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# Response surface-based design of standard inductances for minimizing parasitic capacitances

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***Abstract* – A procedure for reducing both deterministic and uncertainty effects of parasitic capacitance in designing standard inductors is presented. Metrological performance is enhanced while minimizing both deterministic and uncertainty effects simultaneously. In particular, statistical parameter design is exploited, by choosing optimum levels of design variables of the standard inductor. At this aim, initially, a first model is identified in order to define the impact of design parameters on parasitic capacitances considered as deterministic and the configuration for their minimization. Then, in the optimum configuration, a second model defines the impact of the design parameter uncertainty on the parasitic capacitance considered as random in order to assess the corresponding uncertainty budget. The method effectiveness is highlighted by a case study related to the design of an Ironless Inductive Position Sensor (I2PS).**

## I. INTRODUCTION

Parasitic capacitances affect metrological performance of standard inductors significantly. Inductor windings have a distributed parasitic capacitance modeled by a lumped capacitance connected in parallel between the terminals. Thus, the actual and the ideal behaviors of the inductor are drastically different according to the frequency $f$. In particular, for $f < f_r$, the inductor impedance is predominantly inductive, while for $f > f_r$ the inductor impedance is predominantly capacitive, where $f_r$ is the resonance frequency of the inductor and depends from its parasitic capacitance. In literature, parasitic capacitance of an inductor is predicted by model when the curvature radius can be neglected [1, 2, 3]. An extensive model can be used, when the curvature radius cannot be neglected [4].

In order to minimize the parasitic capacitances, a parameter design approach could be used as in advanced quality engineering. In the parameter design, the system output is made as much insensitive as possible both to influence parameters and to component tolerances by selecting a suitable system configuration [5]. The basic idea is to find the configuration capable of minimizing the measurement uncertainty (as well as maximizing the improvement of other metrological characteristics), and, simultaneously, maximizing the sensitivity of the measurement system [6]. In order to achieve this goal, simulations are run for various model parameters, i.e. operating conditions, design and setting parameters, and input range. The simulations could be carried out by an intuitive approach, i.e. the investigation space is explored by either a purely random approach or a one-factor-at-a-time strategy, but these approaches could bring misleading results, because only a reduced portion of the investigation space is explored and not the most significant portion that effectively describes the performance landscape [7]. Another more comprehensive approach is based on the Monte Carlo method to explore the parameter's space as a whole. The simulations are run in each possible configuration to have total comprehension of the performance landscape. However, for high-performance accurate instruments, this technique turns out to be burdensome from a computational point of view, because the simulation burden depends on the number of model parameters, the width of their working range, and the target accuracy of the analysis.

A response-surface approach is used in order to optimize the simulation burden. Response-surface methodology are experimental design techniques allowing a systematic exploration of a multidimensional parameter space with a high degree of resource exploitation [7]. The concept of response-surface approaches is that of sequential experimentation to build an appropriate model that enables one to understand the engineering system. Fundamental to response-surface are models that relate the response of interest to a set of independent variables [8]. In literature, many papers deals with the response-surface methodology [9, 10], with several reviews [8, 11]. Response-surface methodology is widely used in process optimization [12, 13]. In literature of metrology, there are some applications of the surface-response approaches: e.g., uncertainty reduction in measurement systems [14], or modeling of digitizers [15]. In these applications, an analysis on the interest domain as a whole is carried out.

In this paper, a surface-response approach, based on a statistical experimental design, to design of an inductor by minimizing the effects of parasitic capacitance is proposed. Then, a sensitivity analysis in the optimum parameters configuration is carried out. In particular, statistical parameter design is exploited, by choosing optimum levels of design variables of the standard inductor. At this

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aim, initially, a first model is identified in order to define the impact of design parameters on parasitic capacitances considered as deterministic and the configuration for their minimization. Then, in the optimum configuration, a second model defines the impact of the design parameter uncertainty on the parasitic capacitance considered as random in order to assess the corresponding uncertainty budget. In particular, in the following, in Section ii., the procedure for minimizing parasitic capacitances of standard inductors is treated. In Section iii. , the proposed procedure is highlighted by a case study related to the analytical model of parasitic capacitance of an inductor of an Ironless Inductive Position Sensor (I2PS).

## II. PROCEDURE

In this Section, the procedure for minimizing parasitic capacitances of standard inductors is treated. In particular, the discussion is divided in three parts. In Subsection A., the general parasitic capacitance model of standard inductor and the concept of metamodel are explained, by introducing the reader to the problem. In the Subsection B., the basic idea of the proposed approach is explained. Then, Subsections C. and D. are focused on the proposed response-surface-based procedure.

### *A. Parasitic capacitance model and metamodel concept*

In an inductor, its parasitic capacitance $C$ is related to the design parameters. The designer achieves the desired capacitance by suitable design parameters $\mathbf{x} = [x_1, x_2, ..., x_p]^T$.

In general, uncertainty can be classified as arising from two main sources: $inner$, i.e. the uncertainty arisen from the design parameters (e.g. component tolerance ranges, instability of references, etc.), and $outer$, i.e. the uncertainty from the action of influence parameters $\mathbf{u} = [u_1, u_2, ..., u_w]^T$. $\mathbf{u}$ are all the parameters, the environment, which act in uncontrolled way, thus cannot be controlled by the designer (e.g. climatic factors, etc.).

During the conceptual design, behavioral modeling is useful for the sake of generalization. In this way, a general perspective is kept, useful for several applications, owing to its independence from the specific architecture of the instrument and on its physical realization.

The experimental design approach exploits an algebraic regression model assumption about the way $\mathbf{x}$ and $\mathbf{u}$ affect $C$. Such a regression model $F : C = F(\mathbf{x}, \mathbf{u})$ is an approximation of the parasitic capacitance model behavior inside the parameter space $D$; thus, it is a "model of a model", i.e., a metamodel. The metamodel synthetically expresses the analytical relation between the parasitic capacitance and the model design parameters.

### *B. Basic idea*

The basic idea of the proposed approach is to find the design parameters configuration of the inductor that minimizes the parasitic capacitance $C$, in a given range of each parameter (the interest domain $D$). This is a first deterministic approach to the design problem. Furthermore, each design parameter has its relative uncertainty. Therefore, the designer want to understand how this uncertainty affects parasitic capacitance and the related uncertainty.

At this aim, in this paper, a two-parts procedure is used: 1) find the parameters of the inductor, in a given domain, that minimize the parasitic capacitance, 2) carry out the sensitivity analysis in the previously found minimum parameters configuration in order to define the corresponding uncertainty. The two parts of the procedure are detailed in the next subsections.

### *C. Procedure: the first part*

The first part of the procedure is based on three steps: 1) metamodel definition, 2) metamodel identification, 3) minimum prediction and validation.

1) Metamodel definition

The problem is defined by identifying the architecture of the inductor and the environment. The most significant uncertainty sources are identified. Thus, in the first step, parameters $\mathbf{u}$ and $\mathbf{x}$ are defined, according to the most critical aspects of parasitic capacitance model. Finally, the range of parameters is selected, in order to identify their interest domain $D$.

2) Metamodel identification

The order of the metamodel capable of suitably describing the parasitic capacitance model behavior has to be decided. In the practice of experimental design, a combinatorial increase of the problem dimensionality is faced using a full-quadratic model [7]. The dependence of the parasitic capacitance on design setting parameters and uncertainty sources can be expressed by the second-order model:

$$C = \mu + \sum_{j=1}^{n} \delta_{j,q} + \sum_{j=1}^{n} \sum_{k=1}^{n} d_{jk,qr} + \epsilon, \qquad (1)$$

where $\mu$ is the overall mean, $\delta_{j,q}$ takes into account the effect on the parasitic capacitance of the j-th parameter at the level $q$, $d_{jk,qr}$ takes into account the interaction between the k-th and j-th parameters at the level $q$ and $r$, respectively, on the parasitic capacitance , $n = w + p$ is the sum of the number of design setting parameters and uncertainty sources, $\epsilon$ represents the metamodel uncertainty. $\mu$, $\delta_{j,q}$, and $d_{jk,qr}$ are the coefficients of the corresponding response surface. In practice, such a model turns out to be too heavy. Thus, a first screening attempt based on an first-order model is usually carried out:

$$C = \mu + \sum_{j=1}^{n} \delta_{j,q} + \epsilon. \qquad (2)$$

If the first-order model don't suitably describe the parasitic capacitance model behavior, the second-order model is used. In general, when the condition of design parameter independence is not respected, the first-order model is not appropriate to describe the parasitic capacitance model behavior. Afterward, the coefficients of the response surface described by model (1) or (2), which best fit simulation and experimental data, have to be determined. An a-posteriori response surface approach to performance analysis is used. Metamodel coefficients model are estimated by making simulation runs at various input values for the $f$ in the domain $D$ according to the selected simulation plan, recording the corresponding responses, and using ordinary least-squares regression to estimate the coefficients. The suitability of the model (2) is verified by the analysis of mean (ANOM) and the analysis of variance (ANOVA). Instead, the suitability of model 1 is verified by the analysis covariance (ANCOVA).

A simulation plan has to be selected. The whole experimentation of the combinatorial space of the design parameter levels could be burdensome. Therefore, the experimental plans Resolution III are used. In particular, the plans of Genichi Taguchi are used [6]. The Resolution III standard Taguchi experimental plans of are characterized by matrix (design matrix). The $n$ columns of the design matrix represent design parameters and influence parameters. The $N$ rows of the design matrix represent every experiment or simulation that have to be carried out. Once the matrix for the design parameters has been selected, the experiments are carried out. The levels of each parameter are selected according to the portion of the interest domain to be analyzed.

In the ANOM, the mean $\mu$, in the eq. 2 is estimated by the $N$ results of the design matrix:

$$\mu = \frac{1}{N} \sum_{k=1}^{N} C_k. \tag{3}$$

The main effects of each parameter on the mean response $\mu$ are assessed. The effects $\delta_{j,q}$ of the eq. 2 are estimated as: $d_{j,q} = m_{j,q} - \mu$, where $m_{j,q}$ are the averages of the results of the $n_{j,q}$ matrix experiments where the j-th design parameter occurs at the q-th level:

$$m_{j,q} = \frac{1}{n_{j,q}} \sum_{k=1}^{n_{j,q}} C_k. \tag{4}$$

In the ANOVA, the statistically significance of the incidence of each design parameter on the each parasitic capacitance $C$ is assessed. The variance of $C$ caused by the parameter is weighted to the uncertainty of the model (2). In particular, ANOVA is aimed at determining, within a prefixed uncertainty, whether a variation over the mean performance imposed by a corresponding parameter variation is due to the parameter itself or can be confused with the model uncertainty. This is carried out by a Fisher test on the variance ratio:

$$F_j = \frac{\sigma_j^2}{\sigma_\epsilon^2}, \tag{5}$$

where $\sigma_j^2$ is the variance of the j-th parameter and $\sigma_\epsilon^2$ is the error variance of the parasitic capacitance. In particular:

$$\sigma_j^2 = \frac{\sum_{q=1}^{n_{w,j}} n_{j,q} d_{j,q}^2}{\gamma_j}, \tag{6}$$

where $n_{w,j}$ is the number of levels of the j-th parameter and $\gamma_j = n_{w,j} - 1$ is the number of freedom degrees of the j-th parameter. The error variance is:

$$\sigma_\epsilon^2 = \frac{\sum_{k=1}^{N} \epsilon_k^2}{\gamma_\epsilon}, \tag{7}$$

where $\gamma_\epsilon = \gamma_t - \sum_{k=1}^{n} \gamma_k$ is the error number of freedom degrees and $\gamma_t$ is the sum of number of freedom degrees of the all parameters. The error variance $\sigma_\epsilon^2$ is derived from the theorem of deviance decomposition as:

$$\sum_{j=1}^{N} \epsilon_j^2 = \sum_{j=1}^{N} y_j^2 - N\mu^2 - \sum_{j=1}^{n} \sum_{q=1}^{n_{w,j}} \left( n_{j,q} d_{j,q}^2 \right). \tag{8}$$

Given a confidence level, the parameters having negligible values of $F_j$ will be neglected in the minimization. In the identification test, if the parasitic capacitance $C$ is a scalar, the Fisher test can be used to establish the global parameter F-statistic of the model. If $C$ is an array, the Fisher test can also separately be applied to each component [16].

3) Minimum configuration prediction and validation

The minimum configuration is predicted through the model (2) by means of the design parameter effects minimizing the parasitic capacitance $C_{opt}$.

Afterward, the metamodel is validated through simulation and experimental validations. The prediction is verified by measuring or simulating the parasitic capacitance $C_{opt}^*$ in the minimum configuration in order to compute the prediction error: $\epsilon_p = \left| C_{opt}^* - C_{opt} \right|$. Then, $\epsilon_p$ is tested to be inside a confidence interval with amplitude related to the required minimization accuracy:

$$\epsilon_p \leq z \cdot \sigma_p, \tag{9}$$

where $\sigma_p$ is the standard deviation of $\epsilon_p$. The uncertainty $\sigma_p$ has two independent sources: the limited number $n_r$ of replication of the verification experiments and the uncertainty on the estimate of $C_{opt}$:

$$\sigma_p = \sigma_\epsilon \left( \frac{1}{n_r} + \frac{1}{n_0} \right), \tag{10}$$

where $n_0$ is the size of the equivalent sample [14]:

$$\frac{1}{n_0} = \frac{1}{N} + \sum_{j=1}^{n_k} \left( \frac{1}{n_{jopt}} - \frac{1}{N} \right), \tag{11}$$

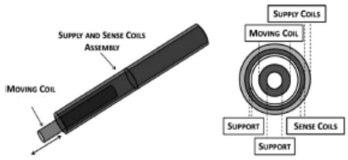


*Fig. 1. Sensor's assembly in three dimensions (all coils are coaxial) and transversal section of the winding and arrangement of the I2PS.*

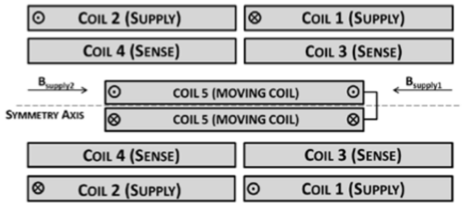


*Fig. 2. I2PS structure in longitudinal section.*

with $n_k$ the number of significant parameters, and $n_{jopt}$ the number of levels where the j-th parameter occurs at the minimum level in the matrix.

### D. *Procedure: the second part*

The second part of the procedure consists of the sensitivity analysis in the minimum parameters configuration. In this analysis, the designer want to understand which parameter mainly affect the parasitic capacitance. In this analysis, the relative uncertainties of each parameter are fixed. In order to achieve this goal, the ANOVA is carried out in the same way of the first part of the procedure. However, the levels of each parameter are selected so that every parameter is considered as varying within a range given from its relative uncertainty and centered in the optimal value defined by the first step of the procedure.

## III. CASE STUDY

In this section, A. first the case study is introduced, then the application of B. the first and C. the second part of the proposed procedure is explained.

### A. *Ironless Inductive Position Sensor (I2PS)*

The case study chosen to test the proposed procedure is an inductor of an Ironless Inductive Position Sensor (I2PS) [17]. The I2PS is a novel linear position-sensing device that should exhibit immunity to external magnetic field since it is characterized by air-cored windings [18, 19]. Simultaneously it is expected to ensure high-precision measurements in harsh environments, such as nuclear plants and particle accelerators (e.g. Large Hadron Collider at CERN). The I2PS has been recently proposed in order to overcome the problems of magnetic interference arising in typical linear position sensors used in harsh environments, such as the Linear Variable Differential Transformer (LVDT) [20] for the LHC collimators. The I2PS is an air-cored structure made of 5 coaxial cylindrical coils (Fig. 1).

Given the presence of multiple-layer windings and the possibility to have a high number of turns per layer, the I2PS is affected by high-frequency phenomena: skin and proximity effects and presence of parasitic capacitances [21]. In particular, the parasitic capacitances modify the main sensor's resonance frequency [22] and alter the inductive coupling between the windings. Therefore, they play a crucial role in the design and optimization of the I2PS, which in principle are focused in maximizing the inductive coupling between coil [17]. The I2PS is made of 5 different windings (two sense coils, two supply coils, and a moving coil Fig. 2), so two different categories of parasitic capacitances can be defined: single-coil capacitances, due to self-capacitances, and cross-coil capacitance, between two different coils, due to sensor's geometrical assembly [22]. Three different analytical models are used to quantify the single-coil capacitances of each inductor in I2PS [22, 4].

### B. *Application of the first part of the procedure*

1) Metamodel definition

In this case study, the parametric optimization is focused on the single-coil capacitance of a sense coil. The single-coil capacitance of a multilayer inductor is due to the number of layer $K$, the number of turns per layer $N$, the curvature radius of the inductor $r_s$, the radius of the turn conductor $r_c$, the thickness $t$ and the insulation material permittivity $\epsilon_r$. For the sense coil, the number of layer is fixed ($K = 3$). When the number of turns per layer is large, variations of $N$ does not appreciably affect the single-coil capacitance of the inductor. Thus, the parameters that considerably affect the single-coil capacitance of the inductor are: $\epsilon_r$, $r_s$, $r_c$ and $t$. These are the design parameters $\mathbf{x}$ of the p-diagram. In Fig. 3, the P-diagram for a behavioral model of a parasitic capacitance in a standard inductor is reported. In the P-diagram, the parameters acting on the capacitance model are summarized according to a black-box approach. The selected central values of the parameters are the following: $\epsilon_r = 3.2$, $r_s = 10.0\ mm$, $r_c = 2.25\ \mu m$, $t = 3.50\ \mu m$. Every parameter is considered varying within a range of the $\pm 25\%$. This is the interest parameters domain $D$.

2) Metamodel identification

The Resolution III standard Taguchi experimental plan L18 is used, owing to its capability to explore a combinatorial space generated by up to seven 3-level parameters and one 2-level parameter, according to a first-order model. The levels of the design parameters are selected as following: central value$-25\%$, central value, central

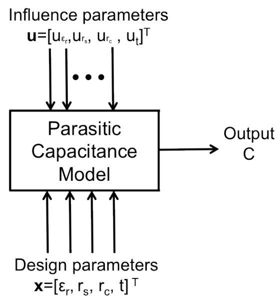


*Fig. 3. P-diagram of the sense coil parasitic capacitance model of I2PS. $\epsilon_r$ is the insulation material permittivity, $r_s$ is the curvature radius of the inductor, $r_c$ is the radius of the turn conductor, $t$ is the thickness of the insulation material, $C$ is the parasitic capacitance of I2PS sense coil.*

value+25%, as depicted in Tab. 1.

*Table 1. Case-study design matrix for resolution III standard Taguchi experimental plan L18 ($e$: empty column).*

| Exp. N° | e | $\varepsilon_r$ | $r_s$[mm] | $r_c$[µm] | t[µm] | e | e | e | C [pF] |
|---|---|---|---|---|---|---|---|---|---|
| 1 | | 2.4 | 7.50 | 16.9 | 2,63 | | | | 1.37 |
| 2 | | 2.4 | 10.0 | 22.5 | 3,50 | | | | 1.82 |
| 3 | | 2.4 | 12.5 | 28.1 | 4.38 | | | | 2.28 |
| 4 | | 3.2 | 7.50 | 16.9 | 3.50 | | | | 1.39 |
| 5 | | 3.2 | 10.0 | 22.5 | 4.38 | | | | 1.93 |
| 6 | | 3.2 | 12.5 | 28.1 | 2.63 | | | | 3.90 |
| 7 | | 4.0 | 7.50 | 22.5 | 2.63 | | | | 2.36 |
| 8 | | 4.0 | 10.0 | 28.1 | 3.50 | | | | 3.02 |
| 9 | | 4.0 | 12.5 | 16.9 | 4.38 | | | | 2.35 |
| 10 | | 2.4 | 7.50 | 28.1 | 4.38 | | | | 1.37 |
| 11 | | 2.4 | 10.0 | 16.9 | 2.63 | | | | 1.82 |
| 12 | | 2.4 | 12.5 | 22.5 | 3.50 | | | | 2.28 |
| 13 | | 3.2 | 7.50 | 22.5 | 4.38 | | | | 1.45 |
| 14 | | 3.2 | 10.0 | 28.1 | 2.63 | | | | 3.12 |
| 15 | | 3.2 | 12.5 | 16.9 | 3.50 | | | | 2.31 |
| 16 | | 4.0 | 7.50 | 28.1 | 3.50 | | | | 2.27 |
| 17 | | 4.0 | 10.0 | 16.9 | 4.38 | | | | 1.88 |
| 18 | | 4.0 | 12.5 | 22.5 | 2.63 | | | | 3.92 |

The model (2) was identified according to the ANOM, using the eq. 3 and 4 by obtaining the parameter effects reported in Fig. 4.

Results of the ANOVA are reported in Tab. 2. A Fisher test on the obtained values of $F_j$ was performed. The Fisher test confirmed the suitability of the first-order model at a confidence level of 0.99. Being larger with respect to the corresponding Fisher statistic, the index $F_j$ turns out to be within the aforementioned prefixed confidence level, because the variation over the mean is due to the parameter variation and not to the metamodel uncertainty.

*Table 2. ANOVA results.*

| | Freedom degree | Variance [$F^2 \cdot 10^{-24}$] | $F_i$ |
|---|---|---|---|
| $\varepsilon_r$ | 2 | 1.02 | 45.4 |
| $r_s$ | 2 | 1.94 | 87.0 |
| $r_c$ | 2 | 0.975 | 43.6 |
| t | 2 | 1.17 | 52.3 |
| error | 9 | $2.23 \cdot 10^{-2}$ | |
| tot. | 17 | 5.13 | |

3) Minimum configuration prediction and validation

From Fig. 4 the optimum configuration is argued easily: $\epsilon_r = 2.4$, $r_s = 7.50\ mm$, $r_c = 16.9\ \mu m$, $t = 4.38\ \mu m$.

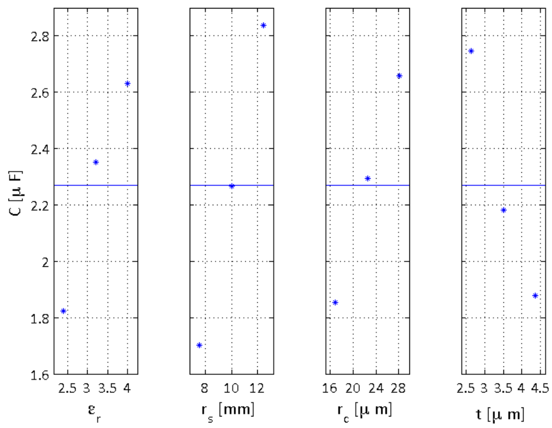


*Fig. 4. ANOM results. The overall mean $\mu$ is represented in solid line. The averages of the simulations where the j-th design parameter occurs at the q-th level $m_{j,q}$ are represented in $*$.*

The metamodel is validated through simulation validation. The test (10) turns out positive.

### C. Application of the second part of the procedure

The sensitivity analysis in the optimum parameters configuration is carried out selecting the following relative uncertainties on the design parameters: $u_{\epsilon_r} = 0.00001$, $u_{r_s} = 0.0001$, $u_{r_c} = 0.01$, $u_t = 0.0001$. The results of the ANOVA for the sensitivity analysis are reported in Tab. 3. A prevailing impact of the radius of the turn conductor $r_c$ was surveyed. Comparing to the other parameters, the insulation material permittivity $\epsilon_r$ slightly affect the parasitic capacitance.

*Table 3. ANOVA results for the sensitivity analysis in the optimum parameters configuration.*

| | Freedom degree | Variance [$F^2 \cdot 10^{-28}$] | $F_i$ [$\cdot 10^3$] |
|---|---|---|---|
| $\varepsilon_r$ | 2 | $3.44 \cdot 10^{-6}$ | 1 |
| $r_s$ | 2 | $5.49 \cdot 10^{-4}$ | 153 |
| $r_c$ | 2 | 2.72 | $759 \cdot 10^3$ |
| t | 2 | $2.71 \cdot 10^{-4}$ | 76 |
| error | 9 | $3.59 \cdot 10^{-9}$ | |
| tot. | 17 | 2.72 | |

## IV. CONCLUSIONS

A systematic procedure, based on surface-response approach, to find the optimal configuration of the design parameters of an inductor in a given parameters domain to reduce both deterministic and uncertainty effects of parasitic capacitances has been presented. First, the best inductor parameters configuration for minimizing deterministic effects of parasitic capacitance is determined. Then, a sensitivity analysis in the optimum parameters configuration is carried out in order to define the impact of inductor parameters uncertainty on parasitic capacitance in order to find the most precise configuration. A case study about an inductor of an Ironless Inductive Position Sensor was analyzed in order to highlight the capability of the proposed procedure of defining (i) which parameters of the inductor mainly affect its parasitic capacitance, and (ii) the optimal configuration of the design parameters to minimize the parasitic capacitance in a given parameters domain.

## V. ACKNOWLEDGMENTS

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