ANALYSIS OF EDDY CURRENT TESTING SIGNALS FOR QUANTITATIVE FLAW CHRACTERIZATION IN STEAM GENERATOR TUBES USING PRINCIPLE COMPONENT ANALYSIS

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Abstract: The model-based interpretation tools for eddy current testing (ECT) signals have been developed by the novel combination of neural networks and finite element modeling for quantitative flaw characterization in steam generator tubes. The performance of inversion system strongly relies on the databases that had been used in the implementation of the specific system. It is also widely recognized that features play the most important role in the interpretation of ECT signals. In the present work, a database was constructed using synthetic ECT generated by the finite element models and principal component analysis (PCA) was adopted in order to optimize the feature set of eddy current signals. The hybrid neural networks of a probabilistic neural network (PNN) classifier and back propagation neural network (BPNN) size estimators were trained using the synthetic signals. Estimation of the flaw parameters was carried out by feeding synthetic signals into the neural networks. The features with PCA improved the performances of signal interpretations. The excellent performance obtained in the present work demonstrates the high potential of the developed inversion tools as a practical interpretation of eddy current signals.

Introduction: Steam generator (SG) tubes are pressure boundaries that separate the secondary unit from the primary one in nuclear power plants (NPPs), so that they play a critical role in safe operation of NPPs. Therefore, the assessment of their structural integrity is very important in both economic and safety aspects. Since defects deteriorate the structural integrity of steam generator tubes, it is very important for nondestructive evaluation techniques that are responsible for detection and estimation of defects to hold capability and reliability. Eddy current testing (ECT) has been widely used in in-service inspection as well as pre-service inspection of the SG tubes in NPP of pressurized water reactor type. Currently, this task is conducted by certified inspectors who interpret the ECT signals while EC probes are scanning inside the SG tubes. The interpretation of ECT signals, however, is truly a difficult task even for well-trained inspectors and accuracy of signal interpretation largely depends on their experiences and knowledge. In order to overcome this problem, extensive work has been carried out for the enhancement of detection and characterization of defects by automated systems, expert system [1], pattern recognition approaches [2] or neural networks [3,4].

Among them, neural network based inversion tools have been paid great attention, since neural networks are ideally suited to the interpretation of ECT signals. The performance of any inversion system, in fact, strongly relies on the databases that had been used in the implementation of the specific system. Experimental databases are ideal, but would be very expensive and time-consuming. To address such a problem, we have previously proposed an intelligent, systematic inversion approach by the novel combination of neural networks and finite element (FE) ECT models [4]. In the previous work, we had addressed following key issues that are critical for the successful application of neural networks: construction of abundant databases of ECT signals, selection of sensitive features and optimization of neural network parameters. Quantitative characterization of flaws was carried out for the experimental ECT signals that were captured from SG tubes by bobbin probe in order to verify the inversion tools proposed in the previous work.

It is widely recognized that features extracted from ECT signals play the most important role in the interpretation of ECT signals using pattern recognition approaches or neural networks. Until now, various features have been proposed in many previous studies. Examples of such features include Fourier descriptors [5], amplitudes [6,7], phase angles [6], partial powers [7], statistical moments [8] and wavelet transform [9]. Once a certain set of features are extracted, a reduced set of features which contains the larger amount of information for the interpretation of ECT signals is selected by use of quantitative feature selection criteria [4]. The extraction of really good features, however, is not an easy task. Principal component Analysis (PCA) is a useful statistical signal processing technique to reduce the dimensionality of datasets for compression, pattern recognition and data interpretation [10]. Using PCA, an optimal set of orthogonal principal components (PCs) that are the linear combination of features can be extracted, so that the best representation of the system can be obtained a few number of PCs. Thus PCA can be applied to the multivariate system such as ECT signals [11].

In the present work, the PCA was applied to the extracting relevant features from the EC signals. For this purpose, a database of synthetic ECT signals was constructed by using two-dimensional FE modeling. 23 features were defined in order to describe ECT signals. Two sets of features were used in the present work: conventional features and the principal components (PCs). The hybrid neural networks of a probabilistic neural network (PNN) classifier and three back propagation neural network (BPNN) size estimator were trained using the synthetic signals in the database. Estimation of the flaw parameters was carried out by feeding synthetic signals into the neural networks. The performances of the neural networks with PCs were compared to those with conventional features.

Results:[Principal Component Analysis] PCA is a statistical tool, which is useful to extract dominant features, principal components (PCs), from a set of multivariate data. They explain the maximum amount of variance possible by linear transforms by projecting the data into orthogonal sub-spaces. In our case, the multivariate can be the features obtained by the previous work. PCA will enable us to reduce the number of the data dimensions and the extracted features should contain the most relevant information, which in turn can be used to classify or to estimate flaw parameters.

The approach requires training where many data set from various flaw signals are required as inputs. To obtain eigensignals, each data set from an observation is formed into a column vector, X_n, whose length N is depending on the number of variables used. For M observations, we will have an array matrix $\mathbf{X}$ the size of $M \times N$. Therefore, we have

$$\mathbf{X} = [X_1, X_2, X_3, \ldots, X_M] \tag{1}$$

The average signal Ψ is defined by:

$$\Psi = \frac{1}{M}\sum_{n=1}^{M} X_n \tag{2}$$

Difference signals are computed by subtracting the average signal from each training signal:

$$\Phi_i = X_i - \Psi \tag{3}$$

These vectors are now subjected to PCA. To find the orthogonal eigenvectors, the covariance matrix $\mathbf{C}$ should be worked out.

$$\mathbf{C} = \frac{1}{M}\sum_{n=1}^{M} \Phi_n \cdot \Phi_n^{\mathbf{T}} = \frac{1}{M}\mathbf{A} \cdot \mathbf{A}^{\mathbf{T}} \tag{4}$$

where $\mathbf{A} = [\Phi_1, \Phi_2, \ldots, \Phi_M]$.

However, the determination of the eigenvectors for covariance matrix $\mathbf{C}$ will have the size of $N \times N$. A better way is considered. v_i are the eigenvectors of $\mathbf{A}^{\mathbf{T}} \times \mathbf{A}$ are the eigenvalues,

$$\mathbf{A}^{\mathbf{T}}\mathbf{A} v_i = \mu_i v_i \tag{5}$$

then the eigenvectors of C can be computer by

$$u_i = \mathbf{A} v_i \tag{6}$$

where $\mathbf{C} = \mathbf{A} \times \mathbf{A}^{\mathbf{T}}$.

These u_i are referred as eigensignals. Having obtained the eigensignals, the most significant M eigensignals are chosen according to the largest corresponding eigenvalues. An signal can be identified as a linear combination of the eigensignals. The PCs for any signal X are defined by:

$$w_k = u_k^T (X - \Psi) \tag{7}$$

The value w_k represents the data mapped into the axis corresponding to the eigenvector. These values are the new features that can be used for classification and sizing, and they might correlate with the flaw parameters.

[ECT Signal Analysis] Using 2D electromagnetic finite element method, we have constructed a database having 600 synthetic flaw signals simulated from two types of symmetric flaws with the variation in the flaw width, flaw depth and tip width. Two flaw types include 'Inner' (ID) and 'Outer' (OD) flaws according to the location of the flaw. 528 signals were used for training of neural networks, and 72 signals were used for the performance evaluation of neural networks.

Even though it is widely recognized that features play the most important role in the interpretation of ECT signals, the extraction of really good features, however, is not an easy task. A feature extraction software was specially developed for the effective searching of sensitive features. In the present work, 23 features (listed in Table 1) that describe major characteristics of the ECT signal were defined by use of the developed software. Fig. 1 schematically presents the definitions of the extracted features.

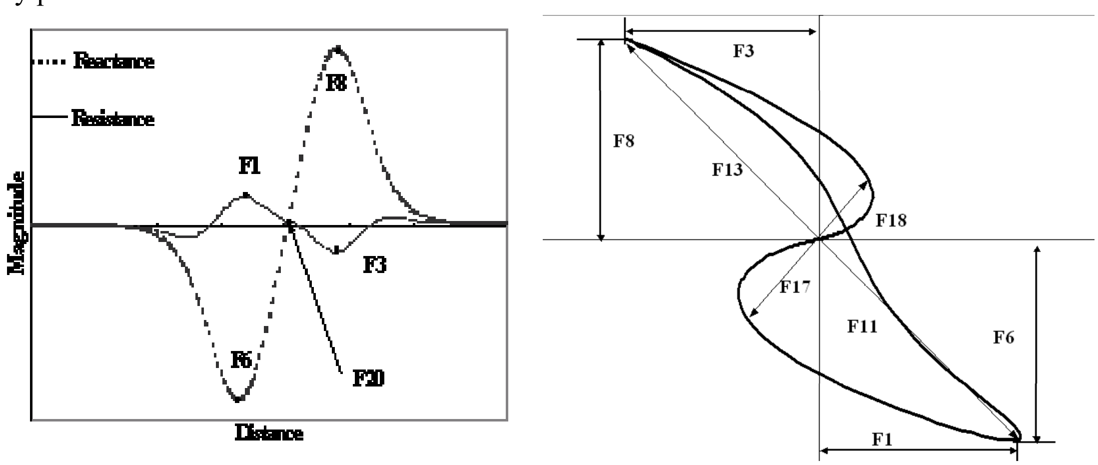


Figure 1 Definition of the features for non-symmetric ECT signals

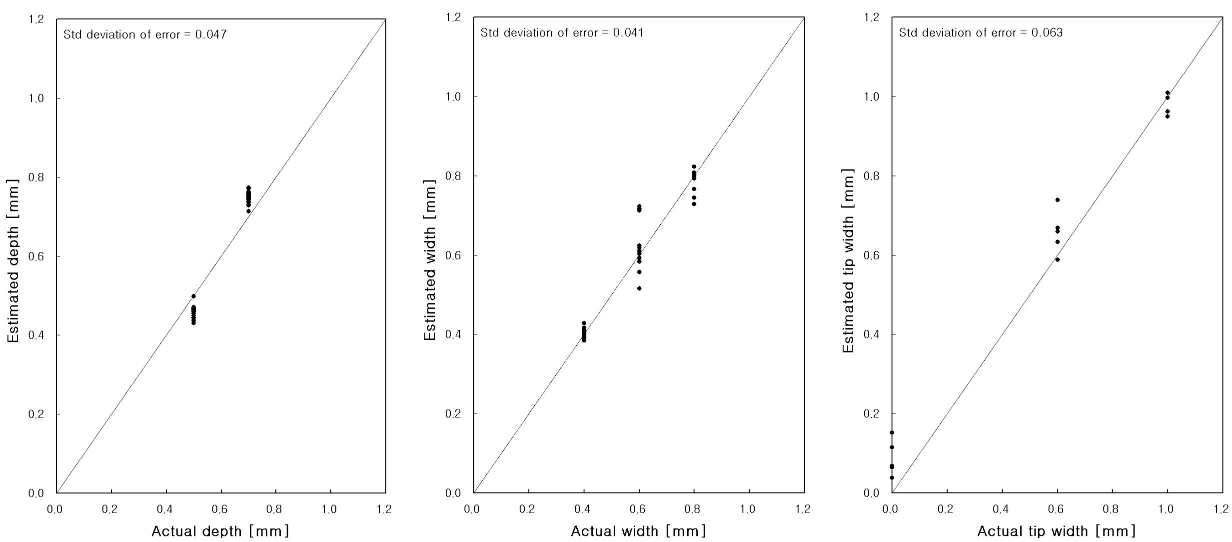
Table 1 The features extracted from non-symmetric ECT flaw signals

F1. First peak Resistance	**F2**. First Peak Resistance Angle
F3. Second Peak Resistance	**F4**. Second Peak Resistance Angle
F5. |First Peak Resistance - Second Peak Resistance|	
F6. First Peak Reactance	**F7**. First Peak Reactance Angle
F8. Second Peak Reactance	**F9**. First Peak Reactance Angle
F10. |First Peak Reactance - Second Peak Reactance|	
F11. First Peak Impedance	**F12**. First Peak Impedance Angle
F13. Second Peak Impedance	**F14**. Second Peak Impedance Angle
F15. Starting Angle	**F16**. Ending Angle
F17. First Middle Impedance	**F18**. Second Middle Impedance
F19. |First Middle-Second Middle|	**F20**. Junction Point magnitude

F21. Junction Point Angle	**F22**. Interception Vector Magnitude
F23. Interception Vector Phase Angle	

[Conventional Features] To reduce the possible redundancy that might exist in the set of extracted features, the feature selections for classification and for sizing were performed separately. For flaw classification, two selection criteria were adopted: the single feature classification performance, which can be defined as the overall correct accept rate to be obtained by use of a specific feature only; and the linear correlation coefficients of the specific feature to other features. The former measures the separability of individual features and the latter quantifies the redundancy of a specific feature in the feature set. For flaw sizing, the sensitivity of individual features to the flaw size parameters (flaw depth, flaw width and tip width) and the linear correlation coefficients were used as the selection criteria.

The hybrid neural networks of a probabilistic neural network (PNN) classifier and three back propagation neural network (BPNN) size estimator were trained using synthetic ECT signals, and the performance evaluation was carried out by feeding ECT signals into the trained neural networks. PNN showed 100% correct classification rate, since the discrimination between OD and ID flaws is a relatively easy task. Figure 2 summarizes the BPNN performances for the estimation of the flaw depth, width and tip width. BPNN showed performance for estimating the flaw depth, width and tip width with average errors of 0.047, 0.041 0.063 mm, respectively.



(a) (b) (c)

Figure 2 The correlations between actual and estimated flaw parameter using conventional features. (a) depth, (b) width and (c) tip width.

[Feature Definition by Using PCA] PCA was carried out for 7 features (F3, F5, F10, F16, F20, F22, F23) selected by considering the linear correlation coefficients. 7 PCs determined from the eigenvalues and eigenvectors of the variance · covariance matrix. PCs for the classification, sizing of ID flaws and sizing of OD flaws were separately defined. The eigenvalues of PCs and their percentage proportions of corresponding variation for classification are listed in Table 2. PCs from PC1 to PC5 represent over than 96% of data variation, and they can be used for the classification of flaw location. PNN with PCs showed 100% correct classification rate as same as with conventional features.

The size estimation of flaws was separately carried out for the ID and OD flaw since the classification of flaw were performed by PCA. The eigenvalues of PCs and their percentage proportions of corresponding variation for sizing of ID flaw, and those for sizing of OD flaw are listed in Table 3 and 4, respectively. PCs from PC1 to PC5 represent over than 96% of data variation for both ID and OD flaws, and they can be used size estimation of flaws.

Table 2 The eigenvalues of PCs and their percentage proportion of corresponding variation for classification

Principal components	Eigen value	Percentage proportion
PC1	0.1501	47.3
PC2	0.0675	21.3
PC3	0.0489	15.4
PC4	0.0272	8.6
PC5	0.0135	4.3
PC6	0.0063	2.0
PC7	0.0036	1.1

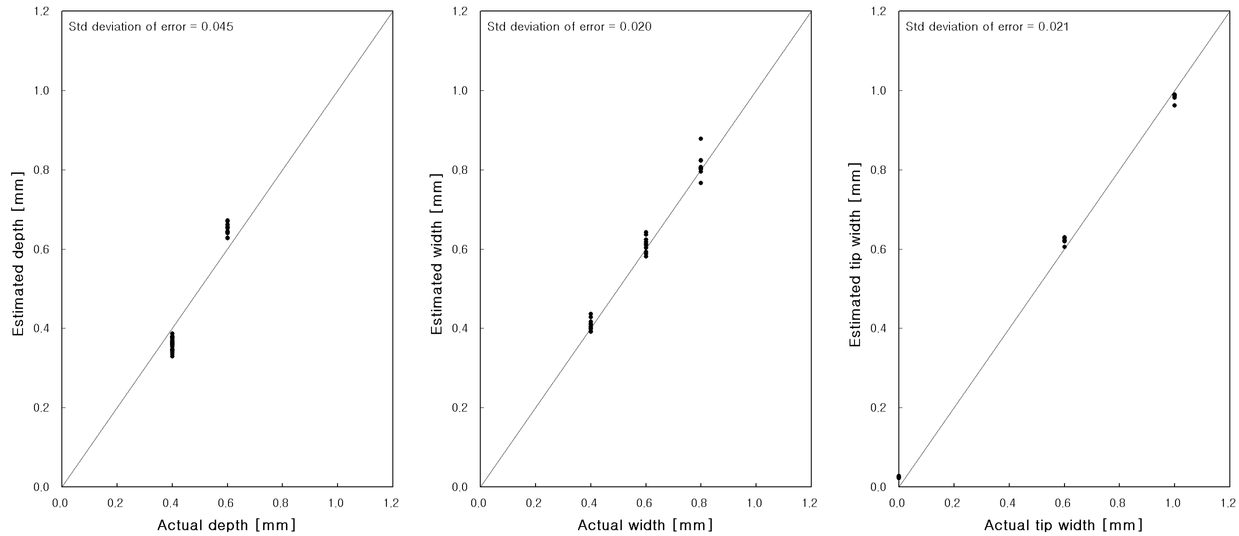
Table 3 The eigenvalues of PCs and their percentage proportion of corresponding variation for sizing of ID flaw

Principal components	Eigen value	Percentage proportion
PC1	0.1373	41.0
PC2	0.0911	27.2
PC3	0.0558	16.7
PC4	0.0224	6.7
PC5	0.0156	4.7
PC6	0.0079	2.4
PC7	0.0050	1.5

Table 4 The eigenvalues of PCs and their percentage proportion of corresponding variation for sizing of OD flaw

Principal components	Eigen value	Percentage proportion
PC1	0.0986	43.9
PC2	0.0583	26.0
PC3	0.0312	13.9
PC4	0.0187	8.3
PC5	0.0090	4.0
PC6	0.0063	2.8
PC7	0.0024	1.1

Figure 3 summarizes the performance of BPNN with PCA features for the estimation of the flaw depth, width and tip width. BPNN showed performance for estimating the flaw depth, width and tip width with average errors of 0.045, 0.020 and 0.021 mm, respectively. The results show that the use of PC features greatly increase the performance of BPNN for the estimation of flaw parameters, especially tip width.



(a) (b) (c)

Figure 3 The correlations between actual and estimated flaw parameter using principal components. (a) depth, (b) width and (c) tip width.

Conclusion: In the present work, the features defined by principal component analysis were introduced for the quantitative interpretation of ECT signals. A database was constructed using synthetic ECT generated by the finite element models and principal component analysis (PCA) was adopted in order to optimize the feature set of eddy current signals. The hybrid neural networks of a probabilistic neural network (PNN) classifier and back propagation neural network (BPNN) size estimators were trained using the synthetic signals. Estimation of the flaw parameters was carried out by feeding synthetic signals into the neural networks. The features with PCA improved the performances of signal interpretations. The excellent performance obtained in the present work demonstrates the high potential of the developed inversion tools as a practical interpretation of experimental eddy current signals.

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