NEXT GENERATION OPTIMIZATION METHODOLOGIES FOR WIRELESS AND MICROWAVE CIRCUIT DESIGN

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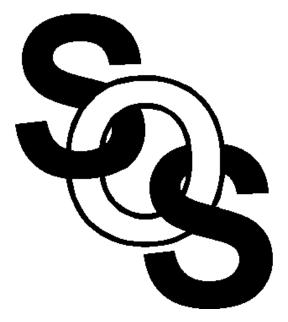
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NEXT GENERATION OPTIMIZATION METHODOLOGIES FOR WIRELESS AND MICROWAVE CIRCUIT DESIGN

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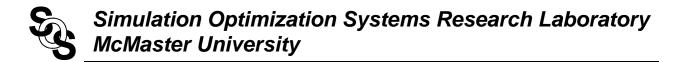
Introduction

commercial CAE systems for high-speed, wireless and microwave circuits and systems are no longer regarded as complete without a variety of design automation capabilities

computer-integrated manufacturing, including CAD, CAM, information management and decision support systems will be a reality facing the design engineer in the next century

CAE practices such as active and passive device, circuit and system design are expected to be physically and electromagnetically based, to include electrical, mechanical and thermal effects

future developments in integrated CAE tools will concurrently link geometry, layout, physical, electromagnetic (EM) and process simulations, with performance, yield, cost, system specifications, manufacturability and testability in a manner transparent to the designer



Paper Outline

we review two exciting concepts:

electronic device modeling through Artificial Neural Network technology

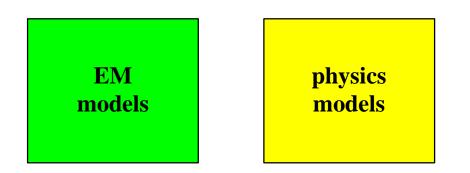
circuit optimization exploiting Space Mapping in the design parameter space

we elaborate on Knowledge Based Neural Network structures for enhanced modeling

we elaborate on Aggressive Space Mapping for efficient electromagnetic optimization

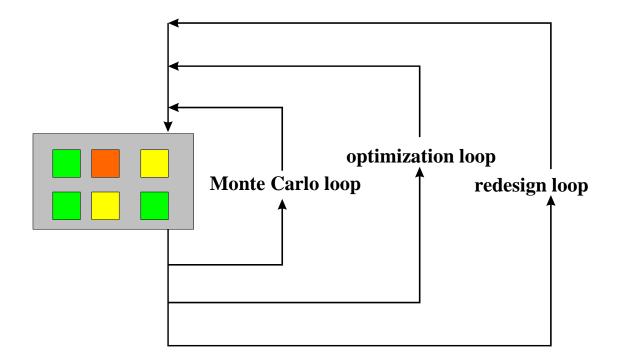


Models are Computationally Expensive





Repetitive Analysis is Expensive



Existing Modeling Approaches

original detailed simulations accurate but slow

empirical models limited accuracy and flexibility but fast

polynomial models

response surface models limited degree of nonlinearity but fast

table lookup models arbitrary nonlinearity fast but limited to low-dimensional problems

Neural Network Approach

multilayer perceptrons

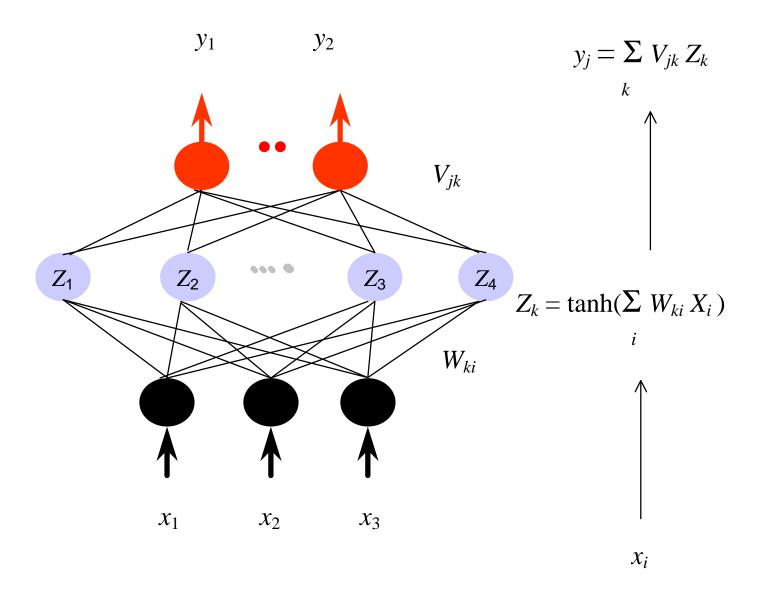
theoretically, models any degree of nonlinearity

handles more variables than, e.g., lookup table models

valid across a larger space than polynomial models

is ultra fast

Structure and Parameters of Multilayer Perceptrons





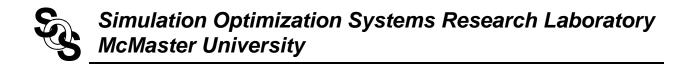
Model Building: Learning Mode

perform detailed device/circuit simulations/measurements to obtain data

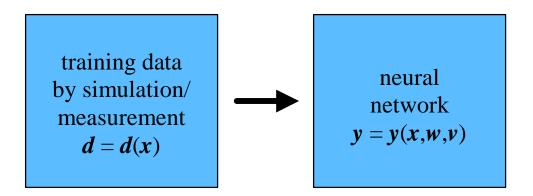
use the data to train the neural network

this procedure could be very slow

it can be performed off-line



Neural Network Training



objective:

to adjust neural network internal weights w, v such that

minimize $\dot{\mathbf{a}} (y - d)^2$ w,v x



Model Usage

given a set of input parameters to the neural network it will predict corresponding outputs

this recalling procedure is very fast and is done on-line during optimization



Neural Network Model for Iterative Design

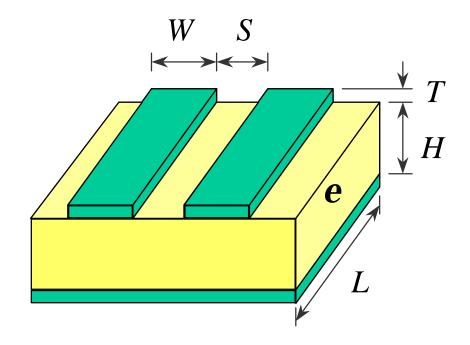
the neural network model is trained off-line only once

the model can then be used many times for different purposes

repeated simulations optimization re-optimization

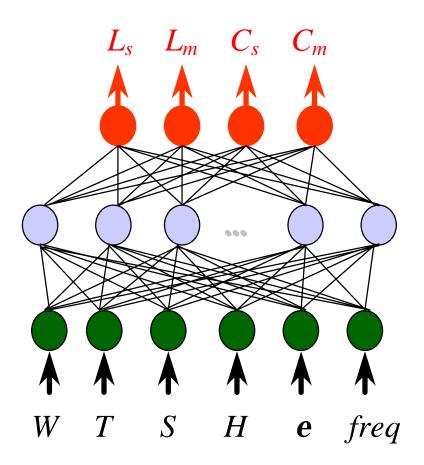


2-Conductor Microstrip Line



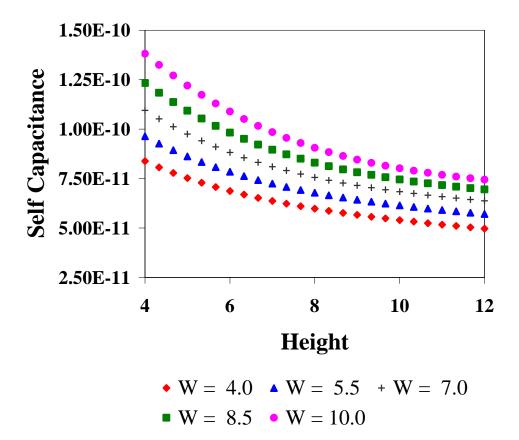


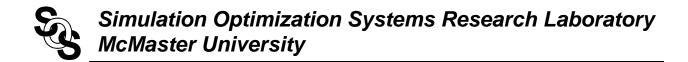
Neural Model for Microstrip Line



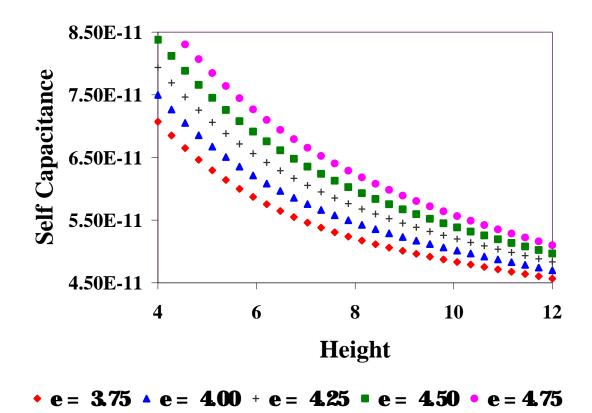


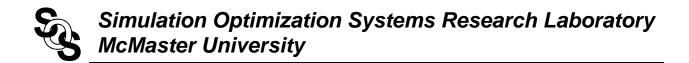
Neural Model for Self Capacitance of Microstrip Line



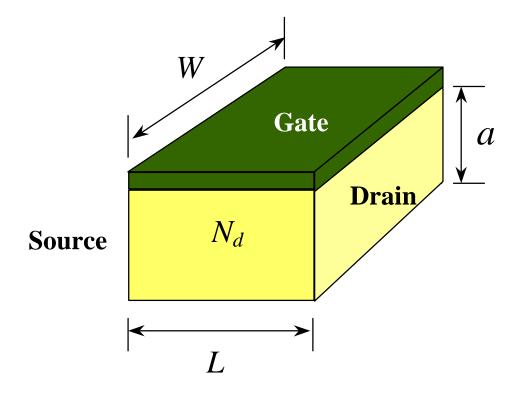


Neural Model for Self Capacitance of Microstrip Line



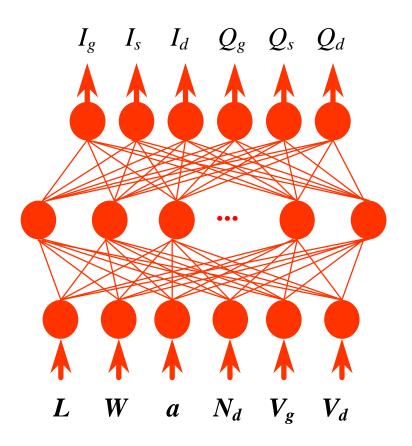


Physics-Based MESFET



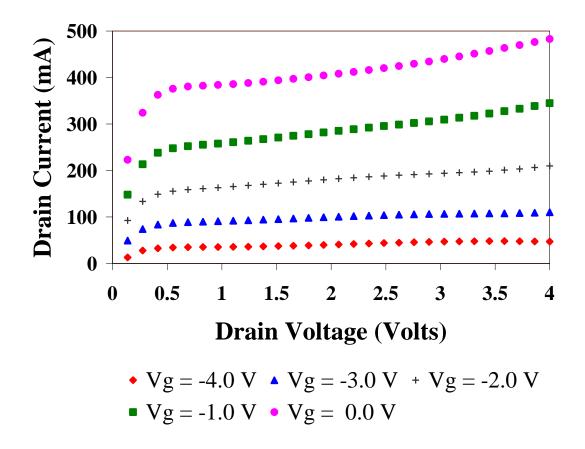


Neural Model for MESFET





FET I-V Curve Neural Network Model

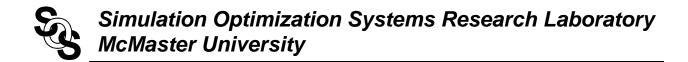


Knowledge Based Neural Networks (KBNN)

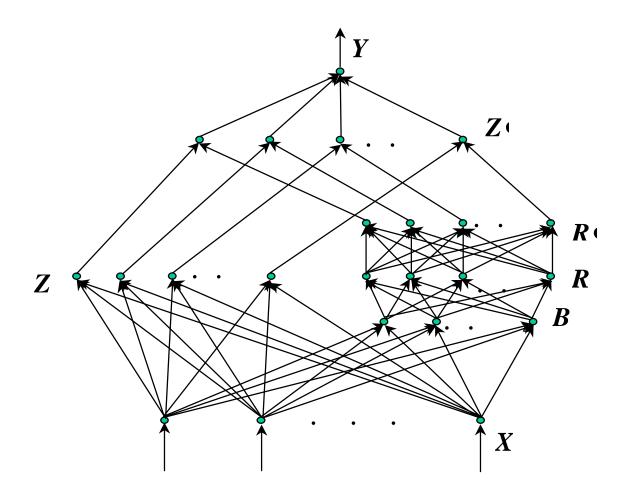
incorporate electrical knowledge into neural networks to

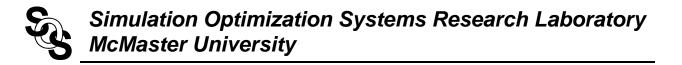
reduce the amount of training data required for model development

improve the accuracy and reliability of the neural network model



KBNN Structure





Conclusions (Neural Networks)

a novel neural based modeling technique has been developed

the feasibility and efficiency of neural models have been demonstrated

the proposed KBNN combines engineering empirical knowledge with the learning power of neural networks

with ultra fast recalling speed, neural models will have significant impact on the development of interactive CAD tools

NeuroModeler is the first tool of its kind dedicated to RF and microwave engineering

NeuroModeler is available from Dr. Q.J. Zhang (Carleton University)



Conclusions (Space Mapping Optimization)

ASM has been applied to a number of design examples exploiting full wave EM simulators

Sonnet's *em* has been used to optimize various filters, including the design of a high temperature superconducting filter

finite element solvers Ansoft and HP HFSS have been used to design various 3D structures such as waveguide transformers and filters

coarse models exploited coarse grid EM models or circuittheoretic/analytical models

coarse models, decomposed into subnetworks, have even consisted of a mixture of EM based subnetworks and empirical elements connected through circuit theory

A new ASM algorithm called TRASM (Trust Region Aggressive Space Mapping) automates the selection of fine model points used in a multi-point parameter extraction process



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