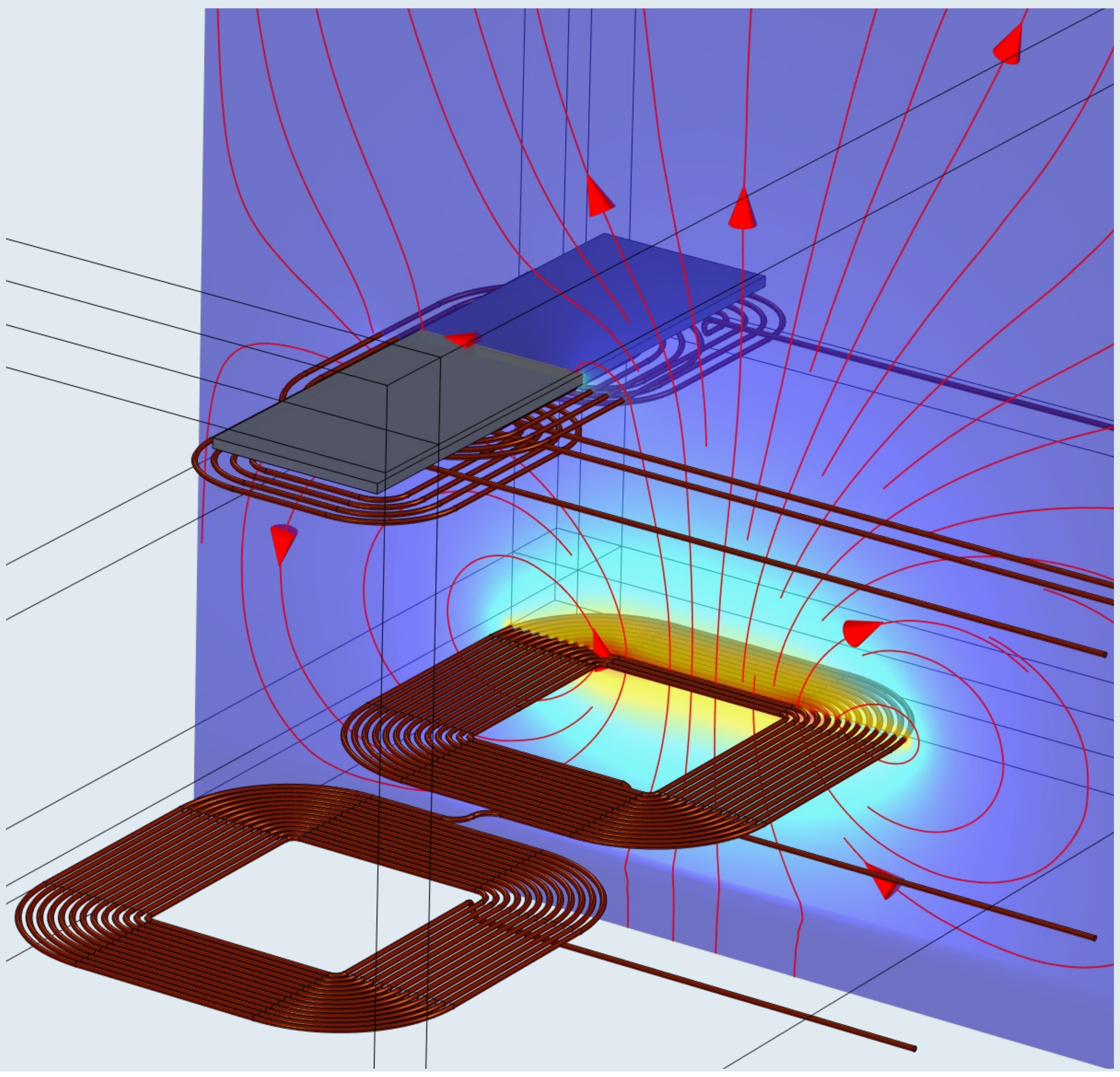

Using Surrogate Models to Predict the Transmission Efficiency of an ERS

3D FEM simulations of an electric road system (ERS) are combined with a deep neural network (DNN).

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3D FEM Simulations

The ERS consists of a transmitter coil integrated into the road and receiver coils underneath an electric vehicle. Accordingly, this technique enables the dynamic charging of the vehicle via inductive power transfer (IPT). To enhance the transmission efficiency, a ferrite plate above the receiver coils can be used to guide the magnetic field.
A multi-scale FEM model of the ERS is built using the AC/DC Module of COMSOL Multiphysics®. The simulation domain consists of the transmitter DD-coil and the receiver DDQ-coils which are surrounded by an air domain (see Figure 1). The transmitter coil is excited by an alternating current (AC), which generates a time-harmonic magnetic field. For the proof of concept, the receiver coils are short-circuited, and the current is used as a measure of the transmission efficiency of the system. In addition, a ferrite plate is considered, which is centered above the receiver coils (see Figure 2).

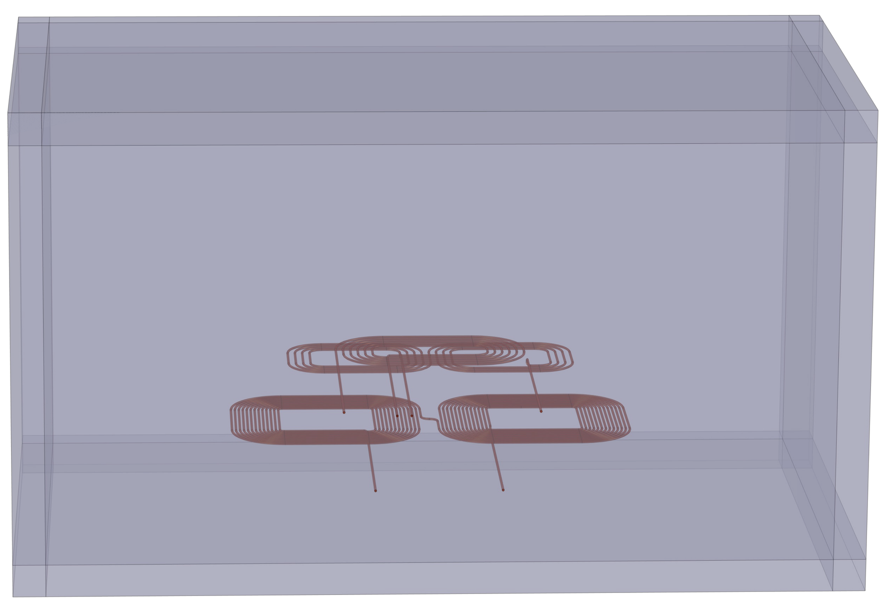

FIGURE 1. The coils are located inside an air domain, which is surrounded by an infinite element domain.

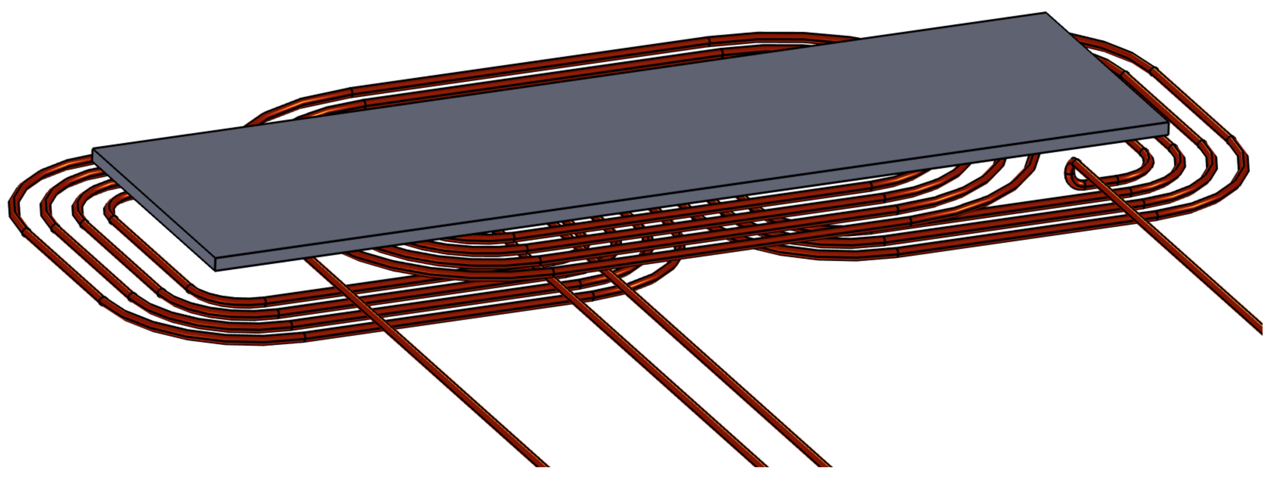

FIGURE 2. Assembly of ferrite plate and receiver coils in the FE model. The lower coil has a DD-shape and the upper coil a Q-shape.

DNN

The 3D FEM model of the ERS is computed many times to generate training data for a deep neural network (DNN). In total, 6 parameters are varied to train the network, namely the dimensions of the ferrite plate (width, length, and thickness) and the relative positions of the transmitter and the receiver coils (the offset in x-, y-, and z-direction). As output parameters, the DNN predicts the mass of the ferrite plate and the currents in both receiver coils. The architecture of the neural network is sketched in Figure 3.

Results & Outlook

In this research, a proof of concept is performed to build a kind of a physics-informed neural network (PINN) by the combination of FEM simulations and DNN. It could be shown that even a PINN with a generic architecture is able to predict the transmission efficiency after the training and validation phase. While the accuracy of the surrogate model is acceptable, the computation time is significantly lower compared to a full FEM simulation. Obviously, the accuracy of the predictions improves with larger training data sets. Additionally, the influence of different hyperparameters of the DNN like the batch size or the learning rate on the performance can be investigated in more detail. Finally, an optimization of the network architecture should lead to a reduction of the training loss and validation loss and significantly improve the PINN performance further. However, if the reliability of this method is ensured, it is a powerful development approach to optimize even a free-shape ferrite core structure in future projects.

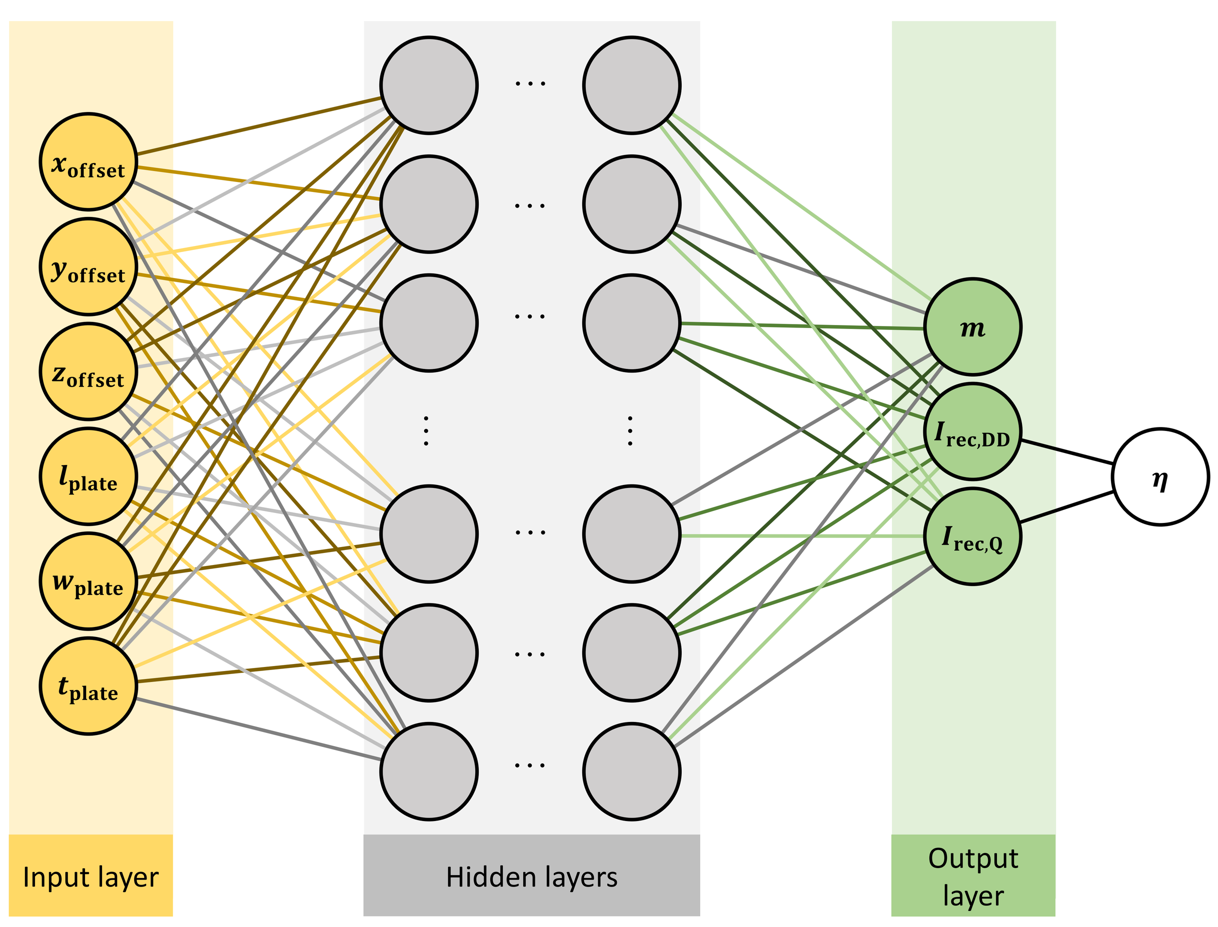

FIGURE 3. The DNN takes 6 inputs and has 3 hidden layers with 10 neurons each. The network outputs 3 parameters.

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