OPTIMIZATION OF FGM-APPLICATION IN HVDC GIL BASED ON DEEP NEURAL NETWORK

H. Hensel, M. Clemens

Chair of Electromagnetic Theory, University of Wuppertal, Germany
hensel@uni-wuppertal.de

Keywords: HVDC, gas insulated lines (GIL), functionally graded materials (FGM), electric conductivity, deep neural network

Abstract

In HVDC GIL high electric field stress, resulting from space charge accumulation due to DC condition, may appear. Functional graded materials (FGM) are a field control technique to reduce the intensity of the electric field. FGM is realized by a spatial distribution of the electric conductivity in the spacer material by filler particles. In this work, an optimized spatial distribution of the electric conductivity in the spacer material is investigated by numerical simulation and by utilizing a deep neural network (DNN), in order to homogenize the electric field distribution optimally and to decrease the maximum electric field. The results show a decisive reduction of the electric field.

1 Introduction

High voltage direct currents (HVDC) are the key technology to transmit electrical energy over long distance [1]. Additionally, space efficient devices are required in areas where space is limited. A possible solution for these challenges are HVDC gas insulated lines (GIL). GIL have the advantages of high power capacity, low losses, reliability and they provide a compact structure. GIL consist of an insulating gas, a conductor, a grounded enclosure and a massive spacer to sustain the system. As an insulating gas sulfur hexalfluoride (SF_6) or SF_6 mixed with nitrogen (N_2) is mostly in use. The insulating material of the spacer is mostly epoxy resin [2]. Under DC conditions however, space charge accumulation occurs and may lead to local electric field stress in the system. This may lead to partial discharge processes or even system failure [3]. Hence, field control techniques are applied to decrease electric field stress. One such technique are functional graded materials (FGM), which are spatially distributed in the spacer material to obtain a spatial distribution of the electric conductivity [4]. Due to the slow charge accumulation, an electro-quasistatic field occurs, where the electric conductivity of the insulating materials is decisive for the electric field distribution. Thus, higher electric conductivity values at high field stress locations lead to a decrease of the electric field. Numerical simulations allow to investigate these field control techniques. Therefore a simulation model is developed with an optimized spatial distribution of the electric conductivity in the spacer material by using a deep neural network [5]. The paper is organized as follows: after the introduction the simulation approach is examined. Subsequently the simulation results without the application of FGM are presented, followed by the description of the DNN approach and the simulation results with the application of optimized FGM based on the DNN and the conclusion.

2 Results

Due to the axially symmetric arrangement of a GIL, modelling a 2D axisymmetric geometry, which is depicted in Figure 1, is sufficient for realistic simulation results and enables to save numerical costs. The boundary conditions are set as follows: the HV conductor has a potential of $\varphi = 320$ kV and the enclosure is grounded ($\varphi = 0$ kV). In both x-directions Neumann boundary condition is defined, which means in these directions the boundaries are perfectly electrically insulated. Between the HV conductor and the enclosure is a temperature gradient of 35 K. The heat flux is zero at the boundaries in x-direction. The simulations are solved with a stationary solver, using a tolerance-based termination of an iterative solver.

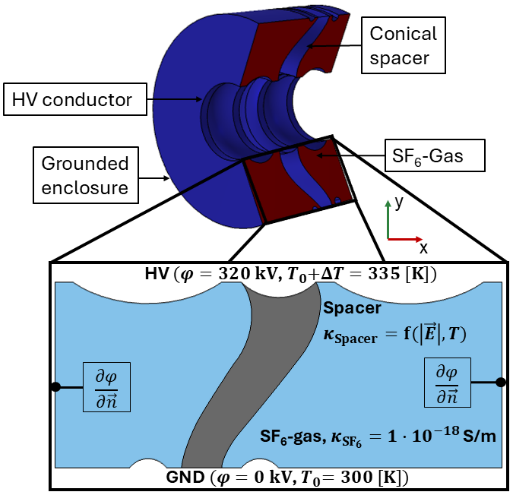

Figure 1: Geometry of the HVDC GIL simulation model.

The electric conductivity of the SF_6-gas is defined with $\kappa_{SF6} = 1 \cdot 10^{-18}$ S/m. The electric conductivity of the spacer material is defined by an empirical nonlinear conductivity model, derived from leakage current measurements of the spacer's epoxy resin material, which fits the measurements results [1]:

$$\kappa(T, |\vec{E}|) = \kappa_0 \exp\left(-\frac{W_A}{k_B T}\right) \exp(\vartheta |\vec{E}|), \qquad (1)$$

where $k_B = 8.617 \cdot 10^{-5}$ eV/K is the Boltzmann constant, $W_\mathrm{A} = 0.095$ the activation energy, κ_0 and ϑ are constants.

2.1 Electric field distribution without FGM

The electric field distribution in the HVDC GIL simulation model without the application of FGM is depicted in Figure 2. Typical for DC condition, the electric field shows an inversion of the field distribution, with higher fields seen at the grounded enclosure and an electric field peak at the triple point between gas, spacer and ground. Here, the maximum electric field value is at 7.91 kV/mm.

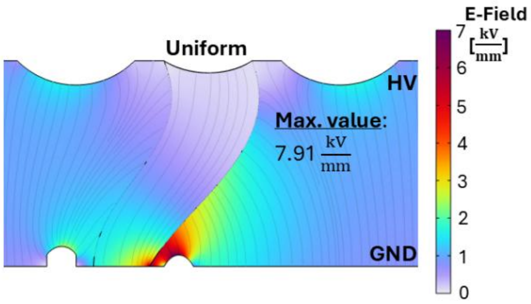

Figure 2: Electric field distribution without FGM.

2.2 Electric field distribution with optimized FGM based on DNN

The FGM is realized in the simulation model by multiplying the electric conductivity model of the spacer material (1) with equation (2), which depends on the radius r:

$$f(r) = [1 + (k_i - 1) \cdot \exp\left(-\frac{r_i - r}{c}\right)] + [1 + (k_a - 1) \cdot \exp\left(\frac{r_a - r}{c}\right)] \quad (2)$$

Equation (2) acts as prefactor function for the model (1) in form of a parabolic function, which represents a typical distribution for FGM [4], where r_i determines the value of the function at the HV side ($r = 0$ m) and r_a the value at the grounded side ($r = 0.35$ m), whereas setting $c = 0.0162$, $k_i = 1.000036$ and $k_a = 1.0102$ leads to a factor of 1 for the prefactor function in the center of the spacer. The DNN is trained by a dataset generated by a surrogate model, where the parameter $\boldsymbol{r_i}$ is varied between 0.081 to 0.2 and $\boldsymbol{r_a}$ between 0.1 and 0.229, which varies the factor of the electric conductivity between 1 and 30 at the HV and grounded side, for 4000 input points. The output is the global maximum electric field value. The DNN is realized with an input layer with 2 input features ($\boldsymbol{r_i}$ and $\boldsymbol{r_a}$) with 32 output features, 2 hidden layers with 16 and 8 output features and the output $\boldsymbol{E}_{\mathbf{max}}$. As an optimization algorithm Adam [6] is set, since it provided the most robust results and efficiency, the learning rate is $1 \cdot 10^{-4}$ and the batch size is set to 512. The loss is calculated by a root-mean-square error function and the DNN passes the training data set in 5500 epochs. The interpolation of the dataset by the DNN results in the lowest maximum electric field value for the parameter $\boldsymbol{r_i}$ = 0.081014 and $\boldsymbol{r_a}$ = 0.15472. The electric field distribution with the application of those parameters is depicted in Figure 3. The electric field distribution is decisively lower and the maximum value of the electric field is decisively reduced from 7.91 kV/mm to 3.44 kV/mm, which is a reduction of 56,5%.

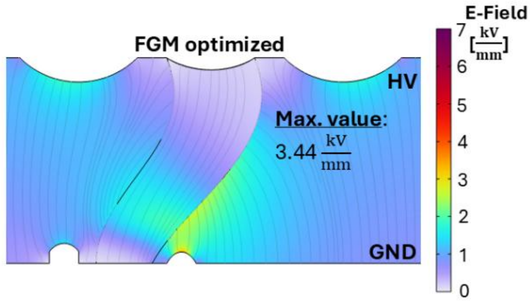

Figure 3: Electric field distribution with the application of optimized FGM based on DNN.

3 Conclusion

An optimization of a spatial electric conductivity distribution in an FGM application for a HVDC GIL simulation model was performed based on a deep neural network. A variation of parameters of the prefactor function, which determines the spatial distribution of the electric conductivity in the spacer material, were used to train the DNN model, with the global maximum electric field value as an output. The optimized parameters were applied in a simulation, with a decisive reduction of the electric field stress and a lower maximum electric field of 56,5%, proving the DNN as a convenient optimization method for FGM applications in numerical simulations.

References

[1] A. Küchler, "High voltage engineering: fundamentals, technology, application", 4th ed., Springer, Germany, 2017.

[2] N. Zebouchi and M. A. Haddad, "A review on real-size epoxy cast resin insulators for compact high voltage direct current gas insulated switchgears (GIS) and gas insulated transmission lines (GIL) – current achievements and envisaged research and development", Energies, (2020).

[3] R. Bodega, "Space charge accumulation in polymeric high voltage DC cable systems", Dissertation, Delft University of Technology, Netherlands, (2006).

[4] N. Hayakawa et. al., "Electric field grading by functionally graded materials (FGM) for HVDC gas insulated power apparatus", IEEE CEIDP, pp. 309-312, 2018.

[5] J. Schmidhuber, "Deep learning in neural networks: an overview", Neural Networks, **Vol. 61**, pp. 85-117, (2015).

[6] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization", 3rd International Conference for Learning Representations, San Diego, USA, (2015).