AI and Machine Learning for Microwaves

Past, Present and Future Trends

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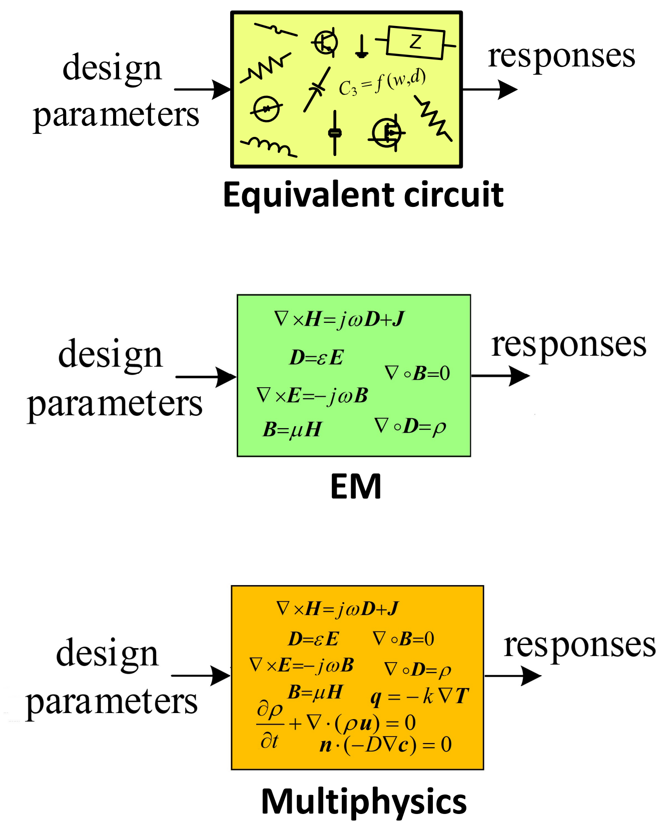
Microwave Modeling/Simulation



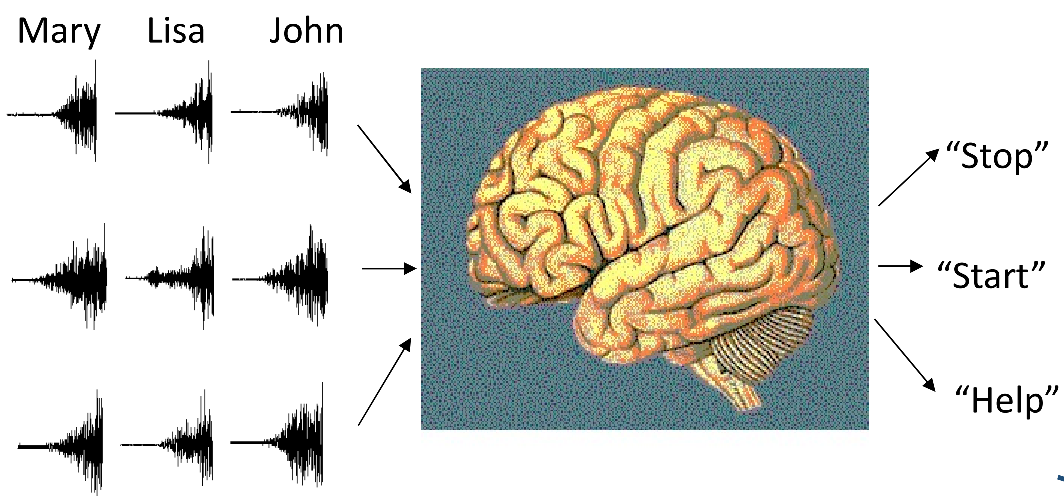
More accurate solutions

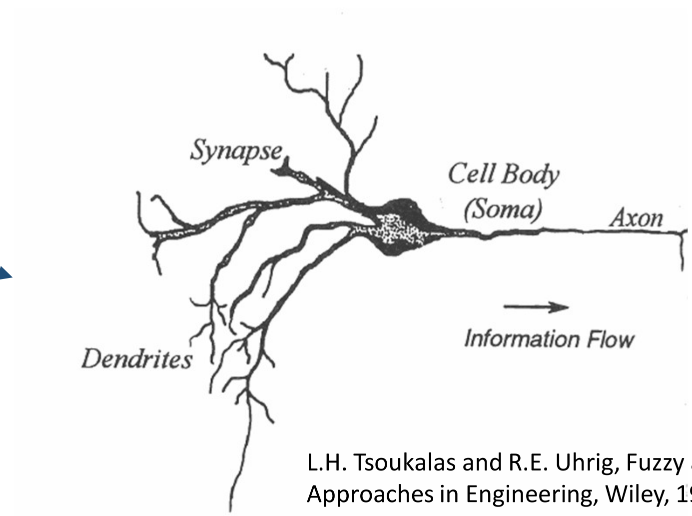
More computationally intensive

More equations
More variables
More complex algorithms

From Biological Learning to Machine Learning

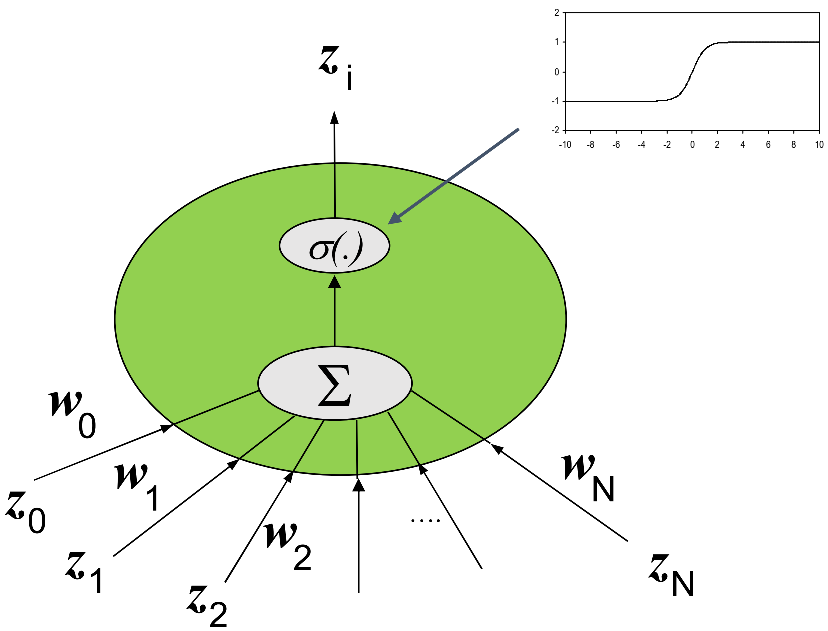
- Biological Neural Network



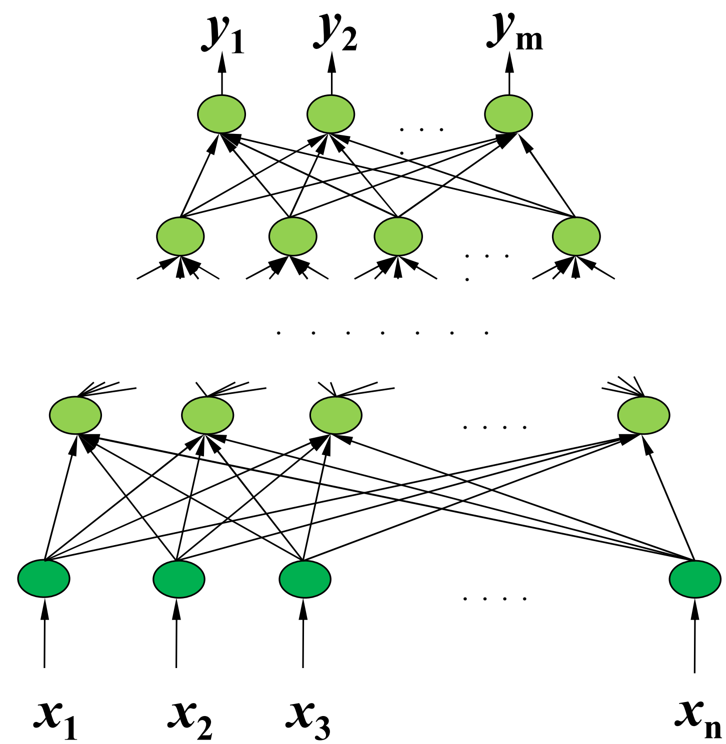


L.H. Tsoukalas and R.E. Uhrig, Fuzzy and Neural Approaches in Engineering, Wiley, 1997

Artificial Neural Network (ANN)



Artificial neuron



Artificial neural network

Neural Network Training

Training Data

by simulation/ measurement

$d = d(x)$

Validation Data

by simulation/ measurement

$d_v = d(x_v)$

$\rightarrow$

Neural Network

$y = y(x)$

Objective:

to adjust *w* such that

$$\underset{w}{\text{minimize}} \sum_{x} (\, y - d \,)^2$$

Early Works of ANN for Microwave Design

- ANN for microwave impedance matching (Vai, Prasad, IEEE MGL 1993)
- ANN for microstrip circuit design (Horng, Wang, Alexopoulos, IMS 1993)
- ANN for microwave analysis and optimization (Zaabab, Zhang, Nakhla, IMS 1994)
- ANN for modeling via interconnects in microstrip circuits (Watson, Gupta IMS 1996)
- ANN for microwave CAD (Creech, Paul, Lesniak, Jenkins, Lee, Calcatera, IMS 1996)

- ANN for microwave optimization and statistical design (Zaabab, Zhang, Nakhla, T-MTT, 1995)
- ANN for microwave circuit analysis and design (Vai, Prasad, T-MTT 1995)
- ANN for modeling vias and interconnects in dataset circuits (Watson, Gupta, T-MTT 1996)

Historical Events of ANN for Microwaves

- 1st Workshop:
  Workshop on Applications of ANN to Microwave Design
  IEEE MTT-S IMS (Denver, Colorado), 1997.
  Chairs: K.C. Gupta and M.S. Nakhla;
  Speakers: L. Mahajan, K.C. Gupta, M.S. Nakhla, G.L. Creech, Q.J. Zhang

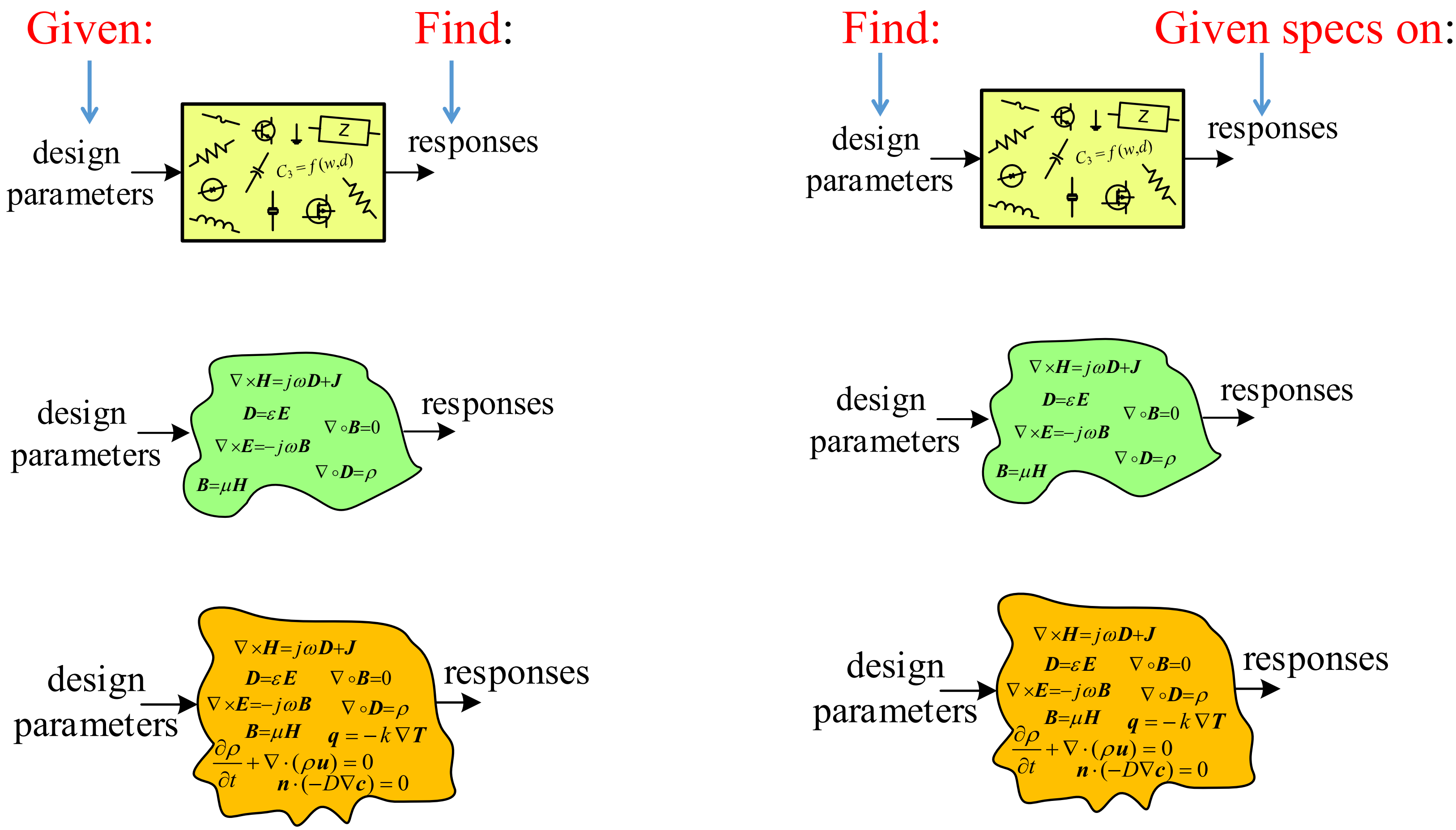
- 1st Short Course:
  Applications of ANN to RF and Microwave Design
  IEEE MTT IMS, (Boston, Massachusetts), June 2000.
  Instructors: K.C. Gupta and Q.J. Zhang

Applications of ANN to RF and Microwave Design

(Special Issue of the Int. J. RF Microwave CAE, 1999)

- Review of ANN, and filter modeling and classification (Burrascano, Fiori and Mongiardo)
- Synthesis of transmission line structures (Watson, Cho and Gupta)
- Microwave circuit design beyond black box models (Vai and Prasad)
- Large-signal device modeling and nonlinear circuit design (Harkouss, Rousset, et. al.)
- RBF models for MESFET and HEMT intermodulation distortion (Garcia et. al.)
- ANN structures and training (Wang and Zhang)
- Use of prior knowledge for ANN development (Watson, Gupta and Mahajan)
- Neurocomputing in IC process applications (Creech and Zurada)
- ANN for filter design trained with FEM EM data (Fedi, Gaggelli, Manetti and Pelosi)
- Wavelet neural net for EM based optimization (Bila, Harkouss, Ibrahim, Rousset et. al.)
- Calculation of the bandwidth of microstrip antennas (Sagiroglu, Guney and Erler)

Simulation vs Design



Simulation vs Design

Simulation

Lot of help from computers

Computation intensive

CPU time

Based on solid physics laws
- Kirchhoff's law
- Maxwell's equation
- ….

Mathematical/numerical formulations
- partial differential equations
- linear/nonlinear equations
- Fourier transforms
- …..
- FEM, FDTD, MOM, TLM, etc
- linear/nonlinear equation solvers
- ….

Design

Partial help from computers

Human intensive

Human time

Use simulation to verify a design solution,
How to find a design solution may require
human knowledge, experience, learning

Human judgement, intuition, trial-error

Simulation >> "Intelligent Simulation"

Cognition-driven design

Simulation vs Cognition

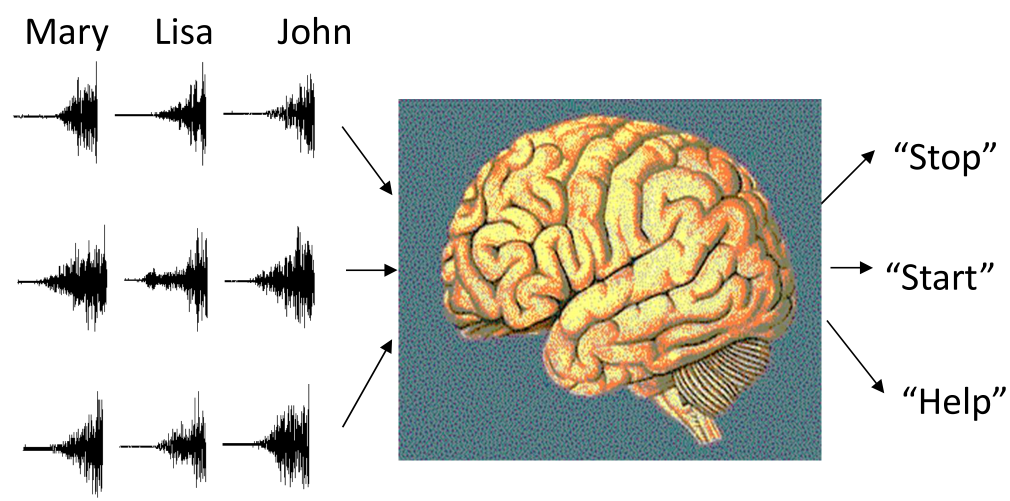
Based on solid physics laws
- Kirchhoff's law
- Maxwell's equation
- ….

mathematical/numerical formulations
- partial differential equations
- linear/nonlinear equations
- Fourier transforms
- …..
- FEM, FDTD, MOM, TLM, etc
- linear/nonlinear equation solvers
- ….

cause -> response relationships often do not have no mathematical formulas

Learning from examples

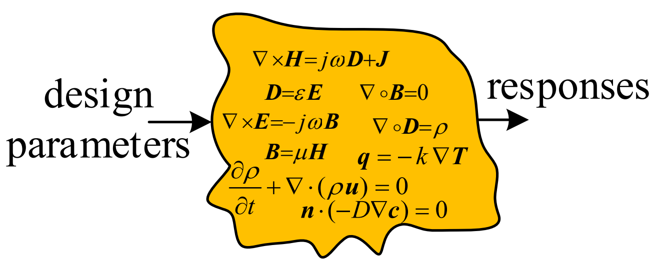
Use of prior knowledge

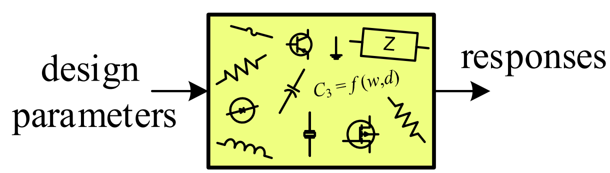


Cognition-Driven Design

Machine learning methods
AI oriented design methods
Computer-based model building algorithms
New optimization algorithms

Equivalent/empirical/EM/multiphysics simulators



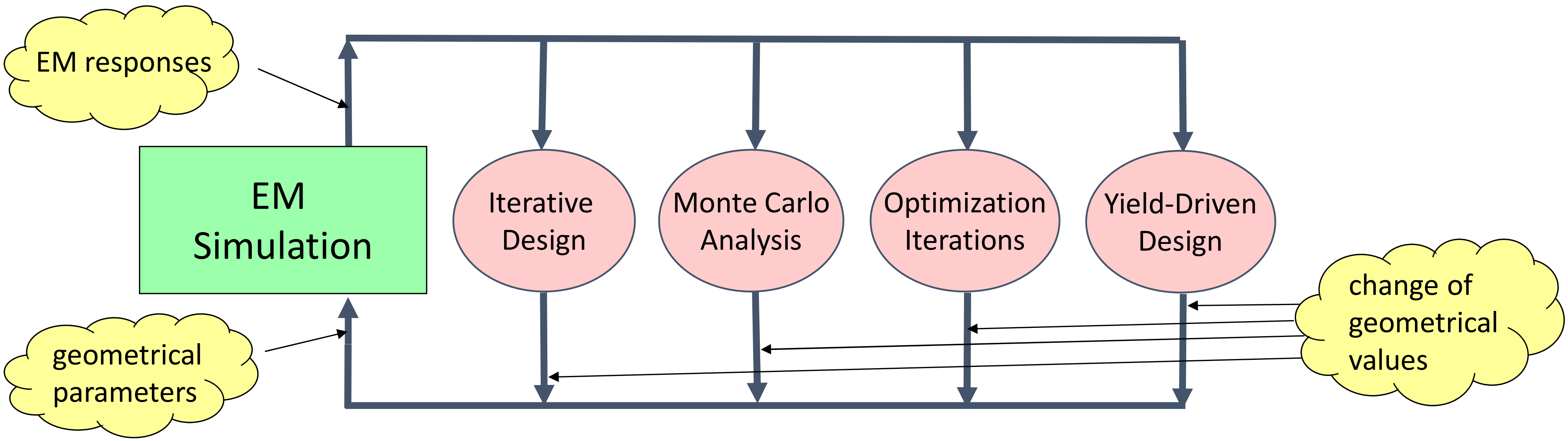


Examples of Research Directions in ANN for Microwave Design

- General applications of ANN to microwave design
- Knowledge-based neural networks
- Neural networks for parameterized modeling of EM structures
- Neural network based models for microwave transistors
- Neural network based behavioral modeling of nonlinear circuits
- Inverse modeling
- Neural network structure and training algorithms

Repetitive EM Simulations in Microwave Design

- Need for fast parameterized models

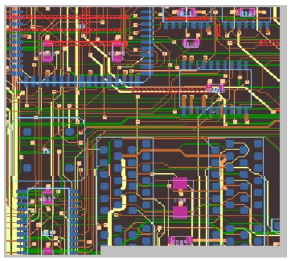


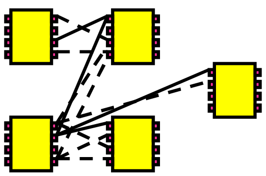
Values of geometrical parameters are repetitively changed during design requiring repetitive evaluations of EM solutions.

Repetitive evaluation using standard EM simulations are expensive.

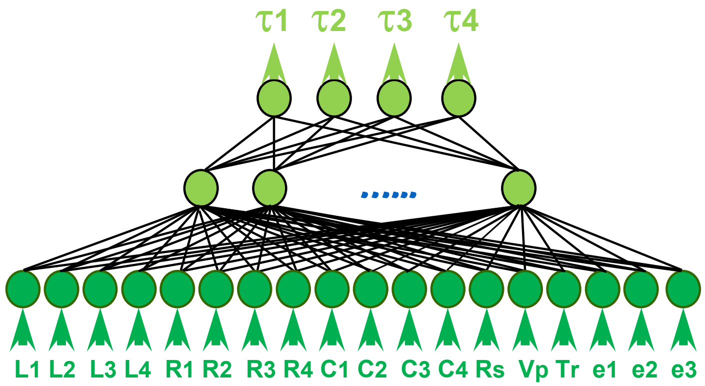
Need parametric models for fast evaluation of EM behavior while geometrical parameters are repetitively changed.

ANN for Parameterized Modeling





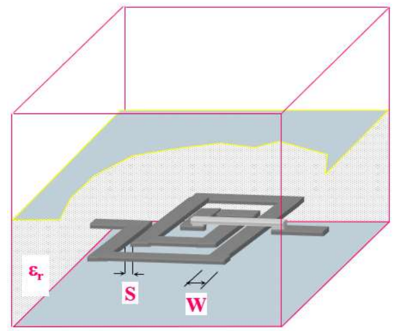
Interconnect delay
analysis in PCB
(slow)



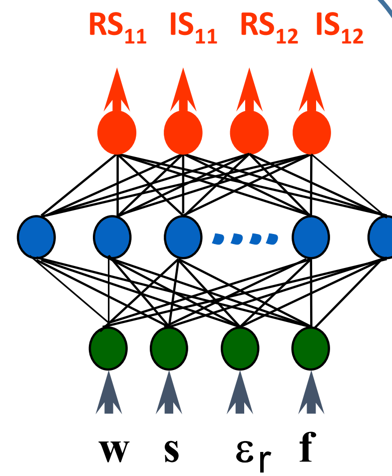
Neural network
(fast)

Massive Analysis of Signal Delay on PCB

(A. Veluswami, Q.J. Zhang and M.S. Nakhla, 1997)



3D EM
(slow)



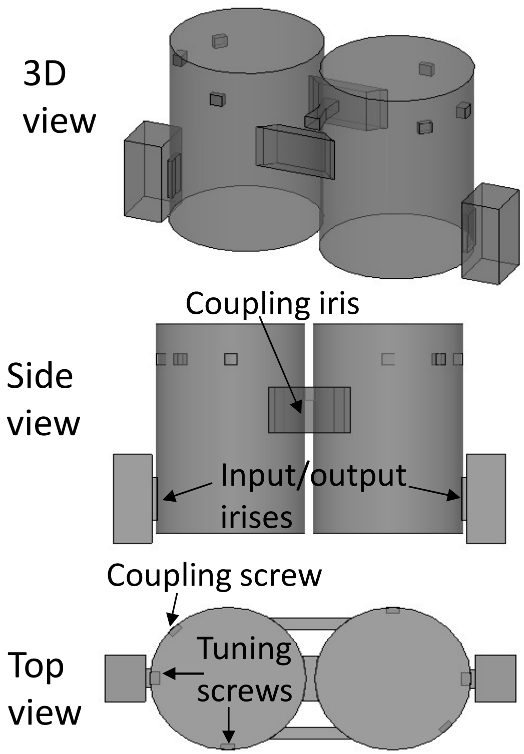
Neural network
(fast)

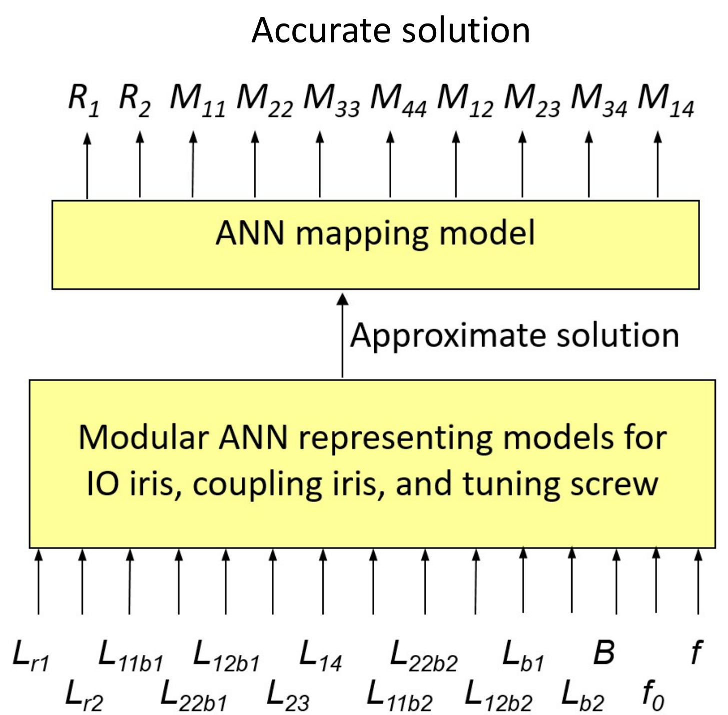
Automated ANN Training for Spiral Inductor Modeling

(V. Devabakhtuni, M. Yagoug, Q.J. Zhang, 2001)

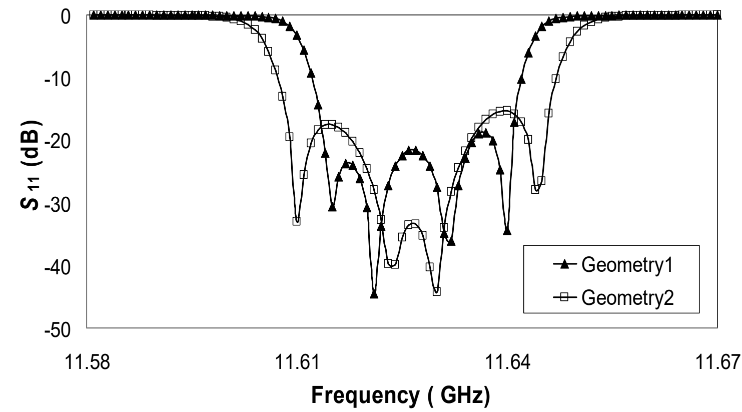
ANN for Modeling of Side-Coupled Circular Waveguide Dual-Mode Filter

(H. Kabir, Y. Wang, Y. Ming, Q.J. Zhang 2010)





Geometrical design variables of the filter

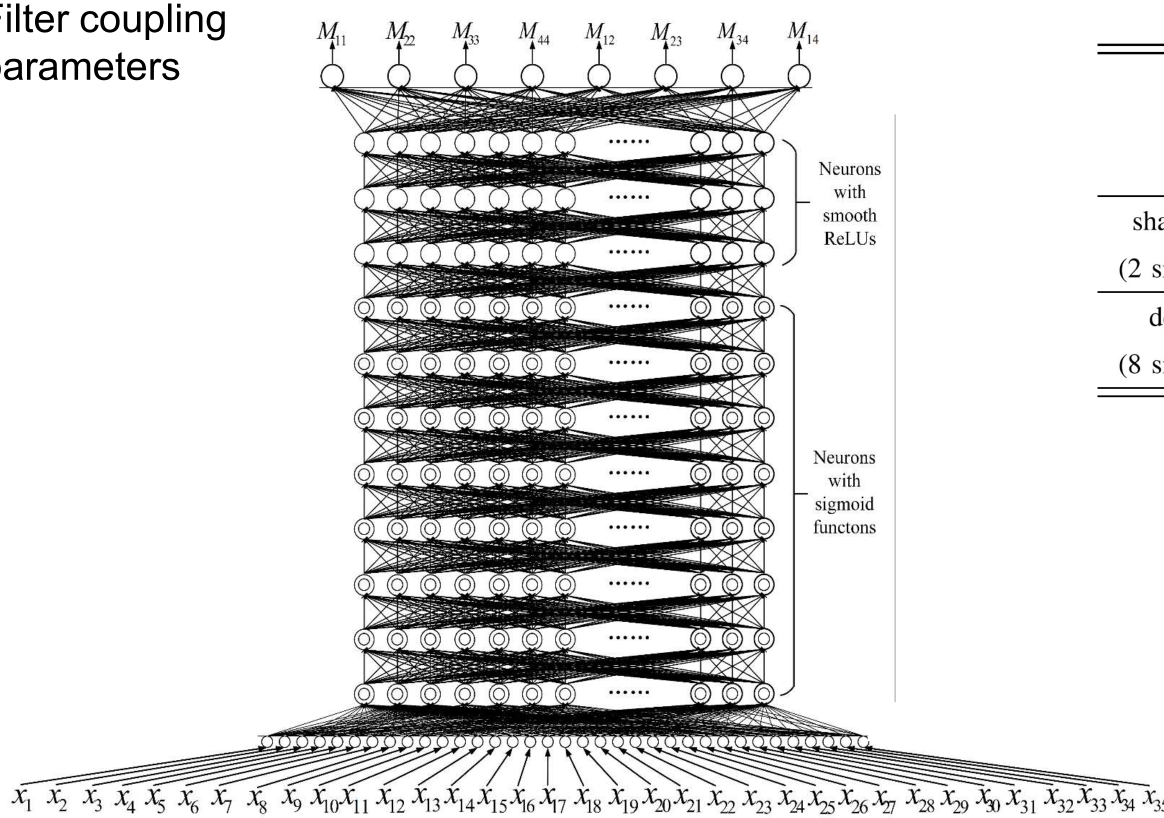


Modeling Method	Evaluation Time
Finite element	45 min
Mode matching	6 min
Modular ANN	0.006 s

Deep Neural Network for Parameter Extraction of Microwave Filters

(J. Jin, C. Zhang, F. Feng, W. Na, J. Ma, and Q.J. Zhang, 2019)

Filter coupling parameters



$|S_{11}|$ at 35 frequency points

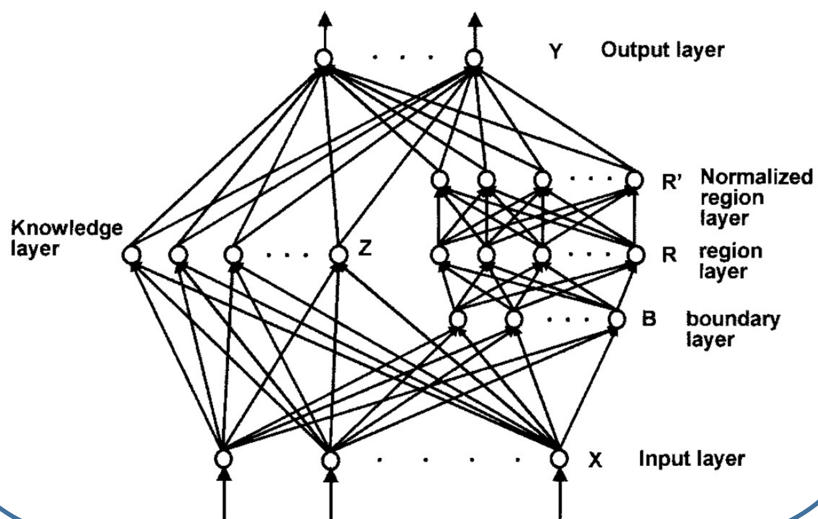
Structure of neural network	Hidden neurons per layer	Number of training parameters	Training error	Test error
shallow neural network (2 sigmoid hidden layers)	514	292k	4.22%	4.89%
deep neural network (8 sigmoid hidden layers)	200	292k	1.95%	2.40%

Structure of deep neural network	Training error	Test error
The proposed 14-layer hybrid deep neural network[1]	1.31%	1.79%
14-layer pure ReLU network	2.68%	3.16%
16-layer pure ReLU network	2.43%	3.00%
20-layer pure ReLU network	2.20%	2.73%

Knowledge-Based ANN

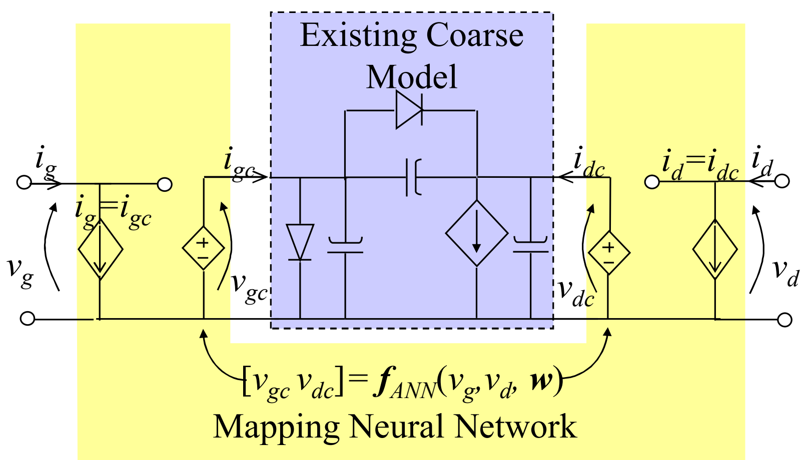
Combine microwave formulas with ANN
(F. Wang and Q.J. Zhang, 1997)

- Reduced amount of training data
- increased extrapolation capability



Neuro-SM for Passive Devices (Rayas-Sanchez, Bandler 1999)
Neuro-SM for Active Devices (L. Zhang and Q. Zhang 2005)

- ANN to map between device coarse models and training data
- Reduced amount of training data needed



Knowledge-based ANN: Neuro-SM for GaN HEMT Modeling

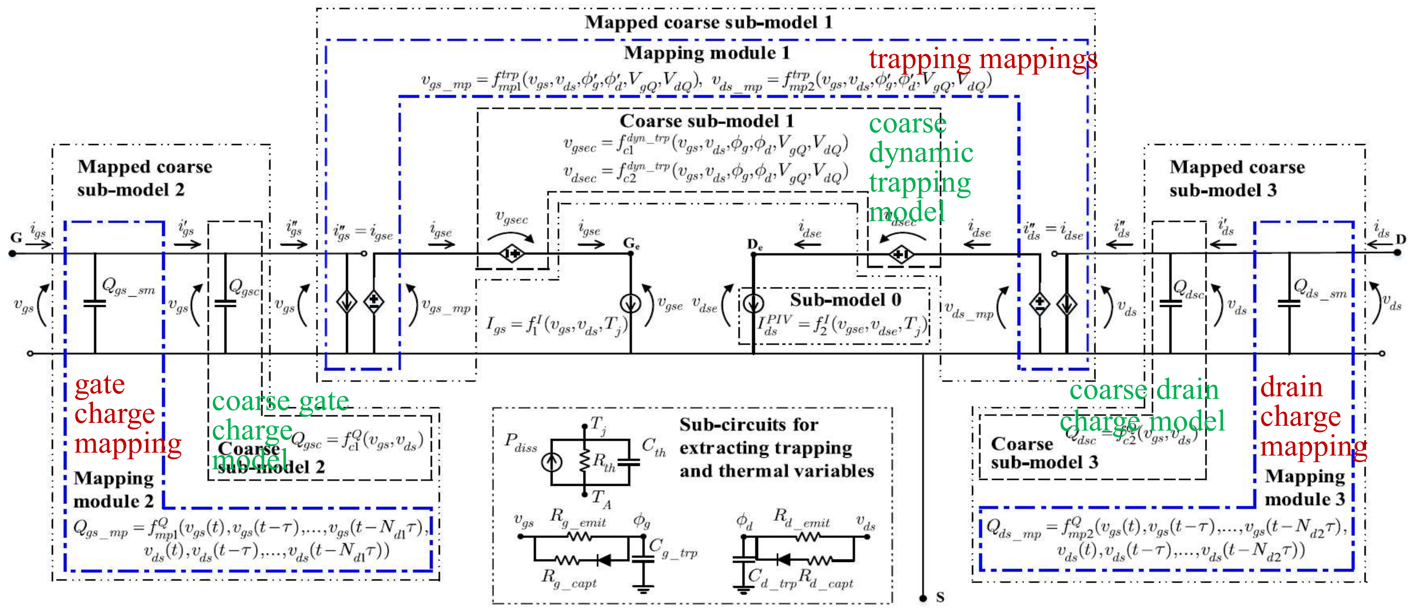
(Z.H. Zhao, L. Zhang, F, Feng, W. Zhang and Q.J. Zhang, 2020)

Problem:

standard equivalent circuit model

does not match

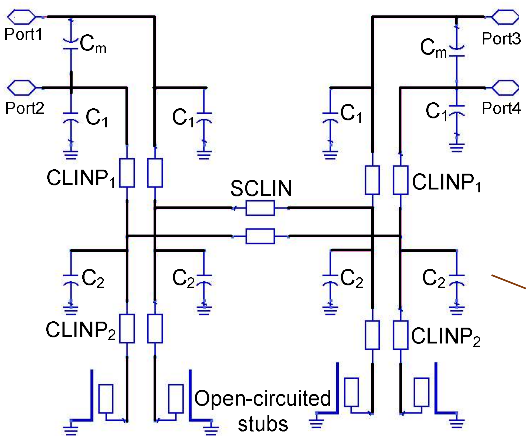
measurement data of
a new device (GaN HEMT)

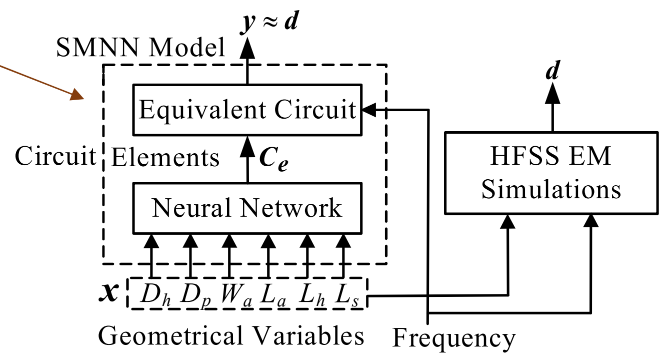


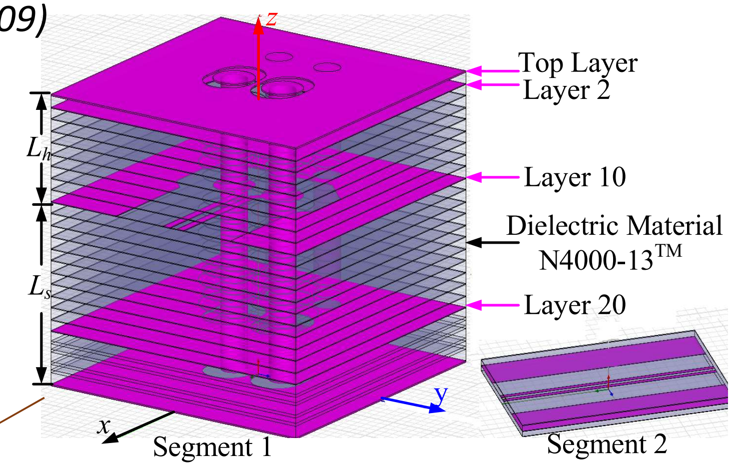
Solution: Train a ANN to map the equivalent circuit model to measurement data of new device.
The resulting knowledge-based model accurately represent the new device behavior
(GaN trapping effect, frequency dispersion, etc)

Knowledge-based Neural Model for Differential Via

(Y.Z. Cao, L. Simonovich, and Q.J. Zhang, 2009)







Equivalent circuit (knowledge) and ANN are combined:

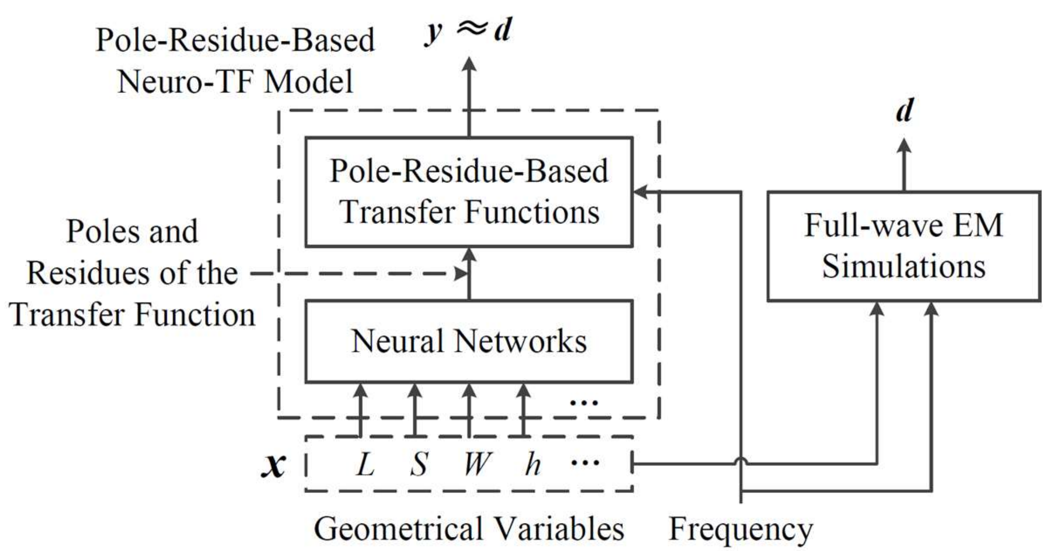
ANN: map the geometrical changes to R, C changes in equivalent circuit

Equivalent circuit: provide S-parameters

Knowledge-based Method: Neuro-TF Model

(F. Feng, C. Zhang, V. M. R. Gongal-Reddy, J. G. Ma, Q. J. Zhang 2016)

If empirical model is not available, transfer function (TF) can be used as the knowledge:



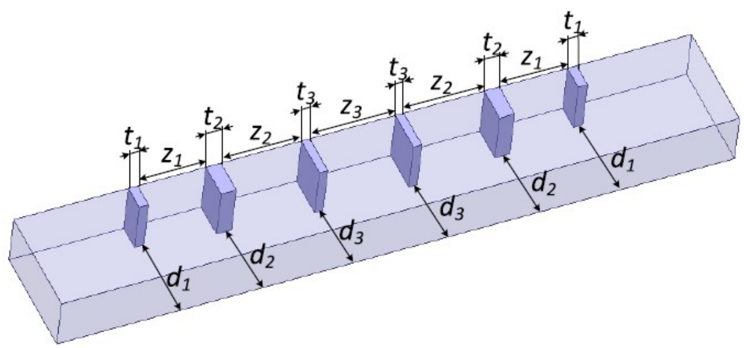
Neural network maps the geometrical variables into pole-residue parameters,

Thus allowing the transfer function to respond to changes in geometrical design variables.

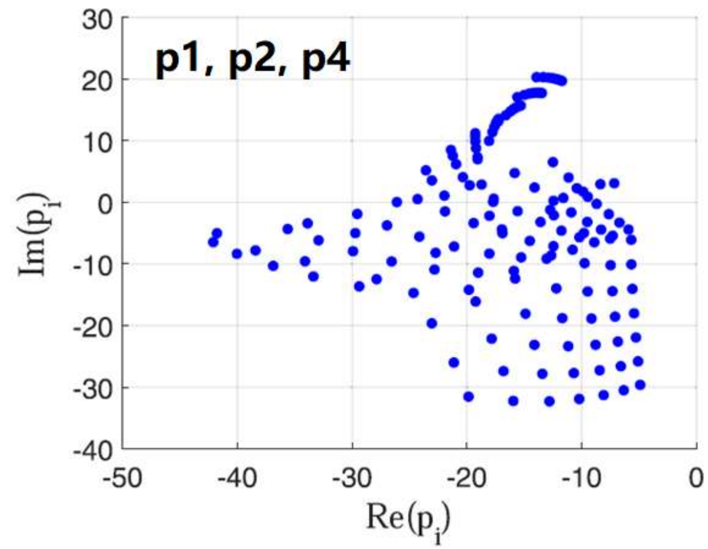
Pole-Tracking for Neuro-TF

(J.N. Zhang, F. Feng, W. Zhang, J. Jin, J.G. Ma and Q. J. Zhang 2020)

An EM example considering only 2 geometrical variables d_1, d_2.



fifth-order waveguide filter with 9 geometrical parameters



Problem: Pole tracking in γ-space while 2 geometrical variables varying (49 samples with d_1 *and* d_2 varying).

Pole p3, p5 are easily separated from other poles.

However, p1, p2 and p4 are mingled and not clearly separatable.

How to separate the 147 poles into 3 groups *p*1 , *p*2 and *p*4 ?, and track the pole movements ?.

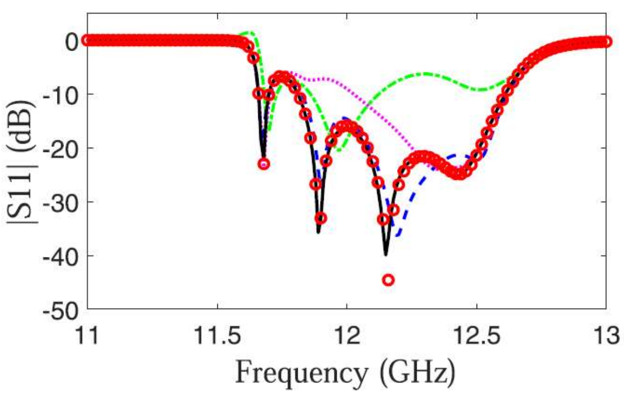
Neuro-TF with Pole-Tracking

(J.N. Zhang, F. Feng, W. Zhang, J. Jin, J.G. Ma and Q. J. Zhang 2020)

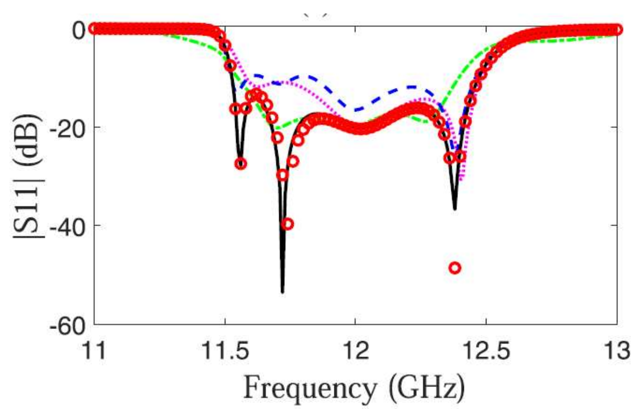
More Challenging Case:

all 9 geometrical variables in the fifth-order waveguide filter.
81 geometrical samples from DOE – harder because they are not grid sample
18 poles – higher order transfer function, harder because more ambiguities between poles

proposed method using EM sensitivity and MPVL is used to train the Neuro-TF model



Test sample 1



Test sample 2

Distance-based method (DBM)
DBM with refinement training
Continuation with refinement
Proposed method
EM data

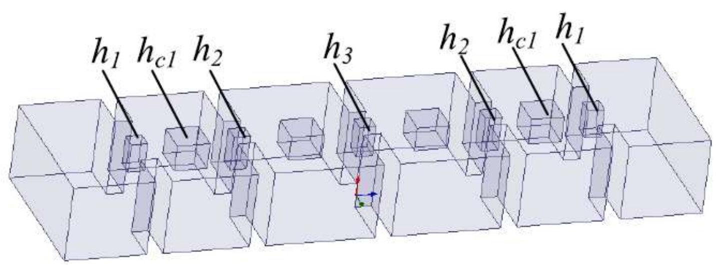
64 DOE test samples used

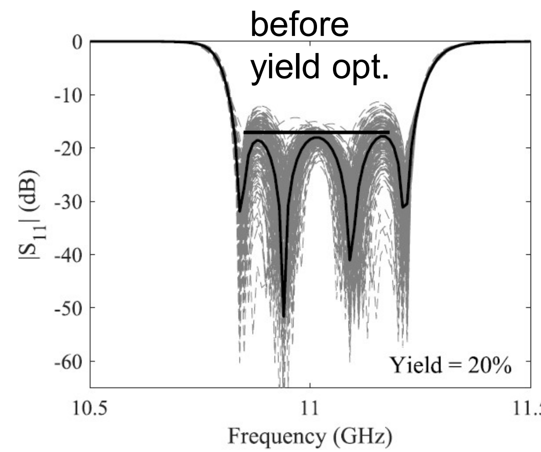
results for 2 of the test samples are shown here.

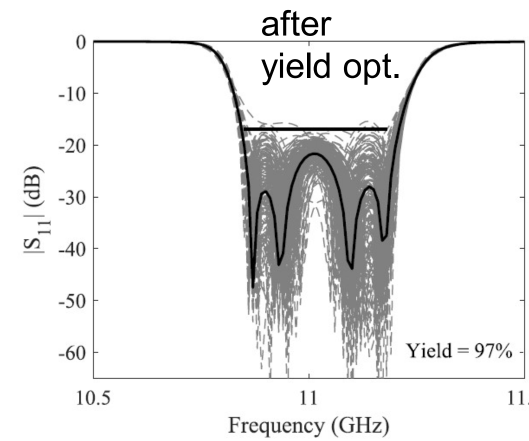
Considering that the data used in the figure are test data (never used in training),
→ the proposed method is more accurate than the three existing methods

Neuro-TF Model for Yield Optimization of EM Structures

(J.N. Zhang, J. Jin, W. Zhang, Z.H. Zhao and Q. J. Zhang 2021)







Order of TF: 12
81 DOE samples for training the neuro-TF
Number of hidden neurons is 10

Adaptive weighting factors for different frequency points in objective function during optimization.

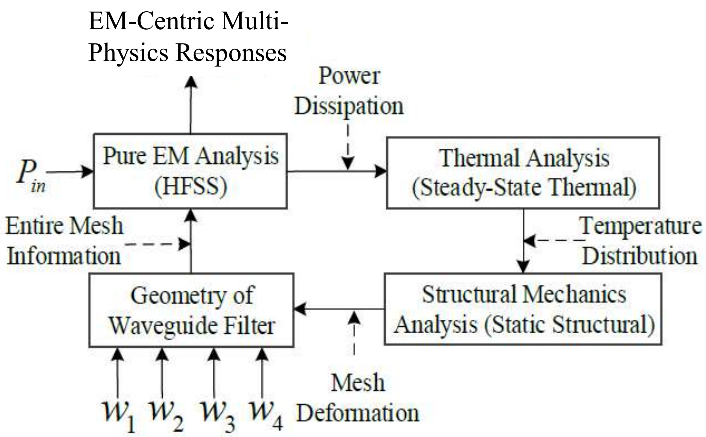
Monte Carlo analysis with 200 random samples of the filter

3 space mapping iterations

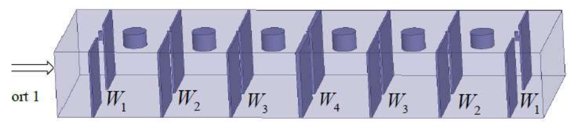
Higher yield solution and faster yield optimization reducing computation time from 72 (Monte-Carlo based) and 12 hours (PC based) down to 5 hours (Neuro-TF).

Neuro-SM for Multiphysics-based Modeling

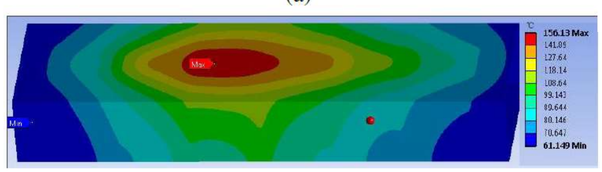
(W. Zhang, F. Feng, V. Gongal-Reddy, J. Zhang, S. Yan, J. Ma and Q. J. Zhang 2018)



Neural space mapping to map pure EM response to multiphysics response, for fast multi-physics modeling including electromagnetic, thermal and mechanical stress effects w.r.t. changes in geometrical variables

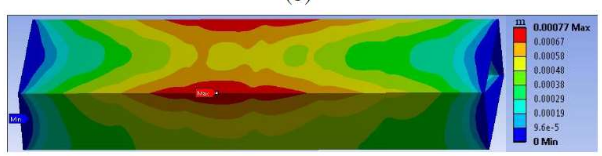


(a)



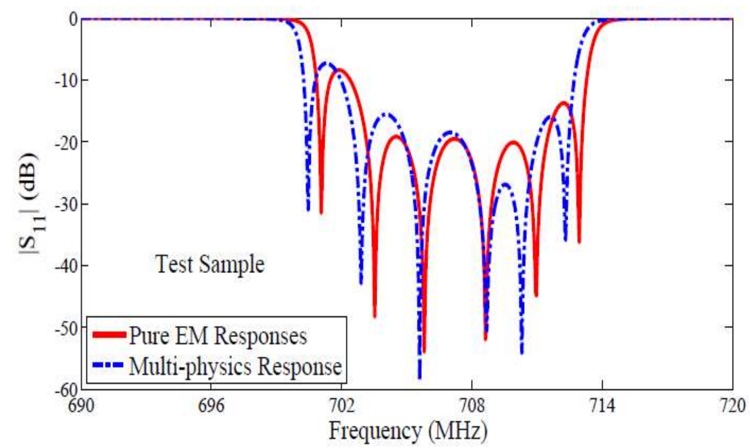
(b)

Temperature distribution



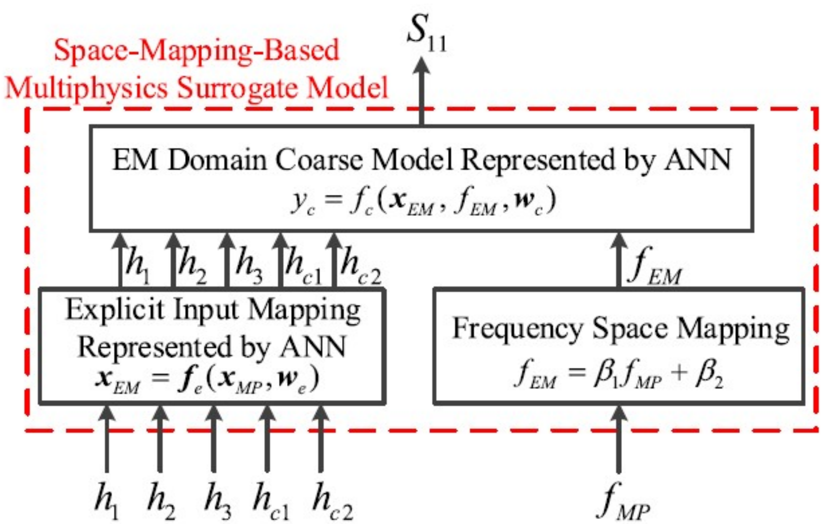
(c)

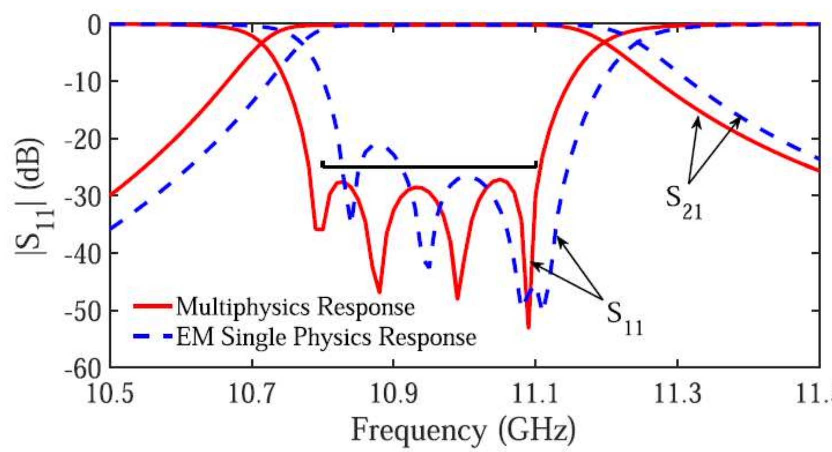
Structural deformation



ANN for Multiphysics Optimization of High-Power Filters

(W. Zhang, F. Feng, W. Liu, S. Yan, J. Zhang, J. Jin and Q. J. Zhang 2021)





9-level DOE with 81 EM samples for training ANN model
5-level DOE with 25 samples for training the space mapped ANN model

CPU time for each Multiphysics simulation is 11.9 min and for each EM simulation is 2.1 min

Multi-physics vs pure EM under P=500W. Space mapping aligns EM and multiphysics responses while the geometrical variables vary during optimization.

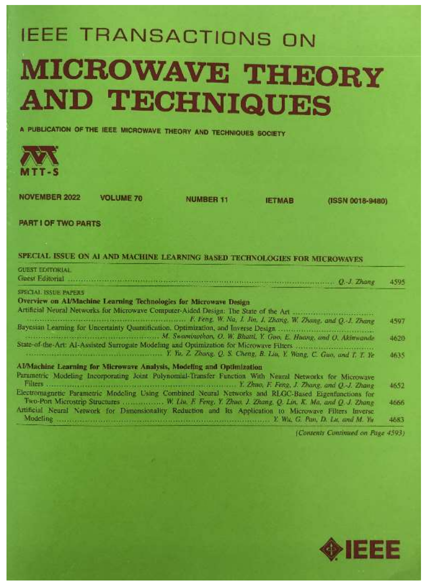
The parallel space mapping with the surrogate ANN model reduced Multiphysics optimization from 59 hours down to 1.7 hours.

AI/ML Based Technologies for Microwaves

Special Issue of the IEEE Trans. MTT (Nov. 2022)
Guest Editor: Q.J. Zhang

209 full-paper submissions

45 accepted/published



IEEE TRANSACTIONS ON
MICROWAVE THEORY AND TECHNIQUES

A PUBLICATION OF THE IEEE MICROWAVE THEORY AND TECHNIQUES SOCIETY

MTT-S

NOVEMBER 2022 VOLUME 70 NUMBER 11 IETMAB (ISSN 0018-9480)

PART I OF TWO PARTS

SPECIAL ISSUE ON AI AND MACHINE LEARNING BASED TECHNOLOGIES FOR MICROWAVES

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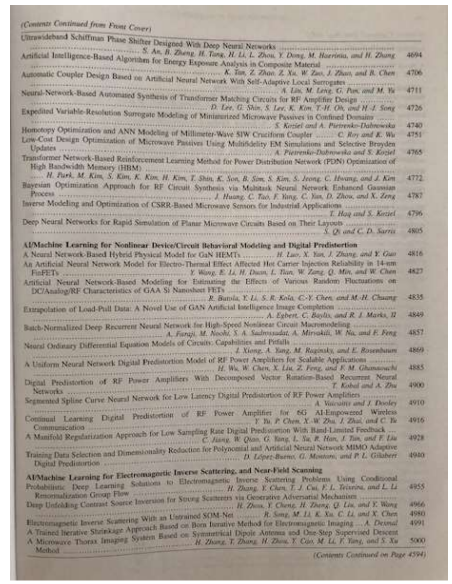
IEEE



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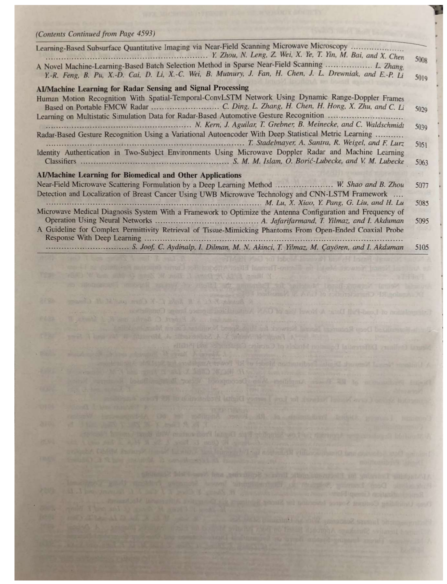

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AI/ML Based Technologies for Microwaves

Special Issue of the IEEE Trans. MTT (Nov. 2022)

Overviews of AI/Machine learning

ANN for microwave computer-aided design (Feng, Na, Jin, J. Zhang, W. Zhang, et al.);

Bayesian learning for uncertainty quantification, optimization and inverse modelling (Swaminathan, et al)

AI-assisted surrogate modelling and optimization of microwave filters (Yu, et al)

AI/ML Based Technologies for Microwaves

Special Issue of the IEEE Trans. MTT (Nov. 2022)

AI/ML approaches for analysis, forward/inverse modelling and optimizations for microwave design

AI/ML technologies for nonlinear device modelling, power amplifier (PA) behavioural modelling and digital predistortion,

AI/ML for electromagnetic inverse scattering, near-field scanning, or electromagnetic imaging

AI/ML for radar sensing and signal processing

AI/ML for biomedical and other applications

AI/ML Based Technologies for Microwaves

Special Issue of the IEEE Trans. MTT (Nov. 2022)

Machine Learning Methodologies

- ANNs
- deep learning
- convolutional neural networks (CNN)
- recurrent neural networks (RNN)
- long-short term memory networks (LSTM)
- generative-adversarial networks (GAN)
- k-means clustering
- support vector machine (SVM)
- Gaussian process (GP) regression
- Bayesian optimization (BO),
- reinforcement learning (RL),
- U-net etc;

AI/ML Based Technologies for Microwaves

Special Issue of the IEEE Trans. MTT (Nov. 2022)

Microwave Applications

modelling and design: passives -	planar and 3D electromagnetic structures
	microwave filters
	SIW circuits
	high-speed IC packages
modelling and design: actives -	GaN-HEMT/FinFET/nanosheet FET
	PA/DPD, MIMO transmitters

Electromagnetic imaging for breast cancer detection/localization, thorax imaging

Doppler radar based human motion recognition, gesture recognition and object identification

AI/ML Day in IEEE MTT-S IMS2023

Organizers: Q.J. Zhang and Costas Sarris

- AI/ML Bootcamp (Q.J. Zhang, C. Sarris, U. Gustavsson) Bootcamp on Sunday
- AI/ML for RF PA Design and Digital Predistortion (A. Zhu, R. Ma) Workshop WMC
- Brain-Inspired Learning for Intelligent Spectrum Sensing (L. Katehi), Invited talk
- AI/ML Technologies for Microwaves (Q.J. Zhang, C. Sarris), Special Session Tu1A
- AI/ML Technologies for Signal and Power Integrity
  (J.E. Rayas-Sanchez, C. Sarris), Focus Session Tu3A
- AI/ML based Wireless System Design and Operation – Hope or Hype ?
  (C. Sarris, Q.J. Zhang, O. Eliezer, B. Sadhu) Panel Session PL2
- Machine Learning for RF to mm-Wave Systems
  (A. Tang and Q.J. Zhang), Technical Session Tu2A

AI and Machine Learning for Microwaves

Machine learning (such as neural networks) exploited in microwave area since 1990s.

Activity in machine learning intensified in recent years

Ongoing Activities and Trends

new algorithms, ML structures, microwave knowledge-based ML methods

component level - EM, GaN HEMTs, ..

circuit/system level - PA, DPD, MIMO, intelligent wireless systems

application level - biomedical, security, autonomous systems, communications

new and emerging applications

Thank You

AI and Machine Learning for Microwaves

Past, Present and Future Trends

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