Space Mapping Based Neuromodeling

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Abstract

A powerful concept in neuromodeling of microwave circuits based on Space Mapping technology is described. The ability of Artificial Neural Networks (ANN) to model high-dimensional and highly nonlinear problems is exploited in the implementation of the Space Mapping concept. By taking advantage of the vast set of empirical models already available for many microwave structures, Space Mapping based neuromodels decrease the number of EM simulations for training, improve the generalization and extrapolation performance and reduce the complexity of the ANN topology with respect to the conventional neuromodeling approach.

Five innovative techniques are proposed to create Space Mapping based neuromodels for microwave circuits: Space Mapped Neuromodeling (SMN), Frequency-Dependent Space Mapped Neuromodeling (FDSMN), Frequency Space Mapped Neuromodeling (FSMN), Frequency Mapped Neuromodeling (FMN) and Frequency Partial-Space Mapped Neuromodeling (FPSM). Excepting SMN, all these approaches establish a frequency-sensitive neuromapping to expand the frequency region of accuracy of the empirical models already available for microwave components that were developed using quasi-static analysis.

We contrast our approach with the conventional neuromodeling approach employed in the microwave arena, as well as with other state-of-the-art neuromodeling techniques. We use Huber optimization to efficiently train the simple ANN that implements the mapping in our SM-based neuromodels.

The five space mapping based neuromodeling techniques are illustrated by two case studies: a microstrip right angle bend and a high-temperature superconducting (HTS) quarter-wave parallel coupled-line microstrip filter.
Outline

conventional ANN approach for microwave modeling

neuromodeling using existing knowledge

SM-based neuromodeling

examples

other applications of SM-based neuromodeling

conclusions
Artificial Neural Networks (ANN) Modeling

Artificial Neural Networks are suitable in modeling high-dimensional and highly nonlinear problems

ANN models are computationally efficient and more accurate than empirical models

multilayer feedforward networks can approximate any measurable function to any desired level of accuracy, provided a deterministic relationship between input and target exists \((White \ et \ al., \ 1992)\)

ANNs that are too small cannot approximate the desired input-output relationship

ANNs with too many internal parameters perform correctly in the learning set, but give poor generalization ability

ANNs are suitable models for microwave circuit optimization and statistical design \((Zaabab, \ Zhang \ and \ Nakhla, \ 1995, \ Gupta \ et \ al., \ 1996, \ Burrascano \ and \ Mongiardo, \ 1998, \ 1999)\)
Conventional ANN Modeling Approach

many fine model simulations are usually needed

the number of learning samples needed to approximate a function grows exponentially with the ratio of the dimensionality to the function’s degree of smoothness (Stone, 1982)

the reliability of multi-layer perceptrons for extrapolation is poor

introducing knowledge can alleviate these limitations
Hybrid “∆S” EM-ANN Neuromodeling Concept

(Gupta et al., 1996)
PKI Neuromodeling Concept
(Gupta et al., 1996)

\[
\omega \rightarrow \text{fine model} \rightarrow R_f \\
\omega \rightarrow x_f \rightarrow \text{coarse model} \rightarrow R_c \approx R_f \\
\omega \rightarrow x_f \rightarrow \text{PKI model} \rightarrow \text{ANN} \rightarrow R_f \\
\omega \rightarrow x_f \rightarrow \text{coarse model} \rightarrow R_c \approx R_f
\]
KBNN Neuromodeling Concept

(Zhang et al., 1997)
Exploiting Space Mapping for Neuromodeling

(Bandler et. al., 1999)

\[ Z_c = f(w) \]

\[ X_c = \nabla D \]

\[ \omega_c = -\nabla E \]

\[ B = \mu H \]

\[ \nabla D = \rho \]

\[ \nabla \times H = j \omega D + J \]

\[ \nabla \times E = j \omega B \]

\[ \nabla \cdot B = 0 \]

\[ \nabla \cdot D = 0 \]

fine model \[ R_f(x_f, \omega) \]

coarse model \[ R_c(x_c, \omega_c) \]

find

\[
\begin{bmatrix}
    x_c \\
    \omega_c
\end{bmatrix} = P(x_f, \omega)
\]

such that

\[ R_c(x_c, \omega_c) \approx R_f(x_f, \omega) \]
Space Mapping Based Neuromodeling

(Bandler et. al., 1999)
Neuromappings

Space Mapped neuromapping

Frequency-Dependent Space Mapped neuromapping
Neuromappings (continued)

Frequency Mapped neuromapping

Frequency Space Mapped neuromapping
Neuromappings (continued)

Frequency Partial-Space
Mapped neuromapping

it is not always necessary to map the whole set of design parameters

coarse model sensitivities can be used to select the mapped parameters
Training the SM-Based Neuromodel

\[ w^* = \arg \min_w \left\| \begin{bmatrix} \cdots & e_s^T & \cdots \end{bmatrix}^T \right\| \]

\[ e_s = R_f(x_{f(l)}, \omega_j) - R_c(x_{c_j(l)}, \omega_{c_j}) \quad e_s \in \Re^r \]

\[
\begin{bmatrix}
  x_{c_j(l)} \\
  \omega_{c_j}
\end{bmatrix} = P(x_{f(l)}, \omega_j, w)
\]

\[ j = 1, \ldots, F_p \quad l = 1, \ldots, 2n + 1 \quad s = j + F_p (l - 1) \]

\( r \) is the number of responses in the model

\( P \) is the neuromapping function and \( w \) contains the free parameters of the ANN

\( 2n+1 \) is the number of training base points and \( F_p \) is the number of frequency points

Huber optimization is used to solve this problem
Starting Point and Learning Samples

we chose a unit mapping ($x_c \approx x_f$ and $\omega_c \approx \omega$) as the starting point for the optimization problem

$2n+1$ points are used for a microwave circuit with $n$ design parameters
Microstrip Right Angle Bend

region of interest
20mil $\leq W \leq 30$mil
8mil $\leq H \leq 16$mil
8 $\leq \varepsilon_r \leq 10$
1GHz $\leq \omega \leq 41$GHz

“coarse” model: equivalent circuit model \((Gupta, Garg and Bahl, 1979)\)

“fine” model: Sonnet’s \(em\)\(^{TM}\)

learning set: 7 base points with “star” distribution
Microstrip Right Angle Bend Coarse Model Errors

comparison between $em^{TM}$ and coarse model at 50 random test points
SM Neuromodel for the Right Angle Bend (3LP:3-6-3)

\[ x_f = [W \ H \ \epsilon_r]^T \]
SM Neuromodel Results for the Right Angle Bend

comparison between \textit{em}™ and the SM neuromodel
FDSM Neuromodel for the Right Angle Bend (3LP:4-7-3)

\[ \mathbf{x}_f = [W \ H \ \varepsilon_r]^T \]
FDSM Neuromodel Results for the Right Angle Bend

comparison between $em^{TM}$ and the FDSM neuromodel
FSM Neuromodel for the Right Angle Bend (3LP:4-8-4)

\[ x_f = [W \ H \ \varepsilon_r]^T \]
FSM Neuromodel Results for the Right Angle Bend

comparison between $em^{TM}$ and the FSM neuromodel
Implementations in *NeuroModeler*

SM based neuromodels of several microstrip circuits have been developed using *NeuroModeler* version 1.2b (1999) they are entered into HP ADS version 1.1 (1999) as library components through an ADS plugin module.
HTS Quarter-Wave Parallel Coupled-Line Microstrip Filter
(Westinghouse, 1993)

region of interest

175mil \leq L_1 \leq 185mil
190mil \leq L_2 \leq 210mil
175mil \leq L_3 \leq 185mil
18mil \leq S_1 \leq 22mil
75mil \leq S_2 \leq 85mil
70mil \leq S_3 \leq 90mil
3.901GHz \leq \omega \leq 4.161GHz

L_0 = 50mil
H = 20mil
W = 7mil
\varepsilon_r = 23.425
loss tangent = 3 \times 10^{-5}

\mathbf{x}_f = [L_1 \ L_2 \ L_3 \ S_1 \ S_2 \ S_3]^T
HTS Microstrip Filter: Fine and Coarse Models

fine model:
Sonnet’s $em^{TM}$ with high resolution grid

coarse model:
OSA90/hope$^{TM}$ built-in models of open circuits, microstrip lines and coupled microstrip lines
HTS Filter Responses Before Neuromodeling

responses using $em^{TM}$ (●) and OSA90/hope$^{TM}$ (−) at three learning and three test points
HTS Coarse Model Error w.r.t. $em^\text{TM}$ before any Neuromodeling

in the learning set

learning set: 13 base points with “star” distribution

in the testing set

testing set: 7 random base points in the region of interest (not seen in the learning set)
FM Neuromodel for the HTS Filter (3LP:7-5-1)

\[ x_f = [L_1 L_2 L_3 S_1 S_2 S_3]^T \]
FM Neuromodel for the HTS Filter (3LP:7-5-1)

responses using \textit{em}^{TM} (•) and FMN model (−) at the three learning and three testing points
HTS FM Neuromodel Error w.r.t. em™

in the learning set

in the testing set
FPSM Neuromodel for the HTS Filter (3LP:7-7-3)

\[ x_f = [L_1 L_2 L_3 S_1 S_2 S_3]^T \quad x_f^\cdot = [L_2 L_3 S_2 S_3]^T \quad x_c^\cdot = [L_{1c} S_{1c}]^T \]
FPSM Neuromodel for the HTS Filter (3LP:7-7-3)

responses using \textit{em}^{TM} (●) and FPSMN model (─) at the three learning and three testing points
HTS FPSM Neuromodel Error w.r.t. $em^\text{TM}$

in the learning set

in the testing set
FPSM Neuromodel for the HTS Filter: Fine Frequency Sweep Results

Comparison between $em^\text{TM}$ (●) and FPSMN model (−) at two learning and one testing points.
Other Applications of SM based Neuromodels
(Bandler et al., 2000, 2001)

Neural Space Mapping (NSM) Optimization

EM-based Statistical Analysis

EM-based Yield Optimization

Neural Inverse Space Mapping (NISM) Optimization
Conclusions

we describe novel applications of Space Mapping technology to neuromodeling

five powerful SM based neuromodeling techniques are described

describe these techniques

- exploit the vast set of available empirical models
- decrease the fine model evaluations needed for training
- improve generalization ability
- reduce complexity of the ANN topology

w.r.t. classical neuromodeling

frequency-sensitive neuromappings expand the usefulness of empirical quasi-static models

Space Mapping based neuromodels can be exploited for efficient EM optimization, statistical analysis and yield optimization
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