Software Implementation of Space Mapping Based Neuromodels of Microwave Components

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Space Mapping Based Neuromodeling

In modeling microwave components using Artificial Neural Networks (ANN), the learning data is obtained from a detailed or "fine" model (typically an EM simulator), which is accurate but slow to evaluate. This is aggravated because simulations are needed for many combinations of input parameter values. We use available equivalent circuits or "coarse" models to overcome this limitation.

In the Space Mapping (SM) based neuromodeling techniques [1] an ANN is used to implement a suitable mapping from the fine to the coarse input space. The implicit knowledge in the coarse model not only allows us to decrease significantly the number of learning points needed, but also to reduce the complexity of the ANN and to improve the generalization performance. Once the ANN is trained, an SM based neuromodel for fast, accurate evaluations is available.

Including Frequency in the Neuromapping

Many empirical models are based on quasi-static analysis: they usually yield good accuracy over low frequencies. We overcome this limitation through a frequency-sensitive mapping from the fine to the coarse parameter space. This is realized by considering frequency as an extra input variable of the ANN that implements the mapping. The Frequency Space-Mapped Neuromodeling (FSMN) technique establishes a frequency-sensitive mapping not only for the design parameters but also for the frequency variable, such that the coarse model is simulated at a mapped frequency f_c to match the fine model response. This is realized by adding an extra output to the ANN that implements the mapping. Three additional techniques to efficiently create frequency-sensitive neuromappings are proposed in [1].

SM Based Neuromodel of a Microstrip Right Angle Bend

Consider a microstrip right angle bend with conductor width W, substrate height H, substrate dielectric constant ε_r, and operating frequency *freq*. An FSMN model is developed for the following region of interest: 20mil $\leq W \leq$ 30mil, 8mil $\leq H \leq$ 16mil, $8 \leq \varepsilon_r \leq 10$, and 1GHz $\leq$ *freq* $\leq$ 41GHz.

Sonnet's ***em***™ [2] is used as the fine model. To evaluate the generalization performance of our neuromodel, 50 random test base-points with uniform statistical distribution within the region of interest are generated using a frequency step of 2 GHz (1050 test samples). Following a star distribution for the learning points [1], only 7 base points are used for learning (147 learning samples).

Gupta's model is taken as the "coarse" model [1]. Fig. 1a illustrates the FSMN neuromodeling strategy for the microstrip bend, which was implemented using *NeuroModeler* [3] as shown in Fig. 1b. The FSMN model as implemented in *NeuroModeler* consists of a total of 6 layers. The first layer, shown in green color, has the input parameters of the neuromapping (W, H, ε_r, and *freq*), which are scaled to ±1 to improve the numerical behavior during training. The second layer from bottom to top corresponds to the hidden layer of the ANN implementing the mapping (see Fig. 1b): optimal generalization performance is achieved with 8 hidden neurons with sigmoid non-linearities. The third layer is linear and contains the coarse design parameters and the mapped frequency f_c before de-scaling. The fourth layer is added to simply de-scale the parameters. Gupta's formulas to calculate L and C are programmed as the internal analytical functions of the fifth hidden layer, using the built-in MultiSymbolicFixed function. Finally, the output layer, shown in blue color, contains a simple internal circuit simulator that computes the real and imaginary parts of S_{11} and S_{21} for the lumped LC equivalent circuit. This layer uses the built-in CktSimulatorPS function.

Fig. 2 shows the learning and testing errors of the bend FSMN model after training using *NeuroModeler*. Conjugate Gradient and Quasi Newton built-in training methods are used. The average and worst case learning errors are 0.43% and 1.00%, while the average and worst-case testing errors are 1.04% and 10.94%. Excellent generalization performance is achieved.

The FSMN model of the right angle bend can now be used in Agilent ADS for fast and accurate simulations within the region of interest: it can be entered as a user-defined model through the plug-in module *NeuroADS* [4].

Conclusions

We present novel realizations of SM based neuromodels of practical passive components using available software. A Frequency Space-Mapped Neuromodel (FSMN) of a microstrip right angle bend is implemented using *NeuroModeler*, and entered into ADS as a library component through an ADS plug-in module.

Acknowledgement

The authors thank Dr. J.C. Rautio, President, Sonnet Software, Inc., Liverpool, NY, for making ***em***™ available.

References

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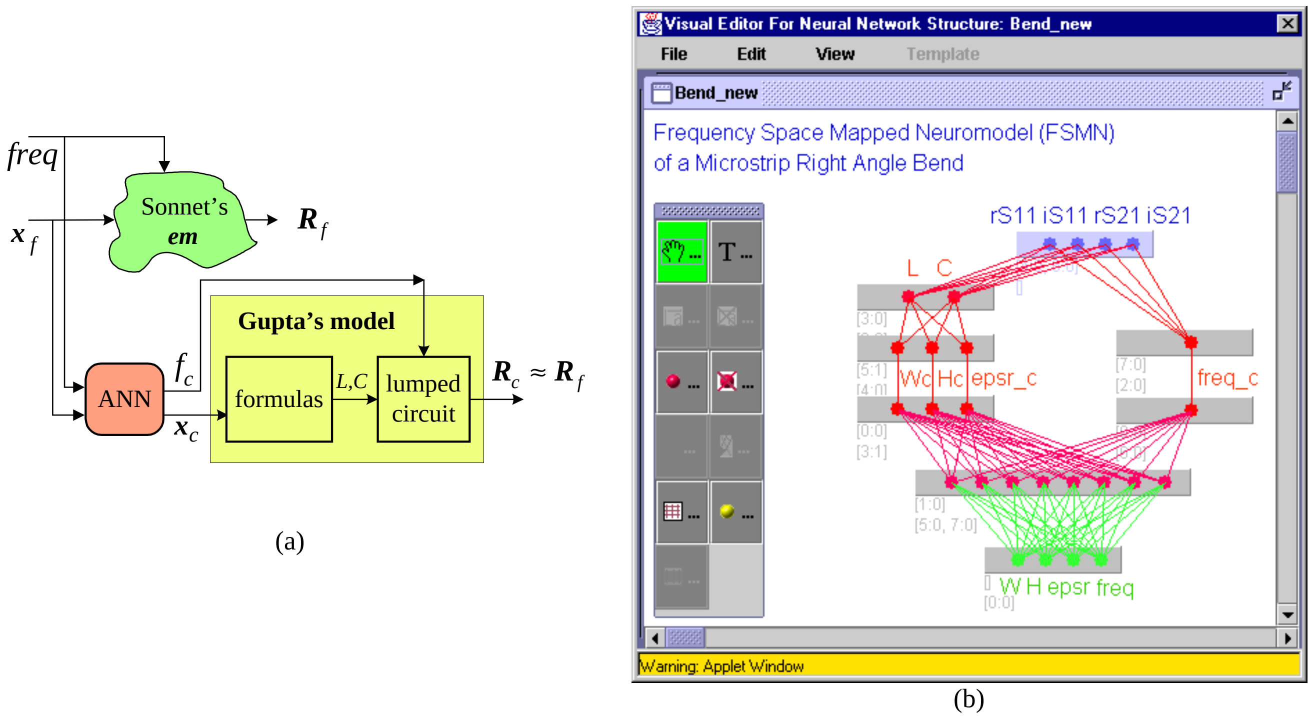

Fig. 1. Frequency Space-Mapped Neuromodel (FSMN) of a microstrip right angle bend: (a) strategy, (b) implementation in *NeuroModeler*.

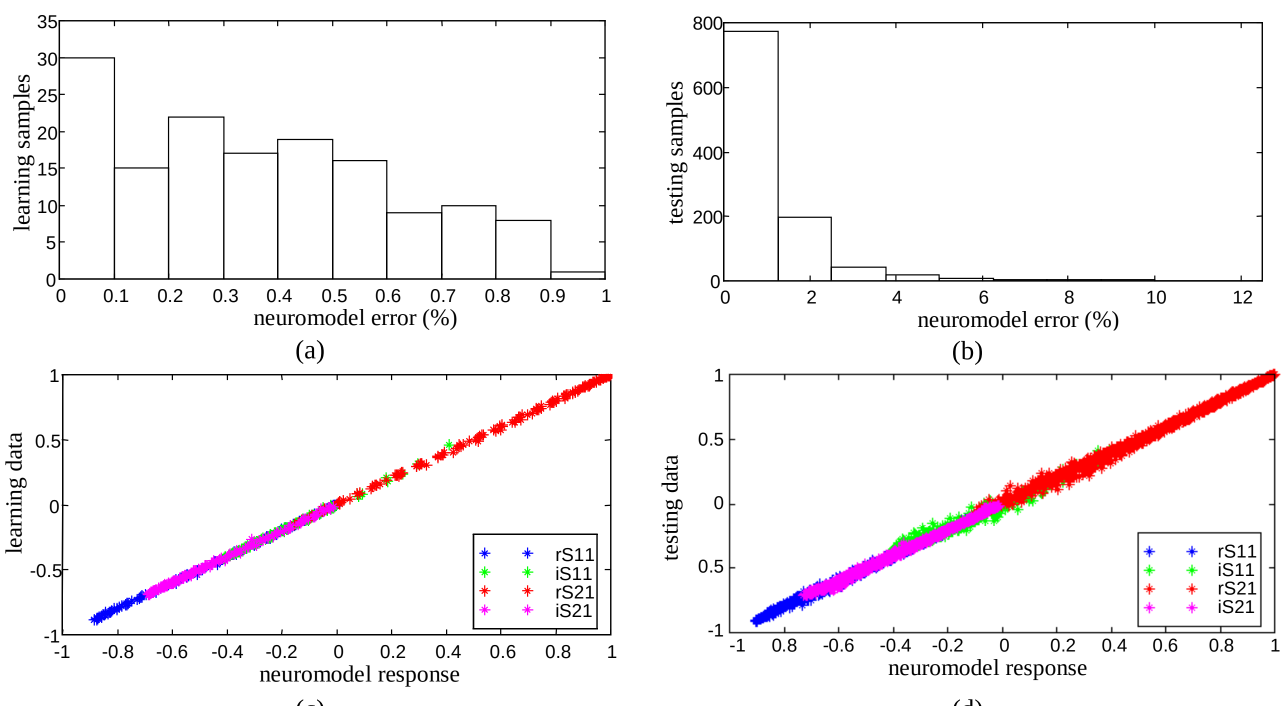

Fig. 2. Learning and testing errors of the FSMN model after training: (a) histogram of learning errors, (b) histogram of testing errors, (c) correlation to learning data, and (d) correlation to testing data.