EM-Based Statistical Analysis and Yield Estimation Using Linear-Input and Neural-Output Space Mapping

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Outline

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- LINO-SM approach to yield estimation
- Constrained Broyden-Based Space Mapping
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EM-based Statistical Analysis

- Statistical analysis and yield prediction are crucial for manufacturability
- Reliable yield prediction typically requires massive amount of high-fidelity simulations (full-wave EM simulations)
- Performing Monte Carlo yield analysis by directly using EM simulations is not feasible for most practical problems
- We propose using linear-input neural-output space mapping

Input Space Mapping

\[ R_f(x_f, \psi) \]

\[ R_c(x_c, \psi) \]

\[ R_f(x_f, \psi) \approx R_c(x_c^*, \psi) \]

\[ R_c(P(x_f^{SM})) \] can not accurately estimate the fine model yield around \( x_f^{SM} \)
**Linear-Input Neural Output Space Mapping**

\[ Q(R_c(P(x_f), \psi), x_f, \psi, w^*) = R_f(x_f, \psi) \]

for all \( x_f \) and \( \psi \) in the training region

**LINO-SM approach to Yield Estimation**

1. **Start**
2. Obtain \( x_f^* \) by optimizing the coarse model
3. Calculate \( x_f^{SM} \) and \( P \) through input space mapping
4. Generate learning and testing data around \( x_f^{SM} \) according to tolerances
5. Obtain \( Q \) by training an output neuro mapping
6. Calculate yield using \( Q(R_c(P(x_f), \psi), x_f, \psi) \)
7. **End**
Obtaining $P$ and $x_f^{SM}$

We apply a constrained Broyden-based algorithm to solve the following system of nonlinear equations

$$f(x_f) = P(x_f) - x^*_c = 0$$

where $x^*_c = P(x_f)$ is evaluated through

$$P(x_f) = \arg \min_{x_c} \left| e^T_1 \ldots e^T_p \right|_2$$

$p$ is the number of points of the independent variable and the $j$-th parameter extraction error vector is given by

$$e_j(x_f) = R_{fs}(x_f, \psi_j) - R_{cs}(x_c, \psi_j)$$

Algorithm for Constrained Broyden-Based SM

```
Begin
find $x^*_c$ solving (1)

$i = 0, x_f^{(0)} = x^*_c, B^{(0)} = I, \delta = 0.3$

$f^{(0)} = P(x_f^{(0)}) - x^*_c$ using (2)

repeat until stopping criterion

solve $B^{(i)}h^{(i)} = -f^{(i)}$ for $h^{(i)}$

$x_f^{(test)} = x_f^{(i)} + h^{(i)}$

while $x_f^{(test)} < x_f^{min} \vee x_f^{(test)} > x_f^{max}$

$h^{(i)} = \delta h^{(i)}$

$x_f^{(test)} = x_f^{(i)} + h^{(i)}$

end

$x_f^{(i+1)} = x_f^{(test)}$

$f^{(i+1)} = P(x_f^{(i+1)}) - x^*_c$ using (2)

$B^{(i+1)} = B^{(i)} + \frac{f^{(i+1)}h^{(i)T}}{h^{(i)}h^{(i)T}}, i = i + 1$

end
```

(1) $x^*_c = \arg \min_{x_c} U(R_f(x_c, \psi))$

(2) $P(x_f) = \arg \min_{x_c} \left| e^T_1 \ldots e^T_p \right|_2$

$e_j(x_f) = R_{fs}(x_f, \psi_j) - R_{cs}(x_c, \psi_j)$

$x_f^{SM} = x_f^{(0)}$

$P(x_f) = Bx_f + c$

where $B = B^{(0)}$ and $c = x^*_c - Bx_f^{SM}$
Generating Learning and Testing Points

- learning base point
- testing base point

2n+1 learning base points in a star distribution
2n testing base points in a rotated star distribution

Training the Output Neuro Mapping

Begin
Generate $R_{CL}$, $R_{CT}$, $R_{FL}$ and $R_{FT}$

\[
\varepsilon_{old}^{L} = ||R_{CL} - R_{FL}||_F, \; \varepsilon_{old}^{T} = ||R_{CT} - R_{FT}||_F
\]

\[h = m, \; i = 1\]

\[
w^{(i)} = \text{arg min}_w ||E_L(w)||_F
\]

\[
\varepsilon_{L} = ||Q_L(w^{(i)}) - R_{FL}||_F
\]

\[
\varepsilon_{T} = ||Q_T(w^{(i)}) - R_{FT}||_F
\]

**while** $\varepsilon_{old}^{T} \geq \varepsilon_{T}$ \land $\varepsilon_{old}^{L} \geq \varepsilon_{L}$

\[
\varepsilon_{old}^{T} = \varepsilon_{T}, \; \varepsilon_{old}^{L} = \varepsilon_{L}, \; i = i + 1, \; h = h + 1
\]

\[
w^{(i)} = \text{arg min}_w ||E_L(w)||_F
\]

\[
\varepsilon_{L} = ||Q_L(w^{(i)}) - R_{FL}||_F
\]

\[
\varepsilon_{T} = ||Q_T(w^{(i)}) - R_{FT}||_F
\]

**end**

\[
w^* = w^{(i-1)}
\]

\[
E_L(w) = R_{FL} - Q_L(w)
\]

**end**

\[Q(R_c (Bx_f + c, y), x_f, y, w^*) = R_f (x_f, y) \]

for all $x_f$ and $y$ in the training region
Two-Section Impedance Transformer

Coarse Model

\[ Z_1 - Z_2 \]
\[ L_1 \quad L_2 \]
\[ C_1 \quad C_2 \quad C_3 \]
\[ R_L \quad 10\Omega \]

`C_1 = C_2 = C_3 = 10\text{pF}`

\[ Z_1 = 2.23615\text{Ω}, \quad Z_2 = 4.47230\text{Ω} \]

Specs:

\[ |S_{11}| \leq 0.5 \text{ for } 0.5 \text{ GHz} \leq f \leq 1.5 \text{ GHz} \]

\[ x_f = [L_1 \quad L_2]^T \]

"Fine" Model

Impedance Transformer – Starting Point

\[ x_c^* = [90^\circ \ 90^\circ]^T \]

\[ |S_{11}| \]

frequency (GHz)
Impedance Transformer – SM Solution

\[ x_f^{SM} = [74.141^\circ, 79.642^\circ]^T \]

Impedance Transformer – Training \( Q \)

\[ \log_{10}(\epsilon_L) \quad \log_{10}(\epsilon_T) \]

tolerance region: ±10%
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Impedance Transformer – LINOSM Solution

Impedance Transformer – LISM Yield

Yield = 88.3%

max dev: ±5%
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Impedance Transformer – Fine Model Yield

![Graph showing impedance transformer fine model yield with yield = 96.8% and max dev: ±5%]

Impedance Transformer – LINOSM Yield

![Graph showing impedance transformer LINOSM yield with yield = 96.7% and max dev: ±5%]
Microstrip Notch Filter

\[ H = 10 \text{mil} \]
\[ W_{s0} = 31 \text{mil} \]
\[ \varepsilon_r = 2.2 \]
\[ \text{loss tan} = 0.0009 \]

(RT Duroid 5880)

\[ x_f = [L_c \ L_o \ S_g]^T \]

Microstrip Notch Filter (cont)

Specifications

\[ |S_{21}| \leq 0.05 \text{ for } 13.19 \text{GHz} \leq f \leq 13.21 \text{GHz} \]
\[ |S_{21}| \geq 0.95 \text{ for } f \leq 13 \text{GHz} \text{ and } f \geq 13.4 \text{GHz} \]
**Microstrip Notch Filter – Fine Model**

- $H_{air} = 60$ mil
- $L_p = \frac{1}{2}(L_o + L_c)$
- $Y_{gap} = L_o$
- grid = 0.5mil × 0.5mil

**Microstrip Notch Filter – Coarse Model**

**Optimization Variables:**
- var $L_c$ 143mil
- var $L_o$ 158mil
- var $S_g$ 8mil

**Preassigned Parameters:**
- MSub RT-Duroid-5880
- $H=10$ mil
- ER=2.2
- TAN D=0.0009
- LEVEL=2

- var $W50$ 31mil
- var $Lp$ 31mil
- var $Lzero$ 1-9mil

Preassigned Parameters:
- MSub RT-Duroid-5880
- $H=10$ mil
- ER=2.2
- TAN D=0.0009
- LEVEL=2

- var $W50$ 31mil
- var $Lp$ 31mil
- var $Lzero$ 1-9mil

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Microstrip Notch Filter – Training $Q$

-1.6 \quad -1.4 \quad -1.2 \quad -1 \quad -0.8 \quad -0.6 \quad -0.4 \quad -0.2 \quad 0

0 \quad 1 \quad 2 \quad 3 \quad 4 \quad 5

hidden neurons, $h$

tolerance region: ±0.5mil

Microstrip Notch Filter – LINOSM Solution

$|S_{21}|$

0 \quad 0.1 \quad 0.2 \quad 0.3 \quad 0.4 \quad 0.5 \quad 0.6 \quad 0.7 \quad 0.8 \quad 0.9 \quad 1

12.7 \quad 12.8 \quad 12.9 \quad 13 \quad 13.1 \quad 13.2 \quad 13.3 \quad 13.4 \quad 13.5 \quad 13.6 \quad 13.7

frequency (GHz)
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**Microstrip Notch Filter – LISM Yield**

Yield = 98%
max dev: ±0.2mil

**Microstrip Notch Filter – LINOSM Yield**

Yield = 58%
max dev: ±0.2mil
Conclusions

- We describe a method for highly accurate EM-based statistical analysis and yield estimation of RF and microwave circuits.
- It consists of applying a constrained Broyden-based linear-input space mapping, followed by a neural-output space mapping, in which the responses, the design parameters and independent variable are mapped.
- The output neuromodel is trained using reduced sets of learning and testing samples.
- The resultant linear-input neural-output space mapped model is used as a very efficient vehicle for accurate statistical analysis and yield prediction.