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Synthesis of On-Chip Square Spiral Inductors for RFIC's using Artificial Neural Network Toolbox and Particle Swarm Optimization

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Abstract

In this paper on-chip square spiral inductors are designed using ANN modeling techniques. Layout geometries form the input of the ANN model and electrical quantities forms the output . The dependency of inductor performances such as inductance (L), quality factor (Q) and self-resonance frequency (SRF) on geometric dimensions are described. Spirals of wide range of RF applications are studied. In our ANN based synthesis approach on-chip spiral inductor layout parameters such as spiral outer diameter(D), width of metal trace(W), number of turns in spiral(N), spacing between the adjutants metal traces(S) are taken as input and Inductance ,Q-factor and Self resonance frequency are the output of our model. Further a PSO based searching algorithm is applied with ANN model for optimization of layout parameters for the electrical parameters. We present several synthesis results which show good accuracy with respect to full-wave electromagnetic (EM) simulations. Since the proposed procedure does not require a time consuming EM simulation in the synthesis loop, it substantially reduces the cycle time in RF-circuit design optimization.

Keywords: Artificial neural networks (ANNs), On-chip inductor, Spiral inductor optimization, Inductance, Q-factor, Self Resonance frequency , electromagnetic simulation , PSO, HFSS.

1. Introduction

Wireless communication systems has stimulated research in low-cost, low-power, and high-performance CMOS RF integrated-circuit (IC) components for system-on-chip solutions .On chip spiral inductors represents one of the major components of the RF ICs that dominates circuit performance and most frequently used passive devices in modern RFICs. The lack of an accurate model for on-chip inductors presents one of the most challenging problems for silicon- based radio-frequency integrated circuits (RF IC's) designers. In conventional IC technologies, inductors are not considered as standard components like transistors, resistors, or capacitors, whose equivalent circuit models are usually included in the process description. However, this situation is rapidly changing as the demand for RF IC's continues to grow [1,8]. Various approaches for modeling inductors on silicon have been reported in past several years [2,3]. Most of these models are based on numerical techniques [13], curve fitting [11], or empirical formulae [12], and therefore are relatively inaccurate or not scalable over a wide range of layout dimensions and process parameters. EM simulations are now widely used for analysis of wide ranges of layout dimensions and process parameters in the RFIC design. Artificial neural network (ANN) is a new technique [14,15] and efficient alternative to above mentioned conventional modeling techniques. It is popular due to its capability of learning any arbitrary nonlinear input–output relationship from corresponding data and also because it produces smooth approximation results from discrete data. The I/O relationships of the model make a closed form expression, and also due to the low latency trained network gives an almost instant output. Neural models are, therefore, much faster than physics/EM models and have a higher accuracy than analytical and empirical models. For deciding the optimal inductor-layout geometries that give maximum quality factor at a particular operating frequency and inductance value within a predefined design space long running simulations are required. We apply the particle-swarm optimization (PSO) algorithm [5] to search the layout space for optimization. In exploration, the ANN model is used to compute the inductance (L), Q, and SRF of each spiral.

2. ANN Design

2.1 ANN Model Structure

Multilayer perceptron (MLP) feed forward network is one of the most effective neural network structures[6,9] .We consider four inductor-layout parameters, namely, outer diameter (d), number of turns (n), metal width (w), and spacing between metal traces (s), forms input of our neural model. The output layer of NN model represents electrical attributes of the inductor which are L, Q, and SRF. Number of hidden layers and neurons in each hidden layer are decided on the platform of best performance of and Quality of the neural model. Wide combinations of hidden layers with neurons in each hidden layer are employed and the best combination is chosen out. We used hyperbolic-tangent activation function for hidden layers and linear activation function for output neurons. For the generation of training and testing data sets, planar square spiral inductors were constructed in the range of geometric dimensions. Out of all the theoretically possible combinations, we have considered a large number of inductors (400 realizable spirals) have been designed and simulated using commercially available high frequency structure simulator[10].

2.2 Data Generation

Data for the ANN model input layout parameters and the output electrical parameters are generated from high frequency simulator tool Ansoft HFSSv.10. Data for layout parameters are taken in a wide range with a sufficient step sizes for each parameter. The step sizes are taken in such a manner to train neural network in a universal platform for the bounds of the parameters ranges. The range distribution via step size in a defined range is a cyclic process until no more error reduction level reached. This level is measurement of how close the ANN output is to the EM simulator output. The electrical quantity forms the output. We use 80% of the inductors designed by EM simulator for the training and 20% inductors are used for the validation, testing. We selected training and test data in a regular interval of five units so that both cover the complete range and adequately represent the original inductor behavior.

2.2.1 Data Preprocessing Step

As input parameters for building the neural model vary over a wide range. The corresponding output-parameter values of the inductors are also quite different. This introduces the requirement of an orderly preprocessing training . For this purpose the input and output data were normalized to [−1 1] with respect to the minimum and the maximum of the data range by means of linear scaling.

$$X' = X'_{min} + \frac{(x - x_{min})}{(x_{max} - x_{min})} * (X'_{max} - X'_{min}) \quad (1)$$

where x, x_{min} and x_{max} represent original data and X', X'_{min} and X'_{max} represent scaled data. The scaled data were used for training.The scaled data is used for neural network training.

2.3 Weights biases and NN training parameters adjustments

During neural-network training, the weight and bias values are adjusted to minimize the training error which is a measure of the correlation between the ANN-model output and the training data. We have used the Levenberg–Marquardt method as the training algorithm in MATLAB's neural-network tool for our Model [7]. We set the learning rate as 0.01 which is found adequate, setting it too large leads to oscillations, and setting it too small value results in longer training time for reaching the level of accuracy. The training error goal was set to 0.001. Further lowering of the error limit reduces the generalization capability of the model. On the other hand, setting it too high would lead to lower mapping accuracy.

3. Synthesis

3.1 Particle Swarm optimization

Particle swarm optimization (PSO) is a population based stochastic optimization technique, inspired by social behavior of bird flocking. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far [4]. (The fitness value is also stored.) This value is called *pbest*. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors of the particle. This location is called local best when a particle takes all the population as its topological neighbors, the best value is called global best. The particle swarm optimization concept consists of, at each time step, accelerating each particle toward its pbest and lbest locations. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and lbest locations. PSO has been successfully applied in many research and application areas. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods.

3.2 Synthesis Methodology

As it is obvious, a target-inductance value can be realized by many different combinations of layout parameters. For a RF designer out of these combinations, only the set of inductor-layout parameters that meet all the design constraints is considered. We have developed a spiral-inductor-synthesis procedure that helps the designer to make a tradeoff analysis between the competing objectives, namely, *Q*, SRF, and outer diameter, for a given *L*. Our synthesis procedure uses ANN and PSO. The PSO optimizer generates a swarm of particles, each representing a combination of layout parameters in the given design space. The ANN takes each combination of layout parameters and produces *L*, *Q*, and SRF as output. Cost function is computed using these electrical parameter values. Particles of the optimizer are then updated according to the minimum cost. This process continues until a desired cost function objective is achieved or the maximum number of iterations executed. Typically the spiral inductor design and optimization problem is formulated to maximize the *Q* value for a target inductance subject to certain constraints. Since, in this synthesis procedure, our aim is to find a set of layout parameters which will give the desired inductance value within acceptable error, the cost function is to

Minimize $L_T - L_{ANN}$ subject to $Nmin \le N \le Nmax$, $Dmin \le D \le Dmax$, $Wmin \le W \le Wmax$, $Smin \le S \le Smax$

Here, L_T, L_{ANN}, are the target inductance, the inductance computed from the trained ANN, and the given minimum SRF, respectively. Nmin, Nmax, Dmin, Dmax, Wmin, Wmax, Smin, and Smax are the minimum and the maximum bounds of the corresponding optimization variables. PSO algorithm provides multiple solutions of layout parameters for a target-inductance value due to the random initialization of particles and the random variables associated with the velocity and position-update process during our synthesis. The search process is terminated if the objective function is less than an acceptable error value or if the number of iterations reaches the maximum. For the synthesis of our spiral inductors, we set the error value is set to 10% and the maximum number of iterations is taken up to be 1000.

4. Results and Discussion

4.1 ANN Results

To verify the accuracy of the neural models, statistical measures, such as the average relative error and the correlation coefficient between the outputs and targets were calculated for each output parameter. The average relative error and the correlation coefficients are calculated as follows:

Average Relative Error = $\boldsymbol{\Sigma_{1}^{n}(x\text{-}y)/ny}$ **(9)**

Correlation Coefficient = $\{(n\Sigma xy - \Sigma x\, \Sigma y)/\{[n\, \Sigma x^2 - (\Sigma x)^2][n\, \Sigma y^2 - (\Sigma y^2)]\}^{0.5}\}$ (10)

Here, n, x and y are the number of samples in the data set, the ANN-model output, and the corresponding EM simulated value, respectively.

Table 1: Accuracy of Neural Model.

ANN Operating Frequency(GHz)	Training Epoch	Type of Data set	% Average Relative Error L (nH) Q SRF(GHz)	Correlation Coefficient L(nH) Q SRF(GHz)
1 GHz	30	Training Testing	0.9231 4.3321 1.2236 1.0021 6.1244 4.2231	0.9999 0.9231 0.9984 0.9999 0.9421 0.9776
3 GHz	44	Training Testing	1.2331 4.2117 2.1453 1.5377 3.2231 5.1123	0.9999 0.9233 0.9833 0.9999 0.9272 0.9728

The relative error signifies the closeness of the ANN outputs to the EM simulated values. The correlation coefficient is a measure of how closely the neural output fits with the target values. If this number is equal to 1.0, then there is a perfect fit between the targets and the outputs. Table 1 percentage average relative error and correlation coefficient of each neural-model output with respect to the EM simulated value. The average relative errors of L, Q, and SRF were found to be less than 5%. This indicates good accuracy of the neural network. In our examples, correlation coefficients are very close to 1.0, which indicates a good fit.

4.2 PSO Results

Particle swarm optimization algorithm is used to find the layout parameters for a given set of constraints. Global version of PSO algorithm is implemented as it is more effective than local best .The synthesis based procedure provides number of sets of layout parameters for a given inductance value(L) and constraints which based on Q and SRF within acceptable error limits. Synthesis results facilitate the designer with more freedom for trade off analysis between objectives, such as area, L, *Q*, and SRF for inductors. In Table2, three sets of layout parameters are shown for a target inductance of 6 nH within ±0.3 nH accuracy. Design constraints are D= 100−300 μm, W = 8−24 μm, N = 2.5−6.5, AND s = 1−4 μm and SRF>6 respectively.

Table 2 Synthesis of 6-nH Inductor with ANN and PSO.

L(nH)	D(um)	W(um)	N	S(um)	Q	SRF(GHz)
5.9881	289	9.9	3.7	3.8	11.0937	6.8041
6.2301	234	11	5.3	2.5	8.4181	7.7816
5.8134	229	10.5	4.8	3.5	9.4672	7.8349

5. Conclusion

We have proposed fast and efficient layout synthesis system for RF on-chip spiral inductors. A four-layer MLP neural model has been developed. All the output parameters of the neural model show good matching when compared with the data generated by an EM simulator. The synthesis procedure is based on a PSO technique that evaluates the electrical parameters from the geometric parameters using the neural model. No EM simulation is required during the synthesis procedure thus making the process efficient. The synthesis procedure provides multiple solutions for a given design specification that helps the designer in making a tradeoff between the competing objectives. Several design examples have been presented using the proposed approach. The synthesized inductors were resimulated using the Ansoft HFSS (v11.0) EM solver. The results obtained by our synthesis approach show good agreement with the EM simulation results.

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