NEURAL SPACE MAPPING EM OPTIMIZATION OF MICROWAVE STRUCTURES

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Artificial Neural Networks (ANN) in Microwave Design

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)

once they are trained, the neuromodels can be used for optimization within the region of training

the principal drawback of this ANN optimization approach is the cost of generating sufficient learning samples

the extrapolation ability of neuromodels is very poor, making unreliable any solution predicted outside the training region

introducing knowledge can alleviate these limitations (Gupta et al., 1999)
Conventional ANN Optimization Approach

step 1

\[ \omega \]

\[ x_f \]

\[ \text{fine model} \]

\[ R_f \]

\[ \approx R_f \]

\[ w \]

\[ \omega \]

\[ x_f \]

\[ \text{ANN} \]

\[ \approx R^* \]

many fine model simulations are usually needed
solutions predicted outside the training region are unreliable
Neural Space Mapping (NSM) Optimization

exploits the SM-based neuromodeling techniques  
(Bandler et al., 1999)

coarse models are used as sources of knowledge that reduce the amount of learning data and improve the generalization and extrapolation performance

NSM requires a reduced set of upfront learning base points

the initial learning base points are selected through sensitivity analysis using the coarse model

neuromappings are developed iteratively: their generalization performance is controlled by gradually increasing their complexity starting with a 3-layer perceptron with 0 hidden neurons
Neural Space Mapping (NSM) Optimization Concept

step 1

$\omega \rightarrow R_c \approx R^*$

coarse model

$\mathbf{x}_c \rightarrow \mathbf{x}_c^*$

$\mathbf{x}_c^*$

step 2

(2n + 1 learning base points for a microwave circuit with n design parameters)
Neural Space Mapping (NSM) Optimization Concept (continued)

step 3

\[ \omega \rightarrow \text{fine model} \rightarrow R_f \]

\[ x_f \]

\[ \omega_c \rightarrow \text{coarse model} \rightarrow R_c \approx R_f \]

\[ w \]

\[ x_f^{(new)} \]

step 4

\[ \omega \rightarrow \text{neuro-mapping} \rightarrow \omega_c \rightarrow \text{coarse model} \approx R^* \]

\[ x_f \rightarrow x_c \]
Neuromappings

Space Mapped neuromapping

Frequency-Dependent Space Mapped neuromapping

\[ \omega \xrightarrow{x_f} P_{SM} \xrightarrow{} \omega_c \]

\[ \omega \xrightarrow{x_f} P_{FDSM} \xrightarrow{} \omega_c \]
Neuromappings (continued)

Frequency Mapped neuromapping

Frequency Space Mapped neuromapping
Neuromappings (continued)

Frequency Partial-Space
Mapped neuromapping

\[
P_{\text{FPSM}}
\]
Neural Space Mapping (NSM) Optimization Algorithm

Start

**COARSE OPTIMIZATION:** find the optimal coarse model solution \( x_c^* \) that generates the desired response \( R^* \)

\[
R_c(x_c^*) = R^*
\]

Form a learning set with \( B_p = 2n+1 \) base points, by selecting \( 2n \) additional points around \( x_c^* \), following a star distribution.

Choose the coarse optimal solution as a starting point for the fine model

\[
x_f^* = x_c^*
\]

Calculate the fine response \( R_f(x_f) \)

SM BASED NEUROMODELING: Find the simplest neuromapping \( P \) such that

\[
R_f(x_f^{(l)}, \omega) \approx R_c(P(x_f^{(l)}, \omega))
\]

\( l = 1, ..., B_p \) and \( j = 1, ..., F_p \)

Include the new \( x_f \) in the learning set and increase \( B_p \) by one

**SMBNM OPTIMIZATION:** Find the optimal \( x_f \) such that

\[
R_{SMBN}(x_f) = R_c(P(x_f)) \approx R^*
\]

End

yes \( R_f(x_f) \approx R^* \) no

Update \( x_f \)
we take $L_0 = 50$ mil, $H = 20$ mil, $W = 7$ mil, $\varepsilon_r = 23.425$, loss tangent $= 3 \times 10^{-5}$; the metalization is considered lossless

the design parameters are

$$x_f = [L_1 \ L_2 \ L_3 \ S_1 \ S_2 \ S_3]^T$$
NSM Optimization of the HTS Microstrip Filter

specifications

\[ |S_{21}| \geq 0.95 \text{ for } 4.008 \text{ GHz} \leq f \leq 4.058 \text{ GHz} \]
\[ |S_{21}| \leq 0.05 \text{ for } f \leq 3.967 \text{ GHz} \text{ and } f \geq 4.099 \text{ GHz} \]

“fine” model: Sonnet’s em™ with high resolution grid

“coarse” model: OSA90/hope™ built-in models of open circuits, microstrip lines and coupled microstrip lines
NSM Optimization of the HTS Filter (continued)

coarse and fine model responses at the optimal coarse solution

OSA90/hope™ (−) and em™ (●)
NSM Optimization of the HTS Filter (continued)

the initial $2n+1$ points are chosen by performing sensitivity analysis on the coarse model: a 3% deviation from $x_c^*$ for $L_1$, $L_2$, and $L_3$ is used, while a 20% is used for $S_1$, $S_2$, and $S_3$. 

coarse and fine model responses at base points

![Graphs showing the response of $S_{21}$ in dB for different frequencies.](image)

**OSA90/hope**

**em**
NSM Optimization of the HTS Filter (continued)

learning errors at base points

before any neuromapping

mapping $\omega, L_1$ and $S_1$ with a 3LP:-7-5-3
NSM Optimization of the HTS Filter (continued)

fine model response (●) at the next point predicted by the first NSM iteration and optimal coarse response (−)

(3LP:7-5-3, ω, L₁, S₁)
Bandstop Microstrip Filter with Quarter-Wave Open Stubs

we take $H = 25$ mil, $W_0 = 25$ mil, $\varepsilon_r = 9.4$ (alumina)

the design parameters are $x_f = [W_1 \ W_2 \ L_0 \ L_1 \ L_2]^T$
NSM Optimization of the Bandstop Filter

specifications

\[ |S_{21}| \leq 0.05 \text{ for } 9.3 \text{ GHz} \leq f \leq 10.7 \text{ GHz} \]
\[ |S_{21}| \geq 0.9 \text{ for } f \leq 8 \text{ GHz} \text{ and } f \geq 12 \text{ GHz} \]

“fine” model: Sonnet’s em™ with high resolution grid

“coarse” model: transmission line sections and empirical formulas
NSM Optimization of the Bandstop Filter (continued)

coarse and fine model responses at the optimal coarse solution

coarse model (−) and \textit{em}™ (●)

the initial \(2n+1\) points are chosen by performing sensitivity analysis on the coarse model: a 50\% deviation from \(x^*_c\) for \(W_1, W_2,\) and \(L_0\) is used, while a 15\% is used for \(L_1,\) and \(L_2\)
NSM Optimization of the Bandstop Filter (continued)

fine model response (●) at the next point predicted by the second NSM iteration and optimal coarse response (−)

\[(3\text{LP:6-3-2}, \omega, W_2)\]
Conclusions

we present an innovative algorithm for EM optimization based on Space Mapping technology and Artificial Neural Networks

Neural Space Mapping (NSM) optimization exploits our SM-based neuromodeling techniques

an initial mapping is established by performing upfront fine model analysis at a reduced number of base points

coarse model sensitivity is exploited to select those base points

Huber optimization is used to train simple SM-based neuromodels at each iteration

the SM-based neuromodels are developed without using testing points: their generalization performance is controlled by gradually increasing their complexity starting with a 3-layer perceptron with 0 hidden neurons