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Deep Neural Networks for the Modelling of Passive Microwave Devices

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Summary

We present a data-driven modelling approach for the scattering parameters of passive microwave devices that is based on fully connected deep neural networks. In addition to the scattering parameters, we use their sensitivities with respect to the material and geometry of the microwave device to train and test the neural network, which allows for significantly smaller data sets. Given that the microwave devices are reciprocal, the sensitivities can be computed (basically) for free and, thus, our approach becomes very efficient. We demonstrate its applicability for two applications: (i) a six-port microwave component intended for inhomogeneous dielectric measurements; and (ii) an H-plane waveguide filter.

1. Introduction

The numerical solution of Maxwell's equations often requires substantial computational resources in terms of floating-point operations and memory requirements. In some applications, it is necessary to compute solutions for a very large number of cases, where the different cases may correspond to problems described by different material parameters and/or geometrical parameters. Given that data for training and testing is available, surrogate models [1] provide a useful complement to the conventional numerical methods applied to Maxwell's equations, such as the Finite-Difference Time-Domain scheme [2] or the Finite Element Method [3]. Such surrogate models have the advantage of (relatively) fast evaluation and small memory requirements. However, conventional surrogate models are often rather limited in their region of validity.

One possibility to extend the region of validity is to use recent advances in deep learning [4]. In this article, we use fully connected deep neural networks to model the scattering parameters of passive microwave devices with respect to the frequency and a substantial number of material/geometry parameters. In particular, we use the finite element method to compute the scattering matrix of the microwave device, where the sensitivities of the scattering parameters with respect to material and geometry is available at (basically) no computational cost as a consequence of the reciprocity of the problem. Thus, it is possible to train and test a deep neural network (and its sensitivities) at a rather low computational cost, which then can be used for the accurate evaluation of the scattering parameters. Since the neural network is very cheap to evaluate and can be executed on graphical processor units (GPUs), it allows for brute-force sampling of the scattering parameters, which can be used to generate statistical data or perform material/shape optimization.

2. Method

The training and test data is generated by means of the finite element method, where we compute the scattering parameters as a function of the frequency for a large number of cases that feature different material/geometry parameters. These computations can be performed in parallel on a cluster and, here, we used the resources available at Chalmers Center for Computational Science and Engineering. To make this procedure practically feasible, we introduce a finite-dimensional representation of the material/geometry for the microwave device and sample this design space in a region of interest. For each sample, we compute the sensitivities for the microwave device with respect to all the material/geometry parameters.

Next, we train a fully connected deep neural network given a loss function that combines the loss with respect to both (i) the scattering parameters themselves and (ii) their sensitivities. This makes it possible to train a deep network with fewer data samples, as compared to the case without sensitivity information. Finally, we assess the accuracy of the neural network by means of a test data set.

3. Results

As test examples, we consider two passive microwave devices: (i) a six-port microwave component intended for inhomogeneous dielectric measurements; and (ii) an H-plane waveguide filter with five cavities. We generate stochastic distributions for the scattering parameters given a stochastic dielectric medium in the six-port microwave component, where the evaluation on GPUs is essential to resolve the high-dimensional probability density function. For the microwave filter, we perform optimization by brute-force sampling of the parameter space, where the figures below show the reflection coefficient and geometry for an optimized microwave filter together.

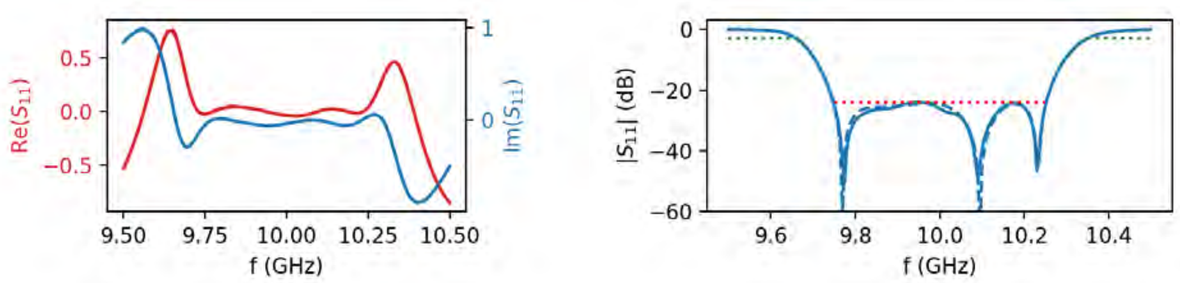

Figure 1. Reflection coefficient for H-plane waveguide filter optimized by means of a deep neural network model: solid curves – neural network; and dashed curves – finite element method. The figure to the right shows (by dotted horizontal lines) the masks that define the objective function for the filter.

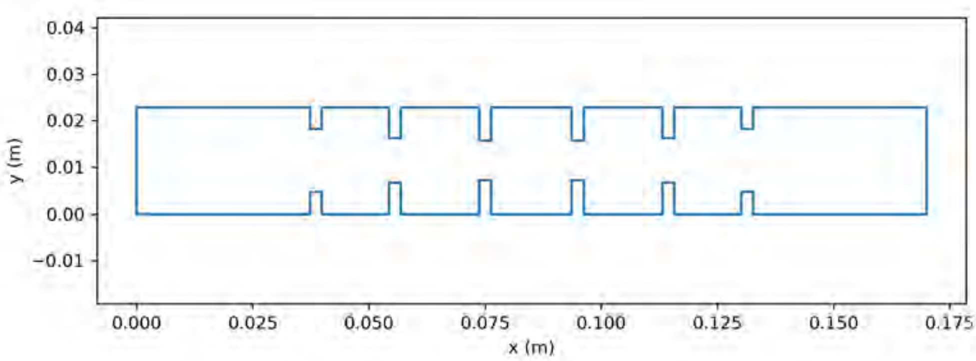

Figure 2. Geometry of the optimized H-plane waveguide filter, where the optimization is performed based on a deep fully connected neural network.

Tests demonstrate that the information embedded in the neural network is indeed much richer than the data used for training and testing. As an example, the neural network that models the scattering parameters of the waveguide filter can find substantially better designs than any of the samples that are present in the train and test data set.

4. Conclusions

We use deep neural networks to demonstrate their applicability for the scattering parameter modelling of passive microwave devices. During the training of the neural networks, we exploit both the scattering parameters and their sensitivities to formulate a combined loss function, which dramatically reduces the number of samples needed for the training data set. As a consequence, a limited and comparatively small computational cost can be devoted to the generation of train and test data. Given the agnostic construction of the neural network, we expect that this approach in combination with measurement data can be applied to numerous electromagnetic devices that may be very difficult and challenging to model based on a first-principles approach starting with Maxwell's equations.

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