

# Geometry Optimization of HVDC GIL Spacer by Deep Neural Network

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High voltage direct current gas insulated transmission lines (HVDC GIL) are becoming more relevant due to the transmission to green energy, since GIL enables the transmission of electrical energy over long distances in a compact structure and with a high voltage capacity. However, due to the DC condition, slow charge accumulation in the GIL insulators occur, which may lead to high electric field stress. GIL consists of a high voltage conductor, an insulating gas, an enclosure and a solid spacer to sustain the system. Especially the interface between the insulating gas and the solid spacer is sensitive to space charge accumulation, hence high electric fields, where surface flashover may occur. Therefore the design of the spacer with regard to high electric fields and space charge accumulation is crucial for the safety of the system. Numerical simulations are a convenient tool to investigate the design of the system and its influence on the electric field distribution. In this work a deep neural network is utilized to optimize the geometrical design of the spacer. Numerical simulation results are used to train the deep neural network. The optimization of the geometry of the spacer by the deep neural network results in a significant reduction of the electric field distribution and the maximum electric field value.

*Index Terms*—HVDC, gas insulated transmission lines, spacers, deep neural network

## I. INTRODUCTION

High voltage alternating current (HVAC) GIL is an established technology to transmit electrical energy. The experience with HVDC GIL is limited however and the resulting electro-quasistatic fields due to the DC condition lead to challenges in their technological development. Despite that HVDC GIL have considerable advantages such as compact size, low fault rate and high transmission capacity [1], [2]. The slow charge accumulation under DC fields requires a careful design of the system, since it may lead to partial discharge or even system failure [3]. HVDC GIL consists of an insulating gas, mainly sulfur hexafluoride ( $\text{SF}_6$ ) or  $\text{SF}_6$  mixed with nitrogen ( $\text{N}_2$ ), a solid spacer, which material is mostly epoxy resin filled with alumina ( $\text{Al}_2\text{O}_3$ ) or silica ( $\text{SiO}_2$ ) [1]. Due to different electric properties of these materials, the interface between the insulating gas and the solid material is sensitive to micro-discharges and high electric fields. Since the electric conductivity of the surface of the spacer is different than the bulk conductivity, there tends to be a charge accumulation especially on the surface of the spacer. Therefore the spacer is the most critical component of the HVDC GIL and the geometrical design of the spacer is crucial for a safe design of the system [1], [4], [5]. The geometry of the spacer should be optimized with regards to minimize electric field peaks and local charge accumulation. Hence, the design should avoid high pointed geometries where micro-discharges may occur. Especially at the triple points between gas, solid insulator and the electrodes high electric field values are likely to appear and therefore the design in these vicinities should be optimized to reduce the electric field stress. A possible technique to examine the design of the system is by utilizing numerical simulations and to simulate the electric field distribution in a digital twin model of a HVDC GIL. Here, numerical simulation results are used as training data for a deep neural network (DNN). The purpose of the DNN is to optimize the geometry of the spacer with regard to the electric field.

This work is organized as follows: after the introduction the geometry of the HVDC GIL and the simulation approach are presented, followed by a description of the DNN settings and its training data [6]. Subsequently, the simulation results are shown in form of a comparison of the electric field distribution with an optimized spacer by the DNN and with a conventional spacer, followed by the conclusion.

## II. APPROACH

### A. Geometry model

The geometry of the simulation model for a HVDC GIL is depicted in Fig. 1. The HV conductor has a potential  $\varphi = 320$  kV and the enclosure is grounded ( $\varphi = 0$  kV). In both x-directions Neumann boundary condition is applied, which means in these directions the boundaries are perfectly electrically insulated. The temperature gradient between enclosure and the HV conductor is 40 K. The heat flux is zero in x-direction. The simulations are solved with a stationary solver, using a tolerance-based termination of an iterative solver. The electric conductivity of the  $\text{SF}_6$ -gas is defined with  $\kappa_{\text{SF}_6} = 1 \cdot 10^{-18}$  S/m. The electric conductivity of the spacer material is defined by the nonlinear conductivity model for epoxy resin

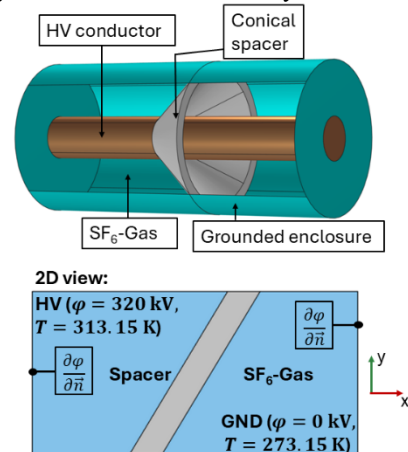


Fig. 1. Geometry of the HVDC GIL simulation model.

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

where  $k_b = 8.617 \cdot 10^{-5}$  eV/K is the Boltzmann constant,  $W_A = 0.095$  J/K·mol the activation energy and  $\kappa_0$  and  $\vartheta$  are constants.

### B. Deep neural network

Here, numerical simulations are used to generate a training data set for the DNN by Latin Hypercube Sampling (LHS) [7]. The topology of the spacer is simulated by an interpolation curve, which is defined by 5 interpolation points. The first and last points of these parameters are constant to define the beginning and the end of the spacer. The 3 middle parameters are optimized by the deep neural network and function as the input parameters. Therefore a dataset is generated by various simulations, where those 3 parameters are varied. For 5000 input points. The interpolation of this data by the DNN leads to the parameters which result in the lowest global maximum electric field within the HVDC GIL ( $E_{\max}$ ), which functions as the output function of the DNN. The DNN is set up with an input layer with 3 input features (3 geometric parameters) with 32 output features, 2 hidden layers with 16 and 8 output features and the output  $E_{\max}$ . The method for the stochastic optimization algorithm is Adam [8], the batch size is set to 512 and the learning rate is  $1 \cdot 10^{-3}$ . The loss is calculated by a root-mean-square error function and the DNN passes the training data set in 5000 epochs. As validation data 10% of the training data is randomly used.

## III. RESULTS

The electric field distribution, simulated with the HVDC GIL model described in section 2, is depicted in Fig. 2. Typically for DC condition, a field inversion occurs, where high electric fields are seen at the grounded enclosure with a maximum electric field of 8.31 kV/mm.

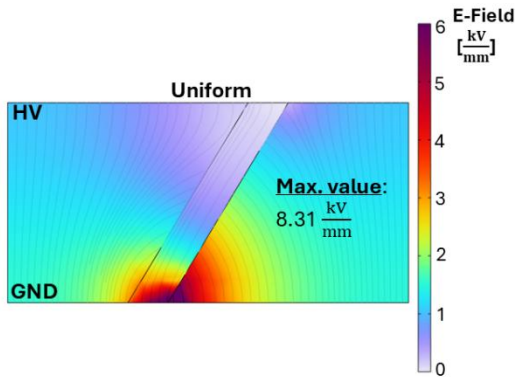


Fig. 2. Electric field distribution without geometric optimization of the spacer.

The electric field distribution with an optimized geometry of the spacer based on parameter optimization by the DNN described in section 2 can be seen in Fig. 3. The spacer features a curved profile and rounded shapes in the vicinity of the triple points to avoid high electric field peaks in these areas. The electric field distribution is lower compared to Fig. 2 and the maximum electric field is reduced from 8.31 kV/mm to 5.71 kV/mm which results in a reduction of 31%.

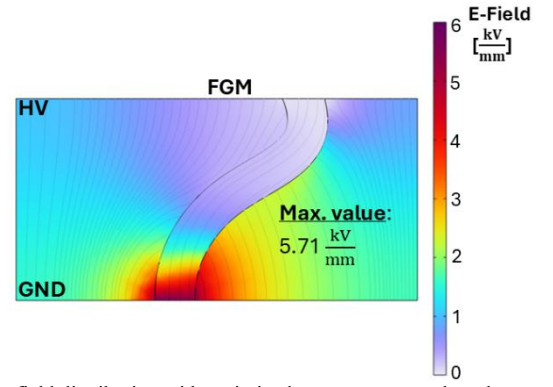


Fig. 3. Electric field distribution with optimized spacer geometry based on DNN.

## IV. CONCLUSION

An optimization of the spacer geometry in a HVDC GIL based on a deep neural network were performed. The parameters of an interpolation curve, which describes the shape of the geometry of the spacer in the simulation model, were varied in a data set to train a deep neural network. The interpolation of the training data by the deep neural network leads to the geometric parameters which result in the lowest global maximum electric field within the HVDC GIL. The application of these parameters result in a decisive reduction of the electric field distribution and the reduction of the maximum electric field by 31%. The geometry of the spacer features a curved and rounded shape, which should be considered for the design of the spacer geometry in HVDC GIL.

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