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On-line Condition Monitoring in Transient Operation of NPP Using Auto Associative Bilateral Kernel Regression

Ibrahim Ahmed, Gyunyoung Heo*
Department of Nuclear Engineering, Kyung Hee University, 1732 Deogyeong-daero, Giheung-gu, Yongin-si, Gyeonggi-do 17104, Korea
**Corresponding author: gheo@khu.ac.kr*

1. Introduction

In nuclear power plants (NPPs), accurate situation awareness is extremely important, particularly for safety. Therefore, to maintain the safety at an acceptable level, preventive measures are necessary to deal with potential issues. During plant operation, faults and failures can occur in sensors, equipment, and processes which can have impact on the performance of the plant. Hence, in order to achieve accurate situation awareness and to ensure safety, on-line monitoring of the process during operation has been adopted. Moreover, the demand for robust and resilient performance has led to the often use of these techniques to monitor process parameters and equipment conditions during operation. These techniques have the capability of providing early warning of impending failure or degradation of plant equipment [1].

The applications of unilateral kernel regression (KR) otherwise known as auto associative kernel regression (AAKR) to process monitoring of industrial components have been largely reported in literature which has been successfully utilized in steady-state equipment condition assessments. However, AAKR has limitation in time-varying data that has several repetition of the same data point of the signals particularly in normal operational transient conditions of the plant; and still lack temporal information in that, only the current query vector has effect on the model [2]. Moreover, the robustness and spillover of AAKR in reproducing the signals expected in normal condition when supplied with the abnormal input signals due to fault have being the issues, especially if the deviations of the signals due to fault is large enough or if the signals are highly correlated. These effects make it difficult for AAKR in some situation to identify the variable responsible for fault. In addition, current solutions to on-line monitoring of industrial processes and components focus mostly on detecting the anomalies from normal conditions during a steady-state operation. Monitoring of the process and equipment condition assessment in the start-up and shutdown mode operations requires a model for normal but transient monitoring which has been largely ignored. Also, some processes and equipment definitely require transient operation.

Motivated by the above observations, this paper proposed a new totally data-driven method for on-line condition monitoring in normal transient operation of NPP based on Auto Associative Bilateral Kernel Regression (AABKR). By introducing the concept of bilateral kernel into the kernel regression, a more representative of the model that utilizes both the spatial and temporal information of the data is formulated and a new weighted distance algorithm that captured the temporal information is proposed. The proposed method is implemented on start-up operational transient of NPP. Monitoring results demonstrate the feasibility and the efficiency of the proposed method, and can be used to improve process and equipment condition assessment in transient operational state.

2. Methods and Results

In this section the overviews of AAKR and bilateral filter (BF) are first presented in order to established background for the proposed method prior to the description of the proposed algorithms. Note that in this paper, only a brief descriptions of these models are presented. At the end of the section, the results of the application of the proposed method to NPP operational transient are given and discussed.

2.1 Overview of AAKR Model

The process of estimating a parameter's value in statistics and empirical modeling by calculating a weighted average of the historical observations is called Kernel Regression. KR is generally represented by the Nadaraya-Watson estimator. The AAKR formulation of KR is an auto-associative in the sense that, it's typically trained to reproduce its own input under normal operating conditions.

Given a matrix $\mathbf{X} \in \mathbb{R}^{m\times p}$ of memory data set of *p* process variables with *m* number of memory vectors, for any given on-line query input vector $\mathbf{x_q} \in \mathbb{R}^{1\times p}$ the mathematical framework of AAKR modeling technique is as follows [3]:

The distance between a query vector and each of the memory vectors is computed using Euclidean distance (L^2-Norm), for which the equation for the *i*th memory vector is

$$d_i(\mathbf{X}_i,\, \mathbf{x}_q) = \left\|\mathbf{X}_i - \mathbf{x}_q\right\|_2 = \sqrt{\sum_{j=1}^{p}\left(\boldsymbol{x}_{ij} - \boldsymbol{x}_{qj}\right)^2} \qquad (1)$$

Then, these distances are used to determine weights by evaluating the Gaussian kernel expressed by

$$k_i(\mathbf{X}_i,\, \mathbf{x}_q) = exp\left(\frac{-{d_i}^2}{2h^2}\right) \qquad (2)$$

where h is the kernel bandwidth.

Finally, these weights are combined with the memory vectors to make predictions using the weighted average of Nadaraya-Watson estimator:

$$\hat{x}_{qj} = \frac{\sum_{i=1}^{m} k_i(\mathbf{X}_i, \mathbf{x}_q). x_{ij}}{\sum_{i=1}^{m} k_i(\mathbf{X}_i, \mathbf{x}_q)} \quad (3)$$

2.2 Overview of Bilateral Filter Model

A bilateral filter (BF), first proposed by Tomasi and Manduchi [4], is a non-linear, edge-preserving and noise-reducing smoothing filter which has been widely used in image processing and denoising. To remove noise while preserving edges, BF uses the weighted average of nearby pixels in a local neighborhood, where weights rely not only on the distance of pixels (spatial differences) but also on the intensity distance (range differences).

Surprisingly, it appears that despite the BF ubiquitous popularity in image processing and denoising applications, its idea are not widely recognized or used in online industrial process monitoring. Indeed, in the last decade, Park *et al* [5] described the feasibility and performance of BF filter to noise filtering of neutron detector signals in NPP, and demonstrated that the BF outperformed both unilateral KR filter with fixed and adaptive bandwidth and the wavelet filter. Their approach of utilizing BF can be described as follows [5]:

The measurement produces a set of random variables $\{t_i, x_i; i = 1, 2, \cdots, N\}$ on the interval $\{0 \le t_i \le T\}$ and assumed that

$$x_i = x(t_i) + \varepsilon$$

where ε is a random noise variable with the mean equal to zero. Since the purpose of the BF used in [5] is to smooth out the small noise details and to preserve edge signals, no specific noise characteristic of ε is assumed. The kernel estimate of $x(t)$ at $t = \tau$ from this data is defined by

$$\hat{x}(\tau) = \frac{\sum_{i=1}^{N} x_i. k(\tau - t_i)}{\sum_{i=1}^{N} k(\tau - t_i)}. \quad (4)$$

The function k is selected as bilateral Gaussian function (a pair of Gaussian distribution), that is,

$$k(t) = k_D(distance) \times k_F(feature) \quad (5)$$

with

$$k_D(distance) = exp\left(-\frac{\|t_i - t_q\|_2^{\ 2}}{2\sigma_t^{\ 2}}\right) \quad (6)$$

$$k_F(feature) = exp\left(-\frac{\|x_i - x_q\|_2^{\ 2}}{2\sigma_x^{\ 2}}\right) \quad (7)$$

where $\sigma_t^{\ 2}$ and $\sigma_x^{\ 2}$ parameters are the variances for noise filtering and feature preservation respectively, and t_q and x_q are the query inputs for time that falls within the interval $\{0 \le t_i \le T\}$ at which the query vector is observed and feature value respectively. However, based on the authors' best knowledge, Auto Associative Bilateral Kernel Regression (AABKR) has not been applied for industrial process monitoring and fault detection tasks.

It is important to note that the BF approach described above cannot be directly utilized in its present form for on-line process monitoring implementation due to the following reasons: (1) the query time input (Eq. (6)) at which a query feature data point occurred is required for on-line implementation. Even though this is known for a particular historical data set within the specified period of time $\{0 \le t_q \le T\}$ at which the data is collected, the query time input becomes indefinite when applied to on-line monitoring, and it is virtually impossible to collect historical data that covered the operational life span of large industrial components; (2) if a fault occurs in a process, depending on the magnitude of the fault, it is very possible that the result of Eq. (7) maybe zero and leads Eq. (5) to have a zero value outcome irrespective of the value of Eq. (6). If this occurs, the model prediction tends to follow the fault occurrence and the fault will not be detected. Therefore in order to utilize the concept of bilateral kernel in this work, several modifications are proposed for on-line condition monitoring particularly in operational transient.

2.3 Description of the Proposed AABKR Model

A transient time-varying data is a sequence of observations which are ordered in time or space. The time in this case, is called the independent variable. Therefore, without any loss of generality, we assumed that the time is discrete; hence a time-varying data is defined as a sequence of pairs $[(x_1, t_1); (x_2, t_2); \cdots; (x_m, t_m)]$ with $(t_1 < t_2 < \cdots < t_m)$ where each x_i is a data point in d-dimensional feature space, and t_i is the time at which x_i occurs. The data for more than one variable signal can be considered as sequences of the p-dimensional time-varying data points, if their sampling rates are the same.

With this definition, consider the sequences of the historical time-varying data set $\mathbf{X} \in \mathbb{R}^{m \times p}$ as a memory data whose elements are functions of the scalar parameter time t, with a p-dimensional variable signals and m number of observations; where $x_{i,j}$ represents the ith observation of the jth variable. For any on-line query observation $\mathbf{x}_q \in \mathbb{R}^{1 \times p}$ at time t_q, the proposed AABKR modeling technique can be expressed in such a way that each neighboring value is weighted on its proximity in space and time, which its mathematical framework is compose of the following steps:

Step 1 – Feature Distance Calculation

The feature range distance between a query vector and each of the historical memory vectors, which measure the feature correlations, is computed by:

$$d_i(\mathbf{X}_i, \mathbf{x}_q) = \|\mathbf{x}_i - \mathbf{x}_q\|_1 = \sum_{j=1}^{p} |\boldsymbol{x}_{ij} - \boldsymbol{x}_{qj}| \quad (8)$$

resulting to a distance vector, $\mathbf{d} \in \mathbb{R}^{m \times 1}$:

$$\mathbf{d} = [d_1 \quad d_2 \quad \cdots \quad d_m]^T. \quad (9)$$

Step 2 –Feature Kernel Quantification

Here, these feature range distances are used to determine feature range weights by evaluating the Gaussian kernel for preservation of feature space, expressed by:

$$k_i^f = exp\left(\frac{-{d_i}^2}{2h_f^2}\right) \quad (10)$$

where h_f is a kernel bandwidth for feature preservation which controls how much the nearby memory feature vector is weighted.

Step 3 – Temporal Weighted Distance Calculation

Here, the temporal distance measures that capture the time variations and dependencies of the data are calculated. This distance is due to the time at which the query vector is observed. In this case, we developed a method for the calculation of the temporal correlation of the query input with memory data without the use of query time input (t_q) to the model. This eliminate the direct use of t_q which becomes indefinite when applied to online implementation. This temporal distance is named a temporal weighted distance, δ, and its calculation is based on the assumption that the time-varying historical data collected for building the model are sampled at a constant time interval, η. If this assumption holds, for any on-line query data vector observed, it is possible to determine the most nearest vector and its time location within the memory data vectors to the observed query vector. The approach used to correctly identify the most nearest vector time location within the memory data vectors is first described.

This time location index can be obtained using derivatives. The basic idea behind this approach is that instead of direct usage of the derivatives for capturing the temporal correlation of the data in the prediction, which may not be a good choice due to measured noises that are inevitable in real processes, the derivative is used herein as a *comparator* to determine the time index within the memory vectors at which the query data vector is most nearest to. This approach can be explained as follows:

The derivative of the matrix $\mathbf{X}$ with respect to t is the $m \times p$ matrix of element-by-element derivatives, $\frac{\partial}{\partial t}(\mathbf{X}) \in \mathbb{R}^{m\times p}$. While, the derivative of the matrix $\mathbf{x}_q$ with respect to t is the $1 \times p$ vector of element-by-element derivatives, $\frac{\partial}{\partial t}(\mathbf{x}_q) \in \mathbb{R}^{1\times p}$.

Note that these derivatives can be approximated from the data itself using finite difference derivative approximation [2]. The backward finite difference derivative approximation is chosen in this work in order to implement real-time online monitoring.

The distance between the derivative of the query input vector and each of the *i*th vector derivative of the memory data is calculated as.

$$\Delta_i = \left\|\frac{\partial x_{ij}}{\partial t} - \frac{\partial x_{qj}}{\partial t}\right\|_1 = \sum_{j=1}^{p}\left|\frac{\partial x_{ij}}{\partial t} - \frac{\partial x_{qj}}{\partial t}\right| \quad (11)$$

This resulted into the derivative distance vector

$$\mathbf{\Delta} = [\mathit{\Delta}_1 \quad \mathit{\Delta}_2 \quad \cdots \quad \mathit{\Delta}_m]^T \quad (12)$$

Then, the index, $i = \varepsilon$ of Δ_i with the minimum value in Eq. (13), which indicates the location of a vector in memory data where the query input vector is closest to, can be obtained. Hence, the index position at which minimum Manhattan distance of derivative of the query input vector from the vectors of the derivative of memory data is determined by:

$$\varepsilon = \underset{i\epsilon[1,m]}{\arg\min}(\mathit{\Delta}_i) \quad (13)$$

Having determined the time position index, the temporal weighted distance, $\boldsymbol{\delta} \in \mathbb{R}^{m\times 1}$ that capture the temporal correlation is then calculated by:

$$\delta_i = \begin{cases} \delta_\varepsilon, & i = \varepsilon \\ \delta_\varepsilon + (i-\varepsilon).\eta, & i > \varepsilon \,\&\, \varepsilon \neq m\,; \quad i\epsilon[1,m] \\ \delta_\varepsilon + (\varepsilon - i).\eta, & i < \varepsilon \,\&\, \varepsilon \neq 1 \end{cases} \quad (14)$$

It can be seen that, once the values of δ_ε and η are known, the other values can be calculated progressively. The second and third equations in Eq. (15) follow arithmetic progression herein the first term and the common difference of the two progressions are δ_ε and η respectively. The value of the first term of the two progressions, $\delta_\varepsilon = 0$ should be used. This is due to the fact that the distance of the most nearest vector to the query input is close to zero.

Step 4 – Temporal Kernel Quantification

The kernel weights can then be calculated using the Gaussian Kernel function which is the kernel for the time-domain preservation and noise rejection as

$$k_i^t = exp\left(\frac{-{\delta_i}^2}{2h_t^2}\right) \quad (15)$$

Step 5 – Bilateral Kernel Quantification

By the combination of Eq. (10) and Eq. (15), the bilateral kernel weight can be obtained as

$$k_i = k_i^f * k_i^t \quad (16)$$

Step 6 – Output Prediction

Finally, these bilateral kernel weights are combined with the memory data vectors to make predictions as:

$$\hat{x}_{qj} = \frac{\sum_{i=1}^{m} k_i . x_{ij}}{\sum_{i=1}^{m} k_i} \quad (17)$$

2.4 Application to NPP Operational Transient

To verify the applicability of the proposed model, Compact Nuclear simulator (CNS) real-time data collected during heating up from cool-down mode (start-up operation) is used as normal start-up transient for training. Six sensor variables are selected for monitoring during this operation which are S1 (Cold leg temperature), S2 (Core exit temperature), S3 (Hot leg temperature), S4 (Safety injection flow) S5 (Residual heat removal flow), and S6 (Sub-cooling margin temperature). The data consist of 1000 observations collected at constant time interval of 1 sec.

Since this data is fault free data, an abnormal condition is simulated on it and used as testing data set, by adding a uniformly distributed signal in the range [0.002, 3] on the S6 from t=51 to t=1000.

The residual plot of the training set from AAKR and AABKR predictions for S3 is shown in Fig. 1. It can be seen that AABKR gives much lower residuals close to 0 and reflected the actual conditions than AAKR.

The residual plots of the testing set from AAKR and AABKR predictions for S2, S3, and S6 are shown in Fig. 2. In Fig. 2(a), faults are also detected by AAKR in S2 and S3 sensors despite the fact that they are fault-free; whereas, in Fig. 2(b), faults are appropriately detected by AABKR. This effect in Fig. 2(a) is due to spillover (i.e. detection of abnormal conditions on signals different from those which are actually impacted by the fault). The consequence of this effect is that, the actual root cause of the fault cannot be determined. That is, the sensor variable responsible for the fault would be wrongly identified, and this will mislead the operator/maintenance engineer's intervention. The detail of this effect can be visualized in Fig. 3 which shows the plot of the residual predictions at time t=71sec. It is discovered, as shown in Fig. 3, that AAKR identified sensor S2 as the variable most impacted by the fault which is a wrong identification, whereas AABKR correctly identified the sensor S6 as the variable impacted by the fault which is actually the signal corrupted with the simulated fault.

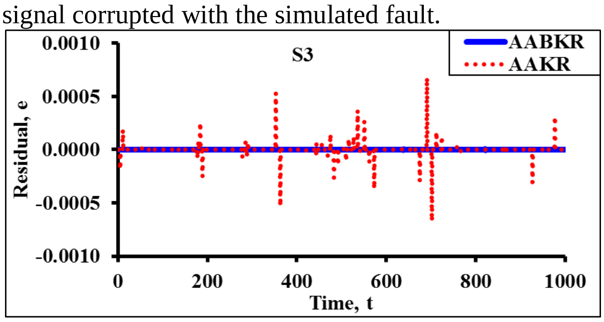
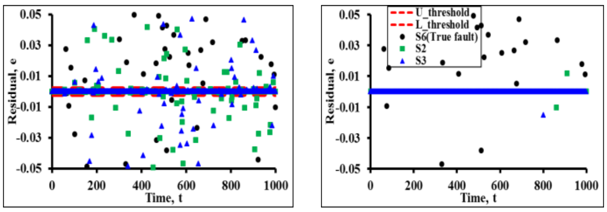
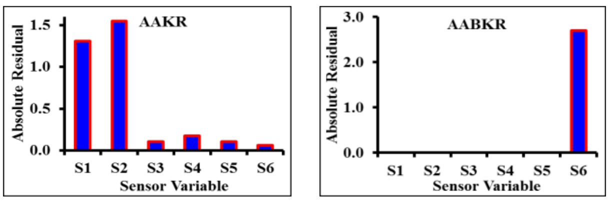


Fig. 1. Residual plot of the training set from AAKR and AABKR predictions for hot leg temperature (S3).



(a) AAKR (b) AABKR

Fig. 2. Residual of the signals obtained from AAKR and AABKR predictions when S6 is in fault condition.



(a) AAKR (b) AABKR

Fig. 3. Absolute residual plot for identification of root-cause when S6 is in fault condition

3. Conclusions

In nuclear power plant (NPP), accurate situation awareness to ensure safety is necessary not only in steady state but also in normal transient operation, which can be achieved through on-line condition monitoring. However, current solutions to on-line monitoring of industrial processes and components focus mostly on detecting the anomalies from normal conditions during a steady-state operation. Monitoring of the process and equipment condition assessment in the start-up and shutdown mode operations requires a model for normal but transient monitoring. In this work, a new data-driven method for on-line condition monitoring in normal transient operation of NPP based on Auto Associative Bilateral Kernel Regression (AABKR) is described and proposed. With the start-up mode of operation dataset, the proposed method works correctly and effectively.

Conclusively, the analysis of the propose method and its application to start-up transient data described in this work have shown how on-line condition monitoring in transient operation of NPP can be achieved. If this approach is adopted, the cause of abnormality can be identified and, thus, proper maintenance intervention can be planned.

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