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Use of automated feature selection algorithms to calibrate a coating thickness measurement signal in eddy current testing for the inspection of Accident Tolerant Fuel

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1. Introduction

The application of chromium coating on nuclear fuel rods has shown important improvements in the safety and lifetime due to an increased corrosion resistance and reduced oxidation rate [1]. To achieve uniform coating thickness a non-destructive evaluation of the coating is required.

Changes in the thickness of a thin electrically conductive layer on a base material with higher electrical resistance correlate with the voltage measurement signal of an eddy current test probe, which is positioned on the layer. This dependency allows the layer thickness to be determined using this non-destructive testing method. [2] The calibration of the voltage measurement signal for the coating thickness inspection depends on the test frequency and the eddy current sensors used. With the test method used at Fraunhofer IKTS, the test probe is excited with many different test frequencies. Overall, a high-dimensional feature space is therefore available when analyzing the measurement signal, which must be tested for its suitability for determining the coating thickness. The aim of this study is to determine the probe design and the test frequency or frequencies whose eddy current data have a significant measuring effect and best represent the coating thickness.

2. Methods and Results

Automated feature extraction is used to determine how large the optimum feature space is, and which features provide the best calibration results. Further, a predictive model is developed for calibration, while also identifying the probe with the best performance in the process.

2.1 Sensors

The sensors used are presented in Fig. 1. The concentric absolute surface probes have been printed as flexible PCBs with the transmitting and receiving coil wound around each other.

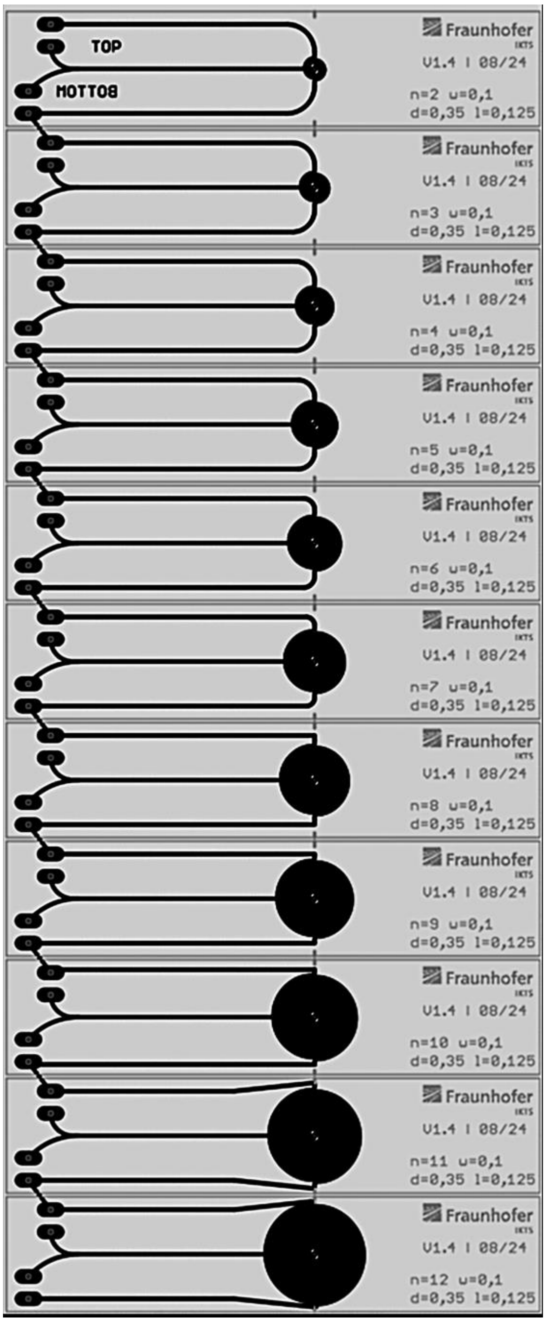

Fig. 1. Layout of circular coils printed as flexible PCBs.

The coil turns n have been varied from 2 to 12. The coil turn is an important parameter that influences the resonant frequency of the coil, but also the eddy current density in the test piece [3]. Since a small number of turns generally increases the resonant frequency and spatial resolution of the probe, but an increase in the number of turns leads to a higher eddy current density in the test object and therefore higher accuracy, this is a trade-off that needs to be investigated.

Fig. 2. Flexible PCB coil mounted on concave probe housing

The conductor track width w = 0,1 mm, the coil separation l = 0,125 mm and the coil spacing d = 0,35 mm have been kept the same for all coils. The eleven flexible PCB coils are mounted on identical probe housings, which are shaped concavely to fit the outer shape of the fuel rod samples as can be seen in Fig. 2.

2.2 Experimental setup

The samples – 15 fuel rods with different chrome thicknesses – have been fixed in the same experimental setup as depicted in Fig. 3 and measured with the eleven different probes.

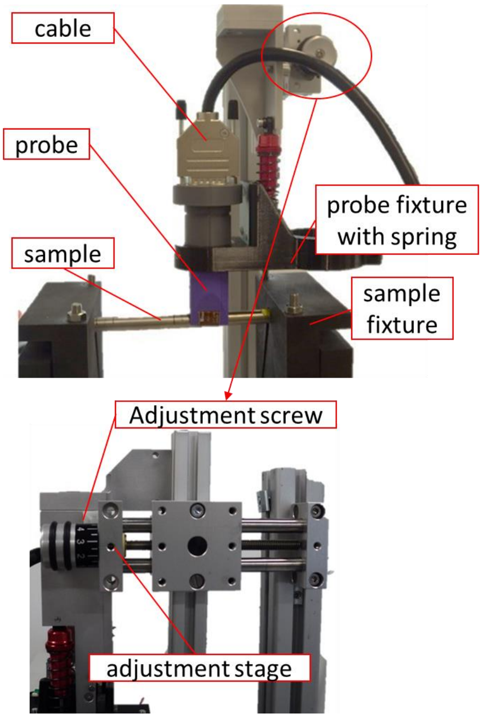

Fig. 3. Experimental setup

2.3 Reference values

To generate reference values for the chrome coating thicknesses (a total of 15 nuclear fuel rod samples), all samples were measured destructively at two positions with calo test as shown in Fig. 4. The calo test measurement result values are recorded in Table I as the average value of three measurements taken at one location.

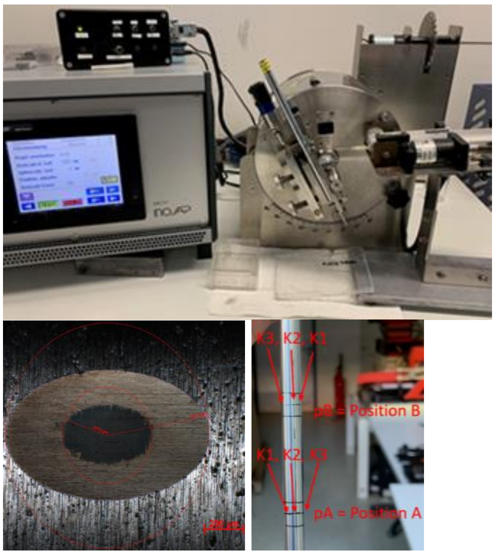

Fig. 4. Calo test measurement

Table I: Reference values generated by calo test

Sample No	Thickness of chrome coating in µm	
	Position A	Position B
1	3.4 ± 0.3	3.5 ± 0.5
2	4.4 ± 0.5	4.2 ± 0.4
3	4.3 ± 0.7	4.5 ± 0.4
4	10.9 ± 0.7	11 ± 0.7
5	11.2 ± 0.7	11.3 ± 0.7
6	11.2 ± 0.7	10.9 ± 0.6
7	11.9 ± 0.8	11.7 ± 0.7
8	12.3 ± 0.7	12.3 ± 0.7
9	11.9 ± 0.7	12 ± 0.7
10	14.3 ± 0.8	14.3 ± 0.8
11	14.2 ± 0.8	14.1 ± 0.8
12	15 ± 0.8	14.1 ± 0.8
13	17.1 ± 0.9	17.1 ± 0.9
14	16.7 ± 0.8	16.8 ± 0.9
15	17.2 ± 0.9	17.4 ± 0.9

B-position data was primarily used for machine learning training and predictive model development, while A-position data was used to evaluate the reliability and stability of the predictive model when applied to new data.

2.4 Feature space and feature reduction

The test method used at Fraunhofer IKTS consists in exciting the test probe with 300 frequencies in the range from 0.5 to 100 MHz. For each frequency a complex voltage is measured with the receiver coil. This results in a high dimensional feature space. For every chrome thickness there are a total of 1200 corresponding measured values - a real part, an imaginary part, a magnitude and a phase of the complex signal for 300 frequencies. The measurement is repeated 400 times at both positions on the sample.

2.5 Prediction model decision

This section describes the process of identifying a linear regression model that delivers the best predictive performance using all 1200 features.

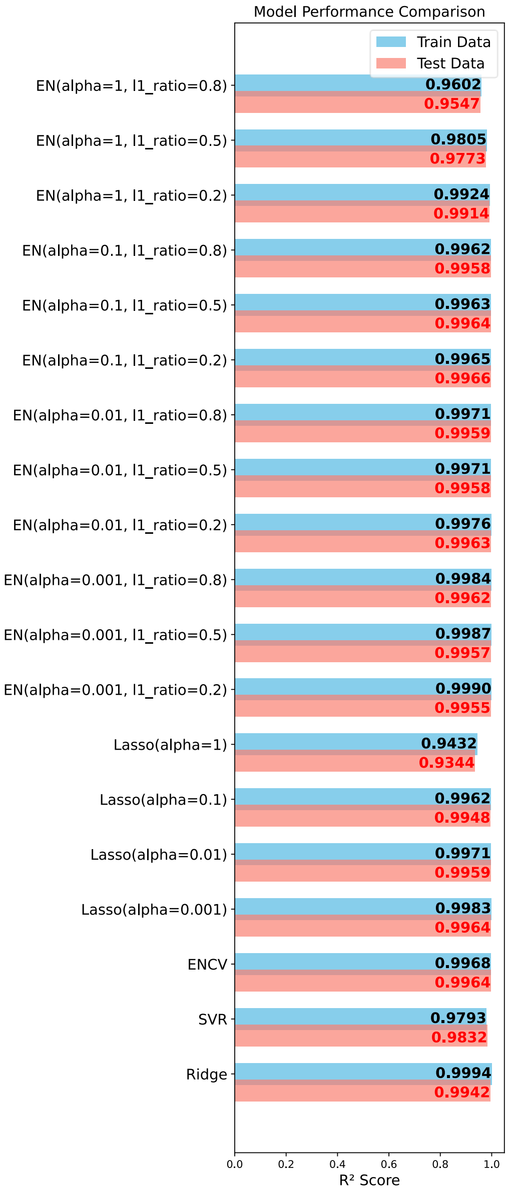

Fig. 5. Model performance comparison

In total four different linear regression models are compared: ElasticNet (EN), Lasso, Support Vector Regressor (SVR), Ridge. For the models ElasticNet and Lasso the hyperparameters for regularization strength have been varied. When comparing the performance of the models on unknown test data (A-Position data), ElasticNet Model with α=0.1 and l1-ratio=0.2 shows the best r^2 value of 0.9966. Therefore, this model is selected for further feature combination analysis and probe evaluation.

2.6 Feature Selection

Some of the features exhibit a linear correlation with the chrome thickness, allowing for thickness prediction through multiple linear regression, while others are not suitable at all and need to be eliminated. The feature space is therefore reduced to 10 features with the highest Pearson's correlation coefficient and therefore the strongest linear correlation to the chrome thickness reference values. To mitigate the risk of eliminating important features due to L1 regularization, this method prioritizes highly linear features before applying model-based selection in the next step.

2.7 Probe evalution

All possible combinations of the 10 selected features are evaluated using ElasticNet Model with α=0.1 and l1-ratio=0.2 to determine the optimal number and combination of features for the best performance. Fig. 6 shows the r^2 values for each predictive model generated with the best combination of 1 to 10 different features from the 10 preselected features while simultaneously comparing the prediction of the different probes used on A-Position data.

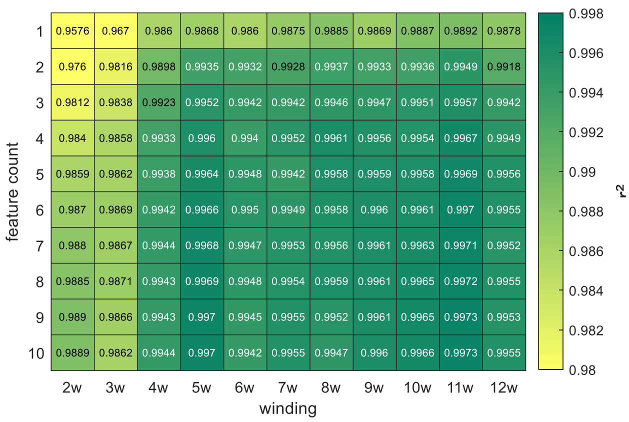

Fig. 6. Probe and feature space evaluation by r^2 metric

Below Fig. 7. exhibits the difference in the range of residuals using the different prediction models generated with different probes and feature spaces on A-Position data.

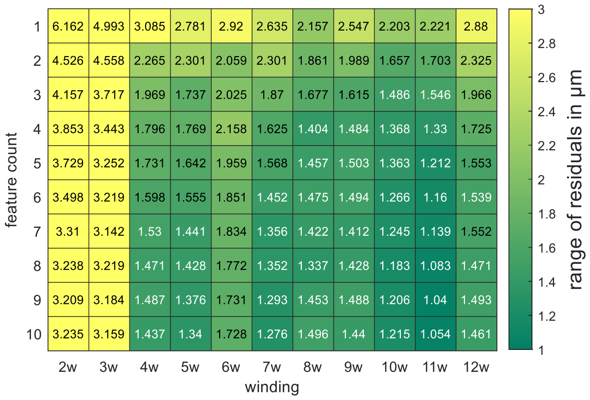

Fig. 7. Probe and feature space evaluation by range of residuals in µm

Both results show that the probe with eleven coil turns has the best r^2 value with 0.9973 and the lowest range of residuals, with only 1.04 µm (approx. ±0.52 µm deviation from the reference value). With this probe the best results are achieved by combining 9 out of 10 pre-selected features. Using only one feature with the highest linear correlation, as would be the case with a conventional approach, results in a range of residuals that is more than twice as high. Nevertheless, the improvement from 7 to 9 used features seems to be small and even declining for some of the probes.
Also, it can be concluded that the probes with only two or three coil turns have the worst results and are not suitable for chrome thickness measurements of chrome layers between 3 and 18 µm.

3. Conclusions

This paper analyzed the possibilities for improving data-based prediction quality by optimizing the feature space obtained by different eddy current probes.

Four different linear regression models have been compared for one probe using the complete feature space available. The model with the best performance on unknown test data has been selected for further analysis of optimal feature space and optimal probe configuration.

Finally, it could be concluded that the combination of 9 out of 10 preselected features delivered the best results with a probe configuration of 11 coil turns. Using an optimal feature space to perform linear regression results in a performance improvement of a factor of two compared to using only one feature, as would be the case with a conventional approach.

Acknowledgments

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