monitoring and signal validation.

This problem has been tackled by resorting to an ensemble-based signal reconstruction procedure. Ensembles of models are indeed effective to tackle complex, large-scale problems since they substitute the development of a single optimal model (i.e. a model capable of providing an accurate reconstruction of all the signals and indeed hard to develop as the number of signal increases) with the use of multiple simple, non-optimal models. These models are easier to develop and to train since they are asked to handle a limited number of signals and they are not required to provide the highest signal reconstruction accuracy which is instead obtained by properly aggregating their outcomes within an ensemble approach.

Diversity between the models in the ensemble is also a crucial aspect to enhance the overall robustness of the approach (Baraldi *et al.*, 2008b; Brown *et al.*, 2005; Yu *et al.*, 2007; Breiman, 1996; Polikar, 2006; Tsymbal *et al.*, 2001; Tsymbal *et al.*, 2005). The concept of diversity in ensembles has been investigated from the theoretical and practical points of view together with various possible techniques for optimally aggregating the outcomes of the diverse models (Brown *et al.*, 2005; Breiman, 1996; Polikar, 2006; Tsymbal *et al.*, 2001; Tsymbal *et al.*, 2005).

This paper illustrates the procedure defined for large-scale signal reconstruction and its application to a realistic case study concerning the reconstruction of large amounts of signals measured at a Swedish nuclear power plant.

2 THE MULTI-GROUP ENSEMBLE APPROACH TO LARGE-SCALE SIGNAL RECONSTRUCTION

The ensemble approach hereby developed is founded on the subdivision of the set of sensor signals into small, diverse, yet overlapping groups (i.e. groups can have signals in common), the development of a simple, yet accurate reconstruction model for each group of signals and the smart aggregation of the outcomes of the individual models to obtain the reconstructed signal values (Figure 1). In the followings, further details are given about each step of the proposed procedure, starting with the definition of the ensemble parameters.

2.1 Setting the ensemble parameters

In the ensemble approach hereby proposed, the three parameters which are to be defined a priori based on the specific case study are the size of the groups (i.e. the number of signals in each group), the redundancy of the signals in the groups and the number of groups (i.e. models) in the ensemble.

The size of the group affects the complexity, accuracy and robustness of the corresponding signal reconstruction models. In fact, large groups will require a more complex training process of the corresponding model. Furthermore, having large groups might lead to include signals which are generally detrimental for the reconstruction of the others. On the other hand, previous studies (Baraldi *et al.*, 2008a) have shown that small groups generally provided less robust models since less mutual information is available to correctly reconstruct signals in case of sensors failures. In this work, the average value of the group size $\langle m \rangle$ is set together with the maximum group size allowed m_{MAX} during the group generation. Groups will therefore range from an undefined minimum number of signals to m_{MAX}, having on average $\langle m \rangle$ signals.

Signal redundancy is indeed a fundamental aspect to account for in order to achieve an effective ensemble signal reconstruction. Within the proposed ensemble approach, having a redundant signal means including it in $R > 1$ groups (only once in each group). Hence, $R > 1$ reconstructions of the same signal will be available form the corresponding models. As explained in the following Sections, if these R reconstructions are diverse and if they are smartly aggregated, then the overall ensemble reconstruction of the signal will be done by including only the reliable reconstructions among the R available, the bad ones being discarded. This is particularly useful if the presence of one or more failed signals in a group spoils the reconstruction of the others: in this case, the ensemble approach is expected to base the reconstruction of the signals only on those models which do not include the failed signals and whose predictions are therefore not affected by the signals' failures.

The total number of groups (i.e. models) K in the ensemble, which is proportional to the overall computational cost of the procedure, must be set in such a way that each of the n total signals to reconstruct appears in R different groups with on average $\langle m \rangle$ signals. To do so, $\langle m \rangle$ and R are first set based on case study under analysis and the number of groups to generate is given as in (Baraldi *et al.*, 2009a) by

$$K = \frac{nR}{\langle m \rangle} \tag{1}$$

This way of proceeding allows balancing the level of accuracy and robustness provided by the individual groups and ensure that during the group generation phase each signal will surely appear in more than one group.

2.2 Generating the groups of signals

The generation of the groups of signals is a crucial aspect of the procedure. The selection of the signals to insert in each group should be driven by both individual properties of the groups and global properties related to the ensemble of models. In other words, two main aspects must be taken into account in this phase:

- the mutual information content of the signals in each group must be high in order to obtain better reconstruction performances of the associated individual model (individual property) (Zio *et al.*, 2007; Baraldi et al., 2008a; Baraldi *et al.*, 2008b);
- groups must be diverse in terms of signal composition in order to have diverse models and therefore diverse predictions which can then be aggregated in such a way to ensure high ensemble robustness (Baraldi *et al.*, 2008b; Polikar, 2006; Baraldi *et al.*, 2009a); on the other hand, groups must partially overlap so each signal is included in more than one group, while still being diverse enough.

This challenging problem of enhancing both the individual and the global ensemble properties has been tackled resorting to a so-called *random-wrapper* approach. This technique is based first on the random sampling of a signal according to the Random Feature Selection Ensemble (RFSE) technique (Baraldi *et al.*, 2009a; Bryll *et al.*, 2003). The randomly sampled signal is then inserted in the group whose corresponding model provides the best signal reconstruction performance. The procedure is carried on until each signal appears in the groups with the preset desired redundancy R. This way of proceeding is indeed very effective in enhancing the groups' individual properties since it directly accounts for the performance of the model effectively used for reconstructing the signals, whilst randomizing the selection of the signals with the RFSE technique allows obtaining highly diverse signal groups.

2.3 Reconstructing the signals

With respect to the type of model to adopt for reconstructing the signals, a number of aspects must be taken into account. Indeed, models must be accurate, i.e. the must provide a correct reconstruction of the signals. Another fundamental aspect to take into consideration is the models' robustness, i.e. their capability of correctly reconstructing the values of a signal when the corresponding sensor fails and conveys wrong measurements by exploiting the mutual information carried by the other signals in the group. Finally, since the multi-group ensemble approach provides for the development of a considerable number of models, the adoption of simpler, yet fast models is preferable to using complex models which require time-consuming training processes.

Evolving Clustering Method (ECM)-based models (Song and Kabasov, 2001) have been here adopted to reconstruct the signals. ECM models are robust and demand a short training process, making them suitable for the multiple-model ensemble approach. In fact, the ECM is a fast, one-pass algorithm for dynamic clustering of an input stream of data. It is a distance-based clustering method where the cluster centers are represented by evolved nodes in an on-line mode. The clustering process starts with an empty set of clusters. The data stream, i.e. the training samples, is used to generate a number of multi-dimensional clusters identified by their position in the sample space and their width r. Given a maximum allowed cluster width r_{MAX}, during the training process, the position and width of the clusters are continuously updated and a near-optimal cluster distribution is eventually obtained. Based on these clusters, the model is expected to generalize by associating with an unseen sample the (multi-dimensional) value of the centre of the closest cluster (Song and Kabasov, 2001).

Coming to the task of reconstructing signals, the generic k-th ECM model is trained and tested using N m_k-dimensional samples $\left(f_1(t),..., f_{m_k}(t)\right)$, $t = 1, 2,..., N$, where m_k is the number of signals $i = 1, 2,..., m_k$ included in group k. Some $N_{trn} < N$ samples are used during the training phase to generate $N_c \in \left[1, N_{trn}\right]$ m_k-dimensional spherical clusters with centers $\mathbf{C}_c = \left(f_1^c,..., f_{m_k}^c\right)$, $c = 1,..., N_c$ representing the training data set. Notice that N_c is strictly dependent on r_{MAX}. During the test phase, i.e. the actual model signal reconstruction, the remaining $N_{tst} = N - N_{trn}$ samples are processed by the ECM using the N_c clusters. In particular, the generic m_k-dimensional test sample $\mathbf{p}_{tst}(t) = \left(f_1(t),..., f_{m_k}(t)\right)$ is fed as input to the ECM model which first computes the normalized Euclidean distance $d_E(\hat{\mathbf{p}}_{tst}, \mathbf{C}_c)$ between the test sample and each of the cluster centers $c = 1,..., N_c$; then, the reconstructed values of the current test sample, i.e. $\hat{\mathbf{p}}_{tst}(t) = (\hat{f}_1(t),..., \hat{f}_{m_k}(t))$, are assigned as those of the center of the nearest cluster $c_{near} = \arg(\min_{f} d_E(\hat{\mathbf{p}}_{tst}, \mathbf{C}_c))$, i.e. $\hat{f}_i(t) = f_i^{c_{near}}, \forall i \in k$.

Since only one cluster is used to assess the reconstructed values of $\mathbf{p}_{tst}(t)$, the refinement of the cluster partition, which depends on r_{MAX}, is a critical issue to determine the accuracy of the reconstruction of the test samples. During the training, if r_{MAX} is large, then few, distant clusters will be generated and the reconstructed values assigned to the test samples will be most likely constant (i.e. their reconstructed values are taken as the center of the same cluster) with considerable jumps to different values when they get closer to a different cluster. On the other hand, if r_{MAX} is too small, then the number of generated clusters is large and the values of their centers will be very close to the values of the training samples. Indeed, this would negatively affect the capability of the ECM model of generalizing, i.e. of reconstructing unseen signal values which differ from those used for training.

2.4 Aggregating the models' outcomes

Regarding the aggregation of the outcomes of the individual models, one must account that the (partly) randomized composition of the signal groups is such that some models might provide largely incorrect signal reconstructions which negatively affect the ensemble aggregate. Thus, discarding the outcomes of some models can enhance the accuracy and robustness of the aggregated output.

To this aim, the median of the outcomes distribution is here retained as the ensemble output. This choice is motivated by the randomness of the models outcomes, which, if unbiased, are expected to distribute around the correct (unknown) signal value. In this view, the outcome lying in the centre of the distribution is conjectured to be close to the correct signal value, whereas those lying on the tails of the distribution are considered fairly incorrect (Baraldi *et al.*, 2009b; Baraldi *et al.*, 2009c; Baraldi *et al.*, 2010).

The median approach simply considers as the ensemble aggregate prediction for the generic sample t the single outcome $\hat{f}_i^{k_C}(t)$ lying in the centre of the distribution of the outcomes for that sample, i.e. $\hat{f}_i^E(t) = \hat{f}_i^{k_C}(t),\ i = 1, 2,..., n$, where k_C denotes the index of the model whose outcome is central with respect to the reconstructed values of the K_i models including signal *i*.

Finally, the performance of the ensemble is evaluated by computing the absolute ensemble reconstruction error ε_i^E for each signal $i = 1,..., n$ as:

$$\varepsilon_i^E = \frac{1}{N_{tst}} \sum_{t=1}^{N_{tst}} \left| f_i(t) - \hat{f}_i^E(t) \right| \qquad (2)$$

3 APPLICATION TO LARGE-SCALE RECONSTRUCTION OF NUCLEAR SIGNALS

The proposed multi-group ensemble approach has been applied on a data set of *n*=792 signals measured at a nuclear Boiling Water Reactor (BWR) located in Oskarshamn, Sweden.

A total number *N*=8476 of 792-dimensional patterns is available. Data signals have been sampled over a 3-year period (2004-2006) from a corresponding number of sensors. Half of the available patterns (randomly sampled) have been used to generate the groups with the *random-wrapper* approach, i.e. to compute the signal reconstruction errors of the models. The remaining samples have been randomly divided in a training set (75% of the patterns) to train the ECM models[*], and a test set to compute the ensemble performances, i.e. the ensemble reconstruction errors.

Regarding the ensemble parameters, the required average group size $\langle m \rangle$ has been set equal to 50. Signal redundancy R has been set equal to 7 for all signals. Once $\langle m \rangle$ and R are set, the number of groups K to generate is equal to 111[†].

As previously mentioned, the goodness of a signal groups ensemble can be measured in terms of the diverse signal composition of the groups, indeed high when using the *random-wrapper* approach. Results have here shown that the combination of high global diversity and elevate individual signal reconstruction capability allows achieving accurate ensemble reconstruction performances when measurements are not corrupted by sensors' failures.

Furthermore, the ensemble approach has been tested for robustness on the reconstruction of faulty signals in case of multiple sensor failures. In fact, a robust ensemble of models must be capable of reconstructing the signals when in presence of sensor failures, such as drifts. Within the proposed method, a faulty sensor sends a faulty signal in input to the reconstruction models which include that signal; in this situation, the ensemble of models should still be capable of providing a good estimate of the true value of the signal by exploiting the high mutual information coming from the non-faulty signals in the groups of the ensemble.

Operatively, ten signals have been chosen as the objects of the analysis. This number reflects a realistic sensor multi-failure scenario in nuclear power plants. Approximately, the first third of the test samples of each of these ten signals has been left undisturbed as in the normal operation, while, in order to simulate a sensor failure, a linear drift has been introduced in the remaining test values of each signal.

Figure 2 shows the reconstruction of drifted signal 792 obtained by the ensemble approach when the sensor starts to drift after 150 time instants. The reconstruction is very close (sometimes superposed) to the real signal value and does not see the drift. This can be also seen by the residual (Figure 3) which is computed as the difference between the measured and reconstructed signal values. Notice that residuals are the parameters upon which sensor monitoring systems usually perform the sensors diagnosis: when residuals exceed some thresholds, the system reports the presence of a sensor failure. For this reason, early sensor fault detection requires right and prompt information from the residuals which is here effectively conveyed by the developed ensemble signal reconstruction procedure.

4 CONCLUSIONS

This work has tackled the problem of large-scale sensor monitoring and has proposed a method to tackle the problem and a practical application of such method to the reconstruction of nuclear signals.

The strategy hereby followed is based on the use of an ensemble of reconstruction models. In this respect, first signals must be grouped into many small, overlapping groups. Then a corresponding number of reconstruction models must be developed and, finally, the outcomes of the models must be opportunely aggregated.

For generating the groups of signals, a so-called *random-wrapper* approach has been adopted which allows obtaining highly diverse groups in terms of signal composition, while accounting for the reconstruction capabilities of the individual models. Evolving Clustering Method has been used as signal reconstruction model, and the median of the model outcomes distribution has been retained as the ensemble aggregate.

The application has concerned the validation of 792 signals measured at the Oskarshamn boiling water reactor. The approach has demonstrated its effectiveness in reconstructing correctly the signals, especially when the corresponding sensors are affected by failures which risk conveying corrupted measurements. In fact, the faults in one or more sensors are mitigated by the combination of robust ECM models in which signals have high mutual information to reconstruct one another thanks to the random-wrapper grouping approach, high models diversity which leads to diverse reconstructions of the same signal, some possibly unaffected by faults in other

[*] Training and test samples have been normalized between 0 and 1. For the ECM models, r_{MAX} =0.02, leading to having on average 93.4 clusters per model.

[†] Notice that increasing the value of R generally brings slight improvements in the ensemble signal reconstruction at the expenses of a much higher computational cost of developing a larger number of models K, see Eq. (1).

sensors, and a smart aggregation of the models outcomes which considers for each signal only those models which provide reliable reconstructions.

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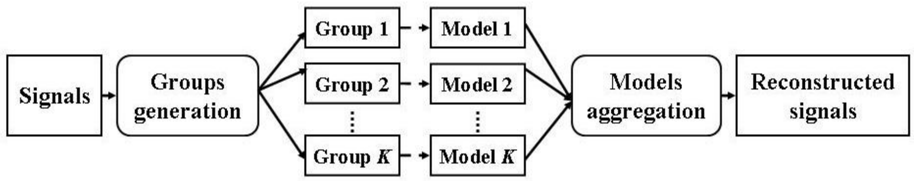

Figure 1: The ensemble approach to large-scale signal reconstruction

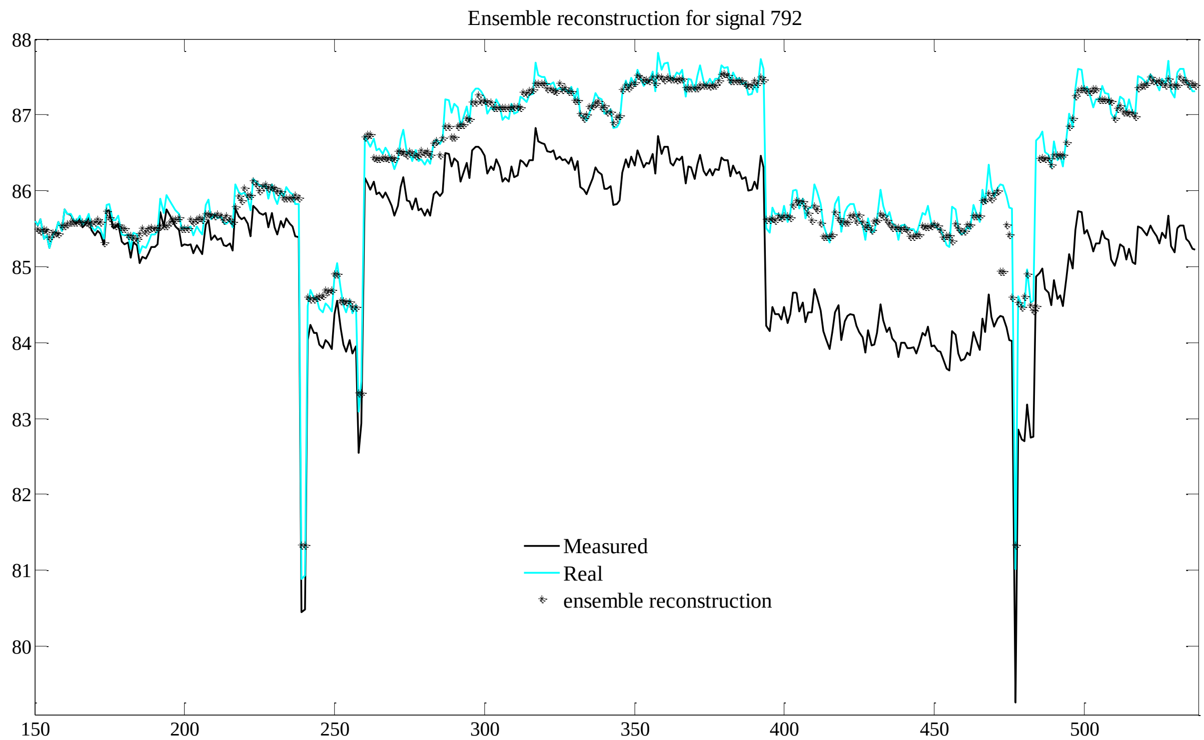

Figure 2: Reconstruction of signal 792 (light line) when drifted (dark line) by the ensemble (dark stars)

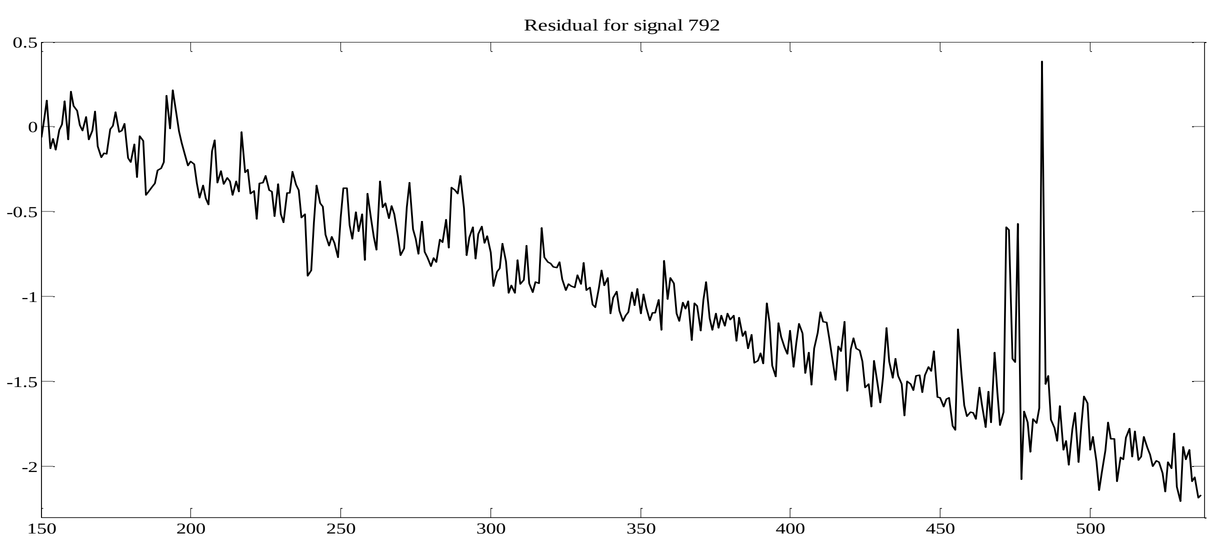

Figure 3: Residual computed for signal 792