



OPEN Simplex-anchored regressors for fast global optimization-oriented miniaturization of microwave circuits

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The small physical size of high-frequency components is an essential prerequisite in an increasing number of applications. While size reduction of microwave circuits can be achieved with a suitable choice of architecture, ensuring the best available compromise between electrical parameters and size necessitates meticulous adjustment of all system dimensions. Due to the complexity of electrically small structures, parameter adjustment should be executed globally. Nevertheless, it is an expensive endeavor because it entails a large number of system evaluations executed through electromagnetic (EM) simulation. This article introduces an innovative approach to expedited miniaturization of microwave passives, in which the primary goal is miniaturization, while the conditions imposed on performance metrics are treated as constraints. Our framework operates in three stages, including parameter space pre-screening, machine-learning (ML)-driven globalized search, and gradient-based fine-tuning. The first stage involves random sampling aimed at identifying the most promising parameter space region. The ML process launched therein employs simplex-based regression models, the use of which contributes to a competitive computational efficiency. On the other hand, the final tuning improves design quality at a low cost, as it is realized as a local optimization process. The performance of the suggested algorithm is illustrated using two planar devices and demonstrated to be superior to several benchmark methods. The major advantages of our technique include low running costs, equivalent to only a few dozen full-wave analyses, and straightforward implementation.

Keywords Microwave engineering, Electrically small circuits, EM-based design, Miniaturization, Parameter tuning, Regression models, Machine learning

Miniaturization has become essential for modern application areas (mobile communications, energy harvesting, internet of things, wearable structures, virtual reality, radio-frequency identification^{1–5}), and necessarily affects high-frequency system design, including passive circuits. As the size of conventional structures is related to the guided wavelength, miniaturization is a challenging task. In practice, it is realized using line folding⁶, the employment of slow-wave phenomenon^{7,8}, the incorporation of defected grounds, metamaterials, stubs, slots, substrate-integrated waveguides, or shorting pins^{9–14}. The resulting circuit architectures are topologically complex, and—due to cross-coupling—they need to be characterized using electromagnetic (EM) simulation^{15,16}. At the same time, involved relationships between circuit dimensions and electrical characteristics make concurrent adjustment of circuit dimensions imperative, preferably using formal optimization algorithms^{17,18}.

The main issue of EM-based microwave optimization are high CPU expenses, which may be considerable even for local methods^{19,20}, yet considerably higher for global and multi-objective search^{21,22}, as well as uncertainty quantification^{23,24}. The research on expediting simulation-based procedures has been extensive^{25–30}. The methods reported in the literature include reducing the cost of sensitivity estimation in gradient-based algorithms^{31–33}, as well as surrogate-assisted techniques involving behavioural models^{34–41}, physics-based surrogates^{42–46}, as well as machine learning frameworks (e.g.,⁴⁷).

For miniaturized microwave circuits, the fundamental goal of parameter tuning is to diminish the structure footprint area⁴⁸. From the numerical perspective, it is a constrained problem with conditions formulated for

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performance figures, e.g., reflection, isolation, power division ratio, or the phase response, all within specified frequency bands^{49,50}. Furthermore, evaluating these conditions is expensive, i.e., it requires EM analysis results. The explicit control thereof is problematic⁵¹ and fosters utilization of alternative methods, especially a penalty function approach^{51–53}. However, proper arrangement of penalty factors is circuit-dependent and normally requires supplementary optimization runs, which entails extra computational expenses. This challenge was tackled by recently reported adaptive strategies^{54,55}, yet, they are only applicable for local parameter tuning. When it comes to global search, it was predominantly carried out using bio-inspired techniques^{56–59}. Although these methods exhibit global search capability, their computational efficiency is exceptionally poor. In fact, straightforward EM-based bio-inspired design is unmanageable in most cases. Instead, surrogate models are often incorporated^{25,60–62}, typically in the form of iterative algorithms, in which a metamodel plays a role of a rapid predictor, and it is enhanced based on EM data acquired during optimization^{63–65}. Such procedures are frequently labelled as machine learning (ML) procedures^{66,67}. However, the utility of behavioral models is impeded by the curse of dimensionality and nonlinearity of microwave circuit outputs⁶⁸. Consequently, ML frameworks are typically demonstrated using low-dimensionality test cases^{69,70}.

This article proposes an alternative methodology for globalized EM-driven miniaturization of microwave passives, with the conditions imposed on performance metrics treated as constraints. It is a three-stage procedure, which includes a pre-screening step, globalized ML search incorporating simplex-based regressors, and final (gradient-based) tuning. The first stage is arranged as random sampling oriented towards determination of the most promising parameter space regions. The ML process is subsequently launched, where the search for an optimum design (in achieving minimum footprint area while preserving required electrical operation) is carried out using regression models spanned over a set of simplex vertices processed by the algorithm. The final tuning stage is then executed to refine the design at low computational cost. The search engine is an accelerated trust-region routine with finite-difference-based derivatives. Our approach is illustrated based on two coupling structures and juxtaposed against several benchmark procedures. Numerical findings indicate that the algorithm exhibits competitive performance, both in terms of the achieved miniaturization rates and computational efficiency. The mean optimization expenses are below a hundred EM analyses.

The contributions of this research are: (i) the employment of simplex-based models for optimization-based miniaturization of microwave components, (ii) the development of a three-stage procedure for global-search-oriented miniaturization, (iii) integration of the algorithmic components into an automated optimization framework, (iv) underscoring remarkable method's efficacy in terms of its ability to reduce the component size as compared to the benchmark, (v) demonstration of exquisite computational efficiency of the technique.

Optimization-driven size reduction

Here, we formulate the optimization problem of interest, which is explicitly diminishing the circuit size while preserving electrical parameters. For the latter, efficient constraint handling methods are essential, which are discussed in Section "Constraint handling". The details of our methodology are given in Section "Global miniaturization by pre-screening and machine learning with simplex-anchored surrogates". It should be emphasized that we assume that the topologies of the microwave components under design have been determined beforehand (during the topology evolution), and only the values of the geometry parameters (i.e., circuit dimensions) undergo explicit numerical optimization. The final footprint of the optimized design results from the optimal circuit dimensions obtained during the optimization process.

Explicit size reduction through numerical optimization

As elaborated on in Section "Introduction", miniaturization of high-frequency components has become essential for many applications from wireless communications, through IoT, to augmented reality devices. Compact size of microwave passives is normally achieved using line meandering, the use of metamaterials and/or compact resonant components^{6,7,10}. Further reduction of physical dimensions necessitates meticulous adjustment of geometry parameters, which is also necessary to provide satisfactory electrical operation of the system. For reliability, it is recommended to carry out the process using rigorous optimization methods.

Below, we provide a formal definition of the simulation-driven size reduction task. Using the terminology collected in Fig. 1, the task can be written as

$$\mathbf{x}^* = \arg \min_{\mathbf{x} \in X_f} A(\mathbf{x}) \quad (1)$$

As explained in Fig. 1, the feasible space X_f encapsulates design satisfying all design constraints assumed for the circuit.

Constraint handling

When solving (1), the conditions imposed on performance metrics (target band, power division ratio, phase margins) are treated as constraints. Explicit handling thereof is troublesome due to high evaluation cost (requires EM analysis). A penalty function approach⁵² offers a workaround by reformulating the problem (1) as follows

$$\mathbf{x}^* = \arg \min_{\mathbf{x}} U_P(\mathbf{x}) \quad (2)$$

In (2), the function U_P takes the form of

$$U_P(\mathbf{x}) = A(\mathbf{x}) + \sum_{k=1}^{n_g+n_h} \beta_k c_k(\mathbf{x}) \quad (3)$$

Symbol	Meaning	Comment
$\mathbf{x} = [x_1 \dots x_n]^T$	Vector of design parameters	Typically, the variables are the circuit geometry parameters (dimensions in mm)
X	Parameter space	Typically, X is an interval $[l \ u]$, where $l = [l_1 \dots l_n]^T$ and $u = [u_1 \dots u_n]^T$ are lower and upper bounds on design parameters so that $l_k \leq x_k \leq u_k$, for $k = 1, \dots, n$
$A(\mathbf{x})$	Circuit size	For planar circuits, $A(\mathbf{x})$ is typically a footprint area in mm^2
$S_{jk}(\mathbf{x}, f)$	Scattering parameters at the design $\mathbf{x}$ and frequency f ; j and k refer to the circuit port numbers	Scattering parameters are complex numbers; in the design process we handle their moduli $ S_{jk} $, expressed in decibels
$g_k(\mathbf{x}) \leq 0, k = 1, \dots, n_g$	Inequality constraints	Typically, expressed using acceptance thresholds for selected circuit characteristics, e.g., $ S_{11}(\mathbf{x}, f) \leq -10$ dB for f within the frequency range of interest
$h_k(\mathbf{x}) = 0, k = 1, \dots, n_h$	Equality constraints	Typically, expressed using target values for selected circuit characteristics
X_f	Feasible space	$X_f \subset X$ contains parameter vectors $\mathbf{x}$ for which all constraints are satisfied, i.e., $g_k(\mathbf{x}) \leq 0$ for $k = 1, \dots, n_g$, and $h_k(\mathbf{x}) = 0$ for $k = 1, \dots, n_h$

Fig. 1. Simulation-driven microwave circuit miniaturization: terminology.

Constraint	Type	Analytical description [§]
Input matching $ S_{11} $ not exceeding -20 dB over the operating bandwidth $[f_1 \ f_2]$	Inequality	$ S_{11}(\mathbf{x}, f) \leq -20$ dB for $f \in [f_1 \ f_2]$
Port isolation $ S_{41} $ not exceeding -20 dB over the operating bandwidth $[f_1 \ f_2]$	Inequality	$ S_{41}(\mathbf{x}, f) \leq -20$ dB for $f \in [f_1 \ f_2]$
In-band transmission ripple not exceeding 0.2 dB over the operating bandwidth $[f_1 \ f_2]$	Inequality	$ S_{21}(\mathbf{x}, f) \geq -0.2$ dB for $f \in [f_1 \ f_2]$
Power split ratio between output ports 2 and 3 equal to K_P at the center frequency f_0	Equality	$ S_{31}(\mathbf{x}, f) - S_{21}(\mathbf{x}, f) = K_P$ at $f = f_0$;
Phase difference between output ports 2 and 3 equal to 90° at the center frequency f_0	Equality	$\angle S_{31}(\mathbf{x}, f) - \angle S_{21}(\mathbf{x}, f) = 90^\circ$ at $f = f_0$;

[§]The symbol $|S_{jk}(\mathbf{x}, f)|$ stands for the modulus of the S-parameter S_{jk} at the design $\mathbf{x}$, and frequency f .

Fig. 2. Optimization-based size reduction: example constraints.

As it can be observed, reduction of size $A(\mathbf{x})$ is the fundamental purpose, and it is accompanied by factors related to constraint violations computed by the penalty functions $c_k(\mathbf{x})$. The said contributions are controlled by β_k . Figures 2 and 3 provide examples of constraints and possible definitions of the penalty functions. The usage of the second power $[\cdot]^2$ makes U_p smooth regarding constraint violation at ∂X_f (the boundary of X_f), which makes its exploration easier. The latter is important as minimum-size designs are normally located in ∂X_f (i.e., one or more constraints are active).

Implicit constraint handling faces a practical issue, which is choosing the penalty factors β_k . If too low, excessive constraint violation are expected; when too high, exploring ∂X_f becomes troublesome. A trial-and-error setup is time consuming and entails extra computational expenses. A possible solution has been offered by the adaptive adjustment schemes^{54,55}, as well as the recent explicit constraint handling strategies^{71,72}. Both yield reasonable compromises between achievable size reduction rates and constraint handling, yet, they are primarily intended for incorporation into local search algorithms.

Global miniaturization by pre-screening and machine learning with simplex-anchored surrogates

Here, we introduce the proposed EM-driven size reduction procedure. The optimization problem has been formulated as the explicit minimization of circuit size through numerical optimization of its geometry parameters, aiming to achieve the smallest possible footprint area (see Section "Explicit size reduction through numerical optimization"), while simultaneously satisfying performance-related requirements treated as constraints (see Section "Constraint handling"). Its three stages, i.e., pre-screening, machine-learning-based globalized search, and final tuning, are elaborated on in Sections "Stage I: Pre-screening" through "Stage III: Design closure", respectively. The complete procedure is put together in Section "Complete algorithm".

Constraint	Penalty function
Input matching $ S_{11} $ not exceeding -20 dB over the operating bandwidth $[f_1 f_2]$	$c(\mathbf{x}) = \left[\frac{\max \{ \max \{ f_1 \leq f \leq f_2 : S_{11}(\mathbf{x}, f) \} + 20, 0 \}}{20} \right]^2$
Port isolation $ S_{41} $ not exceeding -20 dB over the operating bandwidth $[f_1 f_2]$	$c(\mathbf{x}) = \left[\frac{\max \{ \max \{ f_1 \leq f \leq f_2 : S_{41}(\mathbf{x}, f) \} + 20, 0 \}}{20} \right]^2$
In-band transmission ripple not exceeding 0.2 dB over the operating bandwidth $[f_1 f_2]$	$c(\mathbf{x}) = \left[\frac{\max \{ -\min \{ f_1 \leq f \leq f_2 : S_{21}(\mathbf{x}, f) \} - 0.2, 0 \}}{0.2} \right]^2$
Power split ratio between output ports 2 and 3 equal to K_P at the center frequency f_0	$c(\mathbf{x}) = [S_{31}(\mathbf{x}, f_0) - S_{21}(\mathbf{x}, f_0) - K_P]^2$
Phase difference between output ports 2 and 3 equal to 90° at the center frequency f_0	$c(\mathbf{x}) = [\angle S_{31}(\mathbf{x}, f_0) - \angle S_{21}(\mathbf{x}, f_0) - 90^\circ]^2$

Fig. 3. Optimization-based size reduction: example penalty functions.

Stage I: Pre-screening

A fundamental challenge related to global optimization of microwave components is high computational cost. Meanwhile, cost efficiency of bio-inspired routines being the prevalent methods for global search^{73–83} is poor. At the same time, exploring large parameter spaces (both regarding the ranges of geometry variables and frequency) is imperative. The same reason hinders applications of surrogate-based methods: construction of dependable behavioral models over large spaces is simply undoable.

Here, the complexity of the problem is reduced by means of pre-screening, which enables identification—in an approximate manner—the position of the most promising areas from perspective of the considered design task. The pre-screening concept is explained assuming that the underlying problem is size reduction of microwave couplers with extra conditions assumed for the S -parameters. More specifically, the following conditions are to be satisfied:

- $|S_{11}(\mathbf{x}, f)| \leq -20$ dB and $|S_{41}(\mathbf{x}, f)| \leq -20$ dB for $f_1 \leq f \leq f_2$, i.e., $|S_{11}|$ and $|S_{41}|$ are below -20 dB over the frequency range $[f_1 f_2]$;
- $|S_{31}(\mathbf{x}, f)| - |S_{21}(\mathbf{x}, f)| = K$ dB for $f = f_0$, i.e., the coupler should provide power division K at the operating frequency $f_0 = (f_1 + f_2)/2$;

Further, let $f_{1,EM}(\mathbf{x})$ and $f_{4,EM}(\mathbf{x})$ stand for the frequency points associated with minimum of $|S_{11}|$ and $|S_{41}|$ at design $\mathbf{x}$ found from EM simulation data, whereas $dS(\mathbf{x})$ is the power division ratio at frequency $[f_{1,EM}(\mathbf{x}) + f_{4,EM}(\mathbf{x})]/2$, which is the approximated center frequency of the circuit.

The pre-screening is arranged by generating random samples in the parameter space, evaluating the circuit responses using EM analysis, and comparing the estimated performance parameters with the assumed targets. The samples satisfying the imposed conditions are selected for the subsequent search stages. For the considered coupler example, the conditions are as follows:

- The circuit size $A(\mathbf{x})$ satisfies $A_{\min} \leq A(\mathbf{x}) \leq A_{\max}$, where the ranges $A_{\min}$ and $A_{\max}$ are determined based on the previous design work on a particular class of structures as well as general engineering insight;
- $f_{\min} \leq f_{1,EM}(\mathbf{x}), f_{4,EM}(\mathbf{x}) \leq f_{\max}$, where the range $f_{\min}$ and $f_{\max}$ are related to the target center frequency f_0 . In practice, we would use $f_{\min} = 0.75f_0$, and $f_{\max} = 1.25f_0$ (cf. Section "Results");
- $|dS(\mathbf{x}) - K| \leq dS_{\max}$, where $dS_{\max}$ is the acceptance power division error. It is normally set up liberally to, say, $dS_{\max} = 3$ dB (cf. Section "Results").

For the sample to be accepted, all conditions mentioned must be jointly fulfilled. Therefore, the EM analysis is only executed at $\mathbf{x}$ if $A(\mathbf{x}) \geq A_{\min}$ and $A(\mathbf{x}) \leq A_{\max}$ to avoid generating excessive computational expenses. The procedure is terminated as soon as N_{pre} observables have been accepted. As the surrogate model employed by the second stage of the search process (cf. Section "Stage II: Machine learning for globalized optimization") is simplex-based, we have $N_{pre} = n + 1$ vectors, where n is the parameter space dimensionality.

Figure 4 illustrates the pre-screening steps. Meanwhile, Fig. 5 shows its graphical illustration, which also explains the associated benefits. On the one hand, the pre-selected samples are of considerably higher quality than the average observable regarding the alignment of their operating parameters and the respective targets. Furthermore, they are allocated within a relatively small region, which will facilitate surrogate model construction and improve its predictive power.

Although the pre-screening concept has been explained here using a specific class of microwave components and a particular example of a design task, analogous procedure can be carried out for other types of circuits (filters, power dividers, etc.). In any given situation, the acceptance thresholds must be extracted from performance requirements assumed for the circuit characteristics.

1. Input parameters:
 - Target operating bandwidth $F = [f_1 \ f_2]$ and center frequency $f_0 = (f_1 + f_2)/2$;
 - Target power split ratio K ;
 - Minimum circuit size $A_{\min}$;
 - Maximum circuit size $A_{\max}$;
 - Center frequency acceptance range $[f_{\min} \ f_{\max}]$;
 - Acceptance threshold for power split error $dS_{\max}$;
 - Number of pre-screened initial samples N_{pre} ;
2. Set $i = 0$ and $j = 0$;
3. Generate a random sample $\mathbf{x}_{tmp} \in X$;
4. **if** $A(\mathbf{x}_{tmp}) \geq A_{\min}$ **AND** $A(\mathbf{x}_{tmp}) \leq A_{\max}$
 - Perform EM simulation and acquire $\mathbf{R}_{EM}(\mathbf{x}_{tmp})$;
 - $j = j + 1$;
 - $\mathbf{x}_B^{(j)} = \mathbf{x}_{tmp}$;
 - $\mathbf{R}_B^{(j)} = \mathbf{R}_{EM}(\mathbf{x}_{tmp})$;
 - Extract $f_{1,EM}(\mathbf{x}_{tmp})$, $f_{4,EM}(\mathbf{x}_{tmp})$, and $dS(\mathbf{x}_{tmp})$ (frequency location of the first resonance);
 - if** $\min\{f_{1,EM}(\mathbf{x}_{tmp}), f_{4,EM}(\mathbf{x}_{tmp})\} \geq f_{\min}$ **AND** $\max\{f_{1,EM}(\mathbf{x}_{tmp}), f_{4,EM}(\mathbf{x}_{tmp})\} \leq f_{\max}$ **AND** $|dS(\mathbf{x}_{tmp}) - K| \leq dS_{\max}$
 - $i = i + 1$;
 - end**
- end**
5. **if** $i < N_{pre}$
 - Go to 3;
- else**
 - $N_{init} = j$;
 - End**;
- end**

Fig. 4. Pre-screening for optimization-based miniaturization of microwave passive components.

Stage II: Machine learning for globalized optimization

The pre-screening procedure of Section "Stage I: Pre-screening" identifies the region containing decent-quality designs (in terms of their electrical characteristics) that correspond to circuit areas within the range expected as a result of the size reduction process. Globalized optimization being the second stage of the search process involves machine learning (ML) with the underlying surrogate models being linear regressors constructed over the simplex-arranged training points. The ML algorithm processes a set of surrogate models of this form and refines them utilizing the EM data acquired during the algorithm run. The rationale for employing the simplex-anchored surrogate lies in the fact that such a model can be constructed using only a small number of training samples. Specifically, merely $n + 1$ samples are required (n being the dimensionality of the design space). Moreover, this type of surrogate does not require to be trained. Instead, its hyperparameters are computed explicitly as will be explained below. This translates into exceptional cost-efficacy, unmatched by other surrogate-based approaches that necessarily rely on large training datasets to enable global miniaturization. The remaining part of the section discusses surrogate model definition along with the flow of the algorithm.

Simplex-based surrogate model

Below, we employ the following terminology. By $\mathbf{x}^{(j)} = [x_1^{(j)} \ \dots \ x_n^{(j)}]^T$, $j = 0, \dots, n$, we mark $n + 1$ affinely independent vectors found by means of the pre-screening procedure of Section "Stage I: Pre-screening". The symbol $\mathbf{R}^{(j)} = \mathbf{R}_{EM}(\mathbf{x}^{(j)})$ will be used to denote the circuit responses obtained through EM analysis. Affine independence of $\{\mathbf{x}^{(j)}\}$ implies linear independence of $\mathbf{x}^{(j)} - \mathbf{x}^{(0)}$, $j = 1, \dots, n$. Consequently, any design $\mathbf{x} \in X$ can be uniquely written as

$$\mathbf{x} = \mathbf{x}^{(0)} + \sum_{j=1}^n a_j (\mathbf{x}^{(j)} - \mathbf{x}^{(0)}) \quad (4)$$

The expansion coefficient vector $\mathbf{a} = [a_1 \ \dots \ a_n]^T$ can be found analytically as

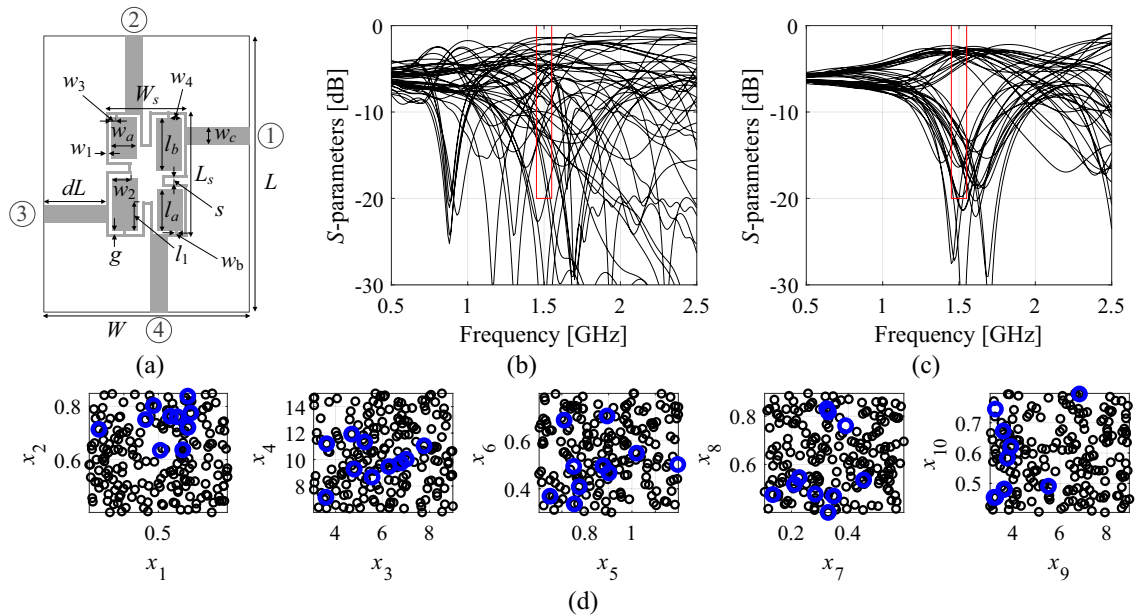


Fig. 5. A compact coupler example: (a) circuit geometry, (b) S-parameters versus frequency at randomly selected designs, (c) S-parameters at pre-screened designs; the target band (1.45 GHz to 1.55 GHz) denoted using the vertical lines. The responses at pre-screened designs are better (regarding the allocation the center frequency relatively close to $f_0 = 1.5$ GHz, and the power division ratio being close to zero dB); (d) two-dimensional projections illustrating allocation of the pre-selected designs (large circles) versus the entire parameter space (small circles corresponding to random samples in X): due to constraints imposed on electrical performance parameters and the minimum/maximum size, the pre-selected set is limited to a small parameter space subset, which facilitates surrogate model rendition.

$$\mathbf{a}(\mathbf{x}) = [a_1(\mathbf{x}) \ \dots \ a_n(\mathbf{x})]^T = \mathbf{X}^{-1}(\mathbf{x} - \mathbf{x}^{(0)}) \quad (5)$$

in which the $n \times n$ matrix $\mathbf{X}$ is defined as

$$\mathbf{X} = [\mathbf{x}^{(1)} - \mathbf{x}^{(0)} \ \dots \ \mathbf{x}^{(n)} - \mathbf{x}^{(0)}] \quad (6)$$

Note that $\mathbf{X}$ is invertible due to the linear independence of $\{\mathbf{x}^{(j)} - \mathbf{x}^{(0)}\}_{j=1, \dots, n}$.

One can now define the simplex model $\mathbf{R}_S(\mathbf{x})$, which represents the circuit frequency responses in the space X . We have

$$\mathbf{R}_S(\mathbf{x}) = \mathbf{R}^{(0)} + \sum_{j=1}^n a_j(\mathbf{R}^{(j)} - \mathbf{R}^{(0)}) = \mathbf{R}^{(0)} + \mathbf{X}_R \mathbf{a}(\mathbf{x}) = \mathbf{R}^{(0)} + \mathbf{X}_R \mathbf{X}^{-1}(\mathbf{x} - \mathbf{x}^{(0)}) \quad (7)$$

The maxtrix $\mathbf{X}_R$ is defined as

$$\mathbf{X}_R = [\mathbf{R}^{(1)} - \mathbf{R}^{(0)} \ \dots \ \mathbf{R}^{(n)} - \mathbf{R}^{(0)}] \quad (8)$$

Globalized search by machine learning

The search is executed using the model $\mathbf{R}_S(\mathbf{x})$ introduced in Section "Simplex-based surrogate model" (cf. (7), (8)). It is arranged as a machine learning (ML) process, in which the candidate vector $\mathbf{x}_{tmp}$ is generated through metamodel optimization in the vicinity of the available dataset and employed to refine the surrogate. The candidate design is found by minimizing the objective function predicted by the surrogate, i.e., we have

$$\mathbf{x}_{tmp} = \arg \min_{\mathbf{x} \in X} U_S(\mathbf{R}_S(\mathbf{x})) \quad (9)$$

The function U_S analytically coincides with the objective function U_p of (3). Nevertheless, it is computed using the model-predicted responses (rather than EM-simulated ones). To stress that, the explicit dependence of U_S on $\mathbf{R}_S$ is shown.

Problem (9) is solved subject to constraints introduced to keep $\mathbf{x}_{tmp}$ in the neighborhood of the convex hull of $\{\mathbf{x}^{(j)}\}$. The extra conditions are formulated as follows

$$\sum_{j=1}^n a_j = 1 \quad (10)$$

$$-\alpha \leq a_j \leq 1 + \alpha, j = 1, \dots, n \quad (11)$$

Therein, $\alpha = 0.2$ in the verification studies (Section "Results"). The simplex vertices are ordered so that $U_p(\mathbf{x}^{(0)}) \leq U_p(\mathbf{x}^{(1)}) \leq \dots \leq U_p(\mathbf{x}^{(n)})$. Thus, $\mathbf{x}^{(0)}$ corresponds to the best vertex regarding U_p . It is also an initial design for solving (9) due to being the best available optimum approximation. Note that $\mathbf{a}(\mathbf{x}^{(0)}) = [0 \dots 0]^T$.

The ML search uses several rules for accepting/rejecting the candidate design and updating the simplex vertices, which have been explained in Fig. 6. In general, $\mathbf{x}_{tmp}$ is accepted if its corresponding EM-simulated objective function is superior to the worst vertex, in which case it replaces the latter. Otherwise, an auxiliary candidate vector $\mathbf{x}_{tmp,2}$ is generated, which may improve the objective function due to being located closer to $\mathbf{x}^{(0)}$ (the best vertex) and because of continuity of the circuit responses as functions of decision variables. This operation requires just one extra EM analysis. If neither $\mathbf{x}_{tmp}$ nor $\mathbf{x}_{tmp,2}$ are of sufficient quality, the simplex is reduced, which—due to the mentioned continuity—will generally lead to improving the objective function at the refined vertices.

The termination criteria for the ML procedure have been summarized in Fig. 7. Therein, we have three conditions, the last two ensuring converge even if the design satisfying the performance criteria determined by A_{global} and U_{global} does not exist or is not attainable.

Stage III: Design closure

The last optimization step is final adjustment of the circuit dimensions, launched upon termination of the ML process of Section "Stage II: machine learning for globalized optimization". It begins from $\mathbf{x}^{(0)}$, the best simplex vertex found so far. The adjustment is conducted with the help of the trust-region (TR) routine⁸⁴. Figure 8 shows the pseudocode. The procedure generates intermediate candidates $\mathbf{x}^{(i)}$, $i = 0, 1, \dots$, approximating $\mathbf{x}^*$. The vector $\mathbf{x}^{(i+1)}$ is identified by (local) optimization of the regressor $L^{(i)}(\mathbf{x})$, set up at the most recent point $\mathbf{x}^{(i)}$. The estimation of sensitivities is obtained using finite differentiation (FD)⁸⁵. When close to convergence, finite differences are taken over by a Broyden formula⁸⁶ to expedite the process.

Complete algorithm

The overall size reduction procedure includes the three stages discussed in Sections "Stage I: Pre-screening" through "Stage III: Design closure": pre-screening, globalized search by machine learning with simplex-based regression models, and final gradient-based tuning. The algorithm's block diagram is illustrated in Fig. 9, while Fig. 10 shows its pseudocode.

1. If the candidate design is better than at least one of the vertices, i.e., when

$$U_P(\mathbf{x}_{tmp}) < \max\{j \in \{0, 1, \dots, n\} : U_P(\mathbf{x}^{(j)})\} \quad (12)$$

then $\mathbf{x}_{tmp}$ replaces the worst vertex $\mathbf{x}^{(j_{worst})}$, where

$$j_{worst} = \operatorname{argmax}\{j \in \{0, 1, \dots, n\} : U_P(\mathbf{x}^{(j)})\} \quad (13)$$

2. If (12) does not hold, an additional design $\mathbf{x}_{tmp,2}$ is generated, where

$$\mathbf{x}_{tmp,2} = \mathbf{x}^{(0)} + \sum_{j=1}^n \frac{a_j(\mathbf{x}_{tmp})}{2} (\mathbf{x}^{(j)} - \mathbf{x}^{(0)}) \quad (14)$$

which is a vector allocated in half of the distance from $\mathbf{x}^{(0)}$ as compared to $\mathbf{x}_{tmp}$. If

$$U_P(\mathbf{x}_{tmp,2}) < \max\{j \in \{0, 1, \dots, n\} : U_P(\mathbf{x}^{(j)})\} \quad (15)$$

then $\mathbf{x}_{tmp,2}$ replaces the worst vertex $\mathbf{x}^{(j_{worst})}$ (cf. (13)).

3. If both $\mathbf{x}_{tmp}$ and $\mathbf{x}_{tmp,2}$ are rejected, the simplex is reduced towards $\mathbf{x}^{(0)}$ using the transformation:

$$\mathbf{x}^{(j)} \leftarrow \gamma \mathbf{x}^{(j)} + (1 - \gamma) \mathbf{x}^{(0)} \quad \text{for } j = 1, \dots, n \quad (16)$$

In (16), γ is the reduction factor, normally set up to $\gamma = 0.5$. For this value, the simplex is reduced by half with $\mathbf{x}^{(0)}$ remaining intact.

Fig. 6. The rules for accepting/rejecting candidate design $\mathbf{x}_{tmp}$ and updating the simplex vertices, used by the globalized ML size reduction procedure.

Termination criteria for the globalized search stage, treated as logical alternatives:

1. $A(\mathbf{x}^{(0)}) < A_{\text{global}}$ AND $U_P(\mathbf{x}^{(0)}) \leq U_{\text{global}}$, where A_{global} and U_{global} are control parameters of the algorithm. Satisfaction of this condition means that the circuit size is reasonably small and the objective function value is decent at the same time, making the design a suitable candidate for final tuning;
2. The computational budget of N_{global} EM analyzes has been exceeded;
3. $D = \max\{j \in \{1, 2, \dots, n\} : \|\mathbf{x}^{(j)} - \mathbf{x}^{(0)}\|\} \leq D_{\text{min}}$, i.e., the simplex size has been reduced beyond the user-defined threshold D_{min} .

Fig. 7. Termination criteria of the ML process.

Problem formulation: Solve $\mathbf{x}^* = \operatorname{argmin}\{\mathbf{x} \in X : U_P(\mathbf{x})\}$ (cf. (3)), with $\mathbf{x}^{(0)}$ being an initial design;

Algorithm operation: Generate a series $\mathbf{x}^{(i)}$, $i = 0, 1, \dots$, of approximations to $\mathbf{x}^*$. The new (candidate) vector $\mathbf{x}^{(i+1)}$ is obtained by solving

$$\mathbf{x}^{(i+1)} = \operatorname{arg} \min_{\|\mathbf{x} - \mathbf{x}^{(i)}\| \leq d^{(i)}} U_L(\mathbf{x}) \quad (\text{T1})$$

where

$$\mathbf{L}^{(i)}(\mathbf{x}) = \mathbf{R}_{EM}(\mathbf{x}^{(i)}) + \mathbf{J}_R(\mathbf{x}^{(i)}) \cdot (\mathbf{x} - \mathbf{x}^{(i)}) \quad (\text{T2})$$

is a first-order Taylor expansion of the EM model $\mathbf{R}_{EM}$ at $\mathbf{x}^{(i)}$

Objective function: The function U_L is identical to U_P of (3), but it is computed based on the first-order linear model $\mathbf{L}^{(i)}(\mathbf{x})$ of antenna characteristics, instead of original, EM-simulated responses.

Gain ratio r : EM-evaluated versus linear-model predicted objective function improvement

$$r = \frac{U_P(\mathbf{x}^{(i+1)}) - U_P(\mathbf{x}^{(i)})}{U_L(\mathbf{x}^{(i+1)}) - U_L(\mathbf{x}^{(i)})} \quad (\text{T3})$$

Trust region size $d^{(i)} > 0$: Adaptively adjusted based on r , $d^{(i+1)} = d^{(i)} m_{\text{incr}}$ if $r > r_{\text{incr}}$, and $d^{(i+1)} = d^{(i)} / m_{\text{decr}}$ if $r < r_{\text{decr}}$; standard control parameter values are $r_{\text{incr}} = 0.75$, $r_{\text{decr}} = 0.25$, $m_{\text{incr}} = 1.5$, $m_{\text{decr}} = 2$ [85].

Acceptance of the new iteration point: $\mathbf{x}^{(i+1)}$ is accepted only if $r > 0$ (i.e., EM-evaluated objective function has been improved); otherwise, the iteration is repeated with reduced TR size;

Algorithm termination: Convergence in argument ($\|\mathbf{x}^{(i+1)} - \mathbf{x}^{(i)}\| < \varepsilon$) or sufficient reduction of the TR size ($d^{(i)} \leq \varepsilon$); the termination threshold is set to $\varepsilon = 10^{-3}$

Algorithm acceleration: The Jacobian matrix $\mathbf{J}_R(\mathbf{x}^{(i)})$ is estimated using finite differentiation (FD) [86] for the initial iterations of the optimization process, which incurs additional n EM analyzes of the antenna. When close to convergence (here, if $\|\mathbf{x}^{(i+1)} - \mathbf{x}^{(i)}\| \leq M_c \varepsilon$, where M_c is the multiplication factor set to $M_c = 10$), FD is replaced by a rank-one Broyden update [53], where the Jacobian matrix is updated using information about the design relocation and antenna response at the latest iteration [87]:

$$\mathbf{J}_R^{(i+1)} = \mathbf{J}_R^{(i)} + \frac{(\mathbf{f}^{(i+1)} - \mathbf{J}_R^{(i)} \cdot \mathbf{h}^{(i+1)}) \cdot \mathbf{h}^{(i+1)T}}{\mathbf{h}^{(i+1)T} \mathbf{h}^{(i+1)}}, \quad i = 0, 1, \dots \quad (\text{T4})$$

where $\mathbf{f}^{(i+1)} = \mathbf{R}(\mathbf{x}^{(i+1)}) - \mathbf{R}(\mathbf{x}^{(i)})$, and $\mathbf{h}^{(i+1)} = \mathbf{x}^{(i+1)} - \mathbf{x}^{(i)}$. This enables considerable computational savings as evaluation of (T4) does not require any extra EM simulations.

Fig. 8. Design closure using the TR algorithm.

The three major input variables of the procedure are the search space X , the EM representation $\mathbf{R}_{EM}$, and the merit function U_P . The first two are associated with the microwave component of interest, whereas the third one is determined by the assumed specifications. Table 1 summarizes the control parameters, which can be split into three categories, corresponding to the optimization stages. The pre-screening-related parameters are dependent on the design task, and the particular items in the table are representative for the coupling structures.

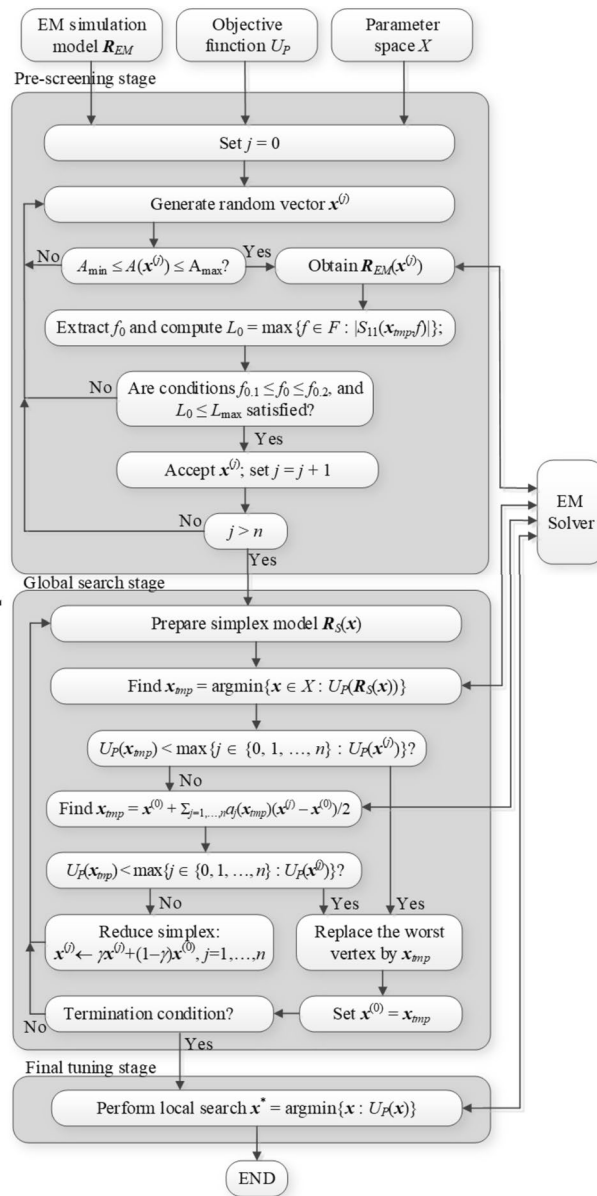


Fig. 9. Proposed EM-based miniaturization procedure: flow diagram.

The parameters of the second group (ML-based search) are generic, apart from A_{global} and U_{global} which are circuit specific. The parameters of the last group (final tuning) are to control the optimization process resolution.

Results

This section validates the size reduction algorithm of Section "Global Miniaturization by pre-screening and machine learning with simplex-anchored surrogates". The purpose of the proposed methodology is the expedited miniaturization of microwave passives, while performance-related requirements are treated as constraints, as explained in Sections "Explicit size reduction through numerical optimization" and "Constraint handling", respectively. The complete framework comprises three stages: design space pre-screening (Stage I, described in Section "Stage I: Pre-screening"), global search using simplex-based models (Stage II, described in Section "Stage II: Machine learning for globalized optimization"), and local refinement using gradient-based algorithm (Stage III, described in Section "Stage III: Design closure").

Numerical experiments involve two microstrip couplers, a rat-race circuit with meandered lines, and a branch-line structure with compact microstrip resonant cells. The results are compared to those produced using the state-of-the-art approaches, which include random-start gradient-based optimization, bio-inspired search (here, particle swarm optimizer, PSO, differential evolution, DE, and grey wolf optimization, GWO), and ML algorithm operating with kriging metamodels. The quality indicators include achievable circuit size, constraint control, and computational efficiency of the search process.

```

1. Set  $j = 0$ ;
2. while 1
    Generate a random vector  $\mathbf{x}^{(j)} \in X$ ;
    if  $A_{\min} \leq A(\mathbf{x}^{(j)}) \leq A_{\max}$ 
        Perform EM analysis at  $\mathbf{x}^{(j)}$  to obtain the response  $R_{EM}(\mathbf{x}^{(j)})$ ;
        Extract  $f_{1,EM}(\mathbf{x}^{(j)})$ ,  $f_{4,EM}(\mathbf{x}^{(j)})$ , and  $dS(\mathbf{x}^{(j)})$  (frequency location of the first resonance);
        if  $\min\{f_{1,EM}(\mathbf{x}^{(j)}), f_{4,EM}(\mathbf{x}^{(j)})\} \geq f_{\min}$  AND  $\max\{f_{1,EM}(\mathbf{x}^{(j)}), f_{4,EM}(\mathbf{x}^{(j)})\} \leq f_{\max}$  AND
             $|dS(\mathbf{x}^{(j)}) - K| \leq dS_{\max}$ 
                Accept  $\mathbf{x}^{(j)}$ ;
                Set  $j = j + 1$ ;
            end
        if  $j > n$ 
            Go to 3;
        end
    end
3. while 1
    Prepare simplex-based models  $R_S(\mathbf{x})$ ;
    Find candidate design  $\mathbf{x}_{tmp} = \operatorname{argmin}\{\mathbf{x} \in X : U_S(R_S(\mathbf{x}))\}$  (cf. (9)-(11));
    if  $U_P(\mathbf{x}_{tmp}) < \max\{j \in \{0, 1, \dots, n\} : U_P(\mathbf{x}^{(j)})\}$ 
        Accept  $\mathbf{x}_{tmp}$ ;
        Identify the worst vertex  $j_{\text{worst}} = \operatorname{argmax}\{j \in \{0, 1, \dots, n\} : U_P(\mathbf{x}^{(j)})\}$ ;
        Replace  $\mathbf{x}^{(j_{\text{worst}})}$  by  $\mathbf{x}_{tmp}$ ;
    else
        Generate design  $\mathbf{x}_{tmp,2} = \mathbf{x}^{(0)} + \sum_{j=1, \dots, n} \alpha_j(\mathbf{x}_{tmp})(\mathbf{x}^{(j)} - \mathbf{x}^{(0)})/2$ 
        if  $U_P(\mathbf{x}_{tmp,2}) < \max\{j \in \{0, 1, \dots, n\} : U_P(\mathbf{x}^{(j)})\}$ 
            Accept  $\mathbf{x}_{tmp,2}$ ;
            Replace  $\mathbf{x}^{(j_{\text{worst}})}$  by  $\mathbf{x}_{tmp,2}$ ;
        else
            Reduce the simplex:  $\mathbf{x}^{(j)} \leftarrow \gamma \mathbf{x}^{(j)} + (1 - \gamma) \mathbf{x}^{(0)}, j = 1, \dots, n$ ;
        end
    end
    if  $[A(\mathbf{x}^{(0)}) < A_{\text{global}} \text{ AND } U_P(\mathbf{x}^{(0)}) \leq U_{\text{global}}] \text{ OR } \max\{j \in \{1, 2, \dots, n\} : \|\mathbf{x}^{(j)} - \mathbf{x}^{(0)}\|\} < D_{\min}$ 
        OR computational budget has been exceeded
        Go to 4;
    end
4. Perform local search  $\mathbf{x}^* = \operatorname{argmin}\{\mathbf{x} : U_P(\mathbf{x})\}$ , using  $\mathbf{x}^{(0)}$  as the starting point
   (cf. Section 3.3).
5. Return  $\mathbf{x}^*$ ; END;

```

Fig. 10. Proposed EM-based miniaturization procedure: the pseudocode.

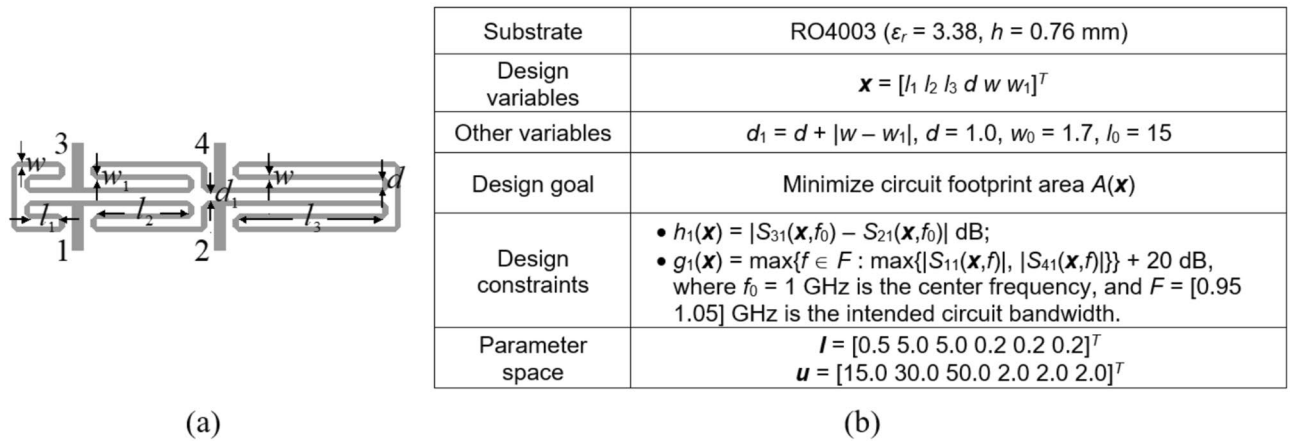
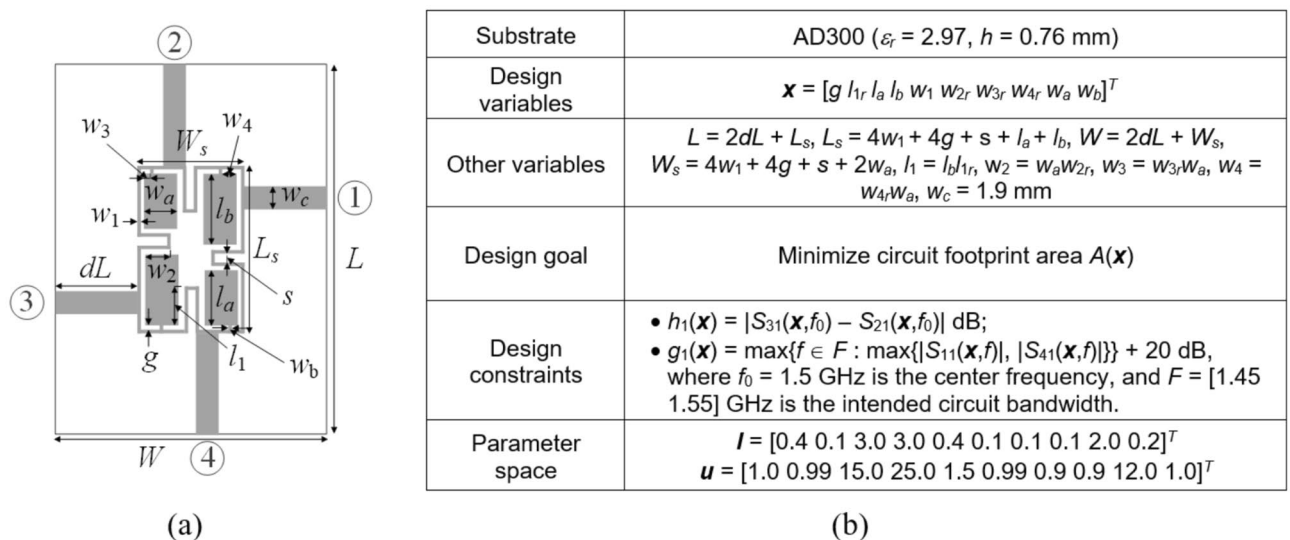
Test cases

Figures 11 and 12 illustrate the architecture and parameters for the two test structures: (i) a rat-race coupler⁸⁷ (Circuit I), and (ii) a miniaturized branch-line coupler with compact microstrip resonant cells (CMRCs)⁸⁸ (Circuit II). In both cases, the EM representations are prepared in CST Microwave Studio and simulated using the time-domain solver. The goal is to diminish the device size $A(\mathbf{x})$ as much as possible, while satisfying two constraints: $h_1(\mathbf{x}) = |S_{31}(\mathbf{x}, f_0) - S_{21}(\mathbf{x}, f_0)|$ (equal power division at the operating frequency f_0), and $g_1(\mathbf{x}) = \max\{f \in F : \max\{|S_{11}(\mathbf{x}, f)|, |S_{41}(\mathbf{x}, f)|\} + 20 \text{ dB}\}$. The merit function employs the penalty function approach. We have

$$U_P(\mathbf{x}) = A(\mathbf{x}) + \beta_1 \left[\frac{\max\{\max\{f \in F : \max\{|S_{11}(\mathbf{x}, f)|, |S_{41}(\mathbf{x}, f)|\} + 20, 0\}}{20} \right]^2 + \beta_2 [(|S_{31}(\mathbf{x}, f_0)| - |S_{21}(\mathbf{x}, f_0)|) - K]^2 \quad (12)$$

in which F is the target range (e.g., 0.95 to 1.05 GHz for Circuit I, cf. Fig. 12), f_0 is the operating frequency (e.g., 1 GHz for Circuit I), and K is the intended power division (here, $K = 0$ dB). The penalty factors are set to $\beta_1 = \beta_2$.

Variable	Explanation	Suggested value
$A_{\min}, A_{\max}$	Minimum and maximum circuit size for the pre-screening stage (cf. Section "Stage I: Pre-screening")	Problem dependent
$[f_{\min}, f_{\max}]$	Acceptance range for the estimated operating frequency of the circuit (pre-screening stage, cf. Section "Stage I: Pre-screening")	A function of the target operating band F (e.g., [0.8 1.2] GHz for the target frequency of 1 GHz)
$dS_{\max}$	Maximum tolerance for power split ratio error (pre-screening stage, cf. Section "Stage I: Pre-screening")	Typically, set at relaxed level, e.g., 2 dB
$A_{\text{global}}, U_{\text{global}}$	Termination thresholds (circuit size and maximum objective function value) for globalized search stage (cf. Section "Stage II: Machine learning for globalized optimization")	Problem dependent
N_{global}	Computational budget for globalized search stage (cf. Section "Stage II: Machine Learning for globalized optimization")	100
α	Search region extension parameter (cf. Section "Stage II: Machine learning for globalized optimization")	0.2
γ	Simplex reduction ratio (cf. Section "Stage II: Machine learning for globalized optimization")	0.5
$D_{\min}$	Termination threshold (minimum simplex size) for globalized search stage, cf. Section "Stage II: Machine learning for globalized optimization"	1% of the space size
ε	Termination threshold for design closure, set to a required process resolution, cf. Section "Stage III: Design closure"	10^{-3}
M_c	Multiplication coefficient for launching the Broyden formula for Jacobian updates (cf. Fig. 9, Section "Stage III: Design closure")	10

Table 1. Control parameters.**Fig. 11.** Circuit I⁸⁷: (a) topology, (b) parameters.

Parameter	Circuit	
	I	II
$A_{\min}$	350 mm ²	350 mm ²
$A_{\max}$	450 mm ²	450 mm ²
$[f_{\min} f_{\max}]$	[0.75 1.25] GHz	[1.2 1.8] GHz
$dS_{\max}$	3 Db	3 Db
A_{global}	400 mm ²	400 mm ²
U_{global}	400	400

Table 2. Pre-screening parameters for test circuits.

Algorithm	Algorithm type	Setup
I	Trust-region gradient-based optimizer ⁸⁴	Algorithm setup: • Random initial design; • Response gradients estimated using finite differentiation ⁸⁵ ; Termination criteria based on convergence in argument and reduction of the trust region size ⁸⁴ .
II	Particle swarm optimizer (PSO) ⁸⁹	Algorithm setup: • Swarm size $N = 10$, • Standard control parameters ($\chi = 0.73$, $c_1 = c_2 = 2.05$); • Number of iterations set to 100.
III	Differential evolution (DE) ⁹¹	Algorithm setup: • Population size $N = 10$, • Number of iterations set to 100.
IV	Grey Wolf Optimizer (GWO) ⁹²	Algorithm setup: • Swarm size $N = 10$, • Standard control parameters ($\chi = 0.73$, $c_1 = c_2 = 2.05$); • Number of iterations set to 100.
V	Machine learning procedure I	Algorithm similar to that of Section "Global miniaturization by pre-screening and machine learning with simplex-anchored surrogates": • Initial surrogate set up to ensure relative RMS error not higher than 10% with the maximum number of training samples equal to 400; • Optimization based on processing the circuit frequency characteristics (unlike response features in the proposed procedure); • Infill criterion: minimization of the projected objective function improvement ⁹⁰ .
VI	Machine learning procedure II	• Surrogate model: artificial neural network (ANN) ⁹³ , • ANN setup: feedforward network with three hidden layers (64-32-16 neurons, followed by a fully connected output layer), • Initial surrogate set up to ensure relative RMS error not higher than 10% with the maximum number of training samples equal to 400, • No pre-selection procedure is applied, • Infill criterion: minimization of the projected objective function improvement.

Table 3. Benchmark methods.

$= 10^3$. Observe that the objective function (12) was formulated in such a way that the constraint violations scaled by the penalty factors complement the main objective function (i.e., the circuit footprint) to be minimized. The adopted values of β_1 and β_2 were chosen so as to ensure that the contribution of the constraints commensurate with the primary objective.

Note that the test problems are demanding, especially in the global search context. On the one hand, the parameters ranges are broad: the mean upper-to-lower variable bound ratio > 13 and ≈ 7 for Circuits I and II. On the other hand, the frequency range of circuit evaluation is broad, from 0.1 GHz to 2.5 GHz. Both factors make the search space difficult to explore, which includes a construction of any sort of surrogate model therein.

Experimental setup

The test circuits are optimized employing the three-stage process of Section "Global miniaturization by pre-screening and machine learning with simplex-anchored surrogates". The control parameters are established as shown in Table 1 (i.e., using default values), except those problem-related, which have been specified in Table 2. Therein, both the minimum and maximum sizes $A_{\min}$ and $A_{\max}$, respectively, come from the previous experience with the said devices.

Our algorithm is juxtaposed against a range of benchmarks summarized in Table 3. The first one is a random-start local algorithm similar to the TR procedure of Section "Stage III: Design closure". It is considered to demonstrate the problem multimodality, which also justifies the necessity of global search. The next three methods are nature-inspired algorithms (PSO, DE, GWO), included to demonstrate the issues pertinent to EM-driven nature-inspired search. It should be noted that the budget for PSO/DE/GWO was set to only 1,000 merit function calls, which is generally insufficient for this type of techniques, yet it is significant for direct simulation-based design, i.e., corresponding to the running times as long as two to three CPU days.

The final benchmark methods are ML frameworks involving kriging and neural network metamodels, and the infill conditions based on the maximization of the predicted merit function enhancement. These techniques are considered to investigate potential advantages of the suggested procedure regarding computational efficiency, especially its second stage (ML search using simplex-based regressors).

Findings

All methods considered were run ten times each. The results are provided in Tables 4 and 5. These include the average circuit size, violations of constraints and their standard deviations. The right-hand-side column reports the CPU cost expressed both in terms of number of EM analyses of the circuit under consideration, as well as in the time units. For all the reported procedures, both our and benchmark ones, the average cost across ten algorithm runs is provided. The computational cost of the proposed procedure splits approximately equally among its three stages: Stage I (design space pre-screening), Stage II (global search), and Stage III (local tuning). The pre-screening stage requires collecting around $3n$ samples (where n is the design space dimensionality) in order to gather the necessary $n + 1$ high-quality samples. The circuit responses for the chosen optimization instances are shown in Figs. 13 and 14.

The slight misalignment of the characteristics in Fig. 13, which presents the responses at the minimum-size solutions for Circuit I, is related to the inherent trade-off between size reduction and electrical performance. In the considered miniaturized structures (especially those employing folded transmission lines, as in Circuit I), footprint minimization typically leads to increased asymmetry in the responses and to a moderate degradation of certain performance metrics. This behavior is well known for compact microwave components. In fact such phenomenon also may affect miniaturized circuits incorporating CMRRS cells, as in Circuit II. Yet, as shown in Fig. 14, this effect is less pronounced than in Circuit I.

Based on the outcomes in Tables 4 and 5, we investigate the operation of our algorithm and compare it to Algorithms I through VI. The quality indicators include computational efficiency, achievable circuit size, and the constraint handling efficiency.

Regarding design quality, our algorithm yields the results that by far surpass those obtained by the benchmark methods. It allows for achieving the smallest circuit areas. This is except for Circuit II and Algorithm III, which prevails but at the expense of considerably higher running costs and inferior constraint control. On the other hand, our methodology offers competitive handling of design constraints. For both circuits, the average inequality constraint violation is less than 2 dB, whereas the equality constraint violation is essentially zero. These numbers are significantly better than those associated with the benchmark algorithms, especially the machine learning procedures (Algorithms V and VI). The latter is indicative of the challenges related to the establishment of reliable surrogate models over large parameter spaces. Algorithms II through IV (nature-inspired optimization) perform considerably worse. The obtained sizes are much larger than for other approaches, and so are standard deviations. The deficiencies of PSO (as well as DE and GWO for that matter) are related to insufficient CPU budget (here, 1,000 merit function evaluations), which was established to avoid excessive execution times. While increasing the budget would arguably improve the algorithm performance, it would also make it even more impractical from computational perspective.

Excellent repeatability of solutions, measured using spread of the footprint area and constraint violations, is another advantage of our technique. The average standard deviation of the circuit area for the benchmark techniques is almost 60 mm² for Circuit I, and over 90 mm² for Circuit II, whereas it is only 11.9 mm² and 6.3

Method	Parameter						
	Size A [mm ²] ¹	Std(A) [mm ²] ²	Inequality constraint		Equality constraint		CPU cost ⁷
			Violation g_1 [dB] ³	Std(g_1) [dB] ⁴	Violation h_1 [dB] ⁵	Std(h_1) [dB] ⁶	
Algorithm I	378.0	59.3	4.5	4.3	0.2	0.2	63 [2.8 h]
Algorithm II	543.1	86.8	−1.0	1.6	0.1	0.1	1,000 [44.4 h]
Algorithm III	575.3	91.1	−0.5	1.1	0.3	0.2	1,000 [44.4 h]
Algorithm IV	531.9	65.4	−0.3	1.3	0.2	0.1	1,000 [44.4 h]
Algorithm V	500.9	25.6	12.3	4.8	6.6	4.4	417.4 [18.5 h]
Algorithm VI	484.3	22.8	7.3	5.2	2.4	2.0	453.1 [20.1 h]
Three-stage algorithm (this work)	367.9	11.9	1.8	1.2	0.03	0.06	58.3 [2.6 h]
							Stage I: Pre-screening 19.6 [0.9 h]
							Stage II: Global search 20.5 [0.9 h]
							Stage III: Local tuning 18.2 [0.8 h]

Table 4. Results for circuit I. ¹Optimized footprint area of the circuit averaged over ten algorithm runs. ²Standard deviation of the optimized footprint area averaged over ten algorithm runs. ³Violation of inequality constraint, defined as $g_1 = \max \{f \in F : \max \{|S_{11}(x, f)|, |S_{41}(x, f)|\} + 20 \text{ dB}\}$, averaged over ten algorithm runs. ⁴Standard deviation of the constraint violation g_1 , averaged over ten algorithm runs. ⁵Violation of equality constraint, defined as $h_1 = |S_{31}(x, f_0)| - |S_{21}(x, f_0)| \text{ dB}$ averaged over ten algorithm runs. ⁶Standard deviation of the constraint violation h_1 , averaged over ten algorithm runs. ⁷Cost expressed in terms of equivalent number of EM analyses. Numbers in brackets correspond to the running times in hours.

Method	Parameter							
	Size A [mm ²] ¹	Std(A) [mm ²] ²	Inequality constraint		Equality constraint		CPU cost ⁷	
			Violation g_1 [dB] ³	Std(g_1) [dB] ⁴	Violation h_1 [dB] ⁵	Std(h_1) [dB] ⁶		
Algorithm I	295.1	24.7	3.6	1.9	0.2	0.1	77 [5.2 h]	
Algorithm II	541.5	240.4	5.5	6.8	0.7	0.1	1,000 [66.7 h]	
Algorithm III	533.5	220.4	4.3	6.3	0.5	0.3	1,000 [66.7 h]	
Algorithm IV	582.1	198.4	6.1	5.2	0.6	0.4	1,000 [66.7 h]	
Algorithm V	270.3	13.3	6.3	3.6	1.0	2.2	398.4 [26.6 h]	
Algorithm VI	308.1	19.2	5.0	3.1	0.7	0.9	428.3 [28.6 h]	
Three-stage algorithm (this work)	284.2	6.3	1.8	0.4	0.01	0.04	103.1 [6.9 h]	
							Stage I: Pre-screening	19.6 [2.3 h]
							Stage II: Global search	20.5 [2.7 h]
							Stage III: Local tuning	18.2 [1.9 h]

Table 5. Results for circuit II. ¹Optimized footprint area of the circuit averaged over ten algorithm runs. ²Standard deviation of the optimized footprint area averaged over ten algorithm runs. ³Violation of inequality constraint, defined as $g_1 = \max \{f \in F : \max \{|S_{11}(x, f)|, |S_{41}(x, f)|\} + 20 \text{ dB}\}$, averaged over ten algorithm runs. ⁴Standard deviation of the constraint violation g_1 , averaged over ten algorithm runs. ⁵Violation of equality constraint, defined as $h_1 = |S_{31}(x, f_0)| - |S_{21}(x, f_0)| \text{ dB}$ averaged over ten algorithm runs. ⁶Standard deviation of the constraint violation h_1 , averaged over ten algorithm runs. ⁷Cost expressed in terms of equivalent number of EM analyses. Numbers in brackets correspond to the running times in hours.

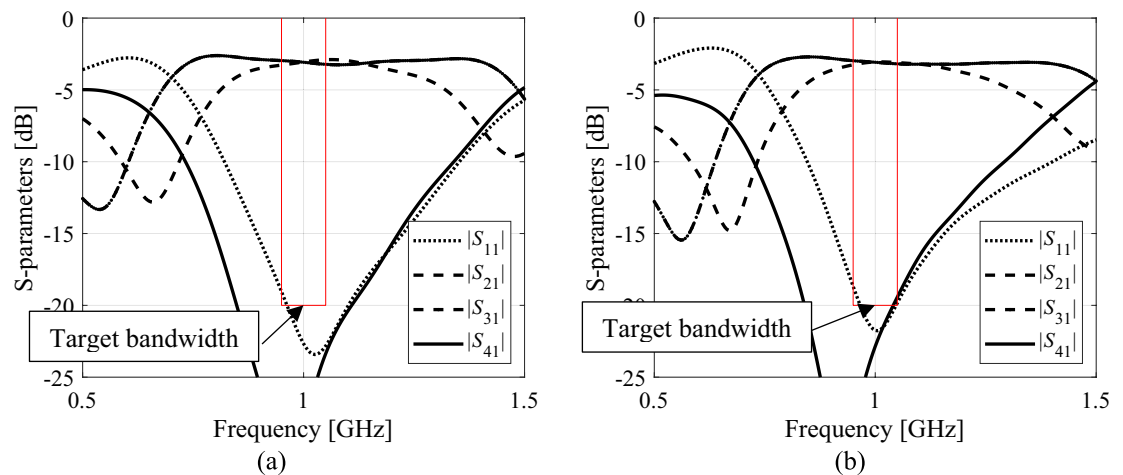


Fig. 13. EM-analyzed S-parameters for Circuit I at the minimum-size solutions produced using our framework, illustrated for the selected algorithm runs: (a) run 1, $A(\mathbf{x}^*) = 374 \text{ mm}^2$, (b) run 2, $A(\mathbf{x}^*) = 372 \text{ mm}^2$.

mm^2 for the proposed algorithm (i.e., five and fifteen times smaller, respectively). Similarly, the average standard deviation of inequality constraint violation for benchmark methods is around four decibels for both test circuits, whereas it is only 1.2 dB and 0.4 dB for Circuits I and II (five and ten times smaller) for our technique. Finally, the average standard deviation of equality constraint violation for the benchmark is 1.5 dB and 0.6 dB for Circuit I and Circuit II, respectively, but only 0.06 dB and 0.04 dB (i.e., virtually zero) for the proposed method. In other words, the procedure suggested in this research yields significantly more consistent results than the benchmark.

Regarding cost efficiency, the our technique is comparable to the local optimization procedure (Algorithm I). At the same time, it is considerably faster than both global techniques. The average savings over Algorithms II through IV are 94%, 75% over Algorithm V, and almost 80% over Algorithm VI. In other words, our algorithm is over twelve times cheaper than PSO, DE and GWO (even though these methods were run under low computational budget), and about nine times faster than Algorithms V and VI.

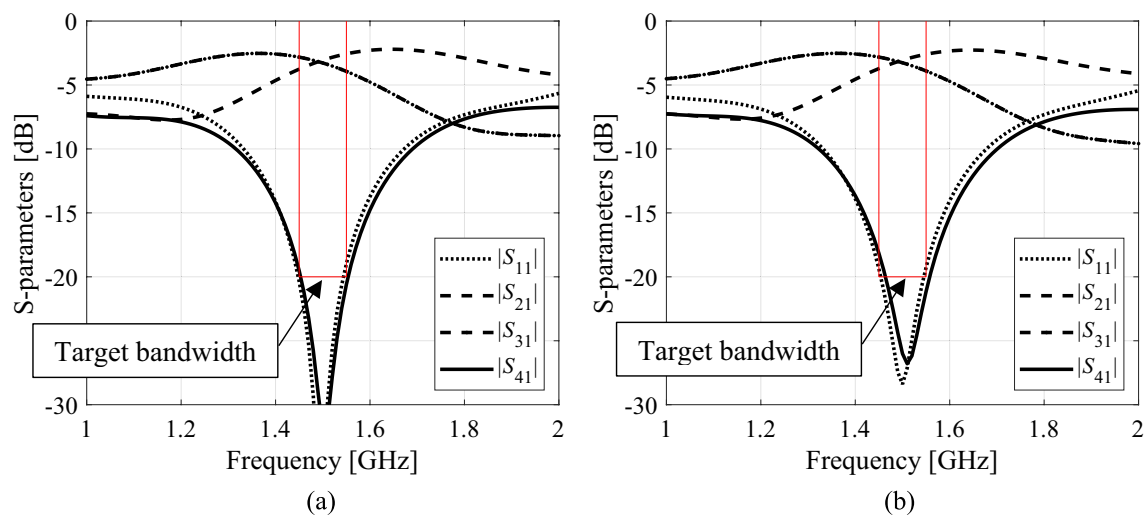


Fig. 14. EM-analyzed S-parameters for Circuit I at the minimum-size solutions produced using our framework, illustrated for the selected algorithm runs: **(a)** run 1, $A(\mathbf{x}^*) = 285 \text{ mm}^2$, **(b)** run 2, $A(\mathbf{x}^*) = 289 \text{ mm}^2$.

Control parameters				Results						
α	γ	$D_{\min}$	M_c	Size A [mm ²]	Std(A) [mm ²]	Inequality constraint		Equality constraint		CPU cost
						Violation g_1 [dB]	Std(g_1) [dB]	Violation h_1 [dB]	Std(h_1) [dB]	
0.2	0.5	1%	10	367.9	11.9	1.8	1.2	0.03	0.06	58.3
0.2	0.5	1%	30	362.1	13.8	2.1	1.3	0.07	0.08	57.6
0.2	0.5	2%	10	370.0	12.1	1.7	1.1	0.04	0.06	56.7
0.2	0.3	1%	10	368.2	10.7	1.5	1.0	0.07	0.10	57.8
0.5	0.5	1%	10	372.1	13.0	1.8	1.3	0.04	0.06	61.4
0.5	0.3	2%	30	363.5	15.0	1.9	1.1	0.10	0.10	54.2

Table 6. The effects of control parameters on algorithm performance for circuit I

In summary, the performance of the framework presented in this research is superior to the benchmark techniques regarding all important aspects: reliability, repeatability of results, and cost efficiency. Competitive size reduction rates are accompanied by improved control of design constraints. The average running time is comparable to that of local search. These features result from meticulous crafting of the mechanisms employed in the presented framework. On the one hand, the pre-screening procedure allows for identifying the parameter space subset to be explored by the machine learning stage. Meanwhile, the employment of simple surrogates (here, spanned over sets of simplexes handled by the algorithm) contributes to diminishing the CPU costs. Finally, expedited design closure initiated with an already decent starting point ensures high quality at minimum expense.

Additional experiments were conducted to investigate the effects of the algorithm control parameters. A few procedure-specific parameters were considered, including the search region extension parameter α , simplex reduction ratio γ , termination threshold for globalized search stage $D_{\min}$, and multiplication coefficient M_c for launching the Broyden formula for Jacobian updates (in fine-tuning stage). Table 6 gathers the results obtained for different configurations of these parameters. As indicated in the table, control parameters have minor effect on the algorithm performance, which is expected due to the specific mechanisms incorporated into the procedure. For example, the computational cost is mainly determined by the number of simplex relocations and termination thresholds, albeit weakly. One trend that can be observed is that the costs are slightly lower if $D_{\min}$ increases. Also, turning into Broyden updates early, i.e., if $M_c = 30$ instead of 10, slightly degrades constraint control. In any case, the observed differences are noticeable yet practically insignificant.

Experimental validation

Selected designs of the test circuits optimized using the presented algorithm were manufactured and experimentally validated. We consider the two designs shown in Figs. 13(a) (Circuit I) and Fig. 14(a) (Circuit II). The circuit prototypes and a juxtaposition between full-wave simulations and measurements can be found in Fig. 15. The alignment between EM analysis and measured S-parameters is satisfactory. There are only small deviations resulting from manufacturing inaccuracies, soldering imperfections, and the impact of connectors.

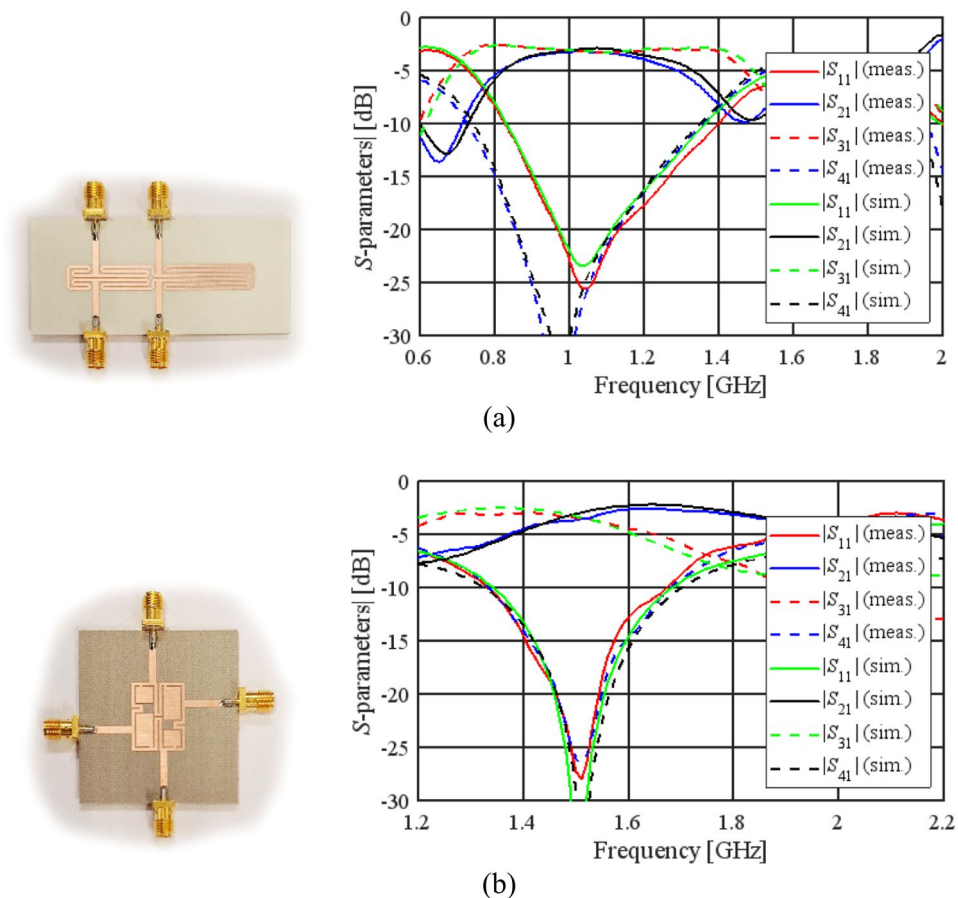


Fig. 15. Experimental validation of representative designs produced by the presented algorithm: **(a)** Circuit I, **(b)** Circuit II.

Conclusion

This article proposed a technique for EM-based explicit size reduction of microwave circuits, where the conditions imposed on performance metrics treated as constraints. Our methodology is developed to reduce the footprint area while maintaining electrical performance regarding center frequency, operating band, power division ratio, etc. To allow for low-cost globalized search, the algorithm has been organized as a three-step process. The initial stage is a randomized pre-screening, which enables determination of the promising parameter space region. The second stage is a machine learning search involving simplex models. The final step is gradient-based design closure. The latter improves design quality without incurring excessive CPU expenses. The proposed methodology was extensively verified using two couplers, and several benchmark algorithms. The results confirm excellent performance of our algorithm regarding all relevant aspects: reliability, repeatability of solutions, as well as cost efficiency. On the one hand, the presented approach offers competitive size reduction rates and improved constraint control over all benchmark procedures. On the other hand, it exhibits remarkable efficiency. The running costs are comparable to those of local search. The average cost reduction regarding global optimization procedures is 94% (over nature-inspired search), and 74% (over kriging-based machine learning framework).

The advantages of the proposed technique demonstrated during the comparative experiments are indicative of its suitability for replacing available methods for size-reduction-oriented globalized parameter tuning. The method is particularly suitable for handling compact circuits that feature complex geometries. Therein, global optimization is highly recommended due to non-intuitive relationships between electrical performance figures and specific arrangements of physical dimensions of constitutive components (e.g., compact resonant units), whereas the employment of conventional methods such as bio-inspired algorithms is normally prohibitive from computational budget perspective. It should be emphasized, that the proposed framework is well suited for handling high-dimensional problems. Its exceptional computational efficiency suggests that it can outperform conventional techniques involving direct simulation-driven miniaturization of microwave circuits, especially using nature-inspired optimization algorithms. Expanding the applicability of the proposed methodology to microwave devices featuring a larger number of geometry parameters will be addressed in future work. Moreover, although the present study utilizes two microwave couplers as verification structures, the proposed miniaturization framework can be extended to a broader class of passive components. Future work will include

validation on additional circuits, such as filters or power dividers, to further demonstrate the versatility of the method.

Data availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Received: 30 December 2025; Accepted: 25 June 2026

Published online: 04 July 2026

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Acknowledgement

The authors would like to thank Dassault Systemes, France, for making CST Microwave Studio available.

Author contributions

Conceptualization, S.K. and A.P.; methodology, S.K. and A.P.; data generation, A.P.; investigation, S.K.; writing—original draft preparation, A.P. and S.K.; writing—review and editing, S.K.; visualization, A.P. and S.K.; supervision, S.K.; project administration, A.P. and S.K.

Funding

This work is partially supported by the Icelandic Centre for Research (RANNIS) Grant 2410297 and by the National Science Centre of Poland Grant 2024/55/B/ST7/01413.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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