
Localization of Axial and Radial Displacement in Air-core Transformer Using Frequency Response Analysis

Capstone Report
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Abstract:

The axial and radial displacement of transformer windings can lead to significant defects, accounting for a large proportion of transformer failures. These defects not only result in power outages but also pose serious safety risks. This paper presents a novel methodology for the localization of axial and radial displacement in air-core transformers. Utilizing Frequency Response Analysis (FRA) coupled with deterministic algorithms. The proposed approach involves analytical modelling of the transformer, data collection through software simulation, and measurements. By creating a comprehensive lookup table for potential winding displacements, this method leverages software simulations in Python and SPICE to accurately predict and identify the location winding deformations. The deterministic algorithm is implemented as a key factor in the reliable prediction of such displacements.

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Contents

Preface	vi
1 Introduction	1
2 Background	3
3 Methodology	5
3.1 Modelling	6
3.2 Data Generation	8
3.3 Measurement	9
3.4 Prediction	10
4 Results and Discussions	14
4.1 Results	14
4.2 Discussions	15
5 Conclusion	16
Bibliography	17

Preface

This project aims to develop an efficient method for condition monitoring of transformers using Sweep Frequency Response Analysis (SFRA) and Artificial Neural Network (ANN). The primary objective of the project is to design and train an ANN model that can accurately predict the condition of a transformer based on SFRA data.

Transformers are critical components in power systems, and their failure can result in severe economic and safety consequences. SFRA is a widely used technique for diagnosing transformer faults and assessing their overall condition. However, the analysis of SFRA data is often time-consuming and requires expert knowledge.

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Chapter 1

Introduction

Transformers are crucial parts of the electrical power transmission system. The failure of one of such devices might lead to inevitable power and economic losses among not only producers but also consumers [1]. The vital infrastructures might suffer a power shortage due to the transformer failure, which can result in inconvenience to the citizens, or, even, impede a hazard to their lives. The health of transformers is an essential aspect of the stability and efficiency of electrical systems. The crucial aspect of the transformer's health is the condition of transformer windings. With an estimated 84 % of transformer defects rooting from winding damage, the focus on monitoring the winding conditions becomes important and essential [2]. The windings in transformers are susceptible to various stresses, including electrical, thermal, and mechanical forces. Over time, these stresses can lead to insulation breakdown, short circuits, and physical deformation of the windings [3]. Such damage compromises the transformer's ability to perform efficiently, potentially leading to catastrophic failures. The impact of winding defects is far-reaching, encompassing not only the immediate risks of power outages and equipment damage but also the broader implications for system reliability and safety. Monitoring transformer windings is, therefore, a critical aspect of preventative maintenance. By regularly assessing the condition of the windings, potential issues can be identified and addressed before they escalate into major failures. This approach shows great potential to minimise unplanned downtime, reduce maintenance costs, and extend the operational lifespan of transformers. As of today, frequency response [3], [4], [5], dissolved gas [6], partial discharge [7], thermographic inspection [8], vibration [9], etc. analysis techniques are available at engineers' disposal. However, FRA is widely considered to be the most sensitive and fastest assessment type among all, therefore this research implies this technique[10]. Moreover, several types of research showed a potential predictive model using machine learning(ML) and deep learning algorithms which show great advancement in predicting the damage to the device [10], [11], [12], [13]. Despite the

effectiveness of FRA and ML models, it is considered to be a challenging task to create a unified methodology for faults in any type of transformer. Most transformers are unique in their structure and operational range [14], [15]; moreover, there are a limited number of devices that researchers can utilize in their prediction models, because of the high cost of such kinds of devices. The range and variety of the prediction data and limited resources available for data acquisition and generation induce a formidable task to create a universal ML model.

Chapter 2

Background

The research on the condition monitoring of transformers using Sweep Frequency Response Analysis (SFRA) and Artificial Neural Networks (ANN) requires a set of skills and background knowledge that are essential for the successful implementation of the research. With my experience in this field, I possess the necessary skills and knowledge to undertake this research and make meaningful contributions to the field of transformer condition monitoring.

Firstly, I have a solid foundation in electrical and electronic engineering. I have taken courses on power systems, electromechanical systems, and control systems, which have equipped me with a good understanding of transformer operation, characteristics, and performance. This background knowledge has helped me understand the importance of monitoring the conditions of transformers to ensure their reliability and longevity. I have also studied digital signal processing, which has given me an understanding of how to process and analyze the SFRA data.

Secondly, I have experience in machine learning, specifically in the design and implementation of Artificial Neural Networks. In my research assistant position, I have developed machine learning models for SFRA data analysis using Tensorflow, which is a powerful machine learning framework. I have applied basic regression and classification ANN models to analyze the conditions of transformers, which has given me a strong foundation for more advanced ANN models. I am confident in my ability to design and implement ANN models for more complex data analysis tasks.

Thirdly, I have practical experience in transformer testing and maintenance. During my internship at a power generation company, I assisted in transformer testing and maintenance, which included SFRA measurements. This experience has given me hands-on knowledge of the practical challenges in transformer condition monitoring and has helped me understand the limitations of current techniques.

Additionally, I have programming skills that are essential for the data analysis

and modeling aspects of the research. I am proficient in Python, which is a popular programming language for data analysis and machine learning. I have experience in using Python libraries such as Pandas and Numpy for data manipulation and analysis. I have also used Python for developing Telegram Bots, which has given me experience in using APIs for data storage and retrieval.

Moreover, I possess excellent analytical skills, which are essential for data analysis and modeling tasks. I have experience in using statistical methods for data analysis and have a good understanding of signal processing techniques. These skills are important for understanding the SFRA data and for designing effective ANN models.

In conclusion, my skills and background knowledge make me a suitable candidate for undertaking research on transformer condition monitoring using SFRA and ANN. With my solid foundation in electrical and electronic engineering, experience in machine learning, practical experience in transformer testing and maintenance, programming skills, and excellent analytical skills, I am well equipped to make meaningful contributions to this field. I am excited to undertake this research and to contribute to the development of more reliable and efficient transformer monitoring techniques.

Chapter 3

Methodology

Table 3.1: Physical properties of windings.

Parameters	Value
Conductor type	Copper
Diameter of the conductor, D_c	2.36 mm
Insulating material	Silicon rubber
Thickness of insulation	1.14 mm
Relative permittivity	4
Diameter of the wire	4.64 mm
Diameter of the core	110 mm

The methodology proposed in this paper involves several stages: analytical modelling of the transformer, data generation and measurement along with confirmation. The procedure consists of modelling the transformer using inter-turn inductance and capacitance analysis proposed by Bagheri et al. [14], the SPICE simulation model made by Nurmanova et al. [12], [13] and the distance algorithm provides a basis for the creation of a look-up table for the prediction of the axial and radial displacements; by introducing the analysis in code, it is possible to efficiently calculate the resulting FRA signal of the theoretical transformer for any kind of damage scenario. The resulting FRA patterns can be used to match the FRA from the potential transformer.

Utilizing Python for the automatization of the simulations, the authors created 200 displacement analytical scenarios for axial and radial displacement, ranging from 0.25 diameter of wire up to 5 diameter of wire. The scenario code represented an equivalent circuit for an air-core transformer in the SPICE program. The SPICE circuit simulation software provided the corresponding FRA, which was stored for the creation of a look-up table. Due to the specifics of the SFRA measuring

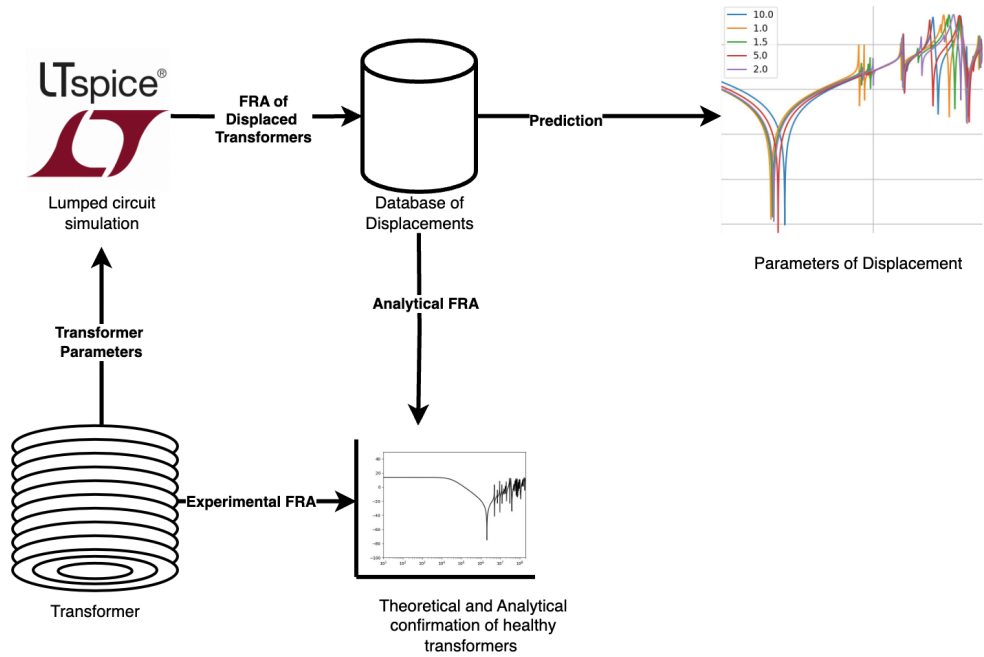


Figure 3.1: Data flow of the methodology

device and SPICE program, authors received FRA signals of different sampling rates, 900 and 7300 data points respectively. Hence, it was concluded to use cubic interpolation in the simulated scenarios to calculate the distance of each recorded data point of the practical FRA to the theoretical one. The proposed methodology allowed authors to identify the location of the damage in the air-core transformer and displacement along either the radial or axial axis by matching the graphs according to the minimal distance between the data points.

3.1 Modelling

To analytically model the transformer, a comprehensive RLC model of the windings must be determined, analyzed and validated. This research focuses on the air-core transformer to eliminate the effect of the magnetic coupling of the iron core and windings, to simplify the analysis of mutual and self-inductance. Since the inductance is only dependent on the geometrical configuration of the windings, such a model facilitates the analysis of lumped parameters of the transformer in the radial and axial displacement. In the proposed model, the windings represent continuously connected ten disks with six turns, using AWG 12 gauge wires, in each as illustrated in Fig. 3.2. The model is selected based on the criteria of fabrication in the laboratory environment. Following Fig. 3.2, it is identified that the

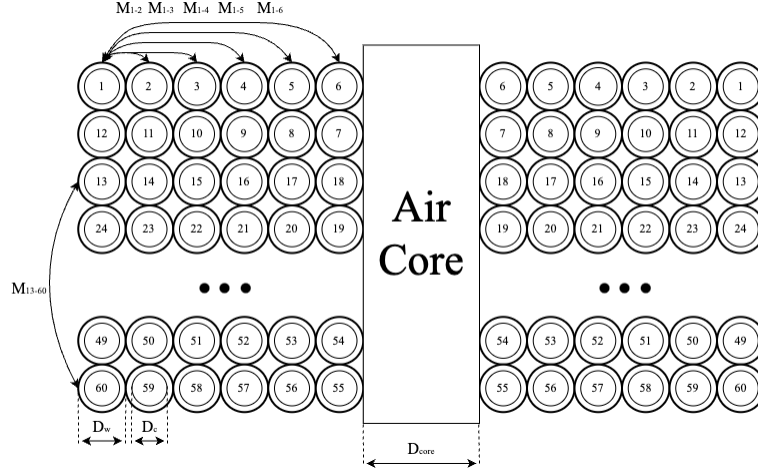


Figure 3.2: Analytical model of a transformer

effect of the distance between neighbouring turns is minimal, therefore in further calculation, the distance is considered to be zero. The crucial properties of the insulation and wire characteristics and dimensions are presented in Table 1. As in the RLC model, the precise calculations of the self-inductances, mutual inductances, inter-turn and inter-disk capacitances and turn resistances are considered in the lumped model. The following formulas, designated for circular wires, are used for the calculation of self-inductances and between individual turn inductances:

$$L = 4 * 10^{-3} * \pi R \left(\ln \frac{8R}{r_c} - 1.75 \right) \mu H \quad (3.1)$$

$$M_{a-b} = f \sqrt{R_a R_b} \mu H \quad (3.2)$$

In Eq. 2, the R_a and R_b represent the radii of the turns in cm and f is determined in the lookup tables[4]. Applying the given equations, the equivalent matrix can be obtained using the following.

$$L_{eq} = \begin{bmatrix} L_1 & M_{1-2} & \cdots & M_{1-60} \\ & L_2 & \cdots & M_{2-60} \\ & & \ddots & \vdots \\ & & & L_{60} \end{bmatrix}_{60 \times 60} \quad (3.3)$$

The inter-turn capacitances C_{tt} for circular wire are calculated using:

$$C_{tt} = \frac{\epsilon_r \epsilon_0 l_t \theta^*}{\ln r_w / r_c} + \epsilon_0 l_t \left(\cot \frac{\theta^*}{2} - \cot \frac{\pi}{2} \right) \quad (3.4)$$

Here, the l_t is a turn length, r_w is a wire radius, r_c is the conductor radius, ϵ_r is a relative permittivity of the insulating material, and θ is a crossing point angle, which is:

$$\theta^* = \cos^{-1}(1 - \ln(D_w/D_c)/\epsilon_r) \quad (3.5)$$

The resistance of the wire was calculated with the consideration of the skin effect in frequencies over 50 Hz:

$$R_{ac} = 0.027678 * \rho_{dc} l_t \sqrt{f/\rho_{dc}} \quad (3.6)$$

Using this analytical model, it was possible to replicate the theoretical damages along the radial and axial axes, by changing the distances of the adjacent disks vertically for axial displacement. While the variance of the centerline of the turns resulted in the radial shift.

3.2 Data Generation

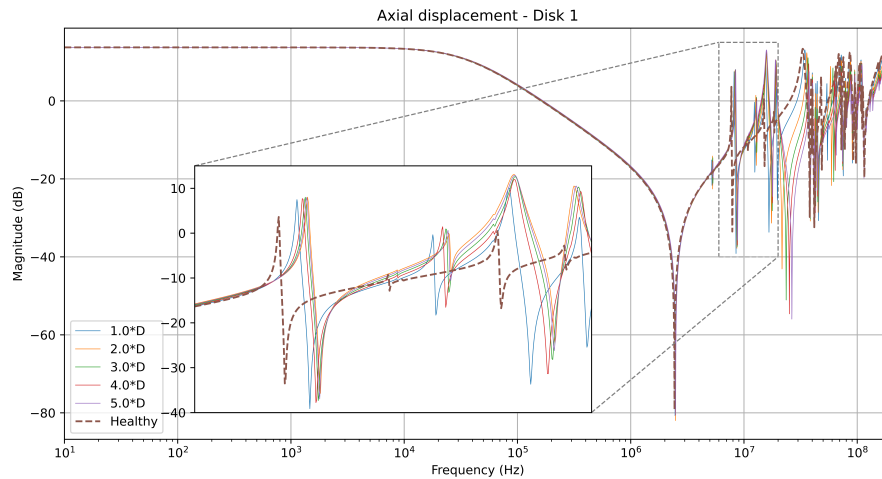


Figure 3.3: Simulation for axial displacement on the 1st disk.

As it was stated previously, by applying analytical models, the authors were able to create a lookup table for the damages in the transformer. The models represented a deviation along the axial and radial axis, in the range of zero to 9 diameters of the wire, with the step of 0.25 diameter of the wire. Writing a Python program, the authors developed 700 scenarios for 5 disks. Simulating the scenarios in LTSpice circuit simulation software, the acquired data was presented as frequency graphs in text format. Figures 3.3 and 3.4 show the retrieved data from the simulations of the scenarios of displacement of the first disk.

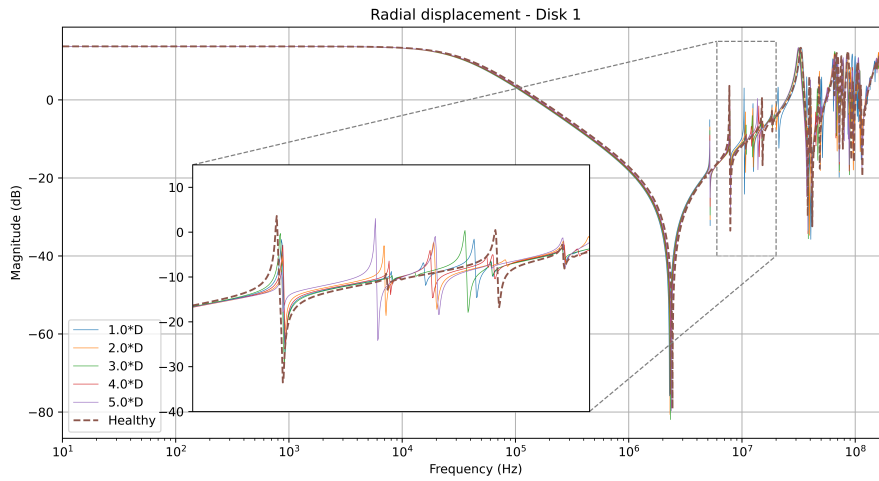


Figure 3.4: Simulation for radial displacement on the 1st disk.

3.3 Measurement

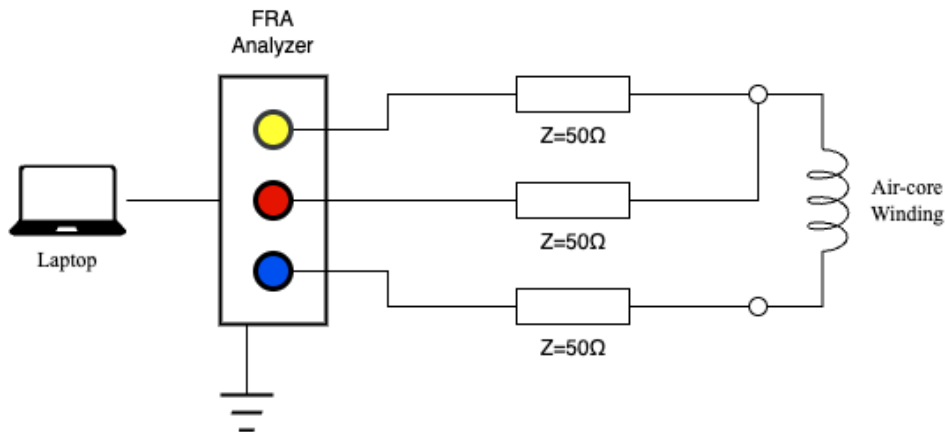


Figure 3.5: Experimental setup for FRA measurement.

FRA is a widely used and well-discussed method for the comparative analysis of transformer windings. By excitation of the winding, either cross or single windings, by an AC signal, unique responses reflecting any changes in the mechanical composition of windings can be received [12], [13]; the collected data is then analysed for identification of the abnormalities and deviation from the expected behaviour. Comparing the resulting response of the healthy and damaged transformer it is possible to indicate the severity and location of the occurring damage. The sweep range, typically from 20Hz up to over 1MHz, was empirically deter-

mined to show turn-to-turn short circuits, open circuits, radial and axial shifts, loosening of the windings insulation damage etc. Usually, the mid-frequency band (5-100 kHz) corresponds to the decreased inductance in the axial displacement, since the windings are moved apart, therefore the capacitive characteristics of the circuit increase [13]. On the other hand, the high-frequency band reveals radial deformation effectively, due to changes in the inductance and capacitance, new resonance peaks and valleys are produced. The setup pictured in Fig 3.5. is used for the measurement of FRA: Laptop connected to OMICRON FRANEO 800, a sweep frequency response analyzer, generate AC signals of 10 V across the 20Hz-25MHz range and records the received signal. The received signal is interpreted in the OMICRON software as 900 points of magnitude and phase shift along the 25MHz range. As mentioned previously, the replicated transformer must be able to displace disks in the radial and axial directions. To achieve such mobility of the separate disks the core of the transformer has to be modulus, so it is possible to displace individual turns in two axes. The authors modelled the mechanical system, Fig. 3.6, in the CAD software and manufactured it using 3D additive technologies.

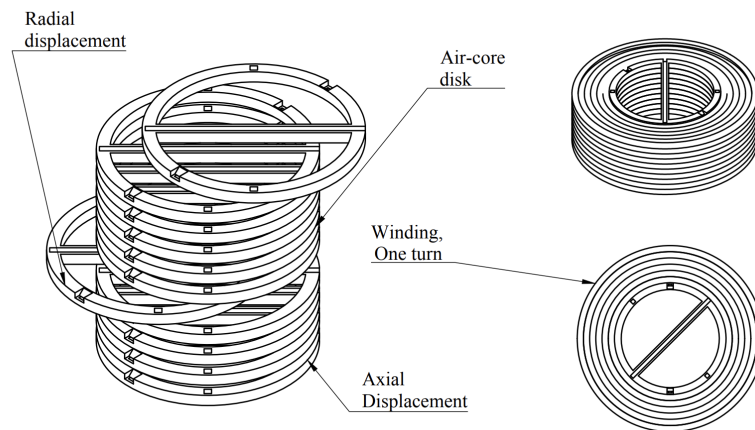


Figure 3.6: CAD model of modular air-core transformer.

3.4 Prediction

To set up the prediction of the algorithm, the theoretical and real models should be matched in the healthy or original position. The point is that if the healthy transformers in simulations and real-world domains are identical, then their behaviours must be similar with respect to axial and radial displacements. For this purpose, the authors compared the FRA signals of the theoretical and experimen-

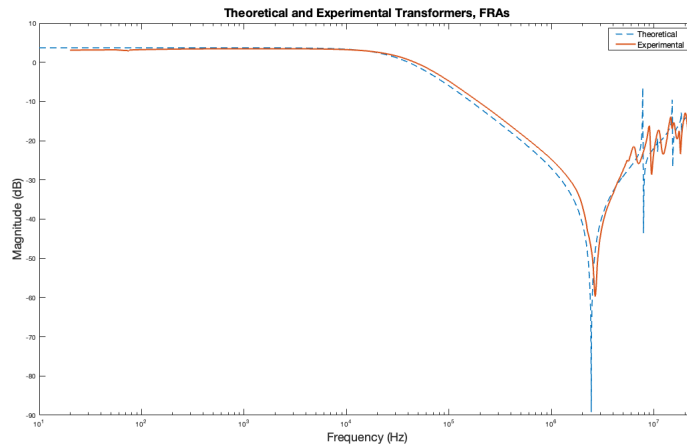


Figure 3.7: Graphs of real and analytical air-core transformers.

tal transformers in Fig. 3.7. However, due to difficulties in replication, the graphs match in middle and high-frequency ranges. The resonant peak is reduced due to capacitance exerted by small deviations in the windings. Nevertheless, these nuances will be mitigated by the model, since in the prediction the minimal distance algorithm is applied that is not affected by the small deviations in the responses.



Figure 3.8: Assembled modular air-core transformer.

As it was mentioned above, the problem of predicting the transformer displacement is deterministic. While it appears that displacements are random and cause different FRA, in fact, due to symmetric geometry, transformers' response is effectively identical and does not vary for a particular displacement in a certain disk. Therefore, for the particular disk, displacement values must be a unique

FRA which can be utilized to make a lookup table for a prospective prediction. $F_{disk}(D_{FRA})$, $F_{displacement}(D_{FRA})$ are disk and displacement values that can be mapped in the lookup table; by calculating the distance of a new input graph, it is possible to acquire the desired values.

$$D_{FRA_i} = \sum y_{lookup_i}(f) - y_{FRA}(f) \quad (3.7)$$

$$F_{disk} = \min(D_{FRA_i}) \quad (3.8)$$

$$F_{displacement} = \min(D_{FRA_i}) \quad (3.9)$$

Here the distance is calculated by using the differences of magnitude with respect to frequencies in the input data. By summing all the differences, the value of the summation can be used to determine the best-fitting prediction out of the range of the simulated data. Furthermore, the displacement and disks are the functions of minimum among all distances of input data to all lookup values. The following algorithm was utilized to calculate distance:

```
def MSE(y, x):
    DIST = {}
    for i in interpolated_data.keys():
        if i not in DIST:
            DIST.setdefault(i, {})
        for j in interpolated_data[i].keys():
            if j not in DIST[i]:
                DIST[i].setdefault(j, 0)
            inter = interpolated_data[i][j]
            for count in range(len(x)):
                diff = inter(x[count]) - y[count]
                DIST[i][j] += abs(diff)

    DIST_min = 0
    disk = 0
    disp = 0
    counter = 0
    for i in DIST.keys():
        for j in DIST[i].keys():
            if counter == 0:
                DIST_min = DIST[i][j]
                disk = i
                disp = j
                counter += 1
```

```
    else:
        temp = DIST[i][j]
        if DIST_min > temp:
            DIST_min = temp
            disk = i
            disp = j
    return disk, disp
```

Here interpolated data is a lookup tables that contain magnitude and frequency interpolated data points. By this, it is possible to calculate the distance in data with different dimensions. 900 data points from SFRA measuring devices are processed on the lookup data of 7300 data points. The function returns then the disk and displacement values regarding the minimal distance between all graphs.

Chapter 4

Results and Discussions

4.1 Results

Applying the algorithm to the experimental setup, authors were able to obtain the following results from a prediction:

Table 4.1: Physical properties of windings.

Radial Displacement			Axial Displacement		
Actual	Predicted	Accuracy	Actual	Predicted	Accuracy
(1, 4)	(1, 3.46)	86.5%	(1, 5)	(1, 4.64)	92.8%
(2, 6)	(2, 5.81)	96.8%	(3, 4)	(3, 4.64)	84.0%

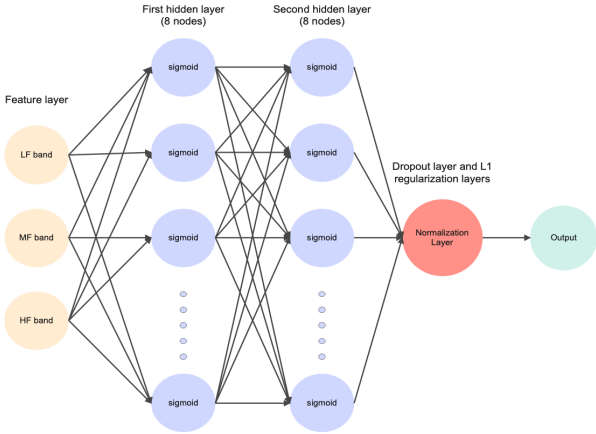


Figure 4.1: Network structure of ANN prediction model for displacement

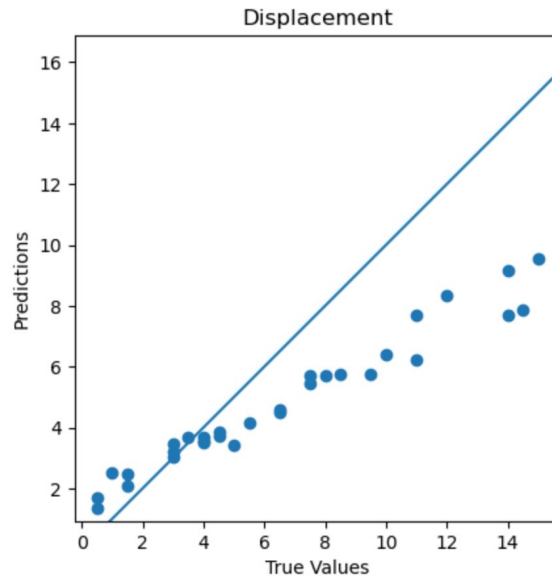


Figure 4.2: Prediction versus the true value of ANN model, validation set

4.2 Discussions

In Table 4.1, the data is predicted as follows: (disk number, deviation in the disk along the given axis). Due to limitations in the resolution of the prediction data, the predicted and actual data are an approximation. The reason for this is that the lookup table consists of the FRA responses that are simulated with respect to the diameter of the wire with a fixed step of $0.25 \times \text{diameter of the wire}$. Taking into account this aspect, it is possible to say that the prediction is accurate to the extent of the simulation data. The accuracy varies in ranges of 84.0 - 96.8 %. The proposed method is effective in the location of the two types of displacement. The localization is accurate in the disk prediction and displacement values. However, it can be assumed that there might be a possibility or instances when the model can falsely predict the outcome. Since the algorithm is deterministic, the effect of the noise, improper contact of FRA, thermal noise and other factors might drastically change the output prediction. Moreover, the algorithm is limited in its prediction capabilities, to be said, it requires more data for the complex predictions, such as the combination of damages: radial and axial, radial and tilt, bending and stretching and others. To increase the prediction capabilities, more instances of the damage must be simulated, however, this might be involved and computationally heavy. In this scenario, machine learning techniques might come into play, as they might interpolate the possible damages into FRA responses, but the accuracy of such predictions of localization cannot be said to be reliable. Therefore, the proposed method is dedicated to proliferating the predictions on this topic.

Chapter 5

Conclusion

To address the negative sides of this methodology, instead of compiling every instance with a small step, it is feasible to use interpolation between the collected simulation data to decrease the computational intensity. By doing this, it is possible to predict the FRA response, in-between the simulation steps, thus, requiring less computing power and time. Furthermore, it is suggested to apply feature selection algorithms to increase the prediction accuracy as the abundance of data in the prediction models can negatively affect the end output of the predictive model. Specifically, in the current model, all points from the FRA analyzer contribute to the decision process. Although this might be seen as a resealable approach, the added weight from the less important data points might distort the prediction, as the accumulation of the less important factors might contribute to the significant deviation of the calculation of minimum error. Nevertheless, to locate and identify the damage the proposed model is powerful in the laboratory environment

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