Optimized Regression Modeling for Predicting Electrical Resistance in 3D Structures

1st Nashaat El Halabi
School of Science and Technology
City St George's, University of London
London, UK
Faculty of Engineering and Computer Science
American University of Science and Technology
Beirut, Lebanon
nashaat.el-halabi@citystgeorges.ac.uk

2nd Enayet Rahman
School of Science and Technology
City St George's, University of London
London, UK
enayet.rahman.2@citystgeorges.ac.uk

3rd Mohamad Rahal
Faculty of Engineering and Computer Science
American University of Science and Technology
Beirut, Lebanon
mrahal@aust.edu.lb

4th Michael Powner
School of Health and Medical Sciences
City St George's, University of London
London, UK
michael.powner@citystgeorges.ac.uk

5th Iasonas Triantis
School of Science and Technology
City St George's, University of London
London, UK
i.triantis@citystgeorges.ac.uk

***Abstract*—Electrical impedance measurements on finite samples are affected not only by material's conductivity, but also by geometric factors. By applying superficial bipolar bio-impedance measurements on rectangular samples, deviations from ideal Ohm's law occur due to current spreading, fringing fields, and electrode–sample contact effects. FEM is widely used to study these effects, while regression and machine learning (ML) offer faster alternatives. This work presents a regression-based approach to predict the impedance of an L×W×H samples at a fixed frequency. A dataset was generated from COMSOL Multiphysics models of samples with constant conductivity (1 S/m), electrode spacing (5 mm), and electrode size (1×1 mm²). However, length, width, and height were systematically varied. Initially, a cubic polynomial regression model was implemented using MATLAB, and it achieved high accuracy (R^2 = 0.9999, RMSE = 6.3604, MAPE = 0.2751%), but the model generated 1 intercept and 43 coefficients, which made it more complex and less practical. Thus, to overcome this problem, an optimized Feature-Engineered regression model was developed by eliminating the coefficients with high p-value, keeping 1 intercept and 10 coefficients only. The optimized model maintained good predictive capability (R^2 = 0.9993, RMSE = 21.5341, MAPE = 1.3394%), making it computationally efficient and suitable for practical engineering applications. The results demonstrate that simple regression models can be used as efficient alternative to FEM, offering a rapid tool to predict the impedance of varying geometries at constant frequency.**

***Index Terms*—Bio-impedance Spectroscopy, Finite Element Modeling, Regression Modeling, COMSOL Multiphysics Simulation, Resistance Prediction, Optimization.**

I. Introduction

Electrical impedance spectroscopy (EIS) is widely used to characterize materials and devices. Accurate prediction of electrical resistance in electrode systems is critical for applications ranging from microelectronics to biomedical devices. While theoretical resistance scales with length-to-cross-sectional area ratio, real superficial bipolar bio-impedance measurements on finite geometries deviate due to current spreading, fringing fields, and electrode–sample contact effects [1], [2].

Traditionally, FEM is used to capture these deviations [3], [4], but running large numbers of simulations is computationally costly. A regression-based model offers a fast alternative for predicting impedance from geometry at constant frequency. This paper evaluates a Feature-Engineered regression model using COMSOL-generated data and MATLAB for rectangular samples with fixed conductivity, zero relative permittivity, and fixed electrodes configuration. The contributions of this paper are:

- Development of a cubic polynomial regression model with near-perfect accuracy.
- Reduction of model complexity through coefficient optimization.
- Validation of the optimized model against independent COMSOL test data.

Prior studies have used FEM to analyze geometric effects on impedance, and recent work has explored ML approaches, but most of them focused on broadband frequency behavior or employed complex black-box models. The novelty of this work lies in showing that simple regression models can be an efficient and accurate alternative for FEM simulations at a fixed frequency. This provides a simple predictive tool for geometry-dependent impedance analysis.

II. Literature Review

Recently, regression and ML have been used in EIS applications, including classification, and impedance prediction.

Studies demonstrated that including physical geometry inputs, such as length, area and length-to-area ratio, improves accuracy [5], [6].

Polynomial regression and Response Surface Methodology (RSM) have been applied in engineering contexts. These methods are easy to use, especially when input variables can be systematically varied through simulations [7], [8]. However, higher-order polynomial regression models produce large number of coefficients and interaction terms [9]. This requires optimization strategies and size reduction techniques to balance model simplicity and predictive performance.

Recent work demonstrates the increasing use of machine-learning-based methods such as Gaussian process regression (GPR), deep neural networks (DNNs), and Bayesian neural networks (BNNs). These methods are effective in nonlinear mappings, offering near real-time prediction capabilities once trained. For example, Huang et al. [10] employed a DNN surrogate for AC loss estimation in superconductors using COMSOL data. Similarly, Davalos-Guzman et al. [11] used Bayesian neural networks to build models that can also measure uncertainty, making the predictions more reliable for engineering applications.

In the context of electrical and electrochemical modeling, ML models have been successfully applied to evaluate resistance, conductivity, and related properties based on geometric and material variations. Studies on electrode systems emphasize the effectiveness of polynomial regression for capturing the relation between resistance and electrode dimensions and spacing [12]. These applications are directly related to the work presented in this paper, which utilizes length, width, height, and length-to-cross-sectional-area proportion as predictive variables.

Finite-Element-Modeling (FEM) studies have increasingly focused on how the geometric and material properties of the sample under test affect measured impedance, especially in biomedical contexts [13]. FEM of thin films and micro/nanoscale dielectric layers have also shown that film thickness, lateral dimensions, and substrate geometry deviate impedance measurements and dielectric properties [14]. Moreover, vascular and tissues FEM studies report that lumen geometry, wall thickness, and surrounding tissue morphology affect impedance responses used for diagnostic and sensing tasks [15]. In addition, environmental effects have been demonstrated via FEM and combined experimental/simulation studies to affect impedance in sensors and sample characterization [16], [17].

To accelerate design and interpretation, recent work combines FEM outputs with ML models to predict electrochemical/biological impedance faster [18], [19], [20]. Thus, these FEM and ML studies justify using COMSOL-generated sample-geometry datasets to build validated models for impedance prediction from geometry inputs, as pursued in this work.

Overall, the literature shows that while high-order polynomial regression models can achieve excellent accuracy, their complexity often limits practical use. Thus, coefficients and interaction terms reduction is needed. This study contributes to this trend by developing an optimized regression model that achieves a balance between simplicity and predictive accuracy. This work builds on these findings by applying regression models to FEM-generated impedance data, focusing on geometry–impedance relationships under constant frequency.

III. Background

A. Impedance of material

The electrical impedance of a material represents its opposition to the flow of alternating current (AC). It is a combination of resistance and reactance. For a material with finite dimensions (length L, width W, and height H), the geometry plays an important role in affecting its impedance characteristics. The resistive component is due to the material resistivity ρ, or material conductivity σ=1/ρ and the physical dimensions:

$$R = \rho \frac{L}{A} = \frac{L}{\sigma A} \tag{1}$$

Where R is the resistance in Ω, ρ is the resistivity in Ω.m, σ is the conductivity in S/m, L is the length in m, and A is the area of cross-section (A=W$\times$H) in m^2. Equation (1) shows that resistance increases with length and decreases with larger cross-sectional area.

For AC, materials also exhibit capacitive behavior, which depends on their permittivity ε and geometry. If we consider the rectangular block as a parallel plate capacitor with plates of area A=W$\times$H separated by distance L, the material capacitance will be:

$$C = \varepsilon \frac{A}{d} = \varepsilon \frac{A}{L} \tag{2}$$

Where C is the capacitance in F, ε=$\varepsilon_0\varepsilon_r$ is the absolute permittivity of the material in F/m, and d is the distance between the parallel plates in m (in this case d=L). The capacitive reactance is then:

$$X_c = \frac{1}{\omega_C} = \frac{L}{\omega \varepsilon A} \tag{3}$$

Where X_c is the capacitive reactance in Ω, ω=2πf is the angular frequency in rad/s and f is the AC frequency in Hz. The total impedance Z of the block combines resistance and reactance:

$$Z = R + jX = \frac{L}{\sigma A} + j\frac{L}{\omega \varepsilon A} \tag{4}$$

Equation (4) shows that the impedance depends explicitly on conductivity, permittivity, and geometry. For higher conductivity, the resistive part decreases, while for higher permittivity, the capacitive reactance decreases.

In this paper, we are focusing on the effect of geometry on the resistance, thus, the samples used in COMSOL simulations are with constant conductivity (σ=1 S/m), and zero relative permittivity (ε_r=0 F/m), this makes the impedance measured purely resistive and eliminates the effect of frequency on impedance measurements.

B. Regression Modeling

Regression analysis is a statistical technique used to model the relationship between a dependent variable y and one or more independent variables (features) x_1, x_2, ..., x_n. Regression helps in predicting the dependent variable, and understanding of how input variables affect the output. In general, in regression model, the dependent variable y can be approximated by a function f of the independent variables:

$$y = f(x_1, x_2, ..., x_n) + \epsilon \tag{5}$$

where ϵ represents random noise or unexplained variation.

a) Linear Regression: Linear regression is the simplest regression technique. It finds a linear relationship between the dependent variable y and independent variables, and possibly their interactions.

b) Quadratic Regression: Quadratic regression extends linear regression by including squared terms of the independent variables, and possibly their interactions.

c) Polynomial Regression: Polynomial regression extends quadratic regression by including higher-order terms up to order m. By increasing the order m, the model can fit more complex, nonlinear relationships. However, high-degree polynomials may lead to large number of coefficients (terms), and sometimes to overfitting.

d) Feature-Engineered Regression: Feature-engineered regression transforms original variables or creates new features to improve the model's ability to capture relationships.

IV. Materials and Methods

A. Simulation setup

In order to create the training/testing/validation datasets, COMSOL Multiphysics has been used. An L×W×H model has been created, where L, W, and H are systematically varied using parametric sweep. The conductivity of the material was chosen to be σ=1 S/m, and the relative permittivity was set to ε_r=0 F/m. Thus, by measuring the impedance of the material we measure the resistance R only. Although frequency has no effect on resistance measurement in this context, the frequency was set to 10 kHz in COMSOL simulations. The mesh was chosen to have a maximum element size of 0.33 mm, a minimum element size of 0.024 mm, a maximum element growth rate of 1.4, a curvature factor of 0.4, and a resolution of narrow regions of 0.7.

To measure the resistance of the sample under test, two fixed 1×1 mm^2 Au-Gold electrodes have been placed on top of the material, separated by 5 mm distance. The COMSOL model is shown in Fig. 1.

B. Sample Size Validation

In order to choose the minimum and maximum values for the length, width, and height of sample under test, the electric field lines were studied in COMSOL simulation. The XZ-plane electric field norm is shown in Fig. 2, thus, the geometric parameters were set to be 6mm to 10mm for length, 1mm to 4mm for width, and 1 mm to 5 mm for height.

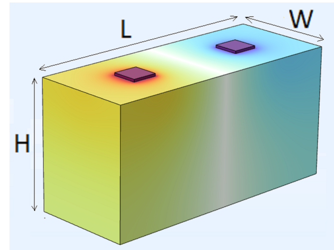

Fig. 1. COMSOL Simulation Model

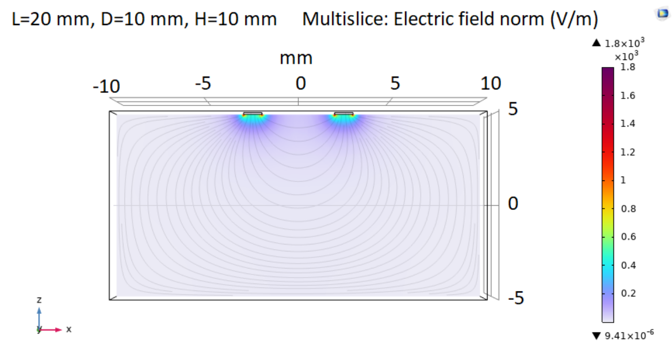

Fig. 2. Electric Field Norm

C. Datasets

The training dataset consists of 7054 samples, created by COMSOL parametric sweep, with L=6 to 10 mm, W=1 to 4 mm, and H= 1 to 5 mm. The inputs are L, W, H, and P (Proportion of length to cross-sectional area). The testing dataset consists of 1500 samples, different than training dataset, but within the same range of geometry. The validation dataset consists of other 100 samples, different than both training and testing datasets, but within the same range of geometry.

D. Regression Models

As a first step, linear regression model with interactions has been tested, the results were promising. Then Quadratic regression model with interactions has been tested and showed better results. in the third step, cubic polynomial regression model has been tested, it achieved the best accuracy in terms of Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE), and R^2 value. However, cubic polynomial regression model resulted in 1 intercept and 43 coefficients (Terms), thus, there was a need for a Feature-Engineered Regression model to reduce complexity by sacrificing accuracy to a certain limit. In the last step, only 1 intercept and 10 coefficients with highest contribution have been selected, and the testing and validation results were still acceptable in terms of accuracy. All regression models have been trained, tested and validated using MATLAB.

V. Results

The first step of modeling consists of training three models; Linear regression with interactions model produced 1 intercept and 13 unique coefficients, Quadratic regression model produced 1 intercept and 18 unique coefficients, and cubic polynomial regression model produced 1 intercept and 43 unique coefficients. The evaluation method was based on Root Mean Square Error (RMSE), R^2 value, Mean Absolute Percent Error (MAPE), Minimum Absolute Percent Error (MinAPE), and Maximum Absolute Percent Error (MaxAPE). The testing results are shown in Table I.

TABLE I
TESTING RESULTS FOR PRELIMINARY MODELS

Model	***RMSE***	$\boldsymbol{R^2}$	***MAPE***	***MinAPE***	***MaxAPE***
Linear with interactions	37.3741	0.9960	1.9771%	0.0002%	9.0553%
Quadratic	20.3931	0.9988	1.0402%	0.0005%	7.2606%
Cubic Polynomial	6.3604	0.9999	0.2751%	0.0000%	2.4558%

In order to simplify the final equation, a Feature-Engineered regression model has been designed by selecting 1 intercept and 10 coefficients with highest contribution.

In order to choose the selected coefficients, the coefficients table resulted from cubic polynomial regression model has been used; all coefficients with pValue>0.05 were rejected, then the remaining coefficients have been sorted, based on the absolute value of the estimate, in ascending order. The intercept and the first 10 coefficients have been selected. Table II shows the selected coefficients with their estimates, Standard Error (SE), t-statistic (tStat) and probability values (Pvalue).

TABLE II
SELECTED COEFFICIENTS FROM CUBIC POLYNOMIAL MODEL

	Estimate	***SE***	***tStat***	***pValue***
Intercept	2615.4253	136.9175	19.1022	2.46×10^{-79}
P	1542.0167	47.4041	32.5292	2.75×10^{-216}
L	-1339.3370	19.8309	-67.5380	0
H	1073.6157	100.8170	10.6492	2.79×10^{-26}
D	833.4222	118.3185	7.0439	2.05×10^{-12}
D × H	-320.3324	92.7741	-3.4528	0.000558042
H × P	233.7832	28.9313	8.0806	7.53×10^{-16}
L × P	-222.6123	3.9128	-56.8930	0
L × H	-209.6523	7.0037	-29.9345	2.27×10^{-185}
L^2	192.7170	1.4174	135.9659	0
L × D × H	39.9397	4.8317	8.2662	1.64×10^{-16}

After selecting the coefficients from the cubic polynomial regression model, a Feature-Engineered has been trained again and tested with the testing data set, the results are shown in III:

TABLE III
TESTING RESULTS FOR FEATURE-ENGINEERED REGRESSION MODEL

Model	***RMSE***	$\boldsymbol{R^2}$	***MAPE***	***MinAPE***	***MaxAPE***
Feature-Engineered	24.8959	0.9982	1.2440%	0.0033%	6.4833%

Table IV shows the coefficients for Feature-Engineered regression model, it includes the estimates for the intercept and the 10 coefficients, Standard Error (SE), t-statistic (tStat) and probability values (Pvalue).

TABLE IV
COEFFICIENTS OF FEATURE-ENGINEERED REGRESSION MODEL

	Estimate	***SE***	***tStat***	***pValue***
Intercept	1684.7597	19.2363	87.5822	0
P	1088.4818	3.6044	301.9818	0
L	-488.7319	4.3157	-113.2438	0
H	444.6392	3.0519	145.6915	0
D	185.5618	1.5610	118.8726	0
D × H	-98.5297	1.0005	-98.47924	0
H × P	124.2855	0.6503	191.1004	0
L × P	-73.1180	0.4106	-178.0698	0
L × H	-38.5333	0.3642	-105.7899	0
L^2	29.3071	0.2765	105.9569	0
L × D × H	8.4691	0.1187	71.3380	0

The final equation, generated from feature-engineered regression model, for resistance R is presented in (6):

$$\begin{aligned} R = {} & 1684.75975904171 \\ & +1088.48180626538 \times P \\ & -488.731933161447 \times L \\ & +444.639224328437 \times H \\ & +185.561865427639 \times W \\ & -98.5297772447885 \times W \times H \\ & +124.285551534430 \times H \times P \\ & -73.1180360052255 \times L \times P \\ & -38.5333486258069 \times L \times H \\ & +29.3071537114573 \times L^2 \\ & +8.46913157893123 \times L \times W \times H \end{aligned} \tag{6}$$

Finally, (6) was validated with the validation dataset, the results are shown in Table V:

TABLE V
VALIDATION RESULTS FOR FEATURE-ENGINEERED REGRESSION MODEL

Model	***RMSE***	$\boldsymbol{R^2}$	***MAPE***	***MinAPE***	***MaxAPE***
Feature-Engineered	21.5341	0.9993	1.3394%	0.0364%	5.3875%

By comparing Table I and Table V, it is clear that Feature-Engineered Regression model performs better than Linear Regression model. Although Quadratic and Cubic Polynomial regression models perform better than Feature-Engineered regression model, however the later wins by its simplicity, since it achieves the lowest number of coefficients, thus simplest final equation for resistance R.

Fig. 3 shows the testing results for the final model, it presents $R_{predicted}$ in function of R_{true}.

Fig. 4 shows the validation results for the final model, it presents $R_{predicted}$ in function of R_{true}.

Fig. 5 shows the validation results for the final model, it presents $R_{predicted}$ and R_{true} in function of P (Length to cross-sectional area ratio).

Fig. 6 shows the validation percentage error in function of P, it demonstrates that the percentage error increases with the decrease of proportion P.

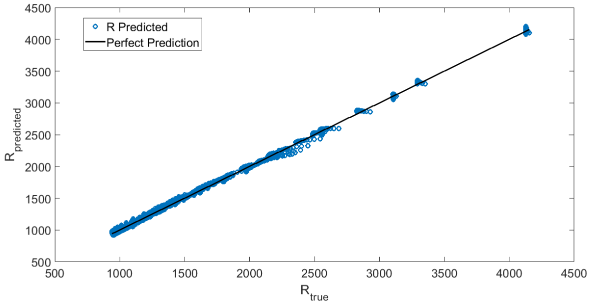

Fig. 3. Feature-Engineered Regression Model Testing Results

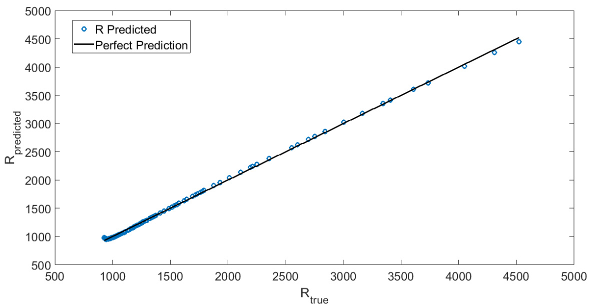

Fig. 4. Feature-Engineered Regression Model Validation Results

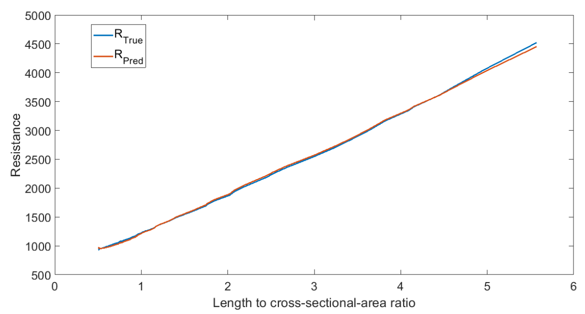

Fig. 5. Feature-Engineered Regression Model Validation Results - Impedance in function of P

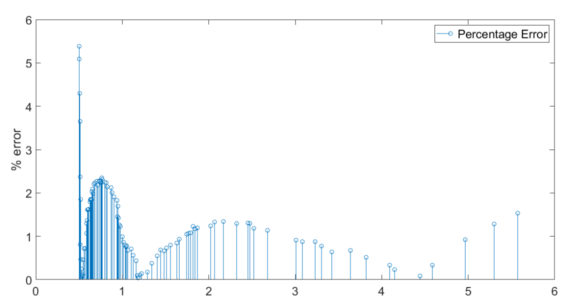

Fig. 6. Feature-Engineered Regression Model Validation Results - % error in function of P

VI. Conclusions and Future Work

The primary goal of this work was to develop an efficient, regression-based model for predicting the electrical resistance of L×W×H samples at a fixed frequency, offering a fast alternative to Finite Element Modeling (FEM). A cubic polynomial regression model initially achieved near-perfect accuracy on the testing dataset, with an R^2 value of 0.9999, an RMSE of 6.3604, and a MAPE of 0.2751%. However, this model was too complex, generating 1 intercept and 43 coefficients, which limited its practicality. To solve this complexity problem, a Feature-Engineered Regression model was developed by selecting 1 intercept and 10 coefficients with the highest contribution. This optimized model achieved a better balance between simplicity and predictive performance; it maintained strong predictive capability with lower number of terms, making the model computationally efficient and suitable for practical engineering applications. The results clearly demonstrate that a simple regression model can serve as an efficient, rapid tool for predicting the impedance of varying geometries at a constant frequency.

Future research will focus on the following areas:

- Extending the modeling approach to predict impedance across a wider range of frequencies (broadband behavior).
- Including the effect of electrode-sample contact impedance to the model, as this is another factor that causes deviations from ideal Ohm's law.
- Applying the developed methodology to the analysis and design of complex biomedical devices, where fast prediction of geometry-dependent impedance is needed.
- Comparing the performance of the optimized regression model with more complex machine learning techniques, such as Gaussian Process Regression (GPR) or Deep Neural Networks (DNNs).

References

[1] K. Davis, A. Dizon, C. L. Alexander, and M. E. Orazem, "Influence of geometry-induced frequency dispersion on the impedance of rectangular electrodes," Electrochimica Acta, vol. 283, pp. 1820–1828, Sep. 2018, doi: 10.1016/J.ELECTACTA.2018.07.080.

[2] R. Wang, F. He, C. Chen, and L. Dai, "Evaluation of electrode-sample contact impedance under different curing humidity conditions during measurement of AC impedance of cement-based materials," Scientific Reports, vol. 10, no. 1, pp. 1–16, Dec. 2020, doi: 10.1038/S41598-020-74925-W;SUBJMETA.

[3] "Electrochemical Impedance Spectroscopy: Experiment, Model, and App — COMSOL Blog." Accessed: Oct. 06, 2025. [Online]. Available: https://www.comsol.com/blogs/electrochemical-impedance-spectroscopy-experiment-model-and-app

[4] S. F. Cogan, J. Ehrlich, and T. D. Plante, "The effect of electrode geometry on electrochemical properties measured in saline," Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference, vol. 2014, pp. 6850–6853, Nov. 2014, doi: 10.1109/EMBC.2014.6945202.

[5] C. Ferguson, Y. Zhang, C. Palego, and X. Cheng, "Recent Approaches to Design and Analysis of Electrical Impedance Systems for Single Cells Using Machine Learning," Sensors 2023, Vol. 23, Page 5990, vol. 23, no. 13, p. 5990, Jun. 2023, doi: 10.3390/S23135990.

[6] J. Chen et al., "Machine learning-directed electrical impedance tomography to predict metabolically vulnerable plaques," Bioengineering & translational medicine, vol. 9, no. 1, Jan. 2023, doi: 10.1002/BTM2.10616.

[7] D. C. Montgomery, E. A. Peck, and G. G. Vining, ”Introduction to Linear Regression Analysis”. Wiley, 2021.
[8] G. E. P. Box, W. G. Hunter, and J. S. Hunter, ”Statistics for Experimenters: Design, Innovation, and Discovery”. Wiley, 2005.
[9] S. S. Rao, ”Engineering Optimization: Theory and Practice”. Wiley, 2019.
[10] Y. Huang, M. Yazdani-Asrami, and W. Song, “A Deep Learning-Based Ultra-Fast Surrogate Model for AC Loss Estimation in Superconductors using COMSOL,” IEEE Access, 2025, doi: 10.1109/ACCESS.2025.3603953.
[11] J. Davalos-Guzman, J. L. Chavez-Hurtado, and Z. Brito-Brito, “Integrative BNN-LHS Surrogate Modeling and Thermo-Mechanical-EM Analysis for Enhanced Characterization of High-Frequency Low-Pass Filters in COMSOL,” Micromachines 2024, Vol. 15, Page 647, vol. 15, no. 5, p. 647, May 2024, doi: 10.3390/MI15050647.
[12] H. Li et al., “Coupling multi-physics simulation and response surface methodology for the thermal optimization of ternary prismatic lithium-ion battery,” Journal of Power Sources, vol. 438, p. 226974, Oct. 2019, doi: 10.1016/J.JPOWSOUR.2019.226974.
[13] F. J. Pettersen and J. O. Høgetveit, “From 3D tissue data to impedance using Simpleware ScanFE+IP and COMSOL Multiphysics - A tutorial,” Journal of Electrical Bioimpedance, vol. 2, no. 1, pp. 13–32, 2011, doi: 10.5617/JEB.173.
[14] Y. Jin, S. Kumar and R. Gerhardt, “Simulation of the Impedance Response of Thin Films as a Function of Geometry,” COMSOL Conference, 2015.
[15] M. Amini, H. Kalvøy, and G. Martinsen, “Finite element simulation of the impedance response of a vascular segment as a function of changes in electrode configuration,” Journal of Electrical Bioimpedance, vol. 11, no. 1, pp. 112–131, 2020, doi: 10.2478/JOEB-2020-0017.
[16] R. C. Titus, R. A. Gerhardt and J. E. Fowler, “Simulating Ideal and Experimental Impedance Response — COMSOL Conference paper,” COMSOL Proceedings, 2024.
[17] J. Tang, W. Yin, and M. Lu, “Bio-impedance spectroscopy for frozen-thaw of bio-samples: Non-contact inductive measurement and finite element (FE) based cell modelling,” Journal of Food Engineering, vol. 272, p. 109784, May 2020, doi: 10.1016/J.JFOODENG.2019.109784.
[18] Y. Pan, H. Ruan, B. Wu, Y. N. Regmi, H. Wang, and N. P. Brandon, “A machine learning driven 3D+1D model for efficient characterization of proton exchange membrane fuel cells,” Energy and AI, vol. 17, p. 100397, Sep. 2024, doi: 10.1016/J.EGYAI.2024.100397.
[19] J. Sun et al., “What is the appropriate data representation of electrochemical impedance spectroscopy in machine-learning analysis?,” Feb. 2024, doi: 10.26434/CHEMRXIV-2024-MDPW8.
[20] A. Odungat and S. Chanda, “Data-driven model for predicting the electro-thermal behavior of lithium-ion pouch cell under varying ambient temperature conditions,” Applied Thermal Engineering, vol. 265, Apr. 2025, doi: 10.1016/J.APPLTHERMALENG.2024.125367.