Development of an Improved Data-Driven Diagnostic Platform for Process Plants: Case Study of Feedwater Heater Leakage

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Abstract: The degradation conditions of process plant components such as Feedwater Heater (FWH) can have a significant effect on the performance of the overall plant efficiency depending on the associated functions of those components. In this regard, there is need for a more robust equipment condition assessment technique that will provide a diagnostic system to detect equipment failures early enough to warn operators in advance of impending failures and to inform maintenance personnel about the nature of the failure. Several data-driven techniques to diagnose the degradation conditions of process plant components have been proposed. However, the actual performance of the data-driven methods when applied to the real-time environment after training depends largely on the quality of data used for training, as actual plant data are noisy. This paper seeks to improve the quality of data used for degradation assessment by introducing a bilateral filter. Bilateral filter is used as a smoothing and prediction technique to preserve the edges in the signal variables in order to eliminate the noise for effective signal predictions. Bilateral filters are applied to both training data and test data with dynamic filter bandwidths in order to extract multiple features thereby make it possible to extract the interest and relevant features from the data and to generate different patterns for each filter bandwidth. That is, multiple features can be obtained. Then, we developed a diagnostic model using Support Vector Machine (SVM) as a classification method. With the diagnostic platform created, the proposed methodology has been validated by applying it to internal leakage diagnosis of Feedwater Heater (FWH) in Nuclear Power Plants (NPPs).

Keyword: Data-Driven Diagnostics, Bilateral Filter, Feedwater Heater

1 Introduction

Recently, performance diagnosis and evaluation technology of plant facilities is actively being developed[1][2][3]. These techniques are aimed to enable accurate diagnosis by analyzing the cause of performance degradation. The performance of the equipment can have a significant impact on the efficiency and safety of the overall system, for example a power plant. Therefore, diagnostic techniques that can detect degradation or failure of the equipment may be very useful in some situations.

In order to increase the applicability of the performance diagnosis technology in the field, it is necessary to develop an accurate and reliable system required in the field. Although there are many studies on the performance diagnosis methodology of a power plant in operation, it is still based on empirical and intuitive judgment because the uncertainties of the process variables such as pressure, temperature, and flow rate, which are mainly measured for the diagnosis of thermal efficiency, make it difficult to give accurate information to the operator.

Since there are various types of noise in actual plant data, accuracy is greatly influenced by data quality when performing diagnosis using real-time environment, especially data-based method. This paper seeks to improve the quality of data used for degradation assessment by introducing a bilateral filter. Bilateral filter is used as a smoothing and prediction technique to preserve the edges in the signal variables in order to eliminate the noise for effective signal predictions.

A bilateral filter is a non-linear, edge-preserving and noise-reducing smoothing filter. This is a technique proposed by Tomasi and Manduchi[4] for images, and an improved version of it was then presented by Elad[5]. The feasibility and performance of bilateral kernel filters to noise filtering of neutron detector signals[6] and to the reactor coolant system leak rate calculation[7] has been carried out. Both demonstrated how bilateral kernel filters can be used to eliminate noise and improve predictions.

In this paper, we conducted a study on internal leakage, which is one of the performance degradation modes of Feedwater Heater (FWH) in Nuclear Power Plants (NPPs). Our purpose is to diagnosis the leakage condition of FWH using the trend of FWH performance indices such as Terminal Temperature Difference (TTD) and Drain Cooling Approach (DCA), which vary in various internal leakage conditions. FWH is one of the key facilities that make up the system in relation to the thermal efficiency of NPPs. It is designed to withstand the given temperature, pressure and corrosive environment during the life of the plant. However, as the operation time elapses, there may be performance degradation such as internal leakage and tube plugging in FWH due to various environmental factors. Many FWHs are replaced due to failures before the design life, or they affect the operation of the plant, resulting in a significant cost.

Especially, the internal leakage of FWHs causes not only the performance degradation itself but also a secondary failure in the adjacent tubes in continuous operation, which may cause simultaneous tube damage. This can greatly reduce the overall efficiency of the plant, so it is important to diagnose it quickly and accurately when there is leakage of FWH. It is difficult to visually inspect the inside of the FWH and the change of state variables is also very fine, so it is difficult to detect the internal leakage of FWH during the normal operation and even if leakage is detected, identifying the exact location can also be difficult.

In previous research, the methodologies such as fuzzy approaches were applied to diagnose the performance degradation of FWHs[8][9][10][11]. Among them, there is a previous study on the detection of internal leakage of FWH using an empirical model[12] and neural networks[13].

Support Vector Machine (SVM) algorithm, which is one of data mining methods widely used for data classification and regression analysis, was used to diagnose FWH internal leakage. In particular, we used bilateral filter method, which simply expresses the change from the normal condition in order to obtain appropriate information on the variables in a noisy environment. Using plant simulation software, we obtained key performance indices data due to internal leakage of FWH and used it to develop a classification model. Finally, the classification model was validated using the FWH leakage data obtained from actual FWH of NPPs.

2 Development of degradation diagnosis algorithm

2.1 Overview of diagnostic algorithm

This section introduces the overall procedure for implementing and validating FWH leakage diagnostic model. First, data is generated through degradation simulations for the component of interest. Then, bilateral filters were applied and the transformed data was used to generate the SVM model. To create an optimal SVM classification model, validation using new data except training data is required. It is common practice to divide the data into training and test data. For this, 10-fold cross validation[14] technique was used. As a result, the SVM model is generated and the performance of the model is evaluated by the validation result of the generated classification model. As a representative index of the classification performance, there is accuracy, and the accuracy can be expressed by the number correctly classified among the total number of classification. All the procedures for the development and validation of the above classification models were performed using Rapidminer[15], a data mining software.

The whole process can be roughly divided into four steps as will be discussed in detail in the following. Fig. 1 shows the diagnosis algorithm for equipment degradation in this study.

Step 1: Generate process variable data by simulating equipment degradation.

Step 2: Select the performance indices from the generated data and calculate the values for the performance indices.

Step 3: Extract feature data by applying bilateral filter to the data of performance indices.

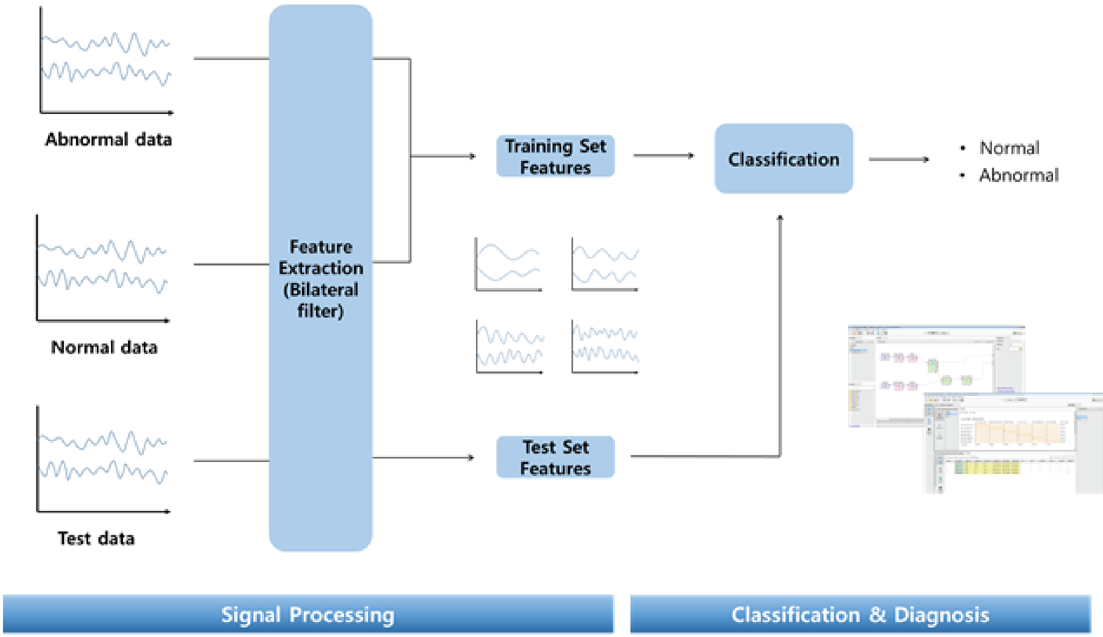

Fig. 1 Equipment degradation diagnostic algorithm

Step 4: Using the cross-validation technique, the extracted data is divided into training and test set, SVM model is built with training, and validation is performed with test set. The validation result is shown as the classification result.

2.2 Data preprocessing using Bilateral Filters

If the equipment degradation occurs, the signals will change based on the normal states. These fluctuations can be used to diagnose degradation. At this time, since the signals actually measured in the plant include noises, it is necessary to provide the fluctuation tendency effectively. In this study, in order to enhance the performance of the diagnostic model, the bilateral filtering is considered as preprocessing step prior to the development of the classification model. A bilateral filter is a non-linear, edge-preserving and noise-reducing smoothing filter. Bilateral filers are used dynamically to extract several features from time series data. By doing so, the performance of the classification model improves, and the difference of the classification class can be effectively distinguished. The bilateral filer algorithm used in this study can be explained as follows.

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m,1} & x_{m,2} & \cdots & x_{m,p} \end{bmatrix} \tag{1}$$

$$\mathrm{x}_q = \begin{bmatrix} x_{q,1} & x_{q,2} & \cdots & x_{q,p} \end{bmatrix} \tag{2}$$

In a range of interval of time-series data, $0 \leq t_i \leq T$, where p (number of columns) is the number of variables, T represents the total time duration of the data, m (numbers of rows) is the number of data vectors, and $x_{i,j}$ is the ith observation of the jth variable. For any observed query vector x_q at time t_q within the interval $0 \leq t_i \leq T$, the bilateral filter can be expressed in such a way that each neighboring value is weighted on its proximity in space and time as presented in Equation (3) through Equation (8).

The Euclidean distance $d_i(X_i,\, x_q)$ due to the observed query vector, which determined how far is the query vector from each vector of the memory data is given by Equation (3). The kernel weight (Gaussian kernel), $K_i(X_i,\, x_q)$, which assigned a weight base on the calculated distance in Equation (3) is give as Equation (4).

$$d_i(X_i,\, x_q) = \sqrt{(x_{i,1} - x_{q,1})^2 + \cdots + (x_{i,p} - x_{q,p})^2} \tag{3}$$

$$K_i(X_i,\ x_q) = exp\left(\frac{-\left(d_i(X_i,\ x_q)\right)^2}{2h_x^2}\right) \tag{4}$$

Then the Euclidean distance $d_i(t_i,\ t_q)$ due to the time at which the query vector is observed is given by Equation (5). Equation (6) then assigned a kernel based on this distance.

$$d_i(t_i,\ t_q) = \sqrt{(t_i - t_q)^2} \tag{5}$$

$$K_i(t_i,\ t_q) = exp\left(\frac{-\left(d_i(t_i,\ t_q)\right)^2}{2h_t^2}\right) \tag{6}$$

The overall kernel weight (Gaussian kernel), K_i, which is expressed as a pair of Gaussian distributions is given by Equation (7).

$$K_i = K_i(X_i,\ x_q) \times K_i(t_i,\ t_q) \tag{7}$$

Finally, the prediction from the bilateral filter is taken as weighted averaged of Nadaraya-Watson[16][17] estimator. The kernel bandwidths for two weights h_x and h_t are the variances of the spatial distances for noise rejection and feature preservation, respectively.

$$\hat{x_i}(\ x_q) = \frac{\sum_{i=1}^{m} K_i . x_i}{\sum_{i=1}^{m} K_i} \tag{8}$$

The bilateral filter allows the user to define the smoothness of the regression by adjusting the bandwidths.

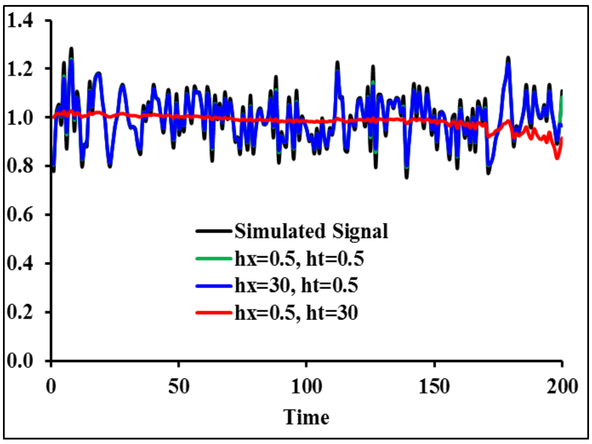

Fig. 2 Demonstration of the bilateral filter performance on bandwidth variations

Fig. 2 shows the performance of the bilateral filter for simulation data. In this study, multiple features were obtained by varying the filter bandwidth to extract various features from given data. The extracted feature predictions from bilateral filters of dynamic bandwidths are then used as the input for classification model.

2.3 Classification using Support Vector Machine (SVM)

The SVM classification was used to diagnose equipment degradation. SVM, one of the supervised learning techniques is used for classification and regression analysis and is known to perform better than conventional linear or nonlinear discriminant. The most important feature of SVM is to nonlinearly map linearly inseparable data to high dimensional space using kernel trick like Equation (9) ~ (11), and then to find classification boundary. Here, σ, γ, κ, and δ are kernel parameters and custom variables. The result of the SVM is sensitive to these parameter settings and kernel function selection[18]. More information on SVM can be found in the references[19][20][21].

RBF Kernel:

$$K(X_i, X_j) = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}} \tag{9}$$

Polynomial Kernel:

$$K(X_i, X_j) = (x_i^T x_j + 1)^r \tag{10}$$

Sigmoidal Kernel:

$$K(X_i, X_j) = tanh(\kappa x_i^T x_j - \delta) \tag{11}$$

3 Case study for diagnosis of feedwater heater leakage in NPPs

3.1 Feedwater heaters in NPPs

Feedwater Heater (FWH) is a facility for regeneration cycle in a power plant. It uses the additional steam of the steam turbine to raise the feedwater temperature supplied to the steam generator, thereby increasing the thermal efficiency of the entire power plant. Therefore, it is a very important facility in terms of reliability and availability of the power plant because the thermal efficiency is reduced as a result of the performance degradation.

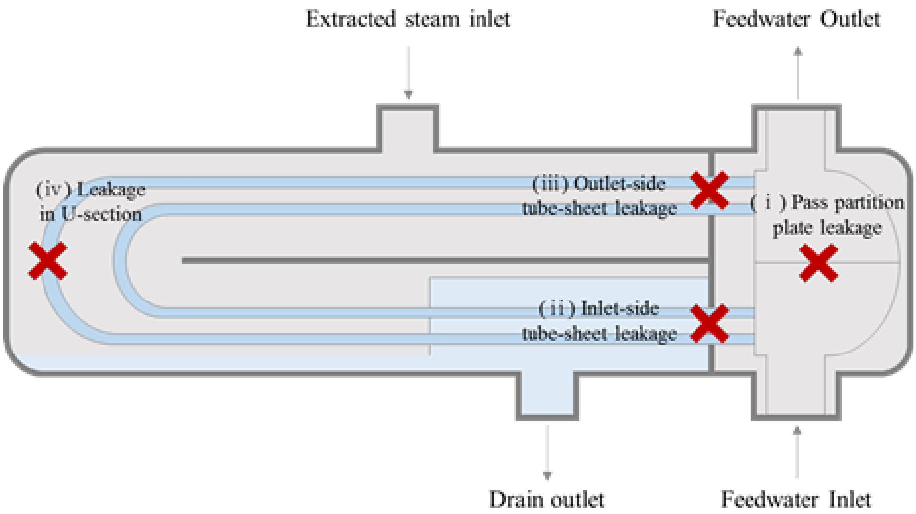

Fig. 3 Location of FWH internal leakage

However, since it is difficult to visually confirm that the performance degradation of FWH occurs, we need to quantify the heater performance. To do this, we use the performance indices. When the performance degradation of the FWH such as internal leakage or tube plugging occurs, the state variables such as temperature and pressure are changed. These state variables can be used to express performance for FWH. In this study, we selected eight performance indices[22] to show the performance of FWH as follows.

- Terminal Temperature Difference (TTD)
  = shell inlet saturated temperature – tube outlet temperature
- Drain Cooling Approach (DCA)
  = shell outlet temperature – tube inlet temperature
- Temperature difference at tube side (TD)
  = tube outlet temperature – tube inlet temperature
- Temperature difference at shell side (SD)
  = shell inlet temperature – shell outlet temperature
- Tube inlet temperature (TI)
- Tube outlet temperature (TO)
- Shell inlet temperature (SI)
- Shell outlet temperature (SO)

3.2 Simulation of internal leakage of FWH

The FWHs installed in NPPs are operated in the environment where a large amount of water in feedwater side and a wet steam flow on shell side. Therefore, various degradation phenomena such as high drain level, low shell pressure, pass partition plate leakage, and tube leakage can occur in FWH. Among them, internal leakage appears to be the main cause of degradation. In this paper, we consider the phenomenon related to the internal leakage of FWH. Causes of internal leakage of FWH include corrosion and erosion due to aging deterioration and accumulation of tube fatigue[22][23].

In order to generate data for FWH leakage diagnosis, detailed modeling and thermal performance analysis of various leakage conditions such as pass partition plate, tube inlet and outlet leakage were performed using a power plant simulation tool. In this paper, we have simulated the following four internal leakage locations of FWH investigated in related studies[13][24]. At the same time, the simulation was repeated by adjusting the input value of the leakage rates to obtain the state variables and the performance indices data of the FWH.

Fig. 3 shows the locations of the four FWH internal leakages considered for the diagnosis in this study. From the simulation, we obtained the values for the eight performance indices according to the leakage location.

Table 1 Classification results of simulation data

	Normal (true)	Pass partition plate (true)	Tube inlet side (true)	Tube outlet side (true)	U-section (true)
Normal (pred)	91.67%	0.00%	0.00%	0.00%	0.00%
Pass partition plate (pred)	1.67%	100.00%	0.00%	0.00%	0.00%
Tube inlet side (pred)	1.67%	0.00%	100.00%	0.00%	0.00%
Tube outlet side (pred)	1.67%	0.00%	0.00%	100.00%	0.00%
U-section (pred)	3.32%	0.00%	0.00%	0.00%	100.00%

Table 2 Classification results of field data

	Normal (true)	Pass partition plate (true)	Tube inlet side (true)	Tube outlet side (true)	U-section (true)
Normal (pred)	100.00%	26.67%	23.33%	20.00%	0.00%
Pass partition plate (pred)	0.00%	73.33%	0.00%	0.00%	0.00%
Tube inlet side (pred)	0.00%	0.00%	76.67%	0.00%	0.00%
Tube outlet side (pred)	0.00%	0.00%	0.00%	80.00%	0.00%
U-section (pred)	0.00%	0.00%	0.00%	0.00%	0.00%

(i) Pass partition plate leakage: feedwater is mixed directly from the tube inlet-side to the tube outlet-side.

(ii) Inlet-side tube-sheet leakage: feedwater leaks from the tube inlet-side and drains to the drain side.

(iii) Outlet-side tube-sheet leakage: feedwater leaks from the tube outlet-side and mixes with the shell side.

(iv) Leakage in U-section: feedwater is leaked from the U-section and mixes with the shell side.

3.3 Development and validation of diagnostic model for FWH internal leakage

3.3.1 Model validation using simulation data

The feature data extracted by bilateral filter from the FWH leakage simulation data was used for model generation. We used a cross validation technique that generates a SVM model with a part of the simulation data as training data and validates the model using the remainder as test data. The validation results of the classification model generated by the simulation data are summarized in Table 1 and the classification accuracy is estimated to be 99.8%. Here, the first row indicates the true leakage location of the test simulation data to be classified, and the first column indicates the predicted location. As a result of the classification, the classification ratios according to the leakage location are shown.

3.3.2 Model validation using field data

In addition, validation using field data is needed to confirm the practical applicability of the classification model but it was not easy to get the field data to the desired format. In this study, we collected very few FWH internal leakage phenomena data from the published data and examined the validity of the developed methodology. Similar to the validation using simulation data, bilateral filter is applied to the field data in the same way, and the feature is extracted and used as the input value of the SVM classification model. Table 2 shows the classification results of the field data pre-processed by the bilateral filter, and the classification accuracy was evaluated as 89.1%.

4 Conclusions

In this paper, we have developed an improved data-driven diagnostic methodology for process plants. Because the actual plant data is noisy, the actual performance of the data-driven method is highly dependent on the quality of the data. This paper introduces a bilateral filter to improve the quality of data used for performance degradation evaluation. The bilateral filter uses filter bandwidth to apply both training and test data to achieve a number of features.

A diagnostic platform was developed and validated by applying the proposed methodology to the internal leakage diagnosis of FWH in NPPs. For this purpose, the leakage conditions according to four internal leakage locations were analyzed and simulated. Then, eight performance indices for FWH were used to represent FWH performances. At this time, the bilateral filter is used to obtain appropriate information of the variables in a noisy environment and then, a classification model was constructed based on this. For this purpose, SVM algorithm was used to diagnose FWH internal leakage. Finally, the field data for FWH internal leakage was used to validate the classification model. As a result, using simulation and field data, the accuracy was evaluated as 99.8% and 89.1%, respectively.

The ultimate goal of performance diagnosis in process plants is the economical operation and maintenance of the plant. If such a diagnostic methodology is applied to other components in process plants, it will be possible to diagnose the degradation of the process plant components more quickly and accurately, and contribute to the efficient operation of the plant.

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