

High Voltage Surrogate Models Creation Using Deep Neural Networks In COMSOL Multiphysics®

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Abstract

This study presents a methodology for developing surrogate models based on deep neural networks (DNNs) within the COMSOL Multiphysics® environment. The influence of selected architectural and numerical parameters on prediction accuracy is investigated. Particular attention is given to network architecture, including the number of layers, neurons, and activation functions, as well as to the preparation of training datasets generated through parametric finite element method (FEM) simulations.

The impact of mesh density, element quality, and solver settings on the quality of training data and surrogate model performance is analysed, highlighting the trade-off between simulation accuracy and computational cost. The surrogate models are evaluated against FEM reference solutions obtained in COMSOL Multiphysics®.

Additionally, an extended artificial neural network (ANN) model was implemented in Python, enabling the assessment of different optimization algorithms.

The results demonstrate that the reliability of surrogate models strongly depends on the appropriate selection of DNN architecture and the quality of training data. The study underscores the importance of systematic validation and comparative analysis in optimizing data-driven modelling workflows.

Keywords: surrogate model, high-voltage string, electric field.

Introduction

One of the most rapidly advancing areas of artificial intelligence is the development of surrogate models based on deep neural networks. The research presented in this paper was conducted within this field.

The reliable operation of power systems is essential for sustainable economic growth and maintaining a high standard of living. Insulator strings are a critical component of high-voltage transmission lines, and ensuring their reliable performance reduces the risk of outages, for example those caused by insulator damage resulting from prolonged exposure to corona discharges. To mitigate the effects of this phenomenon, protective fittings are commonly employed. Selecting an optimal protective fitting design helps reduce the intensity of corona discharges and prevents premature deterioration of insulators.

A surrogate model can support the optimization process by enabling the rapid calculation of voltage distribution along an insulator string. For this purpose, a surrogate model of voltage distribution in an insulator string equipped with protective fittings was developed and evaluated.

The study investigated the impact of the number of neurons in the hidden layers and the learning rate on the accuracy of the surrogate model. The model's predictions were compared with the results obtained from simulations performed in COMSOL Multiphysics®. In addition, directions for further research and future development of the surrogate model were outlined.

1. Complete insulator strings

The complete insulator string is used to support the conductor at an appropriate distance from the ground and to attach it to the tower. The string consists of insulators (porcelain, glass, or composite), fittings (hangers, connectors, yokes, etc.), protective fittings (arcing horns and grading rings), as well as suspension and tension clamps (Fig. 1).

Complete insulator strings can also be structurally divided into several types, depending on their purpose and the locations in which they are used: suspension strings, tension strings, V-strings, etc. Suspension strings are used to support the conductor above the ground, whereas tension strings are used to maintain the appropriate tension in the span of the line.

Considering that the fittings of a complete insulator string are made of hot deep galvanised steel and, in some cases, include aluminium components, while the insulator itself may be made of glass, porcelain, or composite material, depending on the material used in its manufacture, the insulator is the weakest component of the complete string. This study investigated a complete insulator string equipped with a composite insulator, as the effects of corona

discharge on this type of insulator are the most detrimental. Moreover, the electric field distribution along such a string is, in most cases, determined using simulation calculations, since laboratory measurement methods are not standardized and are relatively complex and costly to implement.



Figure 1. Suspension string and V-type suspension string with a composite insulator [1]

On the other hand, many Technical Specifications [2], [3] from different countries specify requirements concerning the permissible electric field strength on the surface of composite insulators and fittings. These parameters can be calculated and analysed using simulation methods, which, however, require a considerable amount of time. Surrogate models can accelerate the calculation process and reduce the time required by a designer when selecting or designing protective fittings.

2. Applied Model of the Complete Insulator String and Electric Field

As mentioned in Chapter 1, a composite insulator string with protective fittings was selected for the calculations and analysis. The protective fittings were represented by two grading rings located at both ends of the insulator, as these have the greatest influence on the electric field distribution and allow an axisymmetric model to be obtained. Other components, such as the fittings and conductors, were excluded due to their smaller influence on the electric field and in order to simplify the computational model.

The calculations were performed using a model of a composite insulator equipped with protective fittings, obtained from the COMSOL Multiphysics® library,

“grading_ring_optimization” (Fig. 2). Due to the axial symmetry of the geometry with respect to the Z-axis, the model was represented as a two-dimensional half-section (Fig. 3). The analysed insulator consists of steel end fittings, a glass-fiber-reinforced core embedded in epoxy resin, and an external composite housing. The protective elements were modelled as steel grading rings. The material properties of all the aforementioned components were defined in the “Materials” section of the Model Builder, with electrical conductivity being a key parameter. The finite element mesh was generated automatically using the built-in

meshing functionality. In subsequent stages of the work, manually generated meshes are also planned to be analysed, together with an assessment of their influence on the accuracy of the developed surrogate model.



Figure 2. Model of a composite insulator

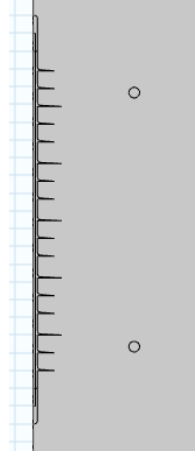


Figure 3. Half-section of a composite insulator with protective fittings

In the model, the boundary conditions were defined such that the upper end fitting of the insulator and the upper grading ring were maintained at a reference potential of 0 V. In contrast, the lower end fitting and the lower grading ring were set to the line potential of 500 kV. Numerical simulations were then performed using the finite element method (FEM) to determine the electric potential distribution along the composite insulator string for the selected protective fitting configuration. Three main geometric parameters were considered in the analysis: the diameter of the grading ring, the diameter of the ring tube, and its distance from the end of the insulator. These parameters were subsequently used as input variables in the development of the equivalent model.

The Electrostatics Interface is used for this model and solves the electric potential equation derived from Gauss's law. The electric field is determined from the potential:

$$\mathbf{E} = -\nabla V \quad (1)$$

where V is the electric potential and E is the electric field strength.

For linear materials, the following relationship applies:

$$\mathbf{D} = \epsilon \mathbf{E} \quad (2)$$

and the Poisson equation takes the form:

$$\nabla^2 V = -\rho / \epsilon \quad (3)$$

where ρ denotes the charge density and ϵ denotes the electrical permittivity of the material. In charge-free regions ($\rho = 0$), the equation simplifies to Laplace's equation:

$$\nabla^2 V = 0 \quad (4)$$

Solving these equations makes it possible to determine the distribution of the electric potential and the electric field strength in the analysed system.

3. Surrogate model in COMSOL Multiphysics®

To create a surrogate model in COMSOL Multiphysics® [4], it is necessary to prepare input data to be used for training deep neural networks. For this purpose, a data table is created that defines the input and output parameters of the network. In our case, the input parameters (shown in Fig. 4) were the coordinates of the points in the computational domain (R, Z), the diameter of the grading ring (D), the diameter of the tube (H) from which the ring is made, and the distance between the ring and the end of the insulator (d) [5]. The output parameters were the voltages at each point within the computational domain. An example of the data table used for training the neural network is presented in Table 1.

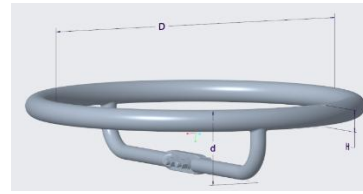


Figure 4. Variable parameters of the grading ring

Table 1. Data for training the neural network

R (mm)	Z (mm)	H (mm)	D (mm)	d (mm)	V (volt)
261.02	-1482.89	28.68	339.21	196.62	271000.02
1931.85	-17.63	28.68	339.21	196.62	256437.21
1414.21	-914.21	28.68	339.21	196.62	265299.38
1586.71	-717.52	28.68	339.21	196.62	263354.80
...	...	...	...	...	...

The next step in developing the surrogate model was to select the number of hidden layers, the number of neurons in each layer, the computational method, the learning rate, the number of epochs, the method for determining the computational error, and other parameters. To date, ten neural network configurations with different numbers of neurons in three hidden layers have been investigated. The number of neurons in each layer varied from 64 to 8 [6], [7] with the number of neurons remaining constant or decreasing from the first to the last hidden layer. The learning rate was set to 0.001, 0.0005, and 0.0001. The number of epochs was set to 1000 in most cases, while in two cases it was set to 5000 and 10,000 epochs. The hyperbolic tangent was used as the activation function for all layers. The Adam optimization algorithm was used. The results of the study are presented in Table 2 in Appendix, which shows the values of the RMSE (Root Mean Squared Error) loss function for the training and validation data.

To obtain a graphical representation of the surrogate model results, a simulation was performed to map the neural network results onto the geometry (Fig. 5 in Appendix). Selected parameters were used, and the simulation results were compared with those obtained from the surrogate model, as described in Chapter 4.

4. Analysis of the Results of the Neural Network Structure Investigation

The results of the study on the surrogate model in COMSOL Multiphysics® are presented in Table 2 in Appendix, which includes the network name (where, if the number of neurons in the hidden layers is the same, the first digit in the name is identical for several networks), the number of neurons in the layers (ranging from 64 to 8), the learning rate (ranging from 0.001 to 0.0001), the training and validation losses, as well as the training time, which varied from approximately 6 to 66 hours.

Figure 5 in Appendix shows, in the first image, the voltage distribution along the insulator with the grading ring obtained from the simulation; in the second and forth images, the result obtained by querying the neural network for the same geometry as that used in the simulation; and in the third and fifth images, the difference between the simulation and neural network results. All results are presented for the case of $H = 30$ mm, $D = 350$ mm, and $d = 150$ mm, which was not included in the training dataset. Figure 6 shows an example of the convergence plot for network 7.1 from Table 2 in Appendix. Analysis of the results shows that increasing the number of neurons in the individual layers improves the accuracy of both training and validation, which is a positive aspect of the model calculations. The training time increases; however, the resulting model can subsequently be queried for parameters for which no direct simulation has been performed. The training and validation errors, as well as the error between the neural network predictions and the simulation results, are low and do not exceed 3%, indicating a high level of network training. Table 2 in Appendix shows that the 5-64-64-64-1 network architecture provides the most accurate results, confirming that a larger number of parameters allows for better fitting to the training data.

Additionally, the computational time of a single simulation can be compared with the time required to query the neural network. A single simulation takes approximately 1–2 minutes, including mesh generation for a model consisting of approximately 5,000 nodes and the assembly of the system of matrix equations. In contrast, querying the trained network for the results at all nodes (assuming approximately 5,000 nodes as well) takes only 80–100 μ s. This represents another significant advantage of using equivalent models for determining the electric field distribution along the insulator string.

5. Conclusions

Among the analysed configurations, the architecture consisting of three hidden layers with 64 neurons each (5-64-64-64-1) achieved the best results, indicating the most favourable compromise between model complexity and prediction accuracy.

The obtained results confirm the high effectiveness of the developed model, with a prediction error not exceeding 3%. At the same time, the use of a neural network enabled a significant reduction in computational time. While a single numerical simulation requires approximately 60 s, the response time of the trained network for a case involving 5,000 nodes is approximately 80 μ s. This corresponds to a computational speedup of several orders of magnitude, demonstrating the high potential for practical application of the proposed approach.

Future research will focus on verifying the possibility of effectively training the model using a smaller training dataset, which could reduce the costs associated with data preparation. Further optimization of the training process is also planned by more precise tuning of the optimizer parameters in order to accelerate algorithm convergence.

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Appendix

Table 2. Results of the Investigation of the Effect of Network Architecture on the Loss Function (RMSE)

Title	Layers	Hidden			Output	Epochs	Learning rate	(training)	(validation)	Training time
	Input	1	2	3				RMSE, $\times 10^{-4}$	RMSE, $\times 10^{-4}$	
Network 1.1	5	64	64	64	1	1000	0,001	7,91264	5,07538	26h 57m 47s
Network 1.2							0,0005	8,02029	4,92833	25h 32m 38s
Network 1.3							0,0001	4,82139	4,15948	26h 43m 25s
Network 2								4,60666	4,02087	23h 21m 42s
Network 3								5,10745	4,53725	27h 46m 56s
Network 4				6,70940				6,32664	27h 23m 17s	
Network 5				9,75385				9,28723	13h 39m 47s	
Network 6				7,28078				6,90153	13h 48m 52s	
Network 7.1			5000	16		7,11651		6,66624	66h 20m 10s	
Network 7.2						10000		6,11320	5,69456	270h 12m 4s
Network 8		16		16	8	1		1000	31,298	31,0871
Network 9			8	1		639,417			640,94	6h 49m 28s
Network 10				1		70,8516			70,7732	9h 58m 35s

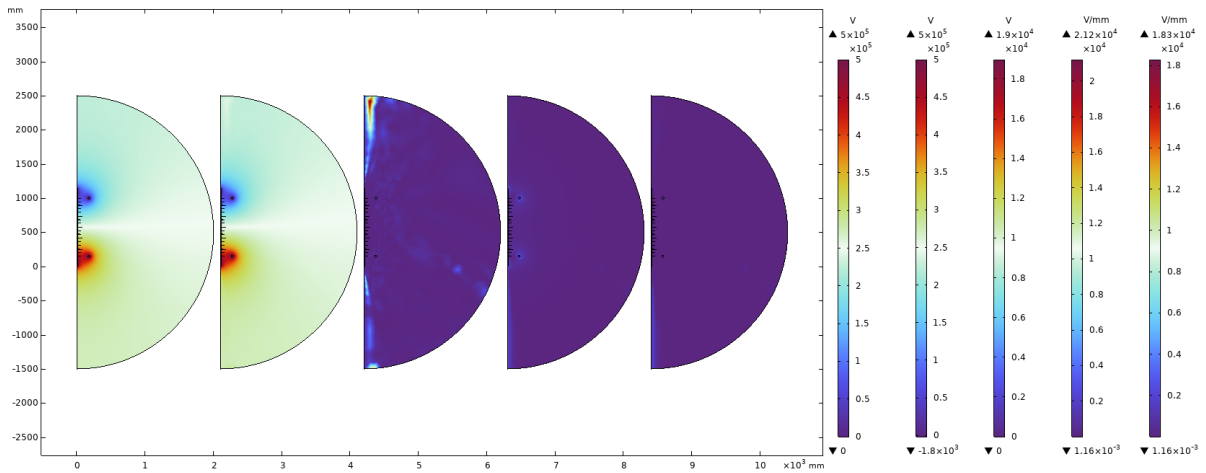


Figure 5. Results of the study for 5,000 epochs (from left to right: voltage distribution obtained from the simulation, voltage distribution calculated using the DNN, difference between the simulation and DNN results for the voltage distribution, electric field strength calculated from the DNN results, and difference between the simulation and DNN results for the electric field strength)

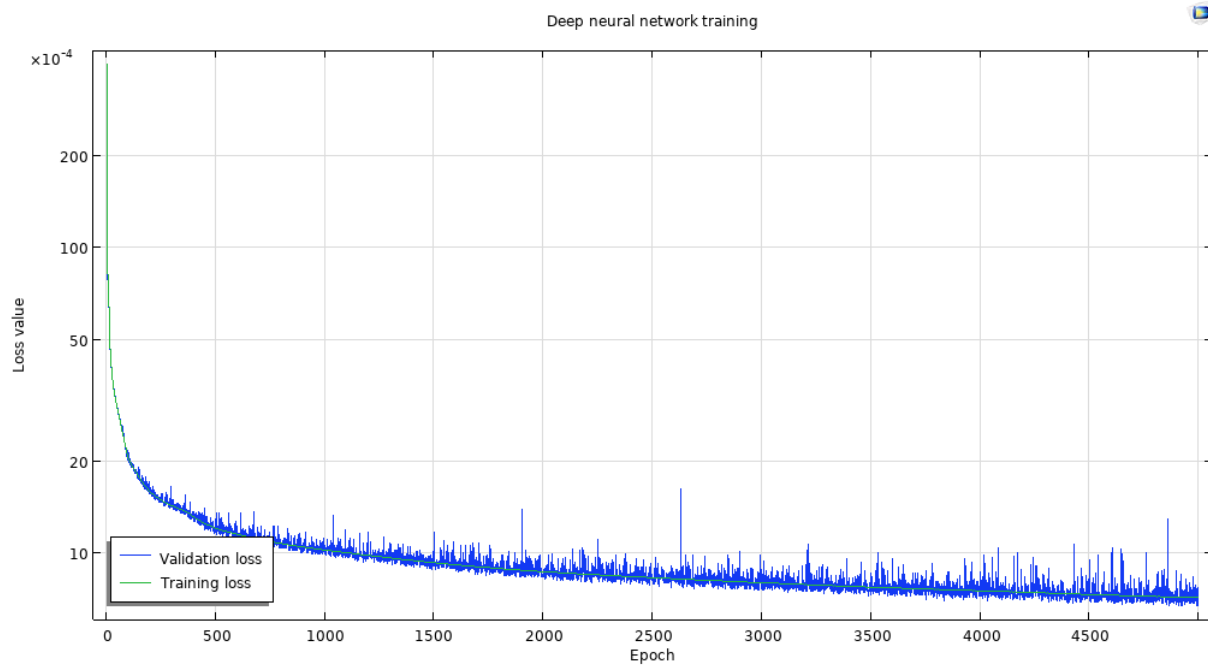


Figure 6. Convergence plot for DNN with layers and neurons 5-64-32-16-1