Modeling Performance of Correlation Coefficient Weighted AAKR

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1. Introduction

Recently, many on-line approaches to instrument channel surveillance (drift monitoring and fault detection) have been reported worldwide. On-line monitoring (OLM) method evaluates instrument channel performance by assessing its consistency with other plant indications through parametric or non-parametric models [1]. The fault detection capability of an auto-associative kernel regression (AAKR) with correlation coefficient weighting on kernel distances is demonstrated. The performance measures of Error Uncertainty Limit Monitoring (EULM) fault detectability and Sequential Probability Ratio Test (SPRT) are selected and the results are compared with auto-associative kernel regression (AAKR) method [2]. Also, the transient modeling capability is demonstrated.

2. Methods and Results

2.1 AAKR with Correlation Coefficient Weighting[3]

The AAKR and AAKR with Correlation Coefficient Weighting methods is described in [2] and [3].

Let's recall the normalized correlation coefficient vector assessing the linear dependence between random variables as :

$$p_j = \left[\frac{\sigma_{j1}}{\sigma_j \sigma_1} \quad \frac{\sigma_{j2}}{\sigma_j \sigma_2} \quad \cdots \quad \frac{\sigma_{jj}}{\sigma_j \sigma_j} \right] / \left(\sum_{i=1}^{j} \frac{\sigma_{ji}}{\sigma_j \sigma_i} / j \right) . \qquad (1)$$

where j is the index of the number of redundant sensors.

The correlation coefficient assesses the linear dependence between two random variables. It is equal to the covariance divided by the largest possible covariance and has a range $-1<p_{xy}<1$. A negative correlation coefficient simply means the relationship is inverse, or as one goes up, the other tends to go down.

The correlation coefficient weighting on distance metric is performed as follows :

$$d_i^p(X_i, x) = \sqrt{\sum_j^p (X_{i,j} - x_j)^2 \times |\, p_j \,|} \,, \qquad (2)$$

where, X_i is weighted average of historical, error-free observations termed memory vectors and x is a $1\times p$ query vector of process variable measurements.

For a single query vector, this calculation is repeated for each of the n_m memory vectors, resulting in an $n_m\times 1$ matrix of distances ***d***. Next, these distances are transformed to similarity measures used to determine weights by evaluating the Gaussian kernel, expressed by:

$$w = K_\sigma(d) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-d^2/\sigma^2) \qquad (3)$$

where σ is the kernel bandwidth, **w** are the weights for the n_m memory vectors.

Finally, these weights are combined with the memory vectors to make predictions according to:

$$\hat{x} = \sum_{i=1}^{n_m} (w_i X_i) / \sum_{i=1}^{n_m} w_i \,. \qquad (4)$$

2.2 Performance Metrics

The performance metrics compared are the auto sensitivity, EULM and SPRT fault detectabilities. The definitions of each metrics can be found in reference [2].

The auto sensitivity is a measure of an empirical model's ability to make correct sensor predictions when the respective sensor value is incorrect due to some sort of fault. An auto sensitivity value of 0 is desirable and means the model is impervious to the input fault. The auto sensitivity metric is of great importance to OLM. If a model' s auto sensitivity is 1, then the model's prediction follows the fault, resulting in a residual of zero, and the fault cannot be detected. If an auto sensitivity value is non-zero, its prediction will underestimate the size of the sensor fault and the OLM system drift limits may need to be adjusted to reflect this fact.

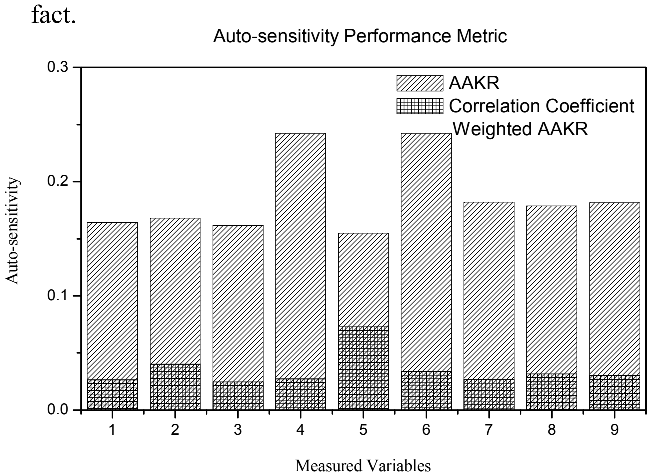

Figure 1. Comparison of auto-sensitivity of the correlation coefficient weighted AAKR over the conventional AAKR.

Figures 1 ~ 3 show the performance metrics of auto sensitivity, EULM and SPRT fault detectabilities of improved performance of the correlation coefficient weighted AAKR over the conventional AAKR.

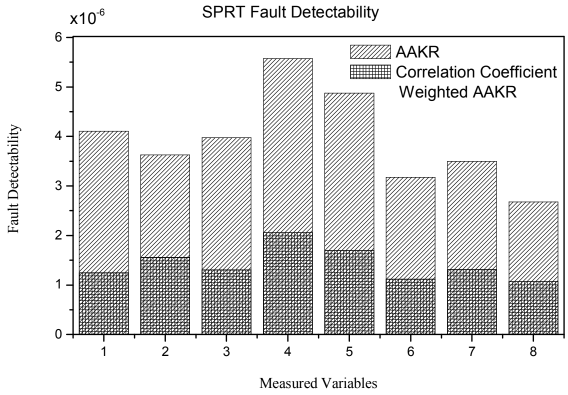

Figure 2. Comparison of SPRT fault detectability

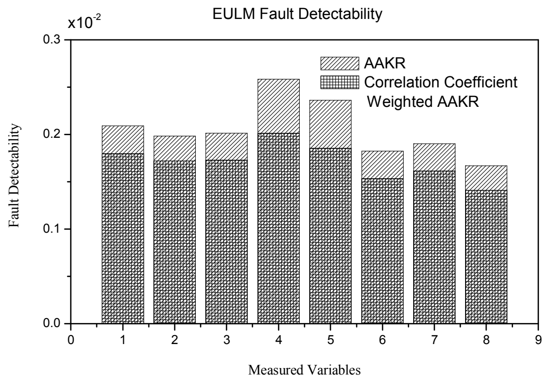

Figure 3. Comparison of EULM fault detectability

2.32 Transient Modeling Capability

The plots presented in Fig. 4 and 5 show the dynamic modeling results of feedwater flow rate and S/G level during a stratup transient. The correlation coefficient weighted AAKR gives very robust and accurate modeling result for measured plant variables.

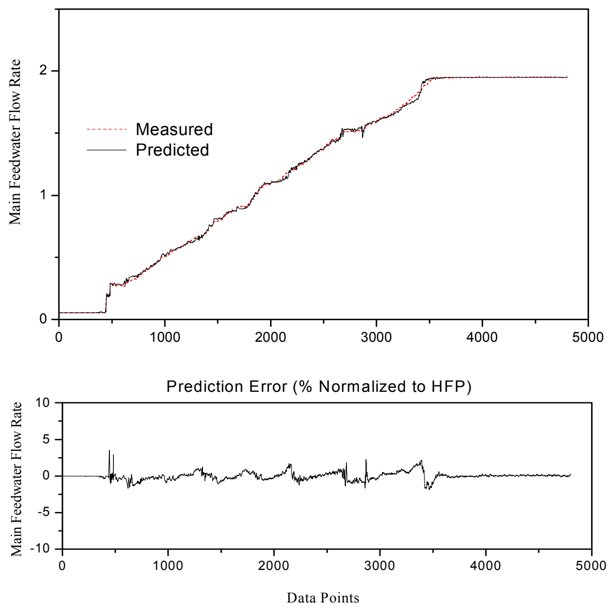

Figure 4. Dynamci modeling result for transient feedwater flow rate with correlation coefficient weighted AAKR.

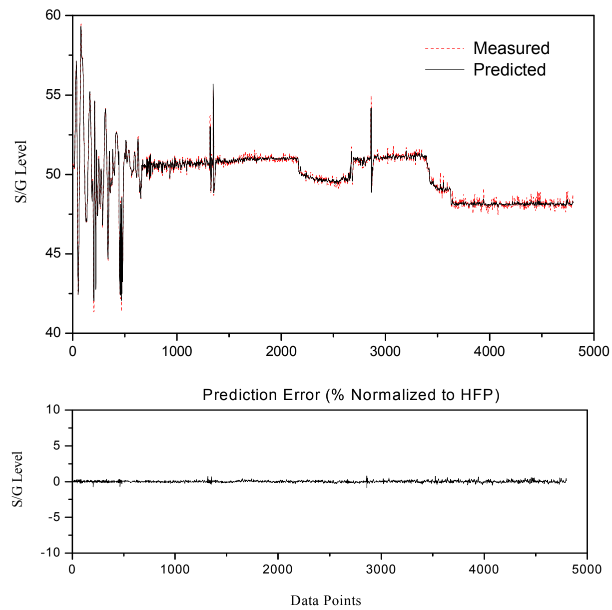

Figure 5. Dynamci modeling result for transient S/G level with correlation coefficient weighted AAKR.

3. Conclusion

This paper introduces the fault detection metrics of modeling capability of an auto-associative kernel regression (AAKR) with correlation coefficient weighting on kernel distances. The developed method shows an improved performance over conventional AAKR. The transient modeling capability is also demonstrated with real plant measurements.

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[3] H. C. Shin, M. G. Park, S. You, "Auto-associative Kernel Regression Model with Weighted Distance Metric for Instrument Drift Monitoring," KNS Autumn Meeting, November 2006.