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ARTICLE

Detection of Sensor Degradation Using K-means Clustering and Support Vector Regression in Nuclear Power Plant

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In a nuclear power plant (NPP), periodic sensor calibrations are required to assure sensors are operating correctly. However, only a few faulty sensors are found to be rectified. For the safe operation of an NPP and the reduction of unnecessary calibration, on-line calibration monitoring is needed. In this study, an on-line calibration monitoring called KPCSVR using k-means clustering and principal component based Auto-Associative support vector regression (PCSVR) is proposed for nuclear power plant. To reduce the training time of the model, k-means clustering method was used. Response surface methodology is employed to efficiently determine the optimal values of support vector regression hyperparameters. The proposed KPCSVR model was confirmed with actual plant data of Kori Nuclear Power Plant Unit 3 which were measured from the primary and secondary systems of the plant, and compared with the PCSVR model. By using data clustering, the average accuracy of PCSVR improved from 1.228×10^{-4} to 0.472×10^{-4} and the average sensitivity of PCSVR from 0.0930 to 0.0909, which results in good detection of sensor drift. Moreover, the training time is greatly reduced from 123.5 to 31.5 sec.

KEYWORDS: support vector regression, k-means clustering, principal component, nuclear power plant

I. Introduction

Considerable research efforts have been made to develop on-line calibration monitoring algorithms[1)]. The Multivariate State Estimation Technique (MSET)[2)] was established in the late 1980s, and the Plant Evaluation and Analysis by Neural Operators (PEANO)[3)] was developed by Fantoni et al. It uses auto-associative neural networks (AANN) and the system has been applied to various plants around the world for equipment condition monitoring and sensor calibration monitoring. The system utilizes a client/server architecture and a modular modeling structure.

Recently, combined principal component analysis (PCA) and support vector regression (SVR) technique was applied to many prediction areas and showed good performance.[4,5)] We developed a PCA-based auto-associative SVR (AASVR)[6)] for on-line monitoring and signal validation. It utilizes the attractive merits of principal component analysis for extracting predominant feature vectors and AASVR.

In this study, we propose a KPCSVR which uses k-means clustering and PC based SVR (PCSVR) for signal validation in NPP. The purpose of this study is to improve the performance of the PCSVR in previous work.

II. Proposed KPCSVR

The outputs of an auto-associative model are trained to emulate its inputs over an appropriate dynamic range. An auto-associative model will estimate the correct input values using the correlations embedded in the model during its training. The estimated correct value from the auto-associative model can then be compared to the actual process parameter to determine if a sensor has drifted or has been degraded by another fault type. **Figure 1** shows the schematic diagram of the proposed KPCSVR method for modeling measurements in an NPP.

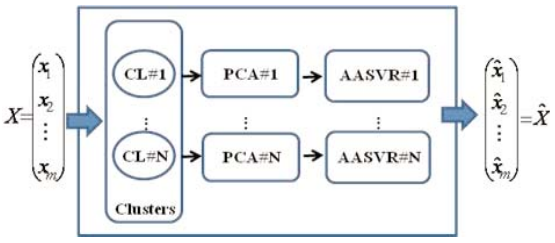

Fig. 1 Schematic diagram of KPCSVR

Two parameters, accuracy and sensitivity, were used for the performance evaluation of the algorithms.[7)] The accuracy metric is simply defined as the mean squared error (MSE) between the model's predictions and the target values. The equation for a single variable is simply:

$$A = \frac{1}{n}\sum_{i=1}^{n}(\hat{x}_i - x_i)^2 \quad (1)$$

where n is the number of test observations, $\hat{x}_i$ is the model prediction of the ith test observation, and x_i is the ith observation of the test data. Although this metric is termed "accuracy", it is actually a measure of error, and a low value is desired. A robust model would produce few to no changes in any of its outputs for errors in each of its inputs.

Model sensitivity is generally defined as a measure of the change in the prediction of the ith variable ($\hat{x}_i$) produced by a change in its respective input (x_i):

$$\boldsymbol{S}_i = \frac{\Delta\hat{\boldsymbol{x}}_i}{\Delta\boldsymbol{x}_i} \quad (2)$$

Auto-sensitivity (S_A) is a measure of an empirical model's ability to make correct sensor predictions when its respective input sensor value is incorrect due to some sort of fault.

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Therefore, this metric involves the following values: sensor *i*'s prediction with no fault in the input $\hat{\boldsymbol{x}}_i$, sensor *i*'s prediction with a faulted input $\hat{\boldsymbol{x}}_i^{drift}$, sensor *i*'s unfaulted input value $\boldsymbol{x}_i$, and sensor *i*'s drifted input value $\boldsymbol{x}_i^{drift}$. Using these definitions, the auto-sensitivity for sensor *i* is found with the following equation:

$$\boldsymbol{S}_{A,i} = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{\hat{\boldsymbol{x}}_{ki}^{drift} - \hat{\boldsymbol{x}}_{ki}}{\boldsymbol{x}_{ki}^{drift} - \boldsymbol{x}_{ki}}\right|, \quad \boldsymbol{S}_{C,ij} = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{\hat{\boldsymbol{x}}_{kj}^{drift} - \hat{\boldsymbol{x}}_{kj}}{\boldsymbol{x}_{kj}^{drift} - \boldsymbol{x}_{kj}}\right| \quad for\ i \neq j \tag{3}$$

The next performance metric is cross-sensitivity (S_C). This value measures the effect a faulty sensor input (*i*) has on the predictions of sensor (*j*). This is illustrated by the above equation, in which *j* is the index of the unfaulted variable whose spillover metric is being calculated.

1. Data Grouping

The computing time for training the PCSVR model increases exponentially as the number of training data points increases. To reduce the training time, we divided the available input data into subsets (groups) and then developed an individual PCSVR model for each group.

A k-means clustering[8] method (KCM) was used to group the available input data. KCM clustering is a clustering method that classifies one set of data into two or more groups. The aim of the KCM method is to minimize the following objective function:

$$E = \sum_{i=1}^{k}\sum_{p\in C_i}\left\|p - m_i\right\|^2 \tag{4}$$

where *p* denotes the object in space, m_i is the centroid of cluster C_i. The smaller *E* is, the more similar within group data is.

2. Principal Component Analysis

In multivariate regression, highly correlated data could result in a multicolinearity problem and are prone to producing unstable regression estimates. It is desired to reduce the data to a smaller subset of predominant feature vectors that give rise to more stable estimates of regression coefficients.

The PCA[9] method involves linearly transforming the input space into an orthogonal space that can be chosen to be of a lower dimension with a minimal loss of information, and is used to reduce the dimension of an input space into the AASVR system. A lower dimensional input space will reduce the time necessary to train the AASVR system. The PCA method can be chosen as a method of preprocessing data to extract uncorrelated features from the data.

3. Signal validation by KPCSVR

We used a KPCSVR method for the signal validation of the measurements in NPPs. The support vector machine (SVM) regression[10] is to nonlinearly map the original data into a higher dimensional feature space. Hence, given a set of data $\{(X_i, y_i\}_{i=1}^{n} \in R^m \times R^m$ where $\mathbf{x}_i$ is the input vector to support vector machines, $\mathbf{y}_i$ is the actual output vector and *n* is the total number of data patterns, the multivariate regression function for each output signal is approximated by the following function,

$$y_k = f_k(\boldsymbol{x}) = \boldsymbol{w}_k{}^T\boldsymbol{\phi}(\boldsymbol{x}) + b_k \tag{5}$$

where $\boldsymbol{w}_k = [w_1, w_2, \cdots, w_n]^T$, $\boldsymbol{\phi} = [\phi_1, \phi_2, \cdots, \phi_n]^T$, $k = 1,2,\cdots,m$ and *m* is the number of sensor measurements. Also, the function $\phi_i(\boldsymbol{x})$ is called the feature. **Eq. (5)** is a nonlinear regression model because the resulting hyper-surface is a nonlinear surface hanging over the *m*-dimensional input space. The parameters **w** and *b* are a support vector weight and a bias that are calculated by minimizing the following regularized risk function:

$$R(\boldsymbol{w}_k) = \frac{1}{2}\boldsymbol{w}_k{}^T\boldsymbol{w}_k + C_k\sum_{i=1}^{n}L_k(y_{k,i}) \tag{6}$$

where

$$L_k(y_{k,i}) = \begin{cases} 0, & \left|y_{k,i} - f_k(\boldsymbol{x})\right| < \varepsilon_k \\ \left|y_{k,i} - f_k(\boldsymbol{x})\right| - \varepsilon_k, & otherwise \end{cases} \tag{7}$$

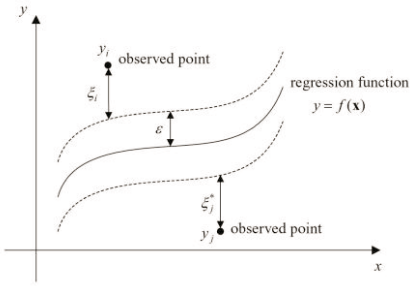


Fig. 2 The Parameters for the AASVR Models

The first term of **Eq. (6)** characterizes the complexity of the SVR models. C_k and ε_k are user-specified parameters and $L_k(y_{k,i})$ is called the ε -insensitive loss function.[10] The loss equals zero if the estimated value is within an error level, and for all other estimated points outside the error level, the loss is equal to the magnitude of the difference between the estimated value and the error level. That is, minimizing the regularized risk function is equivalent to minimizing the following constrained risk function:

$$\text{Minimize} \quad R(\boldsymbol{w}, \xi, \xi^*) = 1/2\boldsymbol{w}_k{}^T\boldsymbol{w}_k + C_k\sum_{i=1}^{n}(\xi_{k,i} + \xi_{k,i}^*) \tag{8}$$

$$\text{Subject to} \quad \begin{aligned} & y_{k,i} - \mathbf{w}_k^T\boldsymbol{\phi}(\mathbf{x}) - b_k \le \varepsilon_k + \xi_{k,i} \\ & \mathbf{w}_k^T\boldsymbol{\phi}(\mathbf{x}) + b_k - y_{k,i} \le \varepsilon_k + \xi_{k,i}^* \\ & \varepsilon_k, \xi_{k,i}, \xi_{k,i}^* \ge 0 \quad for\ i = 1,2,\cdots,n \end{aligned} \tag{9}$$

where the constant *C* determines the trade-off between the flatness of $f(\boldsymbol{x})$ and the amount up to which deviations larger than ε are tolerated, and ξ and ξ^* are slack variables representing upper and lower constraints on the outputs of the system and are positive values.

The constrained optimization problem can be solved by applying the Lagrange multiplier technique to **Eqs. (8)** and **(9)**, and then by using a standard quadratic programming technique. Finally, the regression function of **Eq. (5)** becomes

$$y_k = \sum_{i=1}^{n}(\lambda_{k,i} - \lambda_{k,i}^*)\boldsymbol{K}(\boldsymbol{x}_i, \boldsymbol{x}) + b_k^* \tag{10}$$

where $\boldsymbol{K}(\boldsymbol{x}_i, \boldsymbol{x}) = \boldsymbol{\phi}^T(\boldsymbol{x}_i)\boldsymbol{\phi}(\boldsymbol{x})$ is called the kernel function.

By using different kernel functions for inner product evaluations, various types of nonlinear models in the original space could be constructed. It has been shown that, in

general, radial-basis function (RBF) is a reasonable first choice of kernel functions since it equips with more flexibility and less parameters. The RBF kernel function used in this paper is expressed as

$$K(\mathbf{x},\mathbf{x}_i)=\exp\left\{-\frac{(\mathbf{x}-\mathbf{x}_i)^T(\mathbf{x}-\mathbf{x}_i)}{2\sigma^2}\right\} \tag{11}$$

where σ is the kernel function parameter.

The bias, b, is calculated as follows:

$$b_k^*=-\frac{1}{2}\sum_{i=1}^{n}(\lambda_{k,i}-\lambda_{k,i}^*)[K(\mathbf{x}_r,x_i)+K(\mathbf{x}_s,x_i)] \tag{12}$$

where $\mathbf{x}_r$ and $\mathbf{x}_s$ are called support vectors (SVs) and are data points positioned at the boundary of the ε-insensitivity zone. By replacing principal component $\boldsymbol{\theta}$ with **x,** we can combine PC and AASVR as follows:

$$\begin{aligned} y_k &= f_k(\theta)=\sum_{i=1}^{n}(\lambda_{k,i}-\lambda_{k,i}^*)\boldsymbol{K}(\theta_i,\theta)+b_k^* \\ b_k^* &= -\frac{1}{2}\sum_{i=1}^{n}(\lambda_{k,i}-\lambda_{k,i}^*)[K(\theta_r,\theta_i)+K(\theta_s,\theta_i)] \end{aligned} \tag{13}$$

The three most relevant design parameters for the AASVR model are the insensitivity zone, ε, the regularization parameter, C, and the kernel function parameter, σ. An increase in the insensitivity zone, ε, reduces the accuracy requirements of the approximation and allows a decrease in the number of SVs. In addition, an increase in the regularization parameter, C, reduces larger errors, thereby minimizing the approximation error. The kernel function parameter, σ, determines the sharpness of the radial basis kernel function.

III. Application to the NPP measurements

1. Experimental data

The proposed algorithm was confirmed with the real plant startup data of the Kori Nuclear Power Plant Unit 3. These data are the values measured from the primary and secondary systems of the NPP. The data are derived from the following 11 types of measured signals: the reactor power (the ex-core neutron detector signal, Sensor 1); the pressurizer water level (Sensor 2); the SG steam flow rate (Sensor 3); the steam generator (SG) narrow range level (Sensor 4); the SG pressure (Sensor 5); the SG wide-range level (Sensor 6); the SG main feedwater flow rate (Sensor 7); the turbine power (Sensor 8); the charging flow rate (Sensor 9); residual heat removal flow rate (Sensor 10); and the reactor head coolant temperature (Sensor 11).

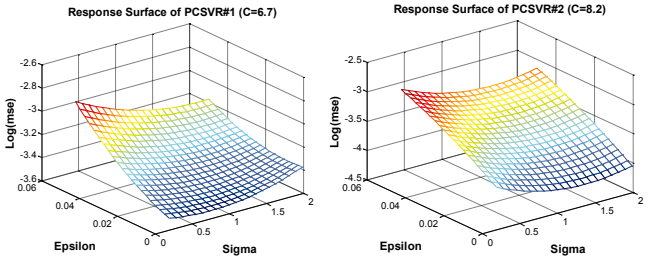
The data were sampled at a rate of 1 minute for about 38 hours. The total observation number of measurement data is 2,290 which was divided into five subsets of equal size, i.e., one subset for training, three subsets for optimization and one subset for test. Notice that data in all subsets were sampled at every 5 minutes. All the data subsets were normalized for the modeling called z1 through z5, and denormalized after the prediction process for the original signals back. We used KCM method to divide the available data into two groups and then developed a PCSVR model for each group.

2. Model parameter regularization by RSM

To optimize the proposed KPCSVR model with response surface method (RSM), we used Central composite design (CCD) for experimental designs. In this study, there SVR hyper-parameters are assumed common in each AASVR model. For every experimental point, AASVR is constructed, and then the corresponding MSE is measured by

$$MSE=\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(z_{ij}-\hat{z}_{ij})^2$$

where z_{ij} is jth input value of ith sensor in the normalized scale, and $\hat{z}_{ij}$ is its AASVR estimator. The response surface plots of $\log(MSE)$ versus σ and ε for two AASVR models are depicted in **Fig. 3.**



(a) AASVR#1 (b) AASVR#2

Fig. 3 Response surface plot

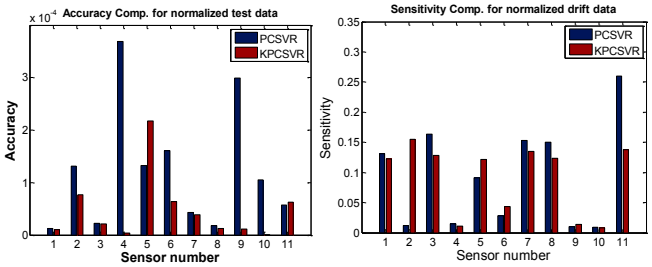
The optimized parameters are as follows:

σ =0.7818, ε =0.0005, C=6.7 for the 1st group

σ =1.4, ε =0.0005, C=8.2 for the 2nd group

3. Test results

Figure 4 shows accuracy and sensitivity of all 11 sensors for the PCSVR and the proposed KPCSVR. The average accuracy and sensitivity in normalized scale for KPCSVR is 0.472×10^{-4} and 0.0909, respectively. While those for PCSVR are 1.228×10^{-4} and 0.0930 respectively. From the figures we can know that not all the accuracy and sensitivity for sensors are improved but their averages are smaller than those for PCSVR. The average accuracy is improved by 300% but only 2.3% in average sensitivity by the proposed algorithm.

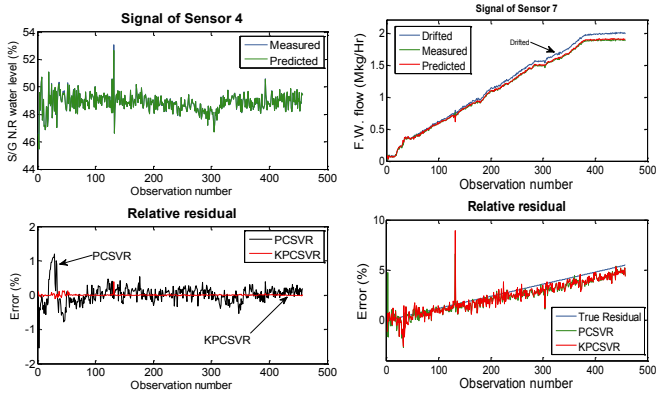


(a) Accuracy (b) Sensitivity

Fig. 4 Comparison of performance

In order to investigate model sensitivity in **Fig. 4**(b), we artificially degraded the SG main feed water flow rate signal in test data, as shown in **Fig. 5**(b). The degraded signal linearly increases at a rate of 3.14% per day from the first observation, i.e. 5% positive drift at the end of the observation.

Figure 5(a) shows relative prediction error of sensor 4 for the test data for two methods. The error for KPCSVR is much smaller than that for PCSVR, as shown in **Fig. 4**(a). **Figure 5**(b) represents relative prediction error for the drifted sensor 7 signal. We can notice that KPCSVR produces a big error for the system transient measured at 130th observation, even though the auto-sensitivity is better than that of PCSVR (see **Fig. 4**(b)).



(a) Test data (b) Drifted data

Fig. 5 Comparison of prediction error

Table 1 summarizes the performance of the proposed signal validation method for the 11 sensors. The results of the second data group are better those of the first data one. This outcome appears to be due to more stable data measured between 370th and 458th observations, as shown in **Fig. 5** (b).

Table 1. Performance of the KPCSVR for 11 signals

Data Group	Data type	Number of data	Avg. # of SV	# of PC	Avg. training time	Avg. accuracy (×1.0e-5)	Avg. sensitivity
1st group	Trn. data	234	173	5	16.8		-
	Opt. data	702	-		-		-
	Test data	234	-		-	5.04	0.094
2nd group	Trn. data	224	186	5	14.7	-	-
	Opt. data	672			-	-	-
	Test data	224			-	4.37	0.087
Total		2,290	359		31.5		

Table 2. Comparison of signal validation methods for 11 signals

Methods	Data type	# of data	# of SV	Avg. training time(sec)	# of PC	Avg. accuracy ×1.0e-04	Avg. sensitivity
Proposed method	Trn. data	458	359	31.5	5	-	-
	Opt. data	1374	-	-	-	-	-
	Test data	458	-	-	-	0.472	0.0909
Previous work[6]	Trn. data	458	286	123.5	7	-	-
	Opt. data	1374	-	-	-	-	-
	Test data	458	-	-	-	1.228	0.0930

Table 2 compares the proposed method with a previous result.[6] As shown in this table, it was possible to improve the performance by dividing the data set by means of the KCM method and using a PCSVR for each data group. Especially, the training time was greatly reduced by using proposed KPCSVR.

IV. Conclusion

A KPCSVR algorithm was proposed for the signal validation and calibration monitoring of NPP, which utilizes k-means clustering, PCA and AASVR for databased statistical learning.

The proposed KPCSVR model was applied to the data of Kori Nuclear Power Plant Unit 3, and the performance was compared with PCSVR in terms of accuracy and sensitivity. By using data clustering, the average accuracy of PCSVR improved from 1.228×10^{-4} to 0.472×10^{-4} and the average sensitivity of PCSVR from 0.0930 to 0.0909, which results in good detection of sensor drift. Moreover, the training time is greatly reduced from 123.5 to 31.5 sec. But it shows a little big error for the system transients. The proposed KPCSVR algorithm can therefore be used for the signal validation and calibration monitoring of NPP.

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