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Feedwater Flowrate Estimation Based on the Two-step De-noising Using the Wavelet Analysis and an Autoassociative Neural Network

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Abstract

This paper proposes an improved signal processing strategy for accurate feedwater flowrate estimation in nuclear power plants. It is generally known that ~2% thermal power errors occur due to fouling phenomena in feedwater flowmeters. In the strategy proposed, the noises included in feedwater flowrate signal are classified into rapidly varying noises and gradually varying noises according to the characteristics in a frequency domain. The estimation precision is enhanced by introducing a low pass filter with the wavelet analysis against rapidly varying noises, and an autoassociative neural network which takes charge of the correction of only gradually varying noises. The modified multivariate stratification sampling using the concept of time stratification and MAXIMIN criteria is developed to overcome the shortcoming of a general random sampling. In addition the multi-stage robust training method is developed to increase the quality and reliability of training signals. Some validations using the simulated data from a micro-simulator were carried out. In the validation tests, the proposed methodology removed both rapidly varying noises and gradually varying noises respectively in each de-noising step, and 5.54% root mean square errors of initial noisy signals were decreased to 0.674% after de-noising. These results indicate that it is possible to estimate the reactor thermal power more elaborately by adopting this strategy.

Key Words : thermal power estimation, fouling phenomena, multivariate stratification sampling, wavelet analysis, autoassociative neural network, signal preprocessing, multi-stage robust training method

1. Introduction

The thermal efficiency in a nuclear power plant(NPP) is determined by the ratio of generator output power to reactor thermal power. Although there are a lot of methods to measure reactor thermal power, it has been known that the method based upon a heat balance within a steam generator is the most accurate among the methods proposed. The role of accurate reactor thermal power measurement can be considered from two aspects. From an economic side, overestimating reactor power results in underutilization of reactor fuel or failure to achieve burnup targets. But the more important point is the case where power is underestimated. From a safety side, the operational margin and safety margin could be threatened, if power is underestimated.

Many parameters should be measured for the calculation of reactor thermal power. One of the most inaccurate measurements among them is secondary feedwater flowrate because fouling phenomena may occur on the converging section of a flowmeter[1]. The over prediction of flowrate due to fouling may result in the overestimation of reactor thermal power. In actual NPPs, reactor thermal power may be derated by ~2% according to the related researches. The hardware-based solutions such as periodic mechanical/chemical cleaning, use of an ultrasonic flow meter, or applying an anti-fouling coating on a venturi meter have been proposed to reduce fouling phenomena. However recently there has been remarkable progress in the development of the software-based techniques which are easy to implement, relatively low in cost, and compatible with the existing facilities. As the one of the conventional techniques, drift correction coefficients from operating experiences have been used to correct a gradually varying noise. Because these deterministic approaches are not able to have adaptation capability according to operating condition, there is limitation to correct the noises accurately. Effective software-based methods should have not only high precision to minimize estimation errors but also adaptation capability to apply to the various states of a plant. For these reasons, many neural networks based on multi-layer perceptrons[2]-[5] have been proposed, but the simple neural networks could not achieve required precision. Therefore autoassociative neural networks(AANN) with extraordinary training methods[6-7], or multivariate state estimation techniques[8] have been proposed, which have the structural characteristics to satisfy enough precision. This paper proposes a strategy to improve the precision of feedwater flowrate estimation on the basis of the separation and removal of noises using the wavelet analysis and an AANN with a robust training method.

Section II of this paper analyzes fouling phenomena and their signal properties. Section III proposes the strategies to improve flowrate measurement accuracy. The validation with the simulated data from a micro-simulator is demonstrated in Section IV. Finally conclusions are presented in Section V.

2. Analysis of Fouling Phenomena

2.1. Effect of Feedwater Flowrate Measurement Errors

Because reactor power calculated by means of heat balance is used for the correction of the power calculation using turbine impulse pressure or nuclear instrumentation system, the accuracy of feedwater measurement is important from the economical point of view. Reactor power is indirectly calculated using the result of heat balance in a reactor and other heat gain/loss through letdown system, charging system, pressurizer heater/spray, or piping. Therefore reactor power can be roughly represented as follows:

$$P_{th} = f\left(f_{FW}, f_{ST}, f_{LD}, f_{CH}, h_{FW}, h_{ST}, h_{LD}, h_{CH}, h_{other}\right), \quad (1)$$

where

P_{th} = reactor thermal power,

f_{FW} = secondary feedwater flowrate,

f_{ST} = secondary steam flowrate,

f_{LD} = reactor coolant system(RCS) letdown flowrate,
f_{CH} = RCS charging flowrate,
h_{FW} = feedwater enthalpy,
h_{ST} = steam enthalpy,
h_{LD} = letdown flow enthalpy,
h_{CH} = charging flow enthalpy,
h_{other} = unmeasured heat gain or loss.

If a plant is in a steady-state operation and other parameters don't have any errors, the absolute error E_a due to feedwater measurement errors can be represented by Eqn. (2).

$$E_a = \left| \Delta f_{FW} \cdot \partial P_{th} / \partial f_{FW} \right| . \qquad (2)$$

One of the main reasons of feedwater measurement errors is fouling phenomena. 5% errors in feedwater measurement can cause nearly 3% errors in the power calculation for a 1000MWe pressurized water reactor by Eqn. (2).

2.2. Noise Characteristics of an Obstruction Flowmeter

The most widely used flowmetering principle is to use a fixed-area flow restriction of some type in the pipe of duct carrying fluid considering its accuracy, applicability and moderateness though there are many kinds of flowmeters[9]. This flow restriction causes a pressure drop according to the flowrate, thus measurement of the pressure drop allows flowrate measurement. Obstruction flowmeters are divided into several kinds according to its shape of a plate which makes a pressure drop, for example, orifice, flow nozzle and venturi tube.

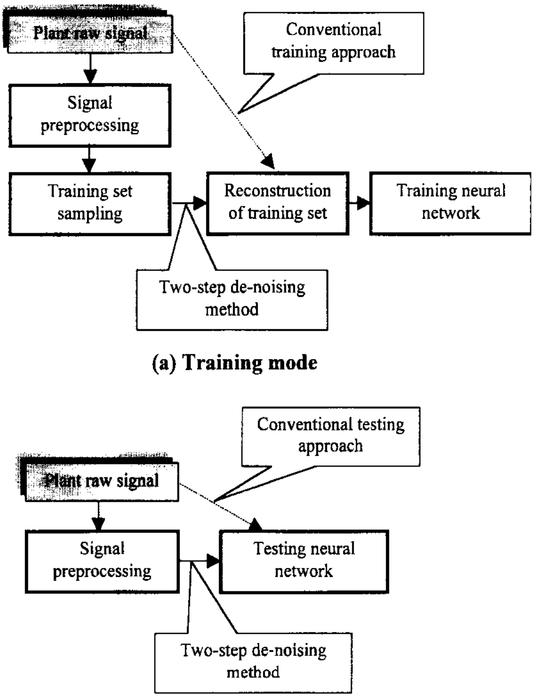
Fouling phenomena are the gradual stochastic process resulting from corrosion product deposition and dissolution, which appear on the converging section of an obstruction flowmeter [10]. Fouling phenomena, which depend on material properties and operating condition, result in the overestimation of feedwater flowrate. Signal drift by fouling phenomena begins after a few months if a clean flowmeter is placed. Raw flow signals can be classified into the three following categories according to their time-dependent characteristics:

- *Gradually varying noise* : distortion due to fouling phenomena, that is sensor drift,
- *Rapidly varying noise* : short-term distortions except gradually varying noises such as thermal effects, and
- *Noiseless flow signal* : clean signal without any gradually varying and rapidly varying noises.

The rapidly varying noises can be randomly come out in all kinds of measurement systems and they have no interrelation with any other operating variables. So it is impossible to remove the rapidly varying noises using techniques based on interrelation. On the other hand, a gradually varying noise is the unique characteristic which appears in only obstruction flowmeters and this has nothing to do with the noises of other detectors. This characteristic makes it possible that a gradually varying noise can be corrected by interrelation among operating variables and time.

3. Strategy for Improving Flowrate Measurement Accuracy

There have been many researches to estimate flowrate measurement using neural networks to utilize their adaptation capability and nonlinear modeling. Generally just a single neural network is used to remove the distortions of flowrate measurement in conventional researches. However in those approaches there are two weak points in correcting flowrate measurement accurately. The one is that the magnitude of rapidly varying noises is comparable to that of



(b) Testing mode

Fig. 1. The Comparison of Feedwater Flowrate Estimation Between the Conventional Approach and the Two-step De-noising Method in (a) Training Mode and (b) Testing Mode

gradually varying noises so the neural networks which are trained by using discrete training data can not distinguish the difference. And the other is that if neural networks are trained until they can eliminate rapidly varying noises, then the results of the training may be an increase in overfitting rather than an increase in accuracy because there is no interrelation among the rapidly varying noises of operating parameters as stated above. Therefore signal processing schemes should be separately made by the relevant methods for each noise as shown in Fig. 1.

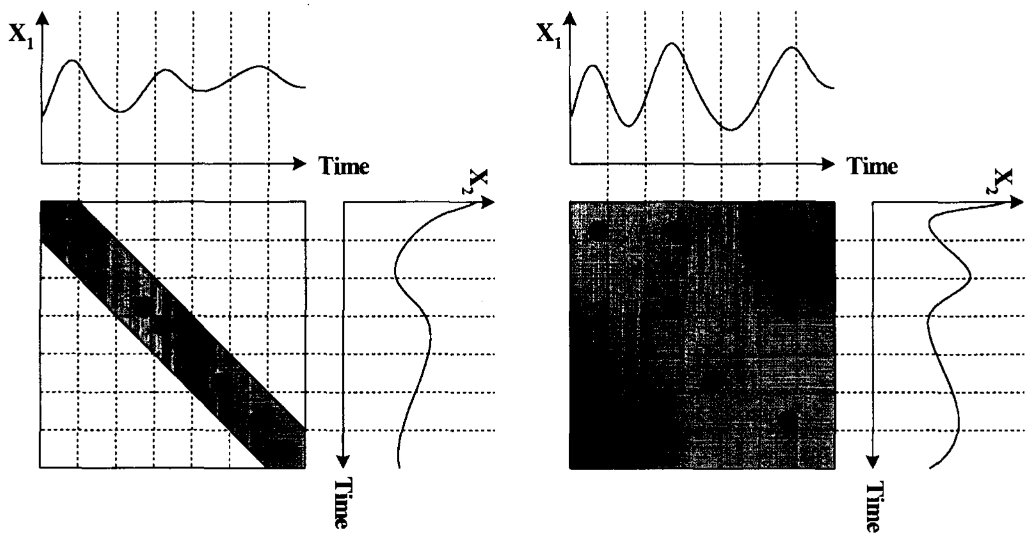
3.1. Signal Preprocessing Using the Wavelet Analysis

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 a low frequency pass filtering.

Traditionally the Fourier analysis is the extremely useful technique but has an important drawback, which is that time information is lost in a frequency domain. Therefore the wavelet analysis is very useful when transitory signals with the specified frequency should be detected in a time domain. In the wavelet analysis a time-scale region rather than a time-frequency region is used for a variable windowing technique. The variable windowing technique can allow longer time intervals when the low frequency is important and shorter intervals when the high frequency is necessary. In addition the wavelet analysis is based on irregular and asymmetric base functions, whish is different from the Fourier analysis on the basis of sinusoidal functions[11].

The de-noising procedures using the wavelet analysis are composed of three steps:

- *Wavelet decomposition* : After the selection of a wavelet and a level, a downsampling is accomplished. The downsampling makes an original signal separate into high frequency part and low frequency part. The downsampling is iterated according to the specified level.
- *Applying threshold* : The selection and application of the threshold for the generation of the detail coefficients are carried out.
- *Wavelet reconstruction* : This is also called the inverse wavelet transform. The decomposed signal is synthesized on the basis of the original approximation coefficients and the modified detail coefficients.



(a) Raw plant signals (b) Random variables

Fig. 2. The Possible Sampling Region (shading area) for (a) Random Variables and (b) Raw Plant Signals

3.2. Acquisition of a Training Set Using Modified Multivariate Stratification Sampling

The sampling of training sets would be accomplished after determining the input parameters to be used in training neural networks. Typically, samples are collected on a fixed schedule based on random sampling theory. However, random sampling is difficult to provide a balance of samples and to economically construct training sets. Generally it is known that Latin hypercube sampling(LHS) is one of the most effective sampling methods due to its nonlinear capture capability and parsimony characteristics but is not applicable to raw signals coupled by time and physical relations because the stratification is done according to the area of the probability distribution in LHS. Fig. 2 shows the possible sampling region for both random variables and raw plant signals.

For this reason a modified multivariate stratification sampling was developed in this study on the basis of a stratified time sequence concept. The modified multivariate stratification sampling is a kind of LHS, which can be applied to the raw plant signals. In the modified multivariate stratification sampling, the modified stratification concept and the MAXIMIN criteria[12] 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 variables is calculated according to the time sequence which is randomly selected for each stratum to satisfy the MAXIMIN criteria.

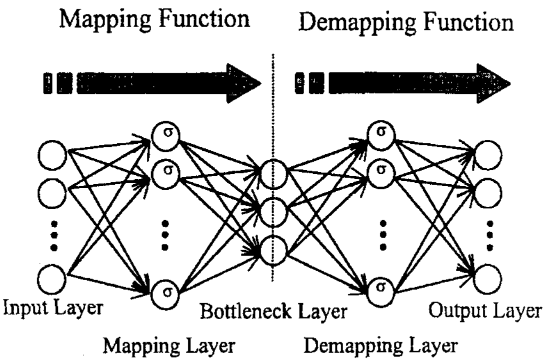


Fig. 3. The Architecture of an Ordinary Autoassociative Neural Network

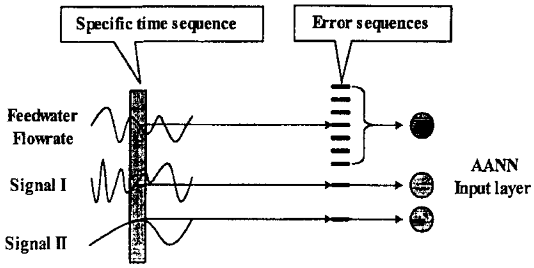


Fig. 4. The Concept of the Multi-stage Robust Training Method

3.3. Multi-stage Robust Training in an Autoassociative Neural Network

There have been many techniques to remove noises using neural networks. The de-noising techniques based on the principal component analysis have the capabilities of the decision of degradation type as well as the correction of signal drift. In general, the principal components contain the desired information without noises, therefore the extraction of the principal components among signals is the main objective of de-noising and can facilitate various multivariate analysis such as signal validation or fault detection[13]. It is worthwhile to notice an AANN from the viewpoint of nonlinear principal component analysis. The architecture of an ordinary AANN is shown in Fig. 3.

The AANN has five layers: input/output layer, mapping/demapping layer and bottleneck layer. The AANN can carry out the principal component analysis using the mapping/demapping layer to which nonlinear transfer function is applied[14]. The previous studies based on robust training methodology adding random noises have shown the good capabilities correcting signal drift but is difficult to guarantee the high precision. In this study, the multi-stage robust training method was developed on the fact that the AANN only corrects gradually varying noises by the assistance of signal preprocessing using wavelet in the two-step de-noising method. The concept of the multi-stage robust training method is shown in Fig. 4.

The basic concept of the multi-stage robust training is based on the fact that an AANN can recall using only trained samples. Since it is assumed that signals except the feedwater flowrate signal are not gradually corrupted, the training set reconstruction algorithm to apply the multi-stage robust training method is implemented as follows:

1. Create an original training set, p by N matrix from the result of the modified multivariate stratification sampling, where p is the number of input parameters, N is the number of samples over the entire input space.
2. Let s_m be the ascending ordered error sequence between the interested intervals. For example, for the feedwater flowrate measurement errors to represent the errors less than 5%, we can define the error sequence, $s_m = \{0, 0.01, 0.02, 0.03, 0.04, 0.05\}$.
3. For each j, where $j = 1, 2, \cdots, N$, and for i^* that is the feedwater flowrate signal, expand x_{ji^*} to $x_{ji^*} \times (1+s_m)$. In this case, preserve any other signal elements x_{ji} as the original state where i

Table 1. The Comparison of the Accumulated Errors According to the Sampling Methodology

Number of Samples	Modified multivariate stratification sampling		Random sampling	
	Accu. value	Mean	Accu. Value	Mean
50	2578.2	51.56	2763.4	55.26
100	10929.1	109.3	11193.8	111.9
150	24617.0	164.1	24920.9	166.1
200	45289.4	226.4	45603.3	228.0

$= 1, 2, \dots, p, i \neq i^*$.

4. Let N' be the new number of samples, where $N' = N \times$ Length of the error sequence, then reconstruct p by N' matrix for the multi-stage robust training.
5. The target set is defined as the original state, p by N matrix.

In this multi-stage robust training, the AANN is trained stage by stage for the error sequence that may occur over the entire input space. The accuracy of the AANN is dependent on the fineness of the error sequence.

4. Test Results

The validation of the proposed methodology was carried out using the data from the micro-simulator of Kori nuclear unit 2[15]. To simulate a steady-state operation, the normal turbine load change mode which uses the ramp input from −5% per minute to +5% per minute was selected. Nearly 4000 data points were acquired, and 2500 points among them were used for training and the others for testing.

The variables which have something to do with controlling feedwater flowrate were selected as the input of the AANN: feedwater flowrate, steam flowrate, turbine first stage impulse pressure and steam generator narrow range level. All the signals were normalized from 0.2 to 0.8 for the performance of the AANN. There are no gradually varying noises in the training parameters so it is necessary to model only rapidly varying noises. To model rapidly varying noises, random number generator that has maximum 2% 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 of the testing parameters. A linearly varying noise of maximum 4% was added to the feedwater flowrate signal. The configuration of wavelets to remove the rapidly varying noises was the level 5, Daubechies family wavelet. Fig. 5 shows the results of the rapidly varying noise removal for feedwater flowrate signal in the training set.

To compare the sampling performance, the data from 50 to 200 were sampled using the random sampling and the modified multivariate stratification sampling respectively. Table 1 represents the accumulated errors between two methodologies. The accumulated mean error is defined as Eqn. (3).

$$E_{acc} = \frac{\sum_{\substack{i,j \\ i \neq j}}^{N} | p_i - p_j |}{N}, \qquad (3)$$

where

p_i : ith input parameter,

N : the number of samples over the entire training set.

Considering training time, the only 50 data

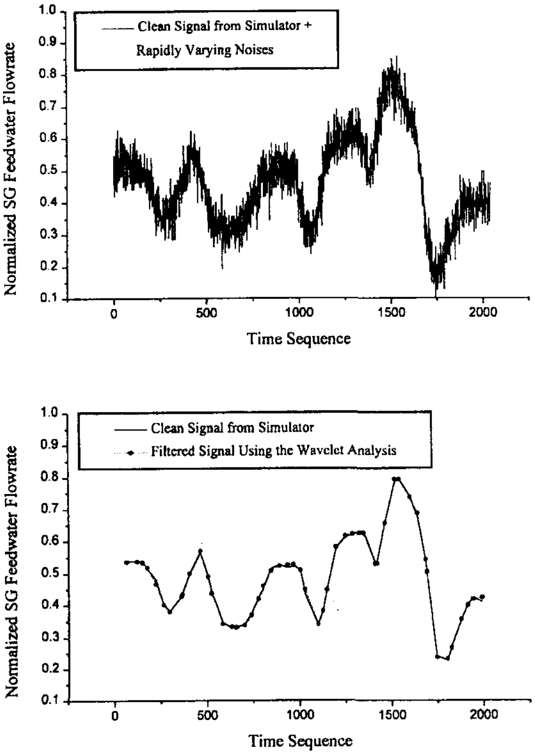


Fig. 5. The Signal Preprocessing Results for the Feedwater Flowrate Signal in the Training Set

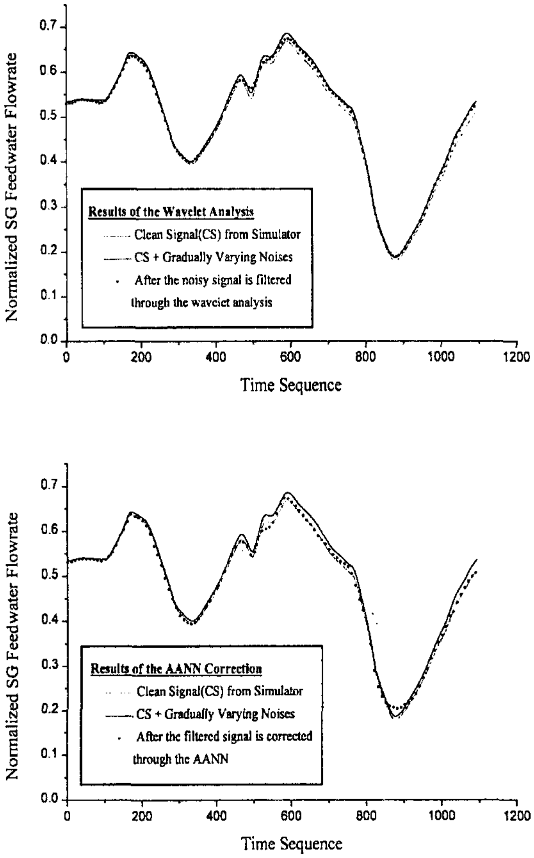


Fig. 6. Plots of the Testing Results in Each De-noising Step

sampled using the modified multivariate stratification sampling were used as a training set. The sampled data were reconstructed according to the multi-stage robust training algorithm using the error sequence s_m = {0.00, 0.01, 0.02, 0.03, 0.04}. The AANN to correct the gradually varying noise has 5-layer symmetric configuration with 4-20-3-20-4 nodes, and was trained using Levenberg-Marquardt algorithm for the training efficiency[16].

The first figure in Fig. 6 shows the results of rapidly varying noise removal and the second shows that of gradually varying noise removal in each de-noising step. In the results of the wavelet analysis, the filtered signal has similar waveform with the noisy signal to which the gradually varying noises are added because the rapidly varying noises are removed through the wavelet transform. This indicates that the AANN reduces just the gradually varying noises. Also the corrected signal in the results using the AANN has similar waveform with the original simulated signal because the gradually varying noises are removed by the AANN. Table 2 represents the statistical comparison between the noisy signals and the corrected signals.

When errors are defined as the deviation between the noiseless signals and the signals which are output from the AANN, the root mean square errors was reduced from 5.54% to

Table 2. The Statistical Results of the Two-step De-noising Method

	Noisy signals (original simulated signal +all kinds of noises)	Corrected signals
Mean Error (absolute value)	1.01×10^{-2}	1.59×10^{-3}
Standard Deviation	5.45×10^{-2}	6.55×10^{-3}
Root Mean Square Error	5.54×10^{-2}	6.74×10^{-3}

0.674%. The signal outputs from the two-step de-noising method have lower standard deviation and root mean square errors. Therefore the two-step de-noising method with the multi-stage robust training can adequately preserve the reliability of the training sets from the rapidly varying noises and provide an accurate correction capability for the gradually varying noises.

5. Conclusions

Though neural networks are considered a good solution for modeling unknown nonlinear functions, they are not easily incorporated in the fields that require high accuracy due to some casual elements such as the use of random numbers for the robust training or the overfitting phenomena. The basic concept of the proposed two-step de-noising method with multi-stage robust training is to assign roles that are suitable to the neural networks, and to find other solutions for the weakness of neural networks.

Enhancing the quality of the training sets is the essential point for solving the weakness of neural networks. This is because neural networks can produce results based on the only sets that are taught in a training mode. Noisy signal due to fouling phenomena is not flowmeter error and doesn' t appear in other signals. On the other hand, signal distortion due to electrical or thermal environment can be found in all instrumentation. Therefore neural networks, which can correct the noise from the coupled relations among variables, are suitable for removing the noise due to fouling but cannot assure the correction of distortion due to random noises. Fortunately, it is possible to enhance the signal quality through categorization of raw signals according to their characteristics in a frequency domain. Through frequency domain analysis, rapidly varying noises and gradually varying noises can be separated. This indicates that a neural network can be applied to correct just gradually varying noises.

The two-step de-noising method was developed based on the above concept. This method consists of a signal preprocessing step, an training set sampling step and a multi-stage robust training step. In the signal preprocessing step, the low pass filter using wavelets minimizes rapidly varying noises. In the training set sampling step, the modified multivariate stratification sampling using stratification according to the time sequence and a MAXIMIN concept was developed. Additionally, the multi-stage robust training method was implemented to assure the training reliability. The effectiveness of the two-step de-noising method was successfully demonstrated through the validation using the simulated operational data.

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