ANN-Based Spiral Inductor Parameter Extraction and Layout Re-Design

A A ILUMOKA, Ph.D and Y. Park, MSEE, Dept of ECE, University of Hartford, CT
Email:ILUMOKANW@HARTFORD.EDU

Abstract

A neural network approach is presented for modeling and characterization of on-chip copper spiral inductors. The approach involves the creation of neural network models to map 3D multi-level spiral inductor geometric characteristics to SPICE equivalent circuit parameters. The neural network replaces computationally expensive FEM-based extraction and field solution. The approach is especially attractive because it is capable of accurately and efficiently predicting important inductor characteristics such as self-inductance, Q-factor, self-resonant frequency and parasitic resistance and capacitance. It also offers substantial computational savings over field solution - evaluation of neural model required on average less than 5% of the cpu time required for field solution.

1. Introduction and Related Work

In today's portable wireless communications market, there is a demand for low cost, low power dissipation, high frequency IC building blocks that incorporate spiral inductors on the silicon substrate. The availability of spiral inductor models that meet the demands of the emerging wireless communication designs is a crucial element of a successful design flow. However, challenges of modeling spiral inductors for Ultra-Wideband (UWB) wireless applications are increasing. In the early 1990s, models were built using a discrete model library where a number of spiral inductors were fabricated and the measured data tabulated in lookup tables. This provided the end user with a model database that offered a limited number of spirals' topologies and an even more limited parameter sets. This approach, even though it offered very good accuracy at the selected points, greatly limited design options. It wass non-predictive and if the process was changed, the entire effort of manually building the model needed to be performed all over again. Although there are many reports in the literature of high performance inductors on silicon substrates, there is relatively little information on modeling and performance prediction of these structures. A brief review of recent relevant literature now follows. Chao et al in [1] present an empirical spiral inductor characterization method in which scattering parameter measurements are made on several on-chip inductors fabricated using Bi-CMOS technology. In [2,7] measurements are made on high Q spiral inductors fabricated on thick insulator-on silicon generating scalable inductor models easily integrated into a CAD framework. Spiral inductor Q is extracted in [3] by a numerical procedure in which a capacitor is added to inductor equivalent circuit and analysis takes place of the resonant behavior of the resulting circuit. In [4] the stacking of metal layers in a multi-level metal process was exploited for Q improvement. In [5] analytic expressions for the DC inductance of spiral inductors are compared with three-dimensional field solver predictions while in [6], inductance expressions are used in a lumped circuit inductor model optimized using geometric programming. The above methods have produced very useful advances in spiral inductor design, however, scalability of inductance values is important for optimized layout design, hence a method for accurate and efficient prediction of spiral inductance metrics given layout parameters (e.g. number of turns, number of levels, coil width and spacing) is essential. Neural networks provide a cost-effective and accurate method for automatic model generation. The neural approach proposed employs a highly parallel form of network architecture - the *modular artificial neural network* MANN [8]. Since neural networks have the ability to learn relationships based on prior training, a training database of spiral inductors is first constructed to reflect a wide range of possible spirals. To construct the database, a field solver which uses the finite element method, a circuit simulator and a neural network multi-paradigm prototyping system are coupled together. Each spiral is constructed using a 3D drawing tool. This is followed by Finite Element Method (FEM) solution of electric and magnetic fields in the structure and extraction of a lumped circuit model comprising self-inductance, parasitic resistance and capacitance (fig 2). This lumped SPICE-compatible equivalent circuit model permits the simulation of the spiral inductor in the frequency range of interest. MANN training takes place to map spiral inductor geometric characteristics to SPICE parameters. Once trained to high degree of prediction consistency, the MANN replaces computationally expensive FEM-based extraction and field solution. In generating the database, inductor characterization was performed for 250 3D spirals with characteristics stated in table 1. Following field solution, inductance values ranging from 0.6nH to 10nH were obtained with Q factors ranging from 0.5 to 5 and self-resonant frequencies in the 30-80Ghz range. Fig 2 is an equivalent circuit representation of a typical spiral inductor from the database showing parasitic capacitance and resistance. A brief description of modular artificial neural networks [8,9] now follows.

2. Modular Artificial Neural Networks

Modular neural networks were first proposed by Jacobs, Jordan, Nowlan and Hinton [9] as *adaptive mixtures of local experts*. They consist of groups of networks competing to learn different aspects of a problem. A gating network controls the competition and learns to assign different regions of the data space (corresponding to different aspects of the problem) to different local experts. Each local expert of a MANN is an MLP network with a single hidden layer. Both the local experts and the gating network have full connectivity with the input layer, furthermore supervised training of the MANN occurs simultaneously for the gating network and the local experts. The learning rule is designed to encourage competition among local experts so that once training is complete, for a given input vector the gating network will tend to choose a single local expert rather than a mixture. Effectively, this translates into the automatic partitioning of the input space into sub-regions each of which is handled predominantly by a single local expert. Training of the local experts and the gating network is achieved via back-propagation of error - a gradient-based learning technique which propagates the global output error backward through the connections to the hidden and input layers with the objective of minimizing the global error function by modifying network weights.

3. Neural Network-Based Inductor Modeling

3.1 Database Generation for Neural Network Training

In order to generate the neural network, a database of 3D rectangular spiral inductors (fig 1) is constructed with geometric characteristics as shown in table 1. A total of 250 replicas of the nominal spiral are produced via Monte Carlo analysis by uniform random variation of 7 spiral geometry parameters (N, M, W, S, T, CL,CW) – see table 1 - within the specified ranges. Using the Maxwell 3D field solver and SPICELINK Extractor, equivalent lumped SPICE models are obtained for each spiral. From the extracted SPICE model, five inductor characteristics are computed for each spiral: self-inductance (L), parasitic capacitance (C), parasitic resistance (R), Q-factor (Q)and self-resonant frequency (fsr). Of the 250 spirals, 230 were employed for training the MANN and 20 for testing.

3.2 Neural-Net Based Spiral Inductor Extraction

For fast spiral inductor circuit extraction, a MANN network having 7 input nodes, 5 output nodes and 3 local experts was constructed and trained (fig 3) to directly map spiral inductor geometry characteristics (N, M, W, S, T, CL, CW) to inductor characteristics (C, L, R, Q, f_{sr}). Training involved repeated presentation of the training data for the 230 spirals in the database to the MANN network accompanied by weight updates as described in section 2 until the rms training error was minimum. For test purposes, the remaining 20 independent spirals were presented to the trained MANN and predictions of inductor characteristics compared with field solver calculations.

4. Results

The MANN (fig 3) was constructed using Neuralware Professional II Plus software and trained as described in section 3 until low rms training and test errors of 0.0288 and 0.0303 respectively were achieved. To demonstrate the accuracy and computational efficiency of the neural approach, extraction results for 20 randomly selected test spirals are presented in figures 4 -7. Spiral inductor metrics (L, R, Q, C, f_{sr}) matched extremely well to within 5%. Field solution for 20 test spirals required 1836 cpuseconds on a Pentium V machine while evaluation of the predictive neural model required 89cpuseconds, a savings of 94% in computational effort (excludes cost of initial setup of spiral database since effort of building database needs to be performed only once).

5. Conclusions

A cost-effective predictive neural network model to accurately characterize multilevel 3D spiral inductors is described. Five spiral inductor metrics - self-inductance, Q-factor, self-resonant frequency, parasitic capacitance and resistance are characterized to 95% accuracy for a given spiral specified using 7 geometrical parameters. The approach involved the creation, training and test of a modular neural network for mapping of spiral inductor geometric characteristics to SPICE equivalent circuit parameters. The neural approach serves as a basis for rapid and computationally efficient inductor equivalent circuit extraction.

6. Bibliography

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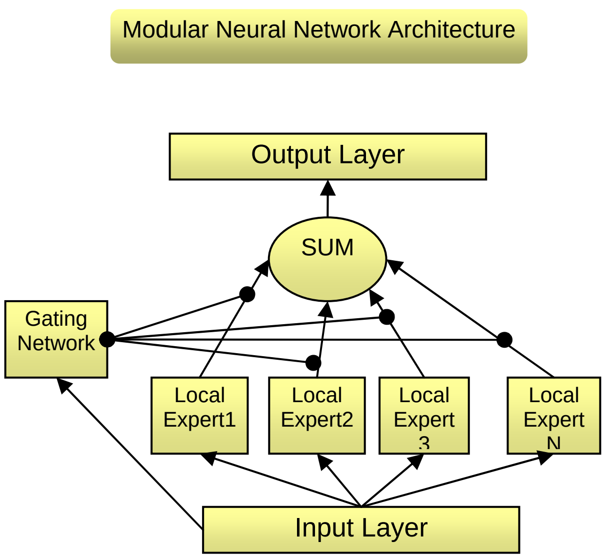
Table 1: Spiral Inductor Geometrical Characteristics

Parameters	Minimum	Nominal	Maximum
# of Turns/level (N)	2	6	10
# of Levels (M)	1	3	6
Metal Thickness T (um)	0.6	0.8	1
Metal Width (W um)	4	8	12
Metal Spacing (S um)	2	4	6
Core Size C L X CW (um)	4X4	8X8	12X12

Fig 3 Modular Artificial Neural Network



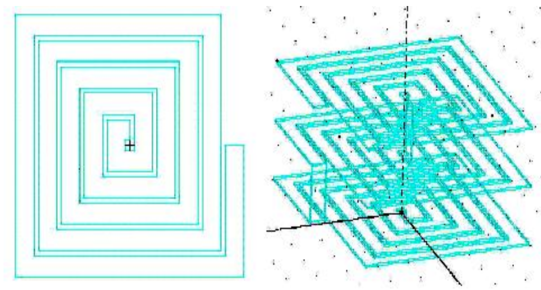


Fig 1: Spiral Inductor Layout (Plan and 3D Views)

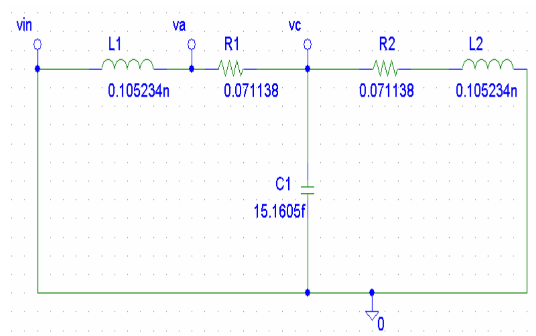


Figure 2: Spiral Inductor Equivalent Circuit N=4, M=3, ε=2.5E+07,T=0.97μm, W=18.3μm, S= 4.6μm, D=119μm Q=3.18 f_{SR} =62GHz

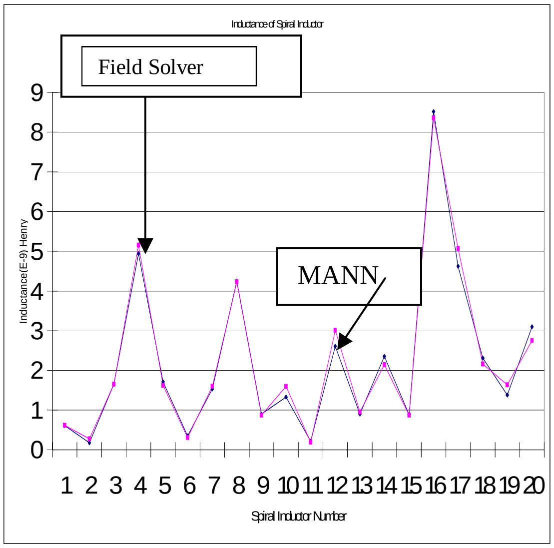


Fig 4 Predicted Self-Inductance L (nH) from Field Solver & MANN for 20 test spirals

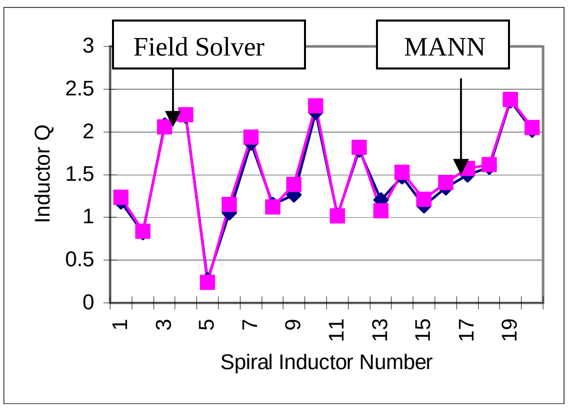


Fig 5 Predicted Q-factor from Field Solver & MANN for 20 test spirals

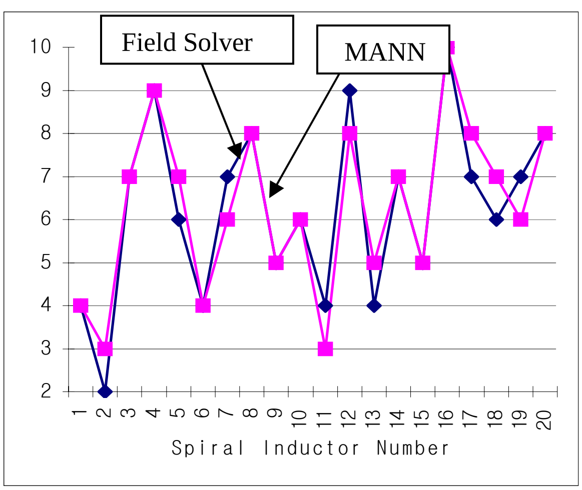


Fig 6: Self-Resonant Frequency fsr (GHz) from MANN and Field Solver for 20 test spirals

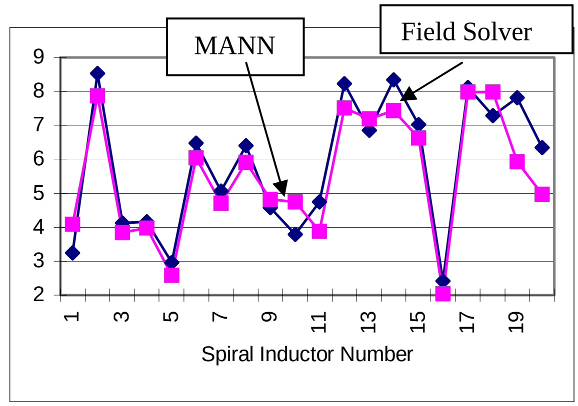


Fig 7: Parasitic Capacitance (fF) from MANN and Field Solver for 20 test spirals