Yield Optimization for Radio Frequency Receiver at System Level

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***Abstract*—This paper is devoted to the yield optimization of the radio-frequency (RF) front-end of wireless receiver. The yield together with the circuit performances are often sensitive to the choice of parameters of its components and blocks, and can be improved at circuit design level. However, it is better evaluated when considering the whole receiver at system level. For this purpose, we first use a design of experiment (DoE) technique to generate meta-models of the building blocks. Then, we apply a version of the stochastic gradient method to find a good approximation of the optimum for the circuit yield.**

I. Introduction

Wireless communication systems remain an intensively developed subject of research, particularly due to continuing growth and attractiveness of mobile telecommunication sector. The enhancement and increasing functionality of mobile devices and especially smart phones require using advanced submicron technologies. In these deep sub-micron technologies, the variability is getting more and more important [1]. It is becoming one major issue for technology scaling. New approaches at CAD level are required to circumvent this problem. Advanced simulation techniques have been proposed in [2]. Robust design approaches have been also developed [3] for digital, analog and RF building blocks but only little work has been done at system level. Nowadays, for complex systems such as RF receivers, the yield constraint is usually applied at building blocks level [4]–[6]. The overall constraints are shared between these blocks and each designer is doing his best to reach the targeted yield. However, since the individual performances of the blocks are highly correlated, high benefit can be taken from a global optimization. In this paper we discuss an approach for optimizing the whole receiver. It takes benefit of the new solutions used to characterize the statistical behavior of the circuits.

The paper is organized as follows. In Section II we briefly describe the RF front-end interface and give its mathematical model in Section III. Section IV states the yield optimization problem and Section V describes the stochastic method for its local solution. Finally, in Section VI we review the simulation results for RF chain yield optimization.

II. RF Front-End

The RF front-end interface contains a chain of sequentially connected blocks which transform the radio signal received by antenna into the electronic signal which is ready to be processed by the DSP part of the receiver. The typical structure of this chain is shown on Fig. 1. The incoming RF signal received by antenna is amplified by the low-noise amplifier (LNA). Mixer then downconverts the signal frequency by means of the output of a local oscillator (for the sake of simplicity, the double quadrature is not shown on this simplified figure). The filtering afterwards selects the required channel of interest. Last block of the chain is an amplifier which controls the gain of the signal before being converted in the digital domain and processed by DSP part. All blocks of this chain are produced using the same technology.

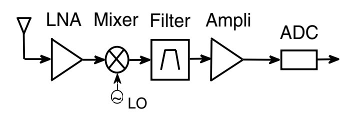

Fig. 1. Block diagram of a typical RF receiver.

A. Block characteristics

Each block and the entire circuit itself have a number of characteristics which describe its performance. The key features are the following: the block gain G, the noise figure F and the input-referred 3rd-order intercept point I. Gain and noise figure are usually measured in dB and intercept point in dBm, i.e. $G_{dB} = 10\log_{10} G$ and $I_{dBm} = 10\log_{10} I$. These characteristics are dependent on the number of block parameters which are introduced in the following paragraph.

B. Block parameters

The block parameters are subdivided into three categories:

1) Design parameters $p \in \mathbb{R}^{n_p}$ *:* the input data of the circuit blocks that can be chosen by the circuit designer. Each block can have about 4 independent design parameters. Typical design parameters are polarization currents or common mode voltages which can be controlled in the final circuit. In a second step, component size might be also considered.

2) Environment parameters $q \in \mathbb{R}^{n_q}$ *:* they characterize the operating conditions for the device. For example, temperature, aging and supply voltage are typical environment data. Normally, there can be from 2 to 6 environment parameters.

3) Technological (process) parameters $\xi \in \mathbb{R}^{n_\xi}$ *:* these data describe the silicon technology used for the production of circuit blocks (oxide thickness, doping concentration, etc). Technological parameters cannot be controlled and are modeled as random variables with some known statistical behavior.

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Since in reality all blocks of the chain are produced jointly on the same chip, these process data are equal for each circuit block. The number of the most influencing technological parameters are considered to be between 10 and 20, but the approach is not limited to this quantity.

The relationship between these parameters and the system performances are highly complex and need to be extracted by time consuming SPICE-like simulations. However, multi-frequency simulations of the whole receiver are really time consuming. Therefore, achieving statistical characterizations of the whole receiver is seldom considered. That's the reason why we have decided to resort to meta-modelling of the building blocks to simplify simulations. Moreover, instead of developing our own modelling technique, we have employed DoE approach, which is more and more used in the industry [7], to replace the time consuming Monte-Carlo simulations. Hence, no additional extraction is required at circuit level.

III. System Modelling

DoE technique is widely implemented in order to get the dependence of block characteristics from technological parameters. This dependence is usually described by polynomial models. We refer the reader to a variety of works (see [7], [8] and the references therein) for details. In most cases, the quadratic polynomial model is a good enough tradeoff between precision and complexity for the circuits. Denote by x an overall parameter vector, $x = (p, q, \xi)^T \in \mathbb{R}^{n_p} \times \mathbb{R}^{n_q} \times \mathbb{R}^{n_\xi}$, and by $y_i \in \mathbb{R}^{n_y}$ a vector of characteristics for i-th block, in our case $y_i = (G_i, F_i, I_i)^T$ and $n_y = 3$. Therefore, for the i-th block we have a vector-valued function

$$y_i = \Phi_i(p, q, \xi) = \left(f_{i1}, ..., f_{in_y}\right)^T \tag{1}$$

which entries are quadratic polynomials

$$f_{ij} = x^T A_{ij} x + b_{ij}^T x + c_{ij}, \quad j = 1, ..., n_y. \tag{2}$$

The vector of design parameters p and the environment parameter vector q are defined on finite intervals $[\underline{p}, \overline{p}]$ and $[\underline{q}, \overline{q}]$ of corresponding dimension. The technological random parameters ξ_j, $j = 1, ..., n_\xi$, are supposed to be mutually independent and follow, e.g., the Gaussian distribution $\xi_j \sim \mathcal{N}(\mu_j, \sigma_j^2)$. Other distribution laws can be easily handled as well.

The connection of blocks in RF chain leads to the following formulas for global performances of the entire circuit. For the cascade of n blocks we have

$$\begin{array}{rcl} G & = & \prod_{i=1}^{n} G_i \\ F & = & F_1 + \frac{F_2 - 1}{G_1} + \frac{F_3 - 1}{G_1 G_2} + ... + \frac{F_n - 1}{G_1 G_2 ... G_{n-1}} \\ \frac{1}{I} & = & \frac{1}{I_1} + \frac{G_1}{I_2} + \frac{G_1 G_2}{I_3} + ... + \frac{G_1 G_2 ... G_{n-1}}{I_n} \end{array} \tag{3}$$

where G, F and I are the total gain, noise figure and intercept point of the entire RF circuit, while G_i, F_i and I_i are corresponding characteristics of the i-th block.

Introduce a vector $z \in \mathbb{R}^{n_z}$ of global performances of the circuit, i.e. we have $z = (G, F, I)^T$ with $n_z = 3$. Then we can summarize the parametric model of the n-block RF chain as follows:

$$\begin{array}{l} y = \Phi(x) = \Phi(p, q, \xi) \\ z = \Gamma(y) \end{array} \tag{4}$$

where the vector-valued function $\Phi = (\Phi_1, ..., \Phi_n)^T$ with $\Phi_i(\cdot)$ as in (1)-(2), and the vector-valued function $\Gamma(\cdot)$ represents the relations (3). The structure of this model is illustrated on Fig. 2.

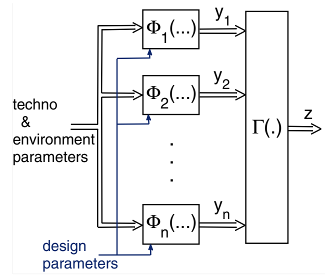

Fig. 2. Structure of parametric model for RF circuit performances.

IV. Yield Optimization Problem

The goal of the paper is to maximize the yield of the circuit over the design parameters. Define the yield function as

$$\mathcal{Y}(p) = \text{Prob}_\xi \left\{ \underline{z} \leq z \leq \overline{z}, \ \forall q : \underline{q} \leq q \leq \overline{q} \right\}. \tag{5}$$

All vector inequalities here and thereafter are understood componentwise. In other words, we would like to maximize the probability that the global circuit performances, which form the vector z, meet the prescribed specifications for all possible environment data.

Set the following vector notations

$$Z = \max_{\underline{q} \leq q \leq \overline{q}} \begin{pmatrix} -z \\ z \end{pmatrix}, \quad \overline{Z} = \begin{pmatrix} -\underline{z} \\ \overline{z} \end{pmatrix}. \tag{6}$$

Note that vector z is a function of p, q and ξ, and maximum over q in (6) is taken componentwise. Then we equivalently rewrite the yield optimization problem as follows

$$\max_{\underline{p} \leq p \leq \overline{p}} \ \text{Prob}_\xi \left\{ Z \leq \overline{Z} \right\}. \tag{7}$$

This simpler form of the problem is more suitable for the further analysis.

Since there are only few environment parameters and vector q has low dimension, one can implement a "reasonably dense" grid over the interval $[\underline{q}, \overline{q}]$ in order to evaluate the maximum over q in (6). Let $\mathcal{Q}^L = \{q_l \in [\underline{q}, \overline{q}], \ l = 1, ..., L\}$ be such a grid, then we say that $Z \approx \max_{q \in \mathcal{Q}^L} \begin{pmatrix} -z \\ z \end{pmatrix}$.

One of the main difficulty in problem (7) is that even for quadratic model for $\Phi(\cdot)$ of (4) it is not clear how effectively compute the above probability since the distribution of vector z and therefore of vector Z can be very complex. Below we propose the stochastic method for solution of the problem (7). This method is based on the computation of stochastic gradient of the yield and gives a good approximation of the local optimum of (5).

V. Stochastic Gradient Approach

We apply the stochastic gradient method (see e.g. [9]) to the problem (7) after modifying the criterion by "concaving" the probability function. This modification improves the properties of the cost function to be maximized and provides better behavior of the optimization method.

A. Concaving the probability

Let's rewrite the probability as an expectation of indicator

$$\text{Prob}\{Z \le \overline{Z}\} = E\ \mathbb{I}\{Z \le \overline{Z}\} \tag{8}$$

where $Z \in \mathbb{R}^m$ and

$$\mathbb{I}\{Z \le \overline{Z}\} = \begin{cases} 1, & \text{if } Z_i \le \overline{Z}_i,\ \forall\, i = 1, ..., m\,; \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

The indicator is not a concave function of Z. Hence the probability (8) is non-concave function of Z. Plus, the gradient of the indicator is always zero outside the point $Z = \overline{Z}$. This pose a problem for the stochastic gradient algorithm to converge. Thus, consider the following modification of the cost function. Since we want to maximize the yield, take the lower piece-wise linear approximation of the indicator

$$\rho_\alpha(Z) = \min_{i=1,\dots,m} \left\{ \min\{-\alpha_i(Z_i - \overline{Z}_i),\, 1\},\, i{=}1,\dots,m \right\} \tag{10}$$

with some positive parameters $\alpha_i > 0,\ i = 1, ..., m$. The form of $\rho_\alpha(Z)$ in 1D-case is shown on Fig. 3. Functional family $\rho_\alpha(Z)$ can be treated as the closest lower concave approximations of $\mathbb{I}\{Z \le \overline{Z}\}$. Parameters α_i can be adjusted separately in order to regularize the inequalities $Z_i \le \overline{Z}_i$ for each i or to emphasize the importance of particular inequalities. Then the optimization problem (7) is reformulated as follows

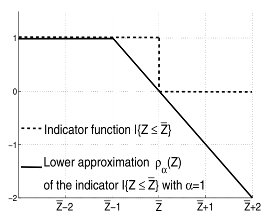

Fig. 3. Concaving the indicator function in 1D-case.

$$\max_{\underline{p} \le p \le \overline{p}} E\left[\, \rho_\alpha\left(Z - \overline{Z}\right)\,\right]. \tag{11}$$

Denote the new cost function as $\widehat{\mathcal{Y}}(p) = E[\rho_\alpha\left(Z - \overline{Z}\right)]$.

Remark: The criterion of optimization problem (7) is different from that of its modification (11). For this reason, the solutions of these problems will be generally different. However, one can expect that this difference will not be significant. □

B. Stochastic gradient algorithm

The stochastic gradient iterative scheme looks as follows. Fix the initial values for the design parameters $p^{(0)} \in [\underline{p}, \overline{p}]$. The upper index means the iteration number. Then consider

$$p^{(k+1)} = \pi_{\mathcal{P}} \left\{\, p^{(k)} \;+\; \gamma_k \cdot \nabla_p \widehat{\mathcal{Y}}(p^{(k)}, \xi_k)|_{\xi_k \sim \mathcal{N}(\mu,\Sigma)} \,\right\} \tag{12}$$

where $k = 0, 1, 2, ...,$ and $\pi_{\mathcal{P}}$ is some projection operator to the set $\mathcal{P} = [\underline{p}, \overline{p}]$, and $\nabla_p \widehat{\mathcal{Y}}(p, \xi)$ is the stochastic gradient by p of the modified yield $\widehat{\mathcal{Y}}(p, \xi) = \rho_\alpha\left(Z - \overline{Z}\right)$ from (11). Recall that Z here is a function of p and ξ.

Different types of projector $\pi_{\mathcal{P}}$ can be considered in (12). Since the constraint set $\mathcal{P}$ in our case is a simple box $[\underline{p}, \overline{p}]$, then the most natural choice is the orthogonal projector in Euclidean metrics. This means that if the point $p^{(k)} + \gamma_k \cdot \nabla_p \widehat{\mathcal{Y}}(p^{(k)}, \xi_k)|_{\xi_k \sim \mathcal{N}(\mu,\Sigma)}$ appears to be lying outside of $\mathcal{P}$, then the nearest point of $\mathcal{P}$ is taken as the next candidate solution $p^{(k+1)}$. This projection is easily implemented for $\mathcal{P}$.

The stochastic gradient $\nabla_p \widehat{\mathcal{Y}}(p, \xi)|_{\xi \sim \mathcal{N}(\mu,\Sigma)}$ can be computed explicitly using its analytic expression via (10) and formulation (4). Alternatively, the numerical computation of the stochastic gradient can be used if it is not expensive.

Step parameter $\gamma_k :\ 0 < \gamma_k < 1$ can be taken constant. But in order to guarantee the algorithm convergence, the reasonable choice of γ_k is as follows

$$\gamma_k = \gamma_0 \,/\, (k+1)^\beta \tag{13}$$

where γ_0 is some positive constant and $0.5 < \beta \le 1$. A particular choice of γ_0 and β can be adjusted for different situations in order to increase the rate of convergence. See [9] for more details. In addition, we can use averaging of the trajectory in order to converge faster.

Remark: The iterative algorithm (12) converges to the local optimum of the function $\widehat{\mathcal{Y}}(p) = E_\xi \widehat{\mathcal{Y}}(p, \xi)$. However if the function $\widehat{\mathcal{Y}}(p, \xi)$ possesses certain nice properties, we can guarantee the convergence to the global optimum. For instance, if $\widehat{\mathcal{Y}}(p, \xi)$ is concave and $\widehat{\mathcal{Y}}(p)$ attains a unique maximum at $p^* \in [\underline{p}, \overline{p}]$, then the scheme (12) converges to p^* from any initial point $p^{(0)} \in [\underline{p}, \overline{p}]$. The rate of convergence depends on the choice of the step parameter γ_k, of the projection operator $\pi_{\mathcal{P}}$ and of parameters α_i for lower bound function $\rho_\alpha(\cdot)$. □

VI. Simulations

In order to validate the proposed approach, we performed simulations on an existing RF receiver. It is a modified version of the work presented in [10] with relaxed performances. The system is a 24 GHz receiver in BiCMOS technology. It is composed of 8 blocks : 3 LNA stages, Mixer, 2 Filter stages and an amplifier followed by some external stages as depicted on Fig. 4. The external stages (which integrate an ADC) are

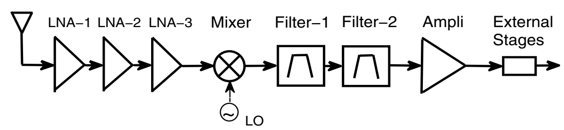

Fig. 4. 8-block RF chain.

considered as fixed since there are not implemented in the same technology. The first seven blocks have been modelled with respect to the technological parameters using DoE. Their performances show a quadratic polynomial dependence with respect to their parameters. The standard deviation estimated by the model differs by only 0.1% from the results obtained in spice-like simulations. The precision of the model is thus sufficient to proceed to yield optimization. There are 2 design parameters for each block (current and voltage polarization) so that totally the whole chain contains 14 design parameters. The designer can tune them independently but no specific design technique has been applied to obtain an extended tunable range. Only fine tuning is possible. There are 2 environment parameters which are the temperature and the voltage supply. Lastly, there are 14 technological parameters which have been extracted to be the most influent on the building blocks performances. The technological parameters for every block are assumed to be Gaussian: $\xi_j \sim \mathcal{N}(0,1)$. Environment and technological parameters are the same for all blocks. All parameters have been normalized to the range $[-3,+3]$.

Consider the following circuit specifications and the yield

$$\mathcal{Y}(p) = \text{Prob}_{\xi} \left\{ \begin{array}{c} \underline{G} \leq \min\limits_{q \in [-3,3]} G_{dB} \leq \max\limits_{q \in [-3,3]} G_{dB} \leq \overline{G} \\ \max\limits_{q \in [-3,3]} F_{dB} \leq \overline{F} \\ \underline{I} \leq \min\limits_{q \in [-3,3]} I_{dBm} \end{array} \right\}.$$

We take the following specification limits $\underline{G} = 35\,[dB]$, $\overline{G} = 49\,[dB]$, $\overline{F} = 11\,[dB]$ and $\underline{I} = -16\,[dBm]$. To evaluate the maximum and minimum over the environment parameters for G, F and I, we consider the grid of cardinality equal to 3 for each component, i.e. $\mathcal{Q}_L$ contains $3^2 = 9$ elements.

As the initial candidate solution $p^{(0)}$ for the iterative algorithm it is reasonable to take the central point in the box [-3; 3], that is $p^{(0)} = zeros(14,1)$. When considering the whole receiver, the yield at this point is equal to 95,4% which shows already a good balance for the entire RF chain.

Applying the stochastic gradient algorithm (12) we get the convergence to the local optimum (Fig. 5). Note the relatively

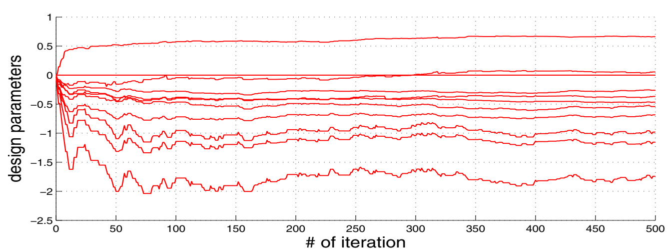

Fig. 5. Convergence of the stochastic gradient iterative scheme (12) for each component of the design vector p.

slow rate of convergence at the close neighborhood of the optimum, since the function $\mathcal{Y}(p)$ can be rather flat around this point. After $N = 500$ iterations we come to the solution which improves the yield up to 97.1%. If we perform more iterations, we come to slightly better yield value. But the maximal yield for this choice of specifications is anyway around 97.3%. The yield improvement is not very high in this case.

On the other side, if we take tighter constraints on circuit performances having lower value for the initial yield, the yield increase can be much more impressive. For illustration, take the same values for $\underline{G}$, $\overline{G}$ and $\overline{F}$ but $\underline{I} = -13\,[dBm]$. Then the initial yield of 35% (the yield at $p^{(0)}$) is increased up to 82%, which is more than twice higher. The box plots for comparison of distribution improvements in circuit performances are presented on Fig. 6.

For the same circuit, we have tried to apply the classical approach of specifying a given yield per building blocks. This is a very sensitive approach since we have to split the yield and the margin among the different building blocks. Moreover, we have to impose some gain limits to each building block which is not needed in the whole receiver. At the end, the yield was close to 0%. With the per block specifications, we had to relax the specifications to $31.8\,[dB] \leq G \leq 52.64\,[dB]$, $F \leq 12.7\,[dB]$, $I \geq -20\,[dBm]$ in order to reach the same

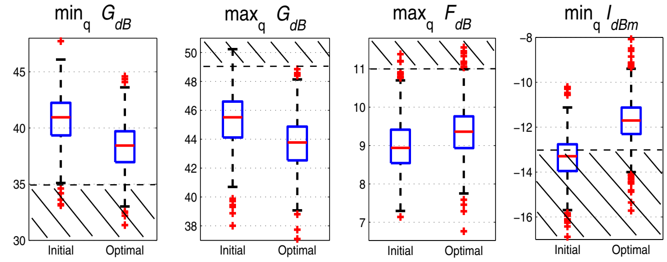

Fig. 6. Box plots for the RF chain specifications at the initial design point $p^{(0)}$ and at $p^{(500)}$ (near optimum). Notice the big improvement in distribution of I_{dBm} which basically influenced the increase of the yield.

yield as in the global evaluation. This shows the advantage of considering globally the whole system.

VII. Conclusion

Meta-modelling combine with stochastic gradient iterative scheme has been applied to the yield optimization problem of an RF receiver system. This method allows the much better evaluation of the overall circuit yield and provides an approximation of its local optimizer. Despite the locality of this solution, the proposed technique provides a good enhancement of the yield. This approach pave the way to better exploitation of the technological capability as well as to tunable system which can adapt to the technology and working conditions. Lastly, since no knowledge about the functional structure of circuit blocks is required, this approach can be applicable to the yield optimization of a wide variety of circuits.

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