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Feedwater Flowrate Monitoring Using the Advanced Signal Processing based on De-noising and Principal Component Analysis in Nuclear Power Plants

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Abstract

In nuclear power plants, it is well known that the monitoring of secondary feedwater flowrate is not accurate due to the fouling phenomena of obstruction flowmeters. To overcome this shortcoming, the monitoring strategy using the signal processing based on the principal component analysis (PCA) has been proposed in this study. In the advanced signal preprocessing, the short-term distortions such as thermal noise are removed using the wavelet transform. The gradually varying noises caused by the fouling phenomena are corrected by the neural network which is carried out in a principal component space. The PCA is applied for the synthesizing of trend signals and for the construction of an autoassociative neural network. The proposed methodology was demonstrated using the signals acquired from a micro simulator and noise modeling.

I. Introduction

Generally the thermal efficiency of a nuclear power plant (NPP) is calculated as the proportion of generator output power to reactor thermal power. Although there are many methods to measure reactor thermal power, it is known that the method based upon the heat balance within a steam generator is the most accurate. The measurement of accurate reactor thermal power is very important for the optimal utilization of reactor fuel and the guarantee of operational safety margin.

Among many parameters that should be measured for the calculation of reactor thermal power, one of the most inaccurate measurements is secondary feedwater flowrate due to fouling phenomena on the converging section of a flowmeter [1]. In actual NPPs, reactor thermal power may be overestimated by approximately 2% according to the related researches. The various solutions such as periodic cleaning, anti-fouling coating, or ultrasonic flowmeter have been proposed for this problem. However recently there has been remarkable progress in the development of software-based techniques which are easy to implement, relatively low cost, and compatible with existing facilities. For instance neural networks [2-4], or multivariate state estimation techniques [5] have been proposed, which are suitable to model highly nonlinear systems and have inherent adaptation and fault-tolerant capability. This paper proposes an improved strategy on the basis of the principal component analysis (PCA) that enables aggregation of multivariate information.

II. Overall Concept of Feedwater Flowrate Monitoring Strategy

II.1. Overall Strategy for the Correction of Fouling Phenomena Effects

Fouling phenomena are the gradual stochastic process resulting from corrosion product deposition and dissolution, which appear on the converging section of an obstruction flowmeter [6]. In general fouling phenomena depend on material properties and operating condition. They may result in a measured feedwater flowrate that is greater than the actual flowrate. This effect begins after a few months if a clean flowmeter is installed. Noises in flowrate signals can be classified into the two following categories according to their time-dependent characteristics:

- *Gradually Varying Noise*: distortion due to fouling phenomena, that is a sensor drift,
- *Rapidly Varying Noise*: short-term distortions except gradually varying noises such as thermal effects.

A Rapidly varying noise can be randomly come out in all kinds of measurement systems. Therefore there is no interrelation among the rapidly varying noises of operating variables and it is impossible to correct the rapidly varying noises using techniques based on interrelation. On the other hand, a gradually varying noise is the unique characteristic that appears in the only obstruction flowmeters. This characteristic makes it possible that a gradually varying noise can be corrected by interrelation among operating variables and time.

In nuclear fields, drift correction coefficients resulting from experiences have been used as the method to correct a gradually varying noise. However there have been many researches to estimate flowrate using neural networks to utilize their adaptation capability and nonlinear modeling because of the limitation of deterministic approache. There are some considerations as follows in neural network approaches.

- The magnitude of a rapidly varying noise is comparable to that of a gradually varying noise so a neural network can not distinguish the noise type.
- If neural networks are trained excessively to eliminate rapidly varying noises, overfitting may occur because there is no interrelation among rapidly varying noises as stated above.
- Since a gradually varying noise is also a stochastic process random, there should be a statistical method synthesizing previous trend signals.
- For the improvement of estimation precision, the sampling method to acquire optimal training data and the robust training algorithm are necessary.

The estimation strategy as shown Figure 1 was proposed considering these facts in this study.

II.2. Removal of Rapidly Varying Noises using the Wavelet Transform

Signal preprocessing helps a neural network correct gradually varying noises and prevent overfitting. The important part in a signal is the low frequency content which gives the signal its identity. Thus signal preprocessing or de-noising means low frequency pass filtering. The design of a low pass filter using the discrete wavelet transform is very useful for the preservation of time information in a frequency domain, the selection of a flexible time window size and the possibility of local analysis although there are many digital low pass filters [7].

The de-noising procedures using wavelets are composed of three steps:

- *Wavelet decomposition*: selection and computation of wavelet and a level,
- *Applying threshold*: selection and applying of a threshold to the detail coefficients, and
- *Wavelet reconstruction*: wavelet reconstruction based on the original approximation coefficients and the modified detail coefficients.

II.3. Trend Signals Synthesizing using the Principal Component Analysis

The PCA is a kind of multivariate statistical methods and its main objective is to aggregate multivariate information that would be difficult or impossible to express using low dimension space otherwise. In this study the PCA is applied for the synthesizing of a stochastic random process, that is a gradually varying noise according to its time sequence. The rationales of trend signal synthesizing are shown in Figure 2. It is difficult for a general monitoring technique to reflect random characteristics. Originally the PCA can be accomplished with a bounded continuous-valued stationary ergodic data vector. However if auto-scaling and steady-state operation are assumed, trend signals can be applied to the PCA too.

According to the PCA theory, a data matrix $\mathbf{X}$ with N rows which show time sequences and p columns which show operating parameters can be decomposed as the sum of the outer product of $\mathbf{t}_i$, that is the principal components (PCs) of this system, $\mathbf{p}_i$, that is the eigenvectors of covariance matrix of $\mathbf{X}$ and $\mathbf{E}$ that is a residual matrix like

$$\mathbf{X} = \mathbf{t}_1\mathbf{p}_1^{\mathrm{T}} + \mathbf{t}_2\mathbf{p}_2^{\mathrm{T}} + \ldots + \mathbf{t}_p\mathbf{p}_p^{\mathrm{T}} + \mathbf{E}, \tag{1}$$

and a PC is calculated by

$$\mathbf{t}_i = \mathbf{X}\mathbf{p}_i. \tag{2}$$

Generally PC according to the larger eigenvalues has more important system feature. This means that original trend signals can be reconstructed using $\mathbf{p}_1, \mathbf{p}_2, .., \mathbf{p}_q$, ($q < p$ and $\lambda_q >> \lambda_{q+1}$, where λ_i is a eigenvalue) and the other PCs are considered as noises. When the PCA is carried out for an operating parameter, the physical meaning of PCs on its principal subspace is the most representative quantity which synthesizes the previous trend signals. Consequently a PC is a statistical measure which can convert a stochastic random process in a specified interval into a single value.

II.4. Removal of Gradually Varying Noises using an Autoassociative Neural Network

It may be necessary to do sampling for the construction of training sets because the training of a neural network is very time-consuming job. The latin hypercube sampling (LHS) is widely used to supplement the shortcomings of random sampling, but it is not applicable to raw signals coupled by time and physical relations because the stratification is done according to the area of probability distribution. For this reason, a modified multivariate stratification sampling on the basis of a stratified time sequence concept was developed and applied in this study, which can be applied to the coupled processing signals. The modified stratification concept and the MAXIMIN criteria [8] in conventional LHS are adopted to select optimal samples from raw plant signals in a possible sampling region. The stratification is accomplished along the time sequence, and the inter-distance between parameters is calculated according to a time sequence which is randomly selected for each stratum to satisfy the MAXIMIN criteria.

After the LHS, another PCA technique is carried out as a form of neural network to remove gradually varying noises. An autoassociative neural network (AANN) accomplishes nonlinear PCA with five layers: input/output layer, mapping/demapping layer and bottleneck layer [4]. Different from trend signal synthesizing, an AANN corrects signal degradation through extracting main features among operating parameters. The correction of gradually varying noises is done after the signals synthesized in a principal subspace are converted to the original time space.

To guarantee the precision of estimation, the multi-stage robust training method was proposed on the basis of the fact that an AANN does nothing but correct gradually varying noises by the assistance of denoising. The concept of the multi-stage robust training method is shown in Figure 3. The basic concept of the multi-stage robust training is based on the fact that an AANN can recall using only trained samples. In the multi-stage robust training, an AANN is trained stage by stage for the error sequence that may occur over the entire input space. The accuracy of an AANN is dependent on the fineness of error sequences.

III. Validations

The validation of the proposed methodology was carried out using the data from the micro-simulator of Kori nuclear unit 2 and noise modeling. To simulate a steady-state operation, the normal turbine load change mode was selected and nearly 3,000 data points were acquired, and 2,500 points among them were used for training and the others for testing. The parameters that have something to do with controlling feedwater flowrate were selected as the input of an AANN: feedwater flowrate, steam flowrate, turbine 1st stage impulse pressure and steam generator narrow range level. To model rapidly varying noises, the random number generator that has maximum 3%, and normal distribution with zero mean and one variance was used. The modeling of the gradually varying noise is only applied to the feedwater flowrate signal in the testing set. A linearly varying noise of maximum 4% and sinusoidal noise of maximum 0.5% were added to the feedwater flowrate signal. Figure 4-(a) shows the feedwater flowrate signal of which the noise modeling is done.

Level 4, Symlets with order of 7 as the wavelet transform was used to remove the rapidly varying noises. The results of rapidly varying noises are shown in Table I. All the operating parameters were converted into an one dimensional principal subspace to aggregate information within a specified interval, that is, previous 50 time sequences. The differences between the role of the wavelet transform and that of the PCA appear clearly in Table II. The wavelet transform is for low frequency pass filtering and the PCA is for the statistical aggregations of signal on the other hand.

The 100 points were sampled using the modified multivariate stratification sampling among the training set in which rapidly varying noises are removed to train the AANN. The sampled signals were reconstructed according to the multi-stage robust training algorithm using the maximum 4% error sequences like {-0.04, 0.00, 0.04}. The AANN has 5-layer symmetric configuration with 4-13-2-13-4 nodes, and was trained using the Levenberg-Marquardt algorithm for training efficiency. Figure 4-(b) shows all the signal processing results for the feedwater flowrate signal and Table III represents the statistical comparison between the noisy signals and the corrected signals.

IV. Conclusions

In this study, a monitoring strategy has been proposed on the basis of the wavelet transform, the PCA, and the AANN to correct fouling phenomena effects. Noises are classified into two categories according to their frequency characteristics and are removed by the low pass filter based on the wavelet transform and the compensator using an AANN. The signal correction by the AANN is accomplished using the signals synthesized in the one dimensional principal subspace to utilize the previous trend signals. Consequently the proposed strategy is a kind of spatio-temporal analysis to detect and correct degradation signals. A validation was carried out using the plant signals acquired by a micro simulator and noise modeling method. The root mean square errors of the feedwater flowrate signal were decreased from 21.26% to 1.87% in the validation test.

References

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Table I. The statistical results of de-noising using the wavelet transform

	Noisy signal	After de-noising

Absolute error (%)	0.45	0.50
Root mean square error (%)	15.27	3.49

*The standard signal is the original clean signal to which linear and sinusoidal varying noises are added.

Table II. The statistical results of signal synthesizing based on the PCA

	After de-noising	After the PCA
Absolute error (%)	0.36	0.37
Root mean square error (%)	6.37	2.12

*The standard signal is the original clean signal to which the only linear varying noises are added.

Table III. The statistical results of signal correction using the AANN

	Noisy signal	After de-noising	After the PCA	After the AANN
Absolute error (%)	10.78	10.83	10.84	0.19
Root mean square error (%)	21.26	18.72	18.34	1.87

*The standard signal is the original clean signal to which no noise is added.

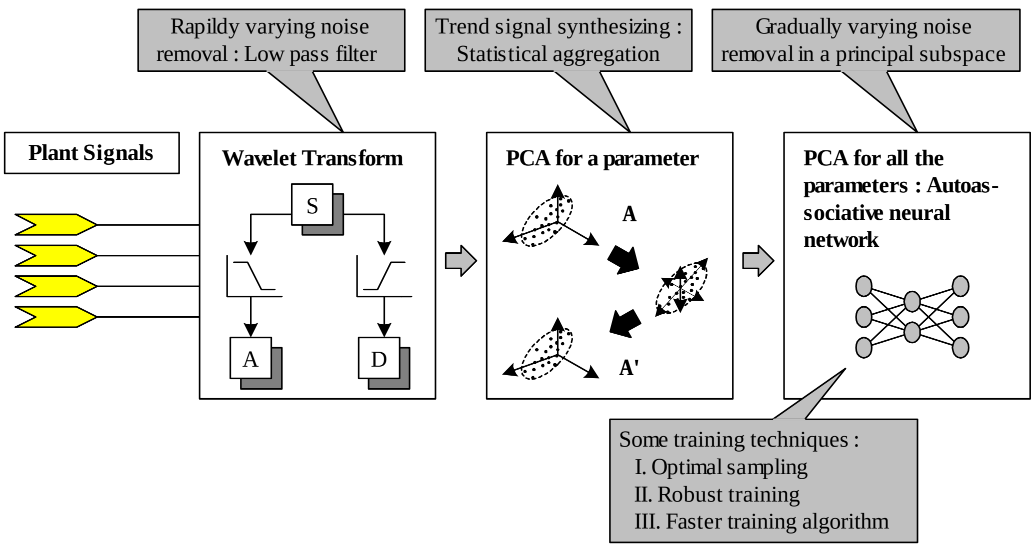


Figure 1. The overall monitoring strategy for feedwater flowrate estimation

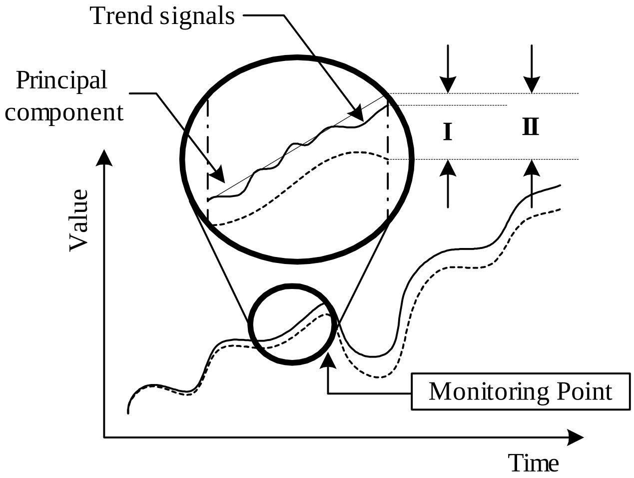


Figure 2. The comparison of monitoring techniques : In the Case I, the deviation is calculated as the difference between the original value and the measured value. In the Case II, the original value is compared to the synthesized value of previous trend signals.

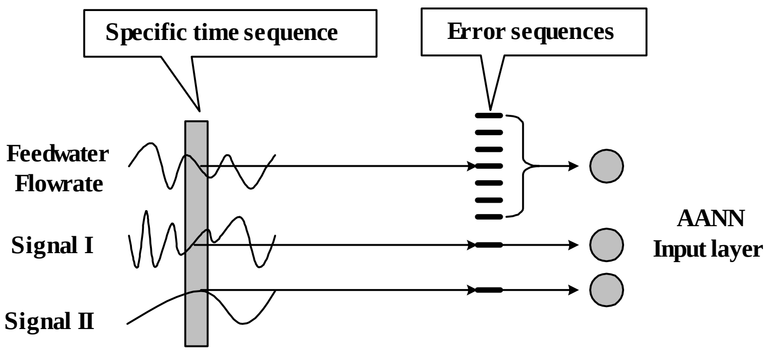
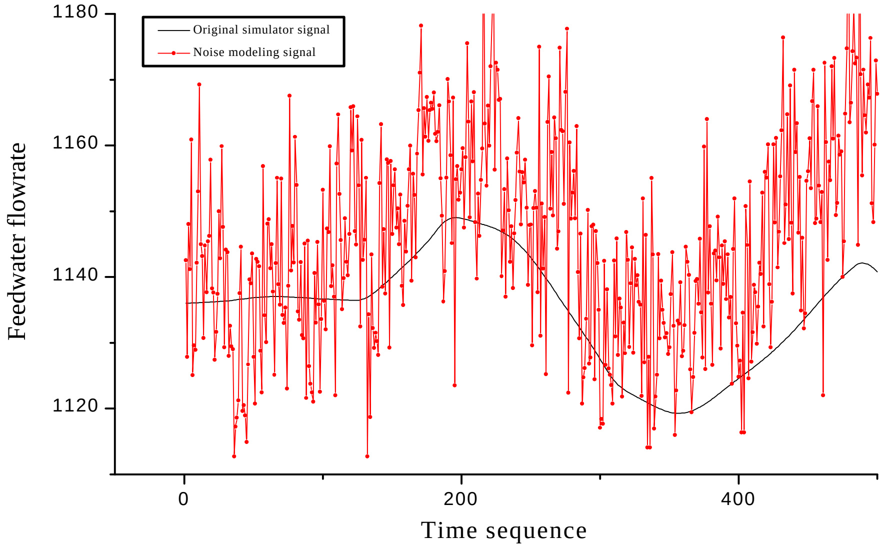


Figure 3. The concept of the multi-stage robust training method

(A)



(B)

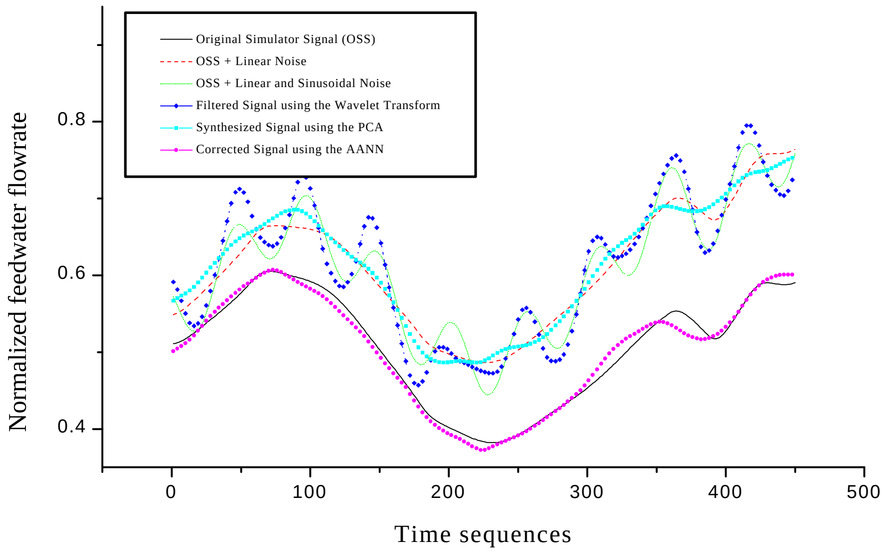


Figure 4. The validation results for the feedwater flowrate signal