Microwaves on the Move!

WORKSHOP WFFE

CAD Design Methodology for Commercial Applications

Friday, May 19, 1995
Orlando, Florida

Microwaves on the Move!

WFFE: CAD Design Methodology for Commercial Applications

Organizer and Chairman: Anthony M. Pavio

Friday, May 19, 1995

ORLANDO

MODELING CHALLENGES FOR COMMERCIAL APPLICATIONS

Mike Golio

Motorola

Semiconductor Products Sector

Tempe, AZ

STATISTICAL MODELING, DESIGN CENTERING, YIELD OPTIMIZATION AND COST-DRIVEN DESIGN

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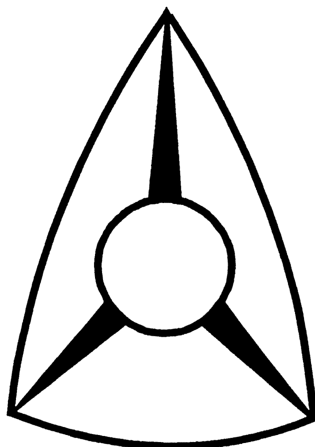


presented at

WORKSHOP ON CAD DESIGN METHODOLOGY FOR COMMERCIAL APPLICATIONS
1995 IEEE MTT-S Int. Microwave Symposium, Orlando, FL, May 19, 1995

Introduction

CAD systems must link geometry, layout, physical and process parameters with performance, yield and system specifications to address the challenges of microwave IC design technology

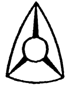
hierarchically structured CAD systems must integrate field theory, circuit theory and system theory into an environment for process-oriented linear, nonlinear and statistical design

fast, predictable, physics-based modeling and simulation of devices and circuits will be important aspects of manufacturable mm-wave designs

CAD technology must account for statistical uncertainties and parameter spreads

CAD modules must be created to facilitate an effective path from process, physical or geometrical description to yield-driven, optimization-oriented man-machine design environment

first-pass success in a fabricated circuit meeting its design specifications is a realistic goal



Overview

statistical device modeling

design centering; yield optimization

cost-driven design

Space Mapping optimization

physical device and circuit optimization

electromagnetic optimization

novel engineering optimization

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Statistical Device Modeling

random variations in the manufacturing environment result in complicated distributions and correlations of device responses

statistical modeling is a prerequisite for statistical analysis and yield optimization (design centering)

device model types for statistical modeling

equivalent circuit models
physics-based and physical models
measurement databases

indirect statistical modeling

parameter extraction/postprocessing (PEP)

direct statistical modeling

cumulative probability distribution (CPD) fitting
histogram fitting

Comparison of Device Models

equivalent circuit models (ECMs)

equivalent circuits with fixed topology containing linear and nonlinear circuit elements

model parameters are extracted from measurements

high computational efficiency

physics-based models (PBMs)

relate the circuit elements to the device physics based on the simplified analytical solution of device equations

slower but, in general, more accurate than ECMs

physical models (PMs) (favored by Snowden and Trew)

based on the numerical solution of fundamental device equations

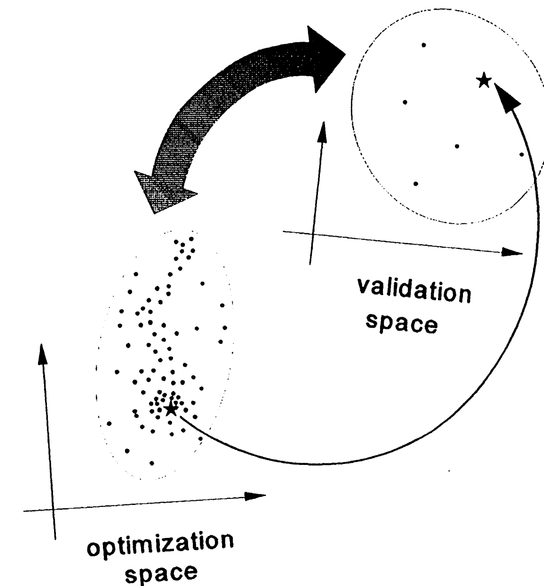
the most accurate but computationally intensive

both PBMs and PMs are capable of performance prediction, permitting device optimization

Space Mapping for Future Physical Optimization

using PBMs for fast optimization

using PMs for accurate validation



Statistical Modeling Using ECMs and PBMs

statistical modeling with ECMs

statistics assigned to the parameters of ECMs

complicated correlations may exist between the model parameters

may not be capable to accurately to represent the actual statistical properties of the device

statistical modeling with PBMs

statistics assigned to physical parameters

correlations between the model parameters are simpler than in ECMs

close to the actual statistical properties of the devices

modeling combining PBMs and PMs: a future promise for exploiting OSA's Space Mapping!

will combine efficiency of PBMs and accuracy of PMs

Comparison of Statistical Modeling Methods

indirect statistical modeling

optimization is applied to extract parameters of individual devices

optimization variables are the parameter values of individual devices

the parameter statistics are obtained by postprocessing the resulting sample of models

statistical model may not be accurate even though the individual device fitting is excellent

direct statistical modeling

optimization is applied to fit the distributions of the model responses to those of the measured data

cumulative probability distributions (CPDs)
histograms

optimization variables are parameter statistics such as the mean values and standard deviations

based on a solid mathematical foundation, more reliable and robust

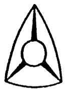
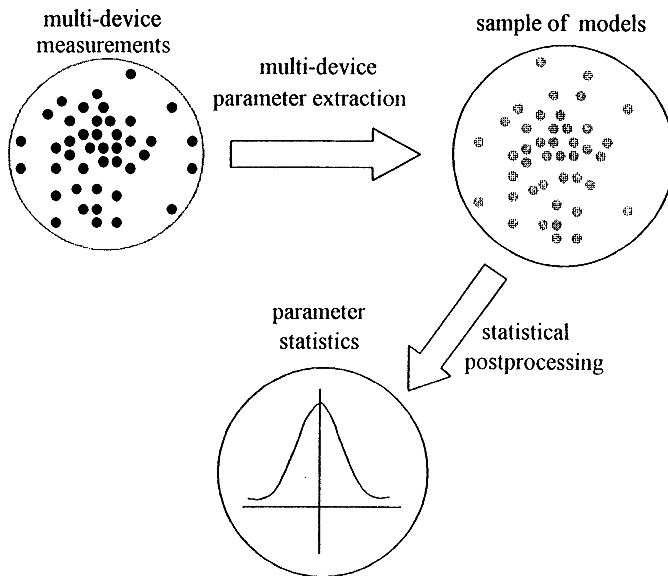
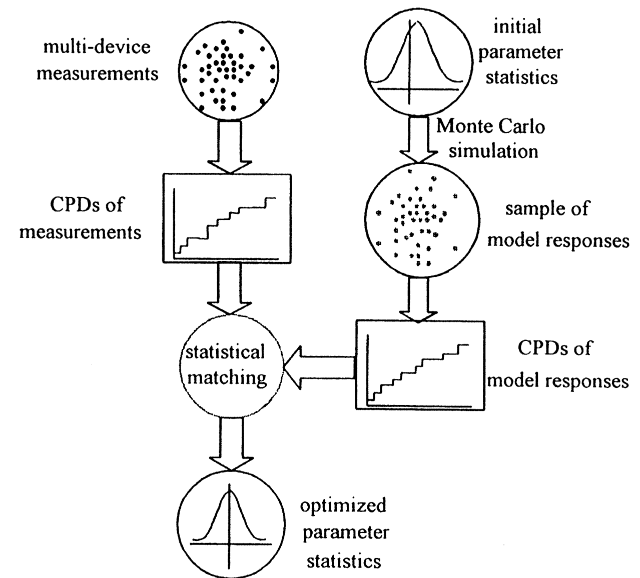
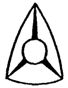


Illustration of Indirect Statistical Modeling

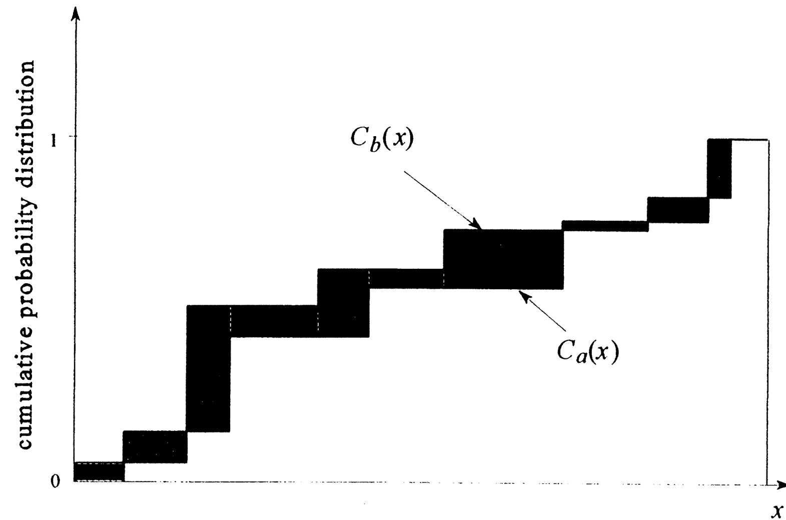


Direct Statistical Modeling Using CPD fitting



 Optimization Systems Associates Inc.

Cumulative Probability Distribution and Matching Error



$C_a(x)$ and $C_b(x)$ are two cumulative probability distributions

CPD matching error is indicated by the shaded area

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Data Alignment and Model Verification

data alignment

- the measurement conditions may vary for different device outcomes
- statistical modeling requires identical measurement conditions for all device outcomes
- measurement data may need to be preprocessed and aligned for statistical modeling

statistical model verification

- comparing the statistics of the model responses generated by Monte Carlo simulation with the statistics of the measurement data
- checking consistency between the yield predicted by the statistical model and the yield estimated from the measurement data

A Robust Physics-Oriented Model for GaAs MESFETs (The KTL Model)

the Ladbrooke model

- an equivalent circuit small-signal model
- ECM element values derived from physical parameters
- attractive statistical properties
- DC operating point must be determined separately

the Khatibzadeh and Trew model

- analytical physics-based model
- suitable for large-signal (or global) simulation
- capable of providing accurate DC solutions
- not reliable for small-signal statistical modeling

OSA's KTL model (HarPE and OSA90/hope)

- the Ladbrooke model for small-signal simulation
- complete and accurate DC/small-signal modeling
- the Khatibzadeh and Trew model for DC simulation
- same physical parameters shared by both models
- integrated and consistently defined statistical model

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Statistical Modeling of a GaAs MESFET
(*Bandler, Biernacki, Cai and Chen, 1994*)

the KTL model with aligned wafer measurement data

35 individual device data containing the S parameters from 1 GHz to 21 GHz with 2 GHz step under the bias condition of V_{gs} = -0.7 V and V_{ds} = 5 V

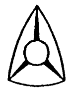
16 statistical parameters

normal distributions assumed

32 optimization variables, namely the mean values and standard deviations of all 16 statistical parameters

indirect statistical modeling (PEP) used to obtain the initial parameter statistics

direct statistical modeling with CPD fitting used to obtain the optimized parameter statistics



CPD OPTIMIZED KTL MODEL PARAMETERS

Parameter	Mean	σ(%)	Parameter	Mean	σ(%)
L(μm)	0.4685	3.57	C_{ds}(pF)	0.0547	1.58
a(μm)	0.1308	5.19	C_{ge}(pF)	0.0807	5.92
N_d(m^{-3})	2.3×10^{23}	3.25	C_{de}(pF)	0.0098	6.22
v_{sat}(m/s)	10.5×10^{4}	2.27	C_x(pF)	2.4231	4.03
μ_0(m^2/Vns)	6.5×10^{-10}	2.16	Z(μm)	300	*
L_{G0}(nH)	0.0396	10.9	ε	12.9	*
R_d(Ω)	1.2867	4.32	V_{b0}(V)	0.6	*
R_s(Ω)	3.9119	1.91	r_{01}(Ω/V^2)	0.35	*
R_g(Ω)	8.1718	0.77	r_{02}(V)	7.0	*
L_d(nH)	0.0659	5.74	r_{03}(Ω)	2003	*
L_s(nH)	0.0409	5.49	a_0	1.0	*
G_{ds}(1/Ω)	3.9×10^{-3}	1.78			

L, Z, a — gate length, gate width, channel thickness
N_d, V_{b0} — doping density, zero-bias barrier potential
v_{sat} — saturation electron drift velocity
μ_0, ε — low-field mobility, dielectric constant
L_{G0} — inductance from gate bond wires and pads
a_0, r_{01}, r_{02}, r_{03} — fitting coefficients
R_d, R_s, R_g, L_d, L_s, G_{ds}, C_{ds}, C_{ge}, C_{de}, C_x extrinsic elements

σ — standard deviation
* — fixed (non-statistical) parameters

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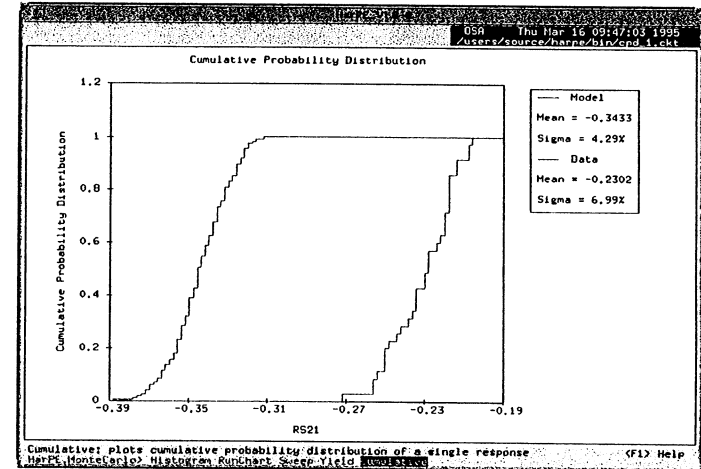
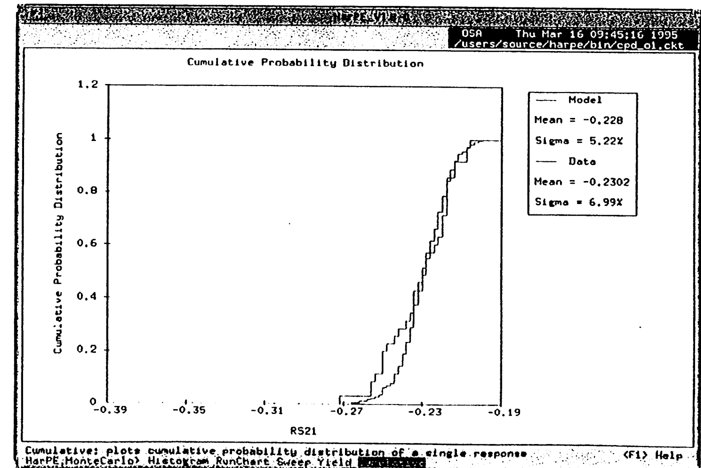
CPDs Before and After Optimization





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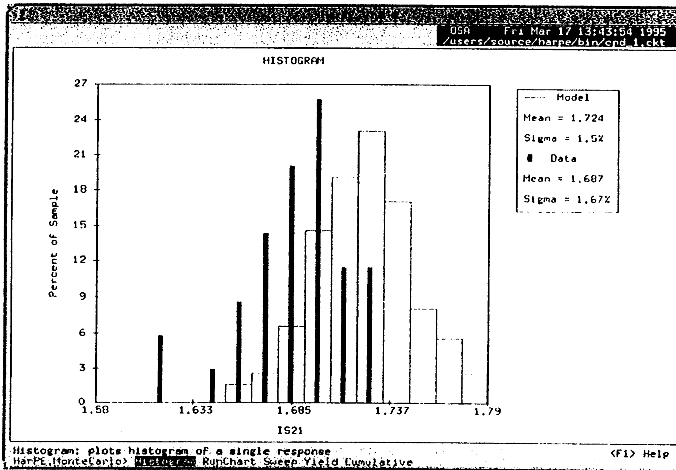
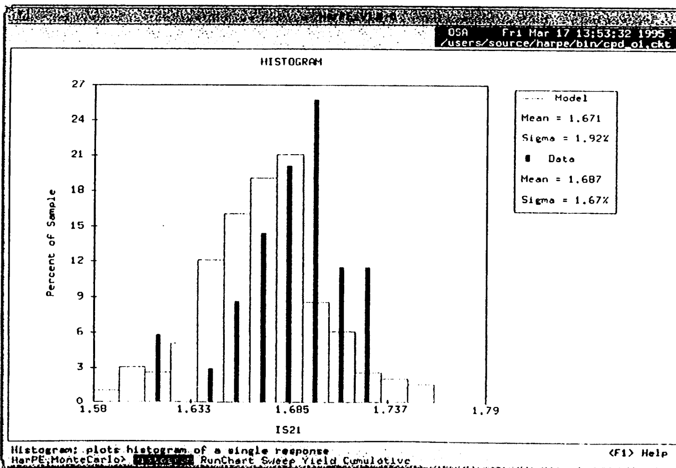
Histograms Before and After Optimization





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Physics-Based Yield Optimization of MMICs

random variations in manufacturing process may lead to some circuits failing to meet design specifications

production tuning of MMICs is restricted and component replacement is not possible

circuits are manufactured in batches rather than individually and the cost is directly affected by yield

the ability to predict and enhance production yield is critical for the continued success of MMIC technology

combined accurate EM simulations of passive elements and physical simulations of active devices enhanced by Space Mapping optimization will become the future CAD tool

Yield Optimization of a Three-Stage MMIC Amplifier
(*Bandler, Biernacki, Cai, Chen, Ye and Zhang, 1992*)

the three-stage X-band MMIC amplifier is based on the circuit topology and fabrication layout originally designed by Thomson-Semiconductors and intended as a gain block for phased-array antennas (*Kermarrec and Rumelhard, 1988*)

the amplifier contains three GaAs MESFETs using an interdigitated structure with two gate fingers of dimensions 150 μm × 1.0 μm

all passive elements are realized using lumped MMIC elements: spiral inductors, MIM capacitors and bulk resistors

37 statistical variables with correlations and 16 design variables

yield optimization carried out by OSA90/hope

yield is improved from 26% at the nominal design to 69% after optimization

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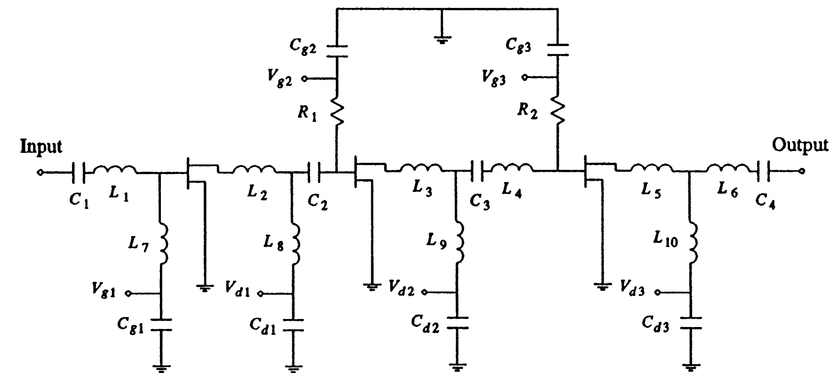
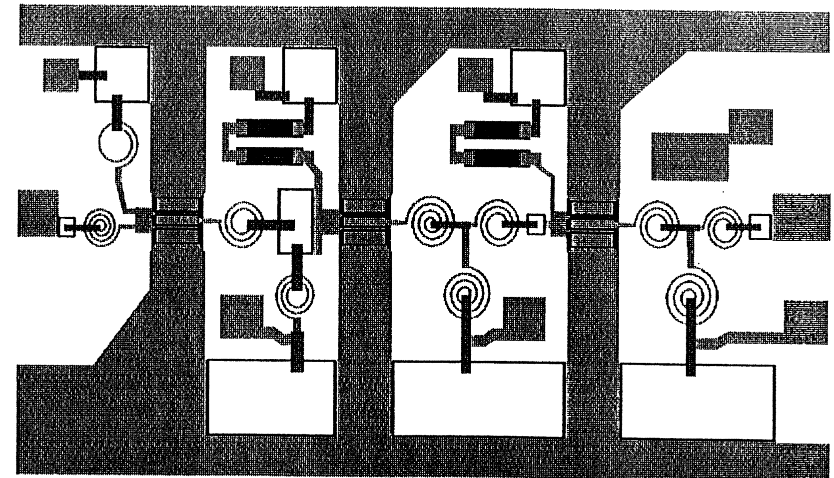
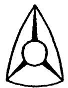
Circuit Schematic and Layout of the Three-Stage Amplifier







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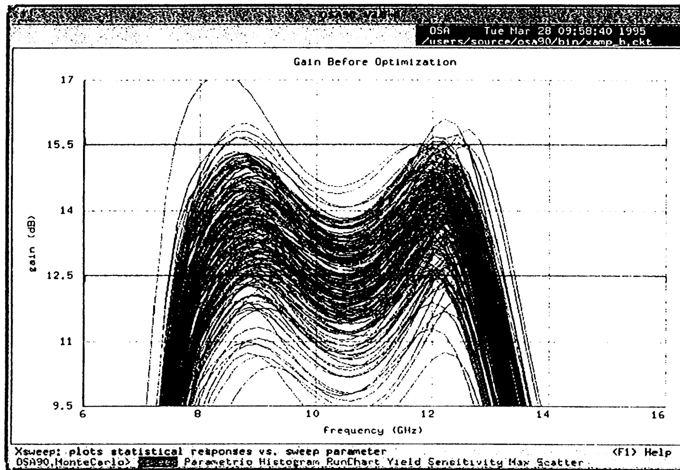
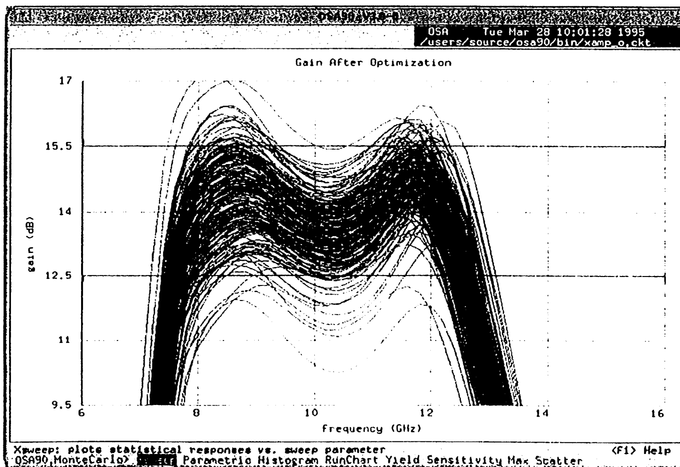
Gain Before and After Yield Optimization





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Predictable Yield-Driven Circuit Optimization
(*Bandler, Ye, Cai, Biernacki and Chen, 1992*)

practical usefulness of yield-driven design depends on the accuracy of the estimated yield using the statistical model

yield predicted by Monte Carlo simulation using the model should be consistent with the yield predicted directly from the device measurement data

the advantage of a statistical model over the measurement data is that the model provides for convenient interpolation

the selection of device parameters for yield optimization can be assisted by yield sensitivity analyses

the yield can be significantly increased by simultaneous circuit-device optimization

design of a small-signal broadband amplifier is investigated using OSA90/hope with the KTL model w.r.t. a number of specifications

the predicted yield is verified using the device data

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YIELD VERIFICATIONS

	Before Yield Optimization		After Yield Optimization	
	Predicted Yield (%)	Verified Yield (%)	Predicted Yield (%)	Verified Yield (%)
Spec. 1	17.5	15.7	67	57.9
Spec. 2	21	20	83	75.7
Spec. 3	44	37.1	98	93.6

Spec. 1: 7.5dB < $|S_{21}|$ < 8.5dB, $|S_{11}| < 0.5$, $|S_{22}| < 0.5$.
Spec. 2: 6.5dB < $|S_{21}|$ < 7.5dB, $|S_{11}| < 0.5$, $|S_{22}| < 0.5$.
Spec. 3: 6.0dB < $|S_{21}|$ < 8.0dB, $|S_{11}| < 0.5$, $|S_{22}| < 0.5$.

200 Monte Carlo outcomes are used for predicted yield, 140 for verified yield.

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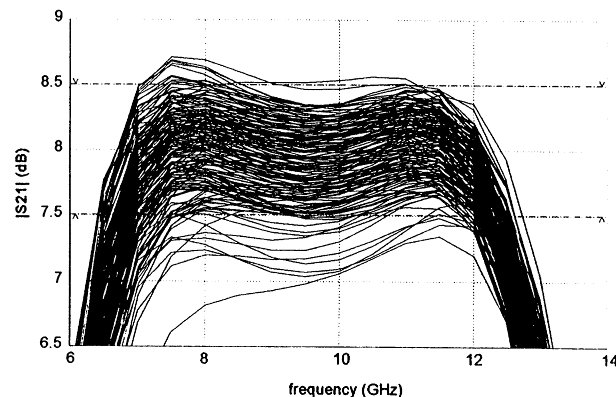
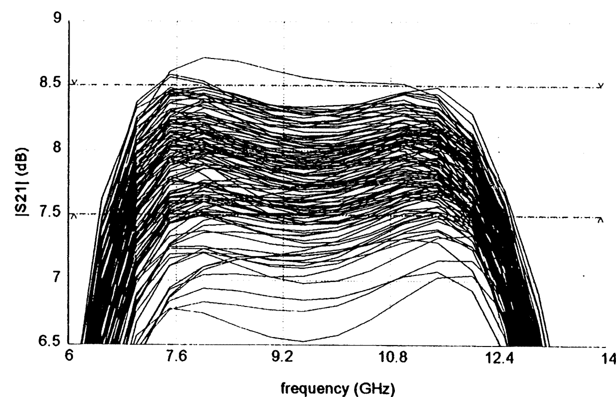
Gain After Optimization from Model and Data





Physics-Based Cost-Driven Design
(*Bandler, Biernacki, Cai and Chen, 1995*)

yield optimization maximizes the yield by adjusting the nominal values of the design variables while keeping their tolerances constant

the cost for obtaining small tolerances may be very high and there is a trade-off between the yield and the cost

cost-driven design minimizes the cost while maintaining the required yield

optimization problem for cost-driven design

$$\underset{\boldsymbol{x}}{minimize} \quad C(\boldsymbol{x})$$

$$subject\ to\ Y \geq Y_S$$

$\boldsymbol{x}$	vector of parameter tolerances
Y	design yield
Y_S	specified yield
$C(\boldsymbol{x})$	cost function, e.g.,

$$C(\boldsymbol{x}) = \sum_{i=1}^{m} \frac{c_i}{x_i}$$

Physics-Based Raytheon (PBR) Model

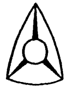
the model structure and the model equations follow the Raytheon model (Statz *et. al*, 1987)

the empirical parameters of the Raytheon model are calculated from the physical parameters using analytical formulas (D'Agostino *et. al*, 1992)

The PBR model is implemented in conjunction with the built-in Raytheon model (FETR) in OSA90/hope and HarPE

facilitates fast large-signal simulation and optimization, particularly useful for yield- and cost-driven design where a large number of outcomes need to be analyzed

a good candidate for Space Mapping optimization validated by accurate physical models



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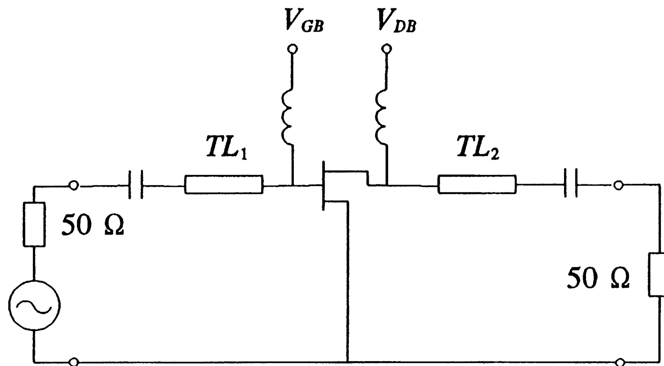
A Single-Stage Power Amplifier Design



PBR is used to model the MESFET

nominal design using minimax optimization

yield optimization using one-sided Huber optimization

cost-driven design by maximizing the parameter tolerances

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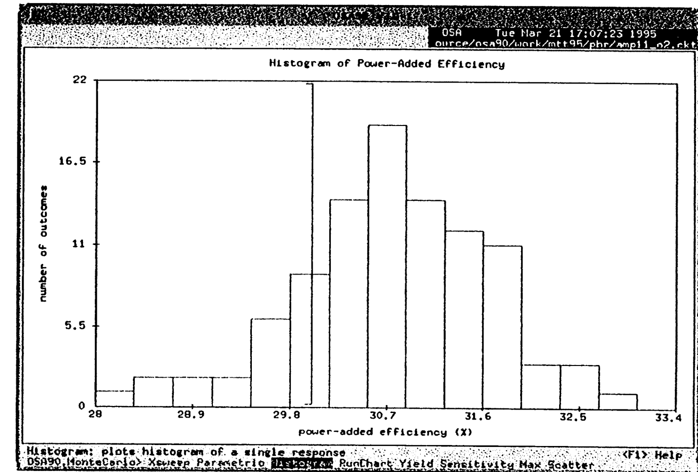
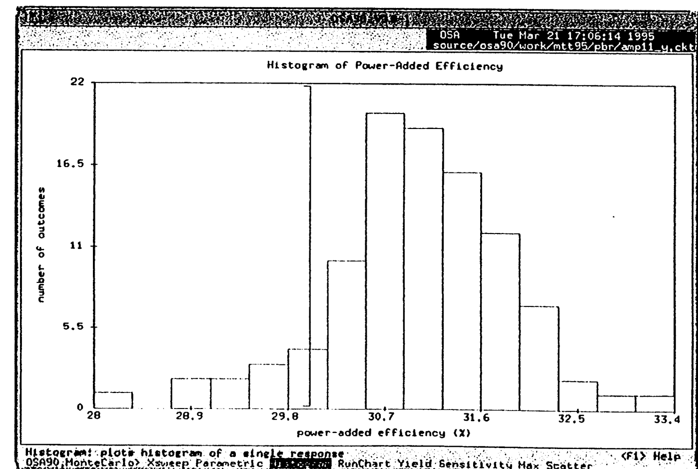
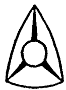
Histograms of PAE Before and After Yield Optimization







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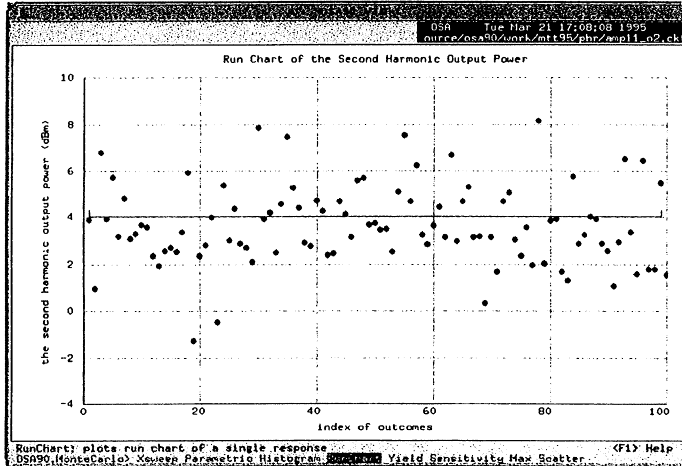
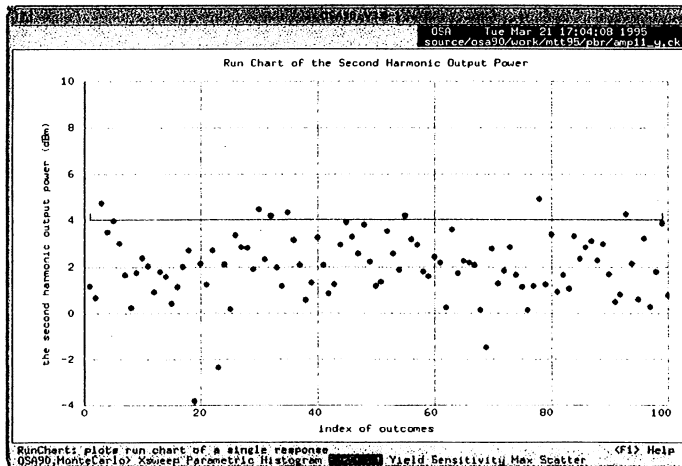
Run Chart of Pout[2] Before and After Yield Optimization





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STANDARD DEVIATIONS FOR COST-DRIVEN DESIGN

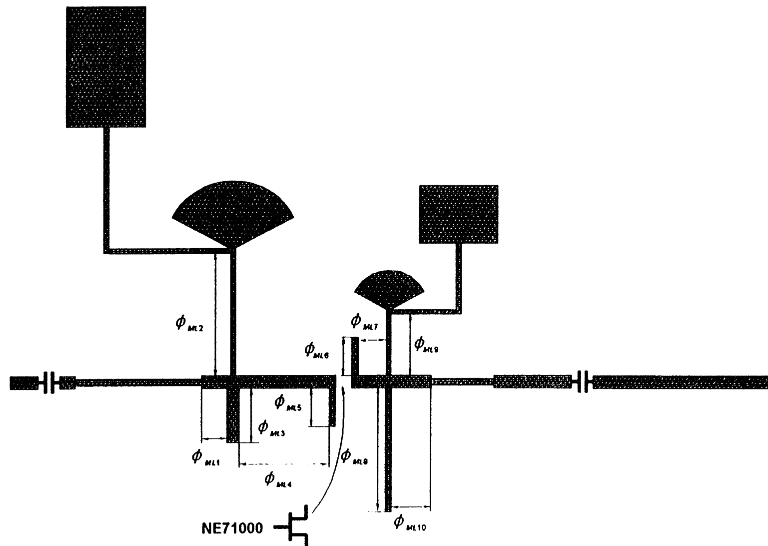
Standard Deviation	Before Optimization	After Optimization Case 1	Case 2	Case 3	Case 4	Case 5
x_L(%)	3	3.1152	3.2366	3.4590	3.7103	3.9781
x_Z(%)	3	3.0517	3.1075	3.2123	3.3351	3.4698
x_a(%)	3	3.3098	3.6150	4.1467	4.7009	5.2722
x_{Nd}(%)	3	3.0517	3.1075	3.2123	3.3351	3.4698
x_{TL}(%)	3	3.0130	3.0272	3.0545	3.0872	3.1241

Case 1: the specified yield is 80%.
Case 2: the specified yield is 75%.
Case 3: the specified yield is 70%.
Case 4: the specified yield is 65%.
Case 5: the specified yield is 60%.

x_L standard deviation of FET gate length
x_Z standard deviation of FET gate width
x_a standard deviation of FET channel thickness
x_{Nd} standard deviation of FET doping density
x_{TL} standard deviation of transmission line lengths of TL_1 and TL_2

the weighting factors are selected as 3, 2, 5, 2 and 1 for x_L, x_Z, x_a, x_{Nd} and x_{TL}, respectively

Nonlinear FET Class B Frequency Doubler
(*Microwave Engineering Europe, 1994*)

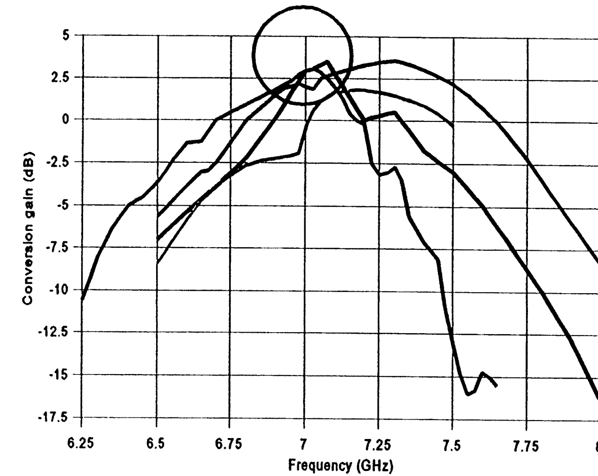


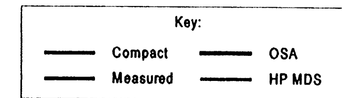
CAD benchmark example

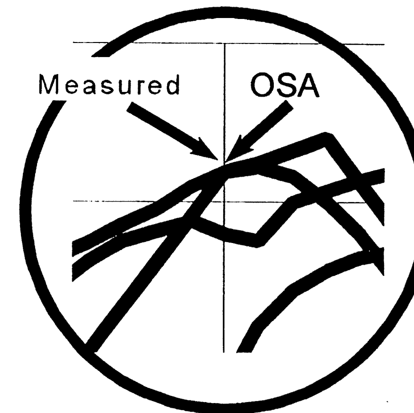
a single FET (NE71000) and a number of microstrip elements including two radial stubs and two large bias pads

significant couplings between the microstrip elements

Comparison of Simulated and Measured results



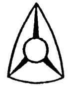




Detail around 7 GHz

The benchmark circuit is a 7 GHz frequency doubler

Microwave Engineering Europe, May 1994



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Direct EM Optimization
(*Bandler, Biernacki, Cai, Chen and Grobelny, 1995*)

OSA's Geometry Capture for optimization of arbitrary planar structures is used

OSA's Empipe handles direct optimization with Sonnet's ***em***

the complete structure between the two capacitors is considered as a whole and simulated by Sonnet's ***em***

the circuit is directly optimized by OSA90/hope through Empipe with 10 optimization variables

design specification:

conversion gain > 3 dB
spectral purity > 20 dB

at 7 GHz and 10 dBm input power

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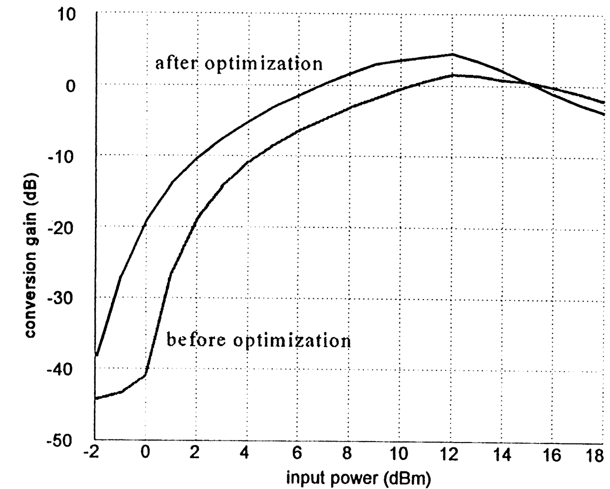
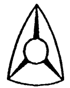
Conversion Gain Before and After Optimization





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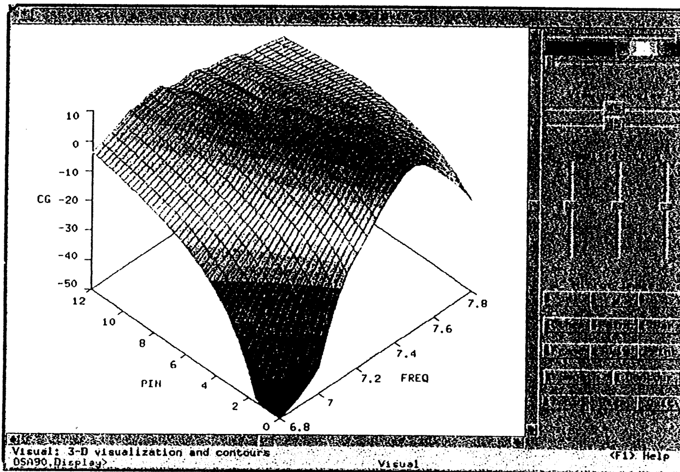
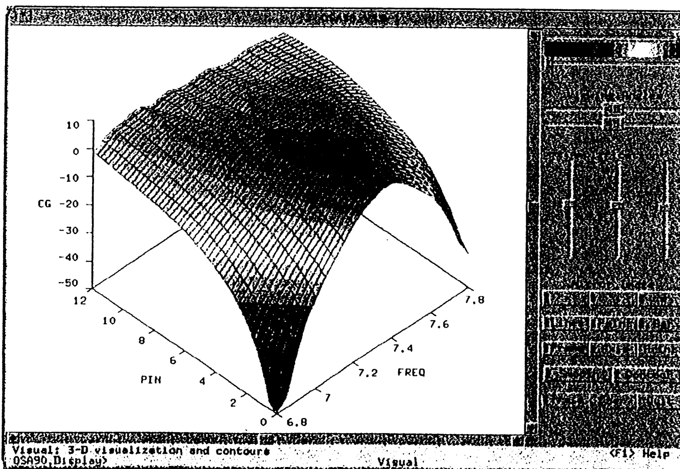
3D View of Conversion Gain Before and After Optimization





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Conclusions

cost-effective yield-driven design technology is indispensable for microwave CAD

accurate statistical modeling is the key to successful statistical design

appropriate cost models need to be developed for future meaningful and practical cost-driven design

integrated EM and physical simulation and optimization capable of handling arbitrary structures will be the future focus of microwave CAD

the Space Mapping technique promises the accuracy of EM and physical simulation and the speed of circuit-level optimization

heterogeneous parallel CAD over a local or wide area network can significantly increase the design power