Fuzzy logic algorithms for classification and parameterization of eddy-current signals

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Abstract. Safety of nuclear power plants operation depends on steam generator safe operation. Russian nuclear power plants with water-water energetic reactors WWER-440 and WWER-1000 use horizontal type steam generators which are cylindrical objects of 3 m diameter and 12 - 15 m length. Steam goes through steam generator tube sheets in the bottom from hot end and passes its energy through heat-exchanger tube system and become colder on the other tube sheet. Reactors WWER-440 have more than 5,000 tubes in one steam generator and reactors WWER-1000 have already 11,000 tubes in one steam generator. Each block of WWER-440 reactor has 6 steam generators, and each block of WWER-1000 reactor has 4 steam generators. A thin-walled steam generator tube can be a threat of nuclear fallout in case of high pressure in primary coolant loop. To be an effective barrier these tubes should be free from corrosion, thinning and cracks.

1. Introduction

Multi-frequency ECT of steam generator tube using inner differential eddy-current probe provides the ability to apply tube’s control on all length and allows to detect the defects, to localize them and to estimate their depth. Multi-frequency method of ECT of steam generator tubes have been used at Russian nuclear power plants for more than 25 years. The problems of ECT results reliability due to subjective expert decisions are still remaining. At the moment in Russia calibration curves are used for classification defects as external, internal and through defects and for parameterization of defects’ signals (defect depth determination). These calibration curves are used for each differential channel (for each testing frequency) [1, 2].

Calibration curve is the dependence of signal phase from the defect’s depth. These curves can be drawn using signal phase data of calibration tube. Calibration tubes contain defects imitations with known geometrical parameters. Usually such tubes contain external defects (from 2 to 5), one through defect and internal defects (1 or 2).

An average length of heat-exchanger tube is 14 m. In ECT the probe passes through inner side of heat-exchanger tube. As a result there is a huge data array – if we can provide testing of all tubes of one steam generator at once, the probe passes 154 km. In Russia, operators examine these data and look for defects’ signals. The conclusions are made using data from calibration curves.

Imperfection of calibration curve is insufficient input data approximation especially in case of few data used for curve drawing. In these cases error of defect’s depth parameterization arises. Also each channel has its own calibration curve so results of defects’ depth determination using different channels become significantly different and operator should determine the final result.
Thus defect’s depth determining doesn’t consider previous testing experience and other parameters influence to signal phase [3]. This paper describes another method and algorithms based on fuzzy set theory and fuzzy logic for defects parameters estimation.

2. Features generation

The system based on fuzzy logic was created for classification and parameterization of defects in eddy-current signals analysis. Input data for this system are most significant features for ECT signal for defect parameter estimation [4].

Features generation was created for three frequencies – 60, 130 and 280 kHz. ECT differential channel signal phases were used as major features.

Signal phase shown in figure 1 is defined as angle between positive axis in complex plane and vector drawn from origin to point with maximum signal value (1):

$$
\text{Phase} = \arctg \left( \frac{\text{Im}(U_{\text{max}})}{\text{Re}(U_{\text{max}})} \right)
$$

(1)

![Figure 1. Sample defect signal on complex coordinate system.](image)

Complex signals used for features calculation were received with multi-frequency ECT of steam generator tubes using inner differential eddy-current probe as well as ECT tubes control simulation using finite-elements method. Signals from tubes inspection and simulations were introduced in large database. The defect database structure is shown in table 1.

|               | External | Through | Internal | Total  |
|---------------|----------|---------|----------|--------|
| Model signals | 585      | 24      | 574      | 1183   |
| Experimental  | 143      | 49      | 2        | 194    |
| signals       |          |         |          |        |
| Total         | 728      | 73      | 576      | 1377   |
3. Defects classification
Defects classification was made for splitting them into three classes: external, through and internal. The classification is based on Mamdani algorithm of fuzzy inference system.

Input data for this system are signal phases from defects at three differential channels. Output data refer to defect class: external, through or internal.

The structure of fuzzy inference system has three inputs, and one output and is shown in figure 2.

![Figure 2: Structure of fuzzy inference system.](image)

Error of classification for external defects is less than 2%. It is due to external defects with depth of more than 80% from heat-exchanger tube thickness can be classified as through. Error of classification for internal defects is less than 3.8%. Internal defects with depth of more than 80% from heat-exchanger tube thickness can be classified as through.

4. Parameterization of defects signals
The Mamdani’s algorithm was applied for creating of parameterization system with various input features and member functions. This algorithm showed quite high error rate due to complex dependence between input and output data. The Sugeno’s algorithm implementation also failed to achieve preferable error rates because of weights calculation problem which values is not obvious for given input data. The system was created using hybrid technology of adaptive-network-based fuzzy inference system – ANFIS. It has simple algorithm and high training speed compared to other methods.

At the first step of parameterization, the system was built for external and through defects. All input data samples were split into three sets: training, validation and test (shown in table 2).

|          | External | Through | Total |
|----------|----------|---------|-------|
| Training set | 101      | 40      | 141   |
| Validation set | 51       | 33      | 84    |
| Test set    | 571      | 5       | 576   |

Training and validation sets were used for hybrid network parameters tuning. The test set is used for checking configured network efficiency.

Member function of gauss type was selected as function dependent of \( c \) and \( \sigma \) parameters. It is shown in figure 3:

\[
f(x, \sigma, c) = \exp \left( -\frac{(x - c)^2}{2 \sigma^2} \right).
\]  (2)
Parameters of member functions for all input and output variables were determined automatically during the generation of fuzzy inference system.

Generation of fuzzy inference system was made in Matlab computer program using genfis2 function based at subtractive clustering, radii parameter was set to 0.15. This parameter defines cluster centers area of influence. Experiments were made to choose the value of radii parameter which leads the preferable error rate of clusterization. Differential channels signal phases at three frequencies – 60, 130 and 280 kHz – are input data for our system. Output value is defect depth which was evaluated in percentage from heat-exchanger tube thickness.

All defects can be split at three classes: not dangerous, dangerous and critical. Not dangerous defects are defects with depth from 0 to 33% from heat-exchanger tube thickness. Dangerous defects have depth 33–67%. Critical defects are all defects with depth more than 67%. Using this classification each input variable should be described with three term-set. And the structure of generated system confirms this guess (2).

Term sets for three input linguistic variables are shown at Figure 4.
Figure 5. System operation results at validation set.

Table 3 summarizes the results of parameterization system operation at training, validation and test sets.

| Parameterization error for external defects |
|---------------------------------------------|
| Training set | Validation set | Test set |
| 4.9% from tube thickness | 4.9% from tube thickness | 4.95% from tube thickness |

The maximum parameterization error for external and through defects reaches 24% from heat-exchanger tube thickness, it was 0.36 mm for 1.5 mm thickness of heat-exchanger tube. Such error is achieved for defects with depth less than 40% from heat-exchanger tube thickness. Average parameterization error is about 5%.

The fuzzy inference system was built also for internal defects. Structure of fuzzy inference system for parameterization of internal defects is the same as the fuzzy inference system for parameterization of external and through defects.

Table 4 contains the results of parameterization system operation in training, validation and test sets for internal defects.

| Parameterization error for internal defects |
|---------------------------------------------|
| Training set | Validation set | Test set |
| 4.3% from tube thickness | 5% from tube thickness | 4.6% from tube thickness |
5. Conclusion

The maximum parameterization error for internal defects reaches 19 % from heat-exchanger tube thickness, average parameterization error is about 4 %. Experimental verification of the system efficiency was conducted using the data received during the tests in Kola Nuclear Power plant and in the laboratory of the Department of Diagnostic Information Technologies MPEI. To obtain data, the TesTex installation was used. Testing tube samples with realistic defects of each type have with following depth values: 20 %, 40 %, 75 %, and 100 % from heat-exchanger tube thickness.

Errors of defect depth estimation are shown in figure 6. Black line (upper line) shows error values for calibration curve defect depth estimation. The red line (lower line) shows error values for fuzzy logic system defect depth estimation. The figure shows fuzzy logic algorithms decreased depth estimation more than two times.

![Figure 6. Errors in determining the depth of defects.](image)

References

[1] Lunin V P, Zhdanov A G, Chegodaev V V and Stolyarov A A 2015 Thermal Engineering 62 (5) 341-346

[2] Shorikov D , Stikhina N , Mel'nikova A and Maksimenko A 2019 SibTest – 2019 Sbornik tezisov dokladov V Mezhdunarodnoy konferentsii po innovatsiyam v nerazrushayushchem kontrole [A book of abstracts of V International Conference on Innovations in non-destructive testing] (June 2019) p 71

[3] Zhdanov A G, Shchukis E G, Lunin V P and Stolyarov A A 2018 Russian Journal of Nondestructive Testing 54 (4) 283–293

[4] Ewald H and Stieper M 2007 Ultrasonic and Advanced Methods for Nondestructive Testing and Material Characterization 1 493-516