Accurate Synthesis of Integrated RF Passive Components Using Surrogate Models

F. Passos, R. González-Echevarría, E. Roca, R. Castro-López, F. V. Fernández
Instituto de Microelectrónica de Sevilla
IMSE, CNM (CSIC, Universidad de Sevilla)
Seville, Spain
{moreira,gonzalez,eli,castro,francisco.fernandez}@imse-cnm.csic.es

***Abstract*—Passive components play a key role on the design of RF CMOS integrated circuits. Their synthesis, however, is still an unsolved problem due to the lack of accurate analytical models that can replace the computationally expensive electromagnetic simulations (EM). Both, physical-based and surrogate models have been reported that fail to accurately model the complete design space of inductors. Surrogate-assisted optimization techniques, where coarse models are locally enhanced during the inductor synthesis process by using new EM-simulated points to update the model, have been proposed, but either the efficiency is dramatically decreased due to the online EM simulations or the optimization may converge to suboptimal regions. In this paper, we present a new surrogate model, valid in the entire design space with less than 1% error when compared with EM simulations. This model can be generated offline, and, when embedded within an optimization algorithm, allows the synthesis of integrated inductors with high accuracy and high efficiency, reducing the synthesis time in three orders of magnitude.**

Keywords—passive RF compenents, integrated inductors, surrogate functions, PSO, optimizations, surrogate assisted models.

I. Introduction

In recent years, methodologies for the design and synthesis of integrated passive components for RF ICs have attracted much attention. It is known that on-chip passive components, e.g. inductors and transformers, strongly influence the performance of RF circuits [1]. For example, the quality factor of an inductor dominates the overall quality factor of an LC tank used on a voltage controlled oscillator (VCO), and the loss of a transformer has a large impact on the power-added efficiency and the output power of a power amplifier (PA). On the other hand, these passive components are usually responsible for most of the area of circuits such as low noise amplifiers (LNA) and the previously mentioned circuits.

When the use of passive components, such as integrated inductors, is needed, designers rely either on inductor libraries provided by the foundries or they use electromagnetic (EM) simulations in order to design inductors. However, both methods have their limitations. The foundries usually provide limited inductor choices, which therefore reduce the possibility of choosing the optimal inductor for a given application. On the other hand, the use of EM simulation is computationally expensive and the design process is mainly based on the designer's experience, limiting the possibility to obtain optimal inductors.

In order to reduce the computational effort in the design process, designers have developed physical/analytical equivalent circuit models, such as the one presented in [2]. However, these models fail to accurately model the complete useful region of the inductor design space.

In the past few years, black-box or surrogate models have been used to replace complex computationally expensive simulation processes, by simpler models that can be much more efficiently evaluated, but without providing any physical insight [3]. However, these surrogate models still present relatively high errors when the entire design space is considered [4].

When these different alternatives for performance evaluation are embedded in an iterative optimization loop for inductor synthesis, different trade-offs between accuracy and efficiency arise. When EM simulation is used, the highest accuracy is achieved at the price of the highest computation time, usually in the range of days [5]. Optimization techniques with physical/analytical models for performance evaluation lie at the opposite end of the accuracy-efficiency trade-off: short synthesis times, typically in the range of few minutes can be achieved, but with the lowest accuracy, because, generally, equivalent circuit models do not allow an accurate modeling of RF passive components.

Such efficiency-accuracy trade-off is significantly improved by the use of surrogate models. However, the difficulties in generating surrogate models sufficiently accurate in the complete design space have hampered the development of these approaches. In order to overcome the inaccuracy problem of the previous modeling strategies, new approaches are being developed based on an initial coarse model, which is locally improved during the optimization process [6][7]. Assuming that the convergence to the global optimum is achieved, the price to pay is a higher computational time, as expensive EM simulations must be executed during the optimization process.

In this paper, the different synthesis strategies are compared and an intelligent global surrogate modeling strategy is proposed, that is able to obtain highly accurate inductor

This work was supported in part by the TEC2013-45638-C3-3-R Project (funded by the Spanish Ministry of Economy and Competitiveness and ERDF), in part by the P12-TIC-1481 Project (funded by Junta de Andalucía), and in part by the CSIC Project PIE 201350E058.

performances over the entire design space. This methodology enables the reduction of the synthesis time by three orders of magnitude when compared to EM-based synthesis methodologies, while providing performance errors well below 1%.

In Section II a detailed description of the alternative methodologies will be given. In Section III the surrogate modeling strategy proposed as well as the optimization algorithm (Particle Swarm optimization) used will be explained in detail. Section IV will present the experimental results where two surrogate model-based methodologies are compared against the EM simulation-based synthesis methodology. Finally, conclusions are drawn in Section V.

II. SYNTHESIS METHODOLOGIES

The synthesis methodologies for integrated inductors can be classified into four categories. They will now be explained in detail, highlighting their advantages and drawbacks.

1) EM simulation as a performance evaluator of an optimization technique (EMO):
The EMO methods provide the most accurate performance evaluation of the passive components because they use EM simulations. When integrated with an optimization algorithm, the quality of the solution is the most accurate from all the available methods. However, its major drawback is the high computational cost of the EM simulations. Despite this limitation, it establishes an excellent comparison benchmark for other techniques.

2) Equivalent circuit model as a performance evaluator of an optimization technique (ECO):
The ECO methods depend on a physical/analytical equivalent circuit model to obtain the performances of the passive component. Their advantage is their high efficiency. However, reported equivalent circuit models are usually not accurate enough for a passive component synthesis, showing errors typically higher than 10% [8]. Hence, when coupled with optimization algorithms, large deviations are observed on the synthesized passive components when their performances are verified with EM simulation. Therefore, these models can only be used for a first order approximation and not for a full inductor synthesis.

3) Offline surrogate model as a performance evaluator of an optimization technique (OFFSO):
With the OFFSO methodology, a surrogate model is created before being used within an optimization algorithm [4]. The surrogate model is first built to be as accurate as possible. Then, the optimization algorithm uses this surrogate model as the performance evaluator to find the optimal solution. The surrogate model is called offline because training data can be generated by EM simulation and the model can be constructed before any optimization specs are set.

Normally, the data set used to build the surrogate model is generated covering the entire design space. When combined with an optimization algorithm, this method has the ability of searching through the entire design space in order to find a global optimum. The generation of the training data is computationally expensive, in the order of 1-2 weeks for detailed EM-simulation in the complete frequency range of 800 inductors in a machine with twin 6-core processors. However, such training data have to be generated only once and are valid for any future optimization problem. Moreover, they can be generated offline, much before they are needed for the first inductor optimization problem.

On the other hand, since the model evaluation is very fast, the optimization process itself is highly efficient, usually in the range of few minutes.

4) Online surrogate model as a performance evaluator of an optimization technique (ONSO):
Due to the inaccuracy of global models, ONSO methodologies, also called surrogate-assisted evolutionary algorithms (SAEA), have lately received great attention [7]. In this methodology, a coarse surrogate model using few training points is first constructed. Then, this coarse model is coupled with an optimization algorithm and, at each iteration, promising solutions (typically one) are simulated electromagnetically. The data from this EM simulation is used to update the surrogate model in order to improve the accuracy in the region where the new simulation point is added, while moving towards the presumed optimal inductor. However, the ONSO methodology depends on the accuracy of the initial coarse model. This leads to two significant challenges for this methodology. Firstly, the best solution found at each iteration outlines the search space and the constructed surrogate model is only accurate in that space. Secondly, the ONSO methodology is based on the assumption that the optimal point of the coarse and fine models is not far away in the design space. However, again, this assumption only holds when the coarse model is accurate enough.

ONSO methods exhibit a delicate trade-off between efficiency and the probability of convergence to the global optimum. Better convergence can be achieved by either increasing the size of training data of the coarse model, or emphasizing the exploration of potentially good regions of the design space during the optimization process, or a combination of both. In all cases, an increase in the number of EM simulations is implied, diluting in this way the efficiency advantage over EMO methods.

In our approach, efficiency is pushed by reclaiming the philosophy of OFFSO methods, and the improvement of accuracy is pursued by a new surrogate modeling strategy. In this way, the efficiency-accuracy trade-off can be pushed well ahead available methods.

III. SURROGATE MODELING AND OPTIMIZATION TECHNIQUE

A. Basics of Surrogate Modeling

Surrogate modeling is an engineering method used when an outcome of interest of a complex system cannot be measured easily (in this case, the simulation is too time consuming), so an approximate model of the outcome is used instead (also called black-box modeling). Generating a surrogate model usually involves four steps:

1) Design of experiments:
If we think of surrogate models as black-box models, it is easy to understand that the objective of these models is to

emulate the output response of a given system. Therefore, the model has to learn how the system responds to a given input. So, the first step in generating surrogate models is to select the samples from which the model is going to learn. Consequently, this first step encompasses the selection of input samples. These samples should evenly cover the design space, so that it can be accurately modeled. In order to perform this sampling, different techniques are available, from classical Monte Carlo (MC) to Quasi-Monte Carlo (QMC) or Latin Hypercube Sampling (LHS) [3]. In this work, LHS is used.

2) Accurate expensive evaluation:

Surrogate models *learn* from expensive and accurate evaluations. Therefore, it is important that these simulations have the best accuracy possible. In our work, these accurate evaluations are electromagnetic simulations (EM), which are performed with Keysight ADS Momentum simulator.

3) Model Construction:

This part concerns the core functions used to build a surrogate model. Literature reports approaches based on artificial neural networks, support vector machines, Kriging functions, etc. Kriging functions, able to provide the best unbiased linear prediction on the continuous space of inputs, were chosen to construct the model. Tools to build Kriging and other surrogate models are available in Matlab toolboxes like SUMO [9] or DACE [10]. In this work, the DACE toolbox is used and ordinary Kriging models are constructed.

4) Model validation:

Apart from the samples used to generate the model, another set of points must be generated in order to validate the model. Since Kriging is an interpolation method the error at the points used to generate the model is zero. Again, these samples were generated using LHS.

B. New Modeling Strategy

In order to understand the strategy used to construct the model and the input parameters used, the design parameters and performances of inductors must first be reviewed. In Fig. 1, an octagonal asymmetric inductor is presented. The geometry of this planar spiral inductor is usually defined by four geometric parameters: number of turns (N), the inner diameter (D_{in}), the turn width (w) and the spacing between turns (s). These geometric parameters will be considered as the inputs for our surrogate model, and the outputs will be the inductor performances: inductance (L), quality factor (Q) and

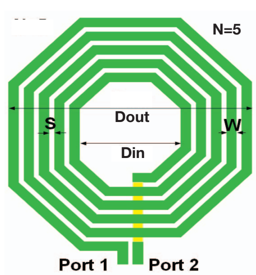

Fig. 1. Inductor geometric parameters for an octagonal asymmetric spiral inductor.

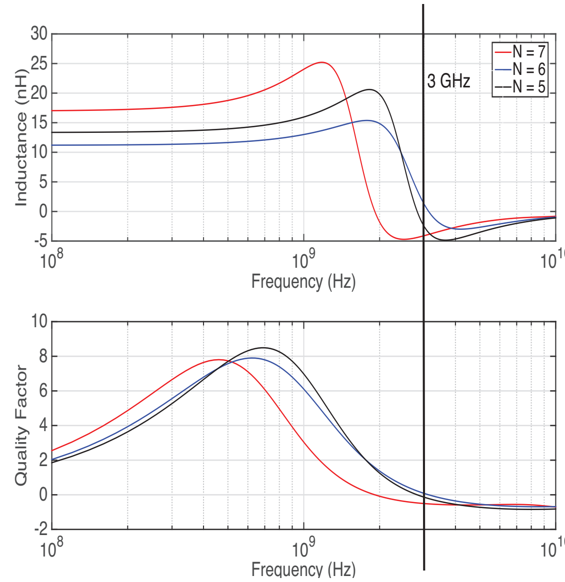

Fig. 2. Illustrating inductance and quality factor as a function of frequency for three different inductors.

self-resonance frequency (SRF). The self-resonance frequency is the frequency where the inductor stops behaving like an inductor and starts having a capacitive behavior. In Fig. 2, three different inductor curves are illustrated, the SRF for each inductor is the point where the inductance curve crosses zero.

The initial strategy to build the model was to create a surrogate model valid in the complete design space using the entire training set. However, by using this strategy, results with limited accuracy have been obtained [11]. The number of inductor turns is far from being continuous in a practical realization (in our implementation, it can only take integer values due to the standardized parameterized cell used for EM simulation). Inductors with different number of turns have different behaviors and the inductor physics changes very significantly with the number of turns (e.g. new mutual inductances, parasitic effects, coupling capacitances, etc.). Therefore, in order to increase the accuracy, several surrogate models were created, one for each number of turns (*e.g.* one model for inductors with two turns, another for inductors with three turns, etc.) and also per frequency point. This new method highly increased the accuracy of the model. However, some test inductors still showed large L and Q errors, especially at high frequencies. This can be explained by the fact that some of the inductors from the sampling set had its SRF below the frequency of operation. Therefore, the use of these inductors in the model construction dramatically decreased the accuracy of the model for test inductors with SRF above the frequency of operation.

TABLE I. COMPARISON OF INDUCTANCE AND QUALITY FACTOR VALUES OBTAINED WITH THE PROPOSED MODEL AND WITH EM SIMULATION.

Geometric Parameters			**100 kHz**				**1 GHz**				**2.5 GHz**			
N	**Din** (µm)	**W** (µm)	**L_{EM} (nH)**	**L_{SUR} (nH)**	**Q_{EM}**	**Q_{SUR}**	**L_{EM} (nH)**	**L_{SUR} (nH)**	**Q_{EM}**	**Q_{SUR}**	**L_{EM} (nH)**	**L_{SUR} (nH)**	**Q_{EM}**	**Q_{SUR}**
1	263.95	12.20	0.68	0.68	0.000	0.000	0.68	0.68	4.40	4.41	0.68	0.68	9.41	9.41
2	212.50	8.25	1.94	1.94	0.001	0.001	1.95	1.95	5.29	5.27	2.00	2.00	10.29	10.29
3	19.55	16.30	0.62	0.62	0.000	0.000	0.61	0.61	3.04	3.03	0.57	0.57	4.54	4.55
4	110.90	8.35	3.42	3.42	0.001	0.001	3.45	3.45	6.61	6.60	3.59	3.59	9.76	9.72
5	111.95	19.15	5.98	5.98	0.002	0.002	6.18	6.19	7.80	7.90	6.81	6.84	3.37	3.36
6	156.25	9.15	10.87	10.87	0.001	0.001	11.68	11.68	8.58	8.57	14.87	14.88	2.78	2.77
7	41.60	16.25	7.20	7.20	0.001	0.001	7.53	7.52	7.04	7.00	8.15	8.15	2.76	2.76
8	84.10	11.50	12.36	12.37	0.001	0.001	13.64	13.64	7.40	7.40	15.29	15.28	1.53	1.54

Therefore, in the proposed strategy, the construction of the model is based on a two-step method where the first step consists on generating surrogate models for the SRF using all training inductors. In the second step, in order to generate highly accurate surrogate models for L and Q, only those inductors from the training set whose SRF is sufficiently above the operating frequency are used. For example, if the operating frequency is 2.5 GHz, only inductors with SRF>3 GHz are used to generate L and Q models. In Fig. 2, it is possible to observe that the inductors with five and seven turns are not useful at 2.5 GHz, since their SRF<3GHz.

Consequently, with this model, whenever a test inductor is going to be evaluated, its SRF value is predicted first. If the predicted SRF is below 3 GHz the inductor is discarded since it is not useful for the selected operating frequency. Table I compares the performance values obtained with the surrogate model for eight randomly selected inductors with their EM simulated value. It can be checked that by following this strategy, the model error for inductance and quality factor is always well below 1%.

This modeling strategy will be used further in Section IV, not only when generating the OFFSO model, but also when generating the ONSO model.

C. Particle Swarm Optimization

Particle swarm optimization (PSO) will be used as optimization technique in this paper. PSO is a single-objective population-based stochastic optimization technique. As in Genetic Algorithms (GA), the system is initialized with a random population and pursuits optimal solutions by updating generations.

However, unlike GA, PSO does not have evolution operators such as mutation and crossover. In PSO, the possible optimal solutions, called particles, fly through the design space with given velocities [12]. At each iteration, the velocity of each particle is updated according to its own inertia, its historical best position and the neighbourhood best position.

The standard PSO algorithm is designed to deal with unconstrained optimization problems. The inductor optimization problem posed in this paper is strongly constrained. Therefore, a tournament selection method has been implemented in PSO to handle design constraints [13].

IV. EXPERIMENTAL RESULTS AND COMPARISONS

In this section, three different methodologies (EMO, OFFSO and ONSO) are applied to the synthesis of integrated inductors. The ECO methodology is not implemented since analytical models are not accurate at all, and therefore the optimization process yields suboptimal, and even invalid, inductors. The EMO method uses Keysight ADS Momentum as a performance evaluator and the OFFSO methodology uses a surrogate model, which was previously created using 800 sample inductors that were EM-simulated. The ONSO methodology has some differences when compared to the previous methods.

The flow diagram of ONSO is presented in Fig. 3. An initial coarse model is created using 40 EM-simulated inductors. In this implementation of ONSO, the model is updated by simulating the best individual from the current population. However, if this individual was already EM-simulated and

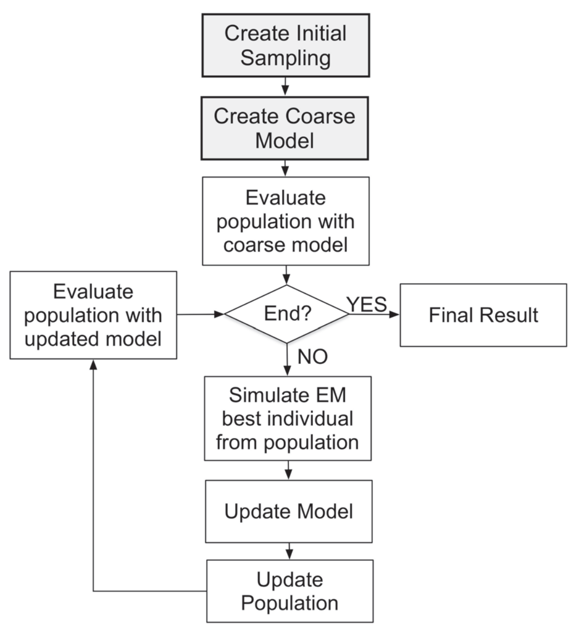

Fig. 3. Flow diagram of ONSO.

TABLE II. INDUCTORS OBTAINED WITH ALL DIFFERENT METHODS FOR AN OBJECTIVE INDUCTANCE OF L=2 nH WHILE MAXIMIZING Q.

	N	Din (µm)	W (µm)	Performances @2.5GHz		Nº of EM simulations	Clock Time
				L (nH)	Q		
EMO	2	225	14.15	1.996	11.07	4000	24 hours
ONSO	2	205	5	2.014	8.159	13	25 minutes
OFFSO	2	225	14.10	2.000	11.06	0	2 minutes

TABLE III. INDUCTORS OBTAINED WITH ALL DIFFERENT METHODS FOR AN OBJECTIVE INDUCTANCE OF L=2.5 nH WHILE MAXIMIZING Q.

	N	Din (µm)	W (µm)	Performances @2.5GHz		Nº of EM simulations	Clock Time
				L (nH)	Q		
EMO	2	259	10.55	2.497	10.73	4000	24 hours
ONSO	3	138	8.60	2.561	10.39	40	1 hour
OFFSO	2	256	10.40	2.498	10.71	0	2 minutes

TABLE IV. INDUCTORS OBTAINED WITH ALL DIFFERENT METHODS FOR AN OBJECTIVE INDUCTANCE OF L=3 nH WHILE MAXIMIZING Q.

	N	Din (µm)	W (µm)	Performances @2.5GHz		Nº of EM simulations	Clock Time
				L (nH)	Q		
EMO	3	156	7.85	2.99	10.38	4000	24 hours
ONSO	4	95	7	3.006	9.92	36	50 minutes
OFFSO	3	157	8.65	2.999	10.37	0	2 minutes

used for the model construction in previous iterations, this individual is not EM-simulated and the model does not have to be updated in that iteration.

The technology used for the inductor synthesis was a 0.35µm CMOS technology[1]. The bounds of both the optimization and the samples used to create the surrogate models are set by the design rules of the technology at the lower end, and by reasonable values at the upper one. The number of turns of the inductor varies from 1 to 8, the inductor inner diameter between 10 and 300µm and the turn width between 5 (the minimum allowed by the technology) and 25µm. The inductor area was limited to a maximum square of 400µm x 400µm. The spacing is fixed to 2.5µm, the minimum allowed by the technology, since larger values do not provide any performance improvements. Inner diameter and turn width are forced to fit in a grid of 0.05µm due to fabrication technology constraints, and for the number of turns only integers are considered due to restrictions of the parameterized layout cell used in the EM simulations, although this means no limitations of the methodology. All the optimizations are performed with 40 particles and 100 generations. As in any other computational intelligence algorithm, PSO also implies the introduction of randomness, and, hence, different runs may provide different results. Therefore, five independent runs were performed for each experiment, all yielding negligible differences between the results.

The objective of the first test is to find an octagonal inductor with 2 nH at 2.5 GHz while maximizing the quality factor. Optimization constraints were defined to guarantee the good behaviour of the inductor at the frequencies of interest. These constraints are: inductance value is sufficiently flat from DC to slightly above the operating frequency, the self-resonance frequency is sufficiently above this frequency, and the value of Q is near its maximum at this frequency and always with a positive slope around it [5]. A constraint was also imposed to limit the maximum area allowed by the inductors. Since PSO is a single-objective algorithm, the objective function was built so that the quality factor was maximized and the difference between the desired inductance and that obtained by the algorithm was minimized.

Results for the best inductor obtained by each methodology are shown in Table II. The performances of such optimal inductors have been EM-simulated so that the accuracy of the results at the table can be fairly compared. Notice that the number of EM simulations, and, therefore, the computation times for the ONSO method only includes the EM simulations performed during the execution of the PSO algorithm. Construction of the initial coarse model requires another 40 simulations (5 for each number of turns), which takes another 3 hours in a machine with a twin 6-core processor. In order to have a fair comparison, this time has not been included in Table II-IV, in the same way that the 800 EM simulations to build the surrogate models for OFFSO methodology were also not included. In both cases, the 40 initial simulations of the ONSO and the 800 inductors of the OFFSO methodology can be performed a priori and only once, since they are independent of the optimization objectives of each experiment.

To understand the lack of proportionality between this CPU time and those in the tables, three considerations must be made. On the one hand, some simulations for the initial models take longer since simulations of inductors with 8 turns require much more effort than e.g. 3 turns, whereas convergence of the ONSO method in this example implies that most additional EM simulations correspond to inductors with less than 5 turns. On the other hand, simulations of the 40 or 800 inductors of the initial models can be parallelized in the processor used, whereas model updating in ONSO is performed with at most one inductor at each iteration, and, therefore, such parallelization is not possible.

In test example 2, the objective is to obtain an inductor with 2.5 nH at 2.5 GHz. The results are shown in Table III. In test example 3, the objective was to obtain an inductor with 3 nH at 2.5 GHz. The results are shown in Table IV. As an illustration example, the performances of the inductor obtained with the OFFSO methodology are presented in Fig. 4 and they are compared against the EM simulation of the same inductor. It is possible to observe that the accuracy of the model is

[1] Although the methodologies proposed here are independent of the technology process, its selection was motivated by the availability of technological information for EM simulation.

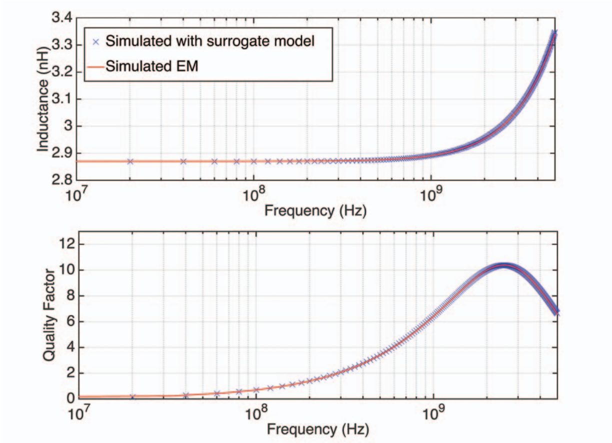

Fig. 4. Performance parameters of the 3nH inductor obtained in test example 3. Inductance and quality factor vs frequency curves.

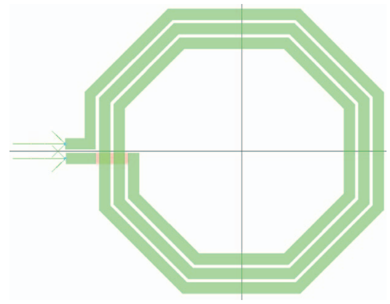

Fig. 5. Layout of the 3nH inductor obtained in test example 3.

remarkable along the whole frequency range. After the optimization process (which takes 2 minutes) the inductor synthesis is complete and the layout of this inductor is presented in Fig. 5.

It is possible to observe that the OFFSO and EMO methodologies converge almost to the same optimum inductor, achieving similar performances. These test examples demonstrate that the accuracy of the surrogate model used in the OFFSO methodology leads to the same design space areas.

In all three examples the quality factor of the inductor obtained with the ONSO methodology was lower, demonstrating that despite the EM simulations used in order to iteratively increase the accuracy of this method, the accuracy of the initial coarse model is crucial for an optimal inductor synthesis, i.e. if during the first iterations, where the model is still quite inaccurate, the optimization algorithm leads to design space areas away from the optimal point; it is unlikely that the optimization algorithm will converge to the global optimum point.

The simulation times are also extremely different. The EMO methodology shows high computation times which are hardly acceptable, the OFFSO methodology clearly is the most efficient methodology (as the heavy computational tasks are performed a priori), with a comparable accuracy to EMO, and the ONSO simulation time is not prohibitive (although much larger than OFFSO) but accuracy of the results is not guaranteed.

V. Conclusions

It is possible to conclude that the OFFSO method achieves high accuracy while having the best efficiency of all three methods (only 2 minutes per optimization). This method uses a highly accurate surrogate model that has to be constructed *a priori* and consumes significantly time, yet it is constructed only once, and independently of the optimization goals. The ONSO method shows a high dependency on the initial coarse model and the initial sampling. Appropriate convergence is not guaranteed and can only be improved by significantly increasing the number of EM simulations and, therefore, the computational cost.

References

[1] Behzad Razavi, *RF Microelectronics*. Prentice Hall Press, Upper Saddle River, NJ, USA, 1998.

[2] C. P. Yue and S. S. Wong, "Physical Modeling of Spiral Inductors on Silicon," *IEEE Transactions on Electron Devices*, vol. 47, pp. 560-568, 2000.

[3] A. I. J. Forrester, A. Sobester, and A. J. Keane, *Engineering Design via Surrogate Modelling - A Practical Guide*. Wiley, 2008.

[4] S.K. Mandal, S. Sural, A. Patra, "ANN- and PSO-Based Synthesis of On-Chip Spiral Inductors for RF ICs," *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, vol.27, no.1, pp.188-192, 2008.

[5] R. González-Echevarría, et al, "Automated Generation of the Optimal Performance Trade-Offs of Integrated Inductors," *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems,* vol.33, no.8, pp.1269-1273, 2014

[6] M. Ballicchia, S. Orcioni, "Design and Modeling of Optimum Quality Spiral Inductors With Regularization and Debye Approximation," *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems,*, vol.29, no.11, pp.1669-1681, 2010.

[7] B. Liu, G. Gielen and F.V. Fernandez, Automated Design of Analog and High-Frequency Circuits. A Computational Intelligence Approach. Springer, 2014.

[8] E.Roca et al, "Computational Intelligence Techniques for Determining Optimal Performance Trade-Offs for RF Inductors", in Computational Intelligence in AMS and RF Circuit Design, M. Fakhfakh, E. Tlelo-Cuautle, P. Siarry, Springer, pp. 277-296, 2015.

[9] D. Gorissen, I. Couckuyt, P. Demeester, T. Dhaene, and K. Crombecq. "A Surrogate Modeling and Adaptive Sampling Toolbox for Computer Based Design," *The Journal of Machine Learning Research*, vol. 11, pp. 2051-2055, 2010.

[10] http://www.imm.dtu.dk/~hbni/dace

[11] F. Passos, et al, "Physical vs. Surrogate Models of Passive RF Devices," *in IEEE International Symposium on Circuits and Systems (ISCAS)*, pp.117-120, 2015.

[12] J. Kennedy, R. Eberhart, "Particle Swarm Optimization," in Proceedings *IEEE International Conference on Neural Networks*, pp.1942-1948, 1995.

[13] K. Deb, "An efficient Constraint Handling Method for Genetic Algorithms," *Computed Methods in Applied Mechanics and Engineering*, vol 186, pp.311-338, 2000.