

Pre-trained deep learning space mapping with intermittent model enhancement for fast multi-fidelity microwave design optimization

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ABSTRACT

Parameter tuning is essential in the development of microwave devices. In recent years, a growing interest in formal optimization methods has emerged, driven by their ability to simultaneously adjust multiple decision variables, even under constraints. Their disadvantage is their high computational cost, which is a serious obstacle to the optimization of electromagnetic (EM) models. This difficulty can be alleviated using multi-fidelity simulations. Problem-independent approaches rely on low-fidelity models constructed through coarse-discretization EM analysis (in contrast to problem-specific equivalent network representations), where a critical factor is the appropriate model correction strategy. This paper introduces a versatile deep-learning space mapping (DLSM) strategy that leverages a reusable pre-trained neural network surrogate. The non-parametric DLSM model implements multi-point response correction, applied independently to the real and imaginary components of relevant S-parameter responses. Furthermore, it is trained as a function of the problem's decision variables and response interrelations. It is embedded in a gradient-based optimization loop, where it is locally retrained using intermittent high-fidelity simulations and sample weighting to place greater emphasis on the neighborhood of the current solution. Comprehensive verification of the procedure involving three planar circuits underscores its competitive efficacy, with a mean running cost of 16 high-fidelity simulations and relative savings over the baseline algorithm up to 87%. Meanwhile, consistent results obtained for multiple scenarios targeting diverse performance specifications corroborate DLSM reusability and applicability across broad ranges of operating conditions.

1. Introduction

Microwave design relies heavily on computational models [1–3]. Electromagnetic (EM) simulation is particularly important as the only means that can account for phenomena such as cross-coupling, substrate anisotropy, dielectric losses, etc. Reliable system evaluation is critical in the development of circuits for modern applications [4–7], especially compact devices [8,9], and structures incorporating metamaterials, substrate-integrated waveguides (SIWs), or employing slow-wave phenomenon [10,11]. Ensuring optimal performance of geometrically complex circuits requires thorough, concurrent adjustment of multiple variables, often under constraints [12,13]. For accuracy, the optimization processes must be carried out using EM models [14–16], which entail considerable computational expenses, even in localized (e.g., gradient-driven) search. Several approaches were developed to address the high-cost issue, such as adjoint sensitivities [17,18], the use of

dedicated fast solvers [19] (both intrusive methods), and parallelization [20].

Lately, surrogate-based optimization (SBO) techniques receive considerable attention in high-frequency design [21–23], using a broad spectrum of modeling methods, such as artificial neural networks [24–32] and conventional regression techniques (kriging, support vector machines, etc.) [33–36]. In simple (low-dimensional) scenarios, one can construct the metamodel upfront, then optimize it (so-called offline methods) [37–39]. However, in most real-world scenarios, online methods are recommended, in which the model is continuously refined and applied to provide predictions of the optimal allocation [40,41]. These machine learning (ML) procedures mitigate some of the difficulties in constructing reliable data-driven representations [42–44], albeit at the expense of leaving most of the parameter space unexamined, as the algorithm quickly focuses on regions believed to be the most promising. Surrogate models are also coupled with bio-inspired

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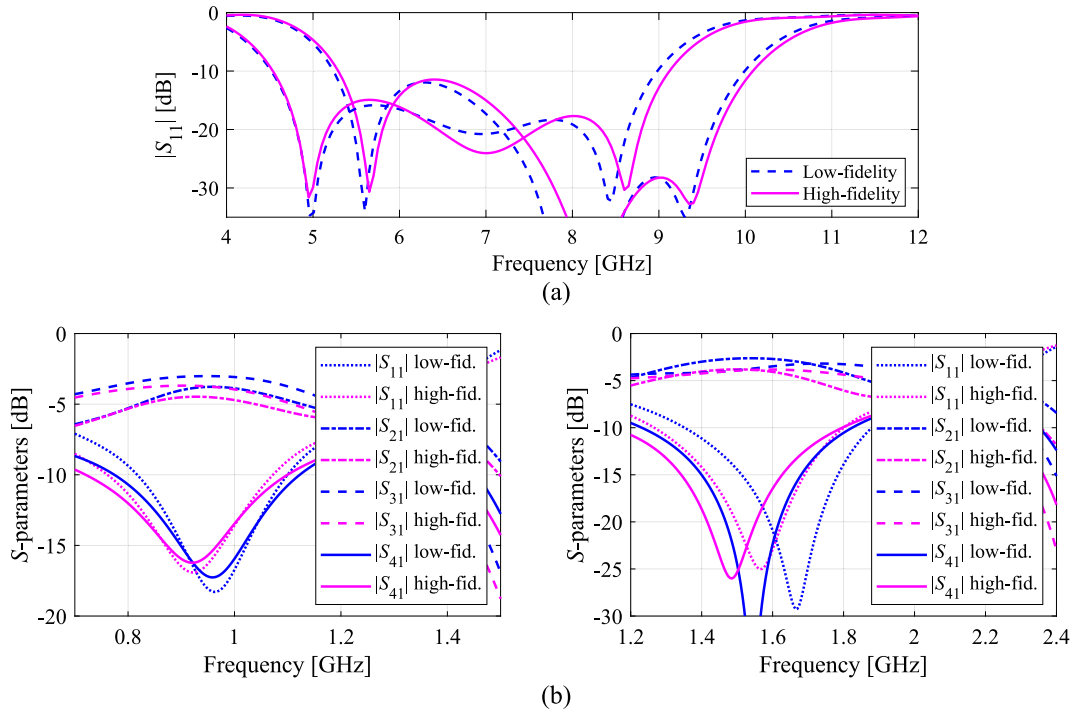


Fig. 1. Typical responses of the high-fidelity EM model $R_h(\mathbf{x})$ (blue lines) and the low-fidelity one $R_l(\mathbf{x})$ (black lines) for: (a) a broadband filter (two designs in separate plots), (b) a compact coupler (two designs at the same plot). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

algorithms such as differential evolution [45,46], particle swarm optimizers [47,48], or evolutionary algorithms [49]. A fundamental problem of SBO is building a sufficiently accurate replacement model, which is primarily impeded by the curse of dimensionality. Possible workarounds include domain restriction [50,51], multi-resolution EM analysis [52], physics-informed modeling [53–55], or the response feature technology [56–59].

Among different EM-driven design scenarios (design closure, global optimization, multi-objective design, uncertainty quantification), local tuning is undoubtedly the most widely used procedure. It stems from the fact that a reasonable initial design is often available, generated in earlier design stages such as equivalent network-based circuit development, topology evolution, or parametric studies. Nonetheless, even with a decent starting point, fine-tuning still requires dozens or hundreds of EM simulations, depending on the problem's complexity. Some possible acceleration techniques were briefly mentioned earlier. Another option is to use low-resolution EM analysis. This option is attractive because adjusting the discretization density of the computational model provides a convenient means to control the trade-off between EM analysis speed and accuracy. In microwave engineering, the lower-fidelity model is often implemented as an equivalent network [60]; however, this type of model is problem-dependent. Furthermore, parameterized network representations may no longer be reliable (or even available) for many modern passive structures, especially for miniaturized circuits or devices that integrate metamaterials, SIWs, etc. Perhaps the most recognized algorithmic framework for incorporating multi-fidelity models is space mapping (SM) [61–66]. According to SM, which is mainly employed in local optimization, the low-resolution model is enhanced by adding a low number of highest-fidelity simulations, often restricted to the last few designs evaluated throughout the optimization process [61]. SM-based model enhancements are typically implemented as simple input, output, or implicit transformations [61,67] and the appropriate selection of these transformations affects the SM algorithm performance [68]. Furthermore, the locality of SM limits the surrogate's reusability across problems with diverse specification targets (center frequencies,

bandwidths, substrate parameters).

This paper proposes an alternative space mapping (SM) procedure for expedited design closure of microwave devices. The technique employs a deep learning (DL) surrogate implementing a multi-point low-fidelity EM model correction. The DLSM correction is trained to independently improve the alignment between the real and imaginary components of complex S -parameter characteristics of the lower- and high-fidelity system representations. The network hyperparameters are trained to incorporate interdependencies between different characteristics (e.g., return loss, transmission, and port isolation) and decision variables (geometry parameters), thereby enhancing versatility and generalization. The surrogate is applied as the primary system representation within the gradient-based optimization loop. Therein, the high-fidelity EM analysis is carried out occasionally and near convergence, and the collected data is employed to (locally) re-train the metamodel, emphasizing the neighborhood of the current solution. The latter is achieved by distance-based weighting of the training samples. Our methodology was extensively demonstrated using three planar circuits (two couplers and a broadband filter). The results showcase significant acceleration over baseline (high-fidelity) search, with a relative speedup of up to 86%, matching the design cost of approximately 16 high-fidelity EM simulations. Furthermore, the reusability of the DLSM surrogate has been demonstrated by optimizing test circuits under diverse specifications for center frequencies, bandwidths, and power division ratios, and by using the same pre-trained model at the onset of the optimization process.

This study offers the following original contributions: (i) the development of a versatile space mapping correction scheme for a low-fidelity EM model using a deep neural network, (ii) application of the deep learning SM (DLSM) surrogate to accelerate parameter tuning of microwave circuits, (iii) the implementation of DLSM surrogate enhancement strategy involving sparse high-fidelity model evaluation and distance-based weighting of the training samples, (iv) demonstrating the competitive and consistent performance of the suggested technique and reusability of the DLSM metamodel across a broad range of design

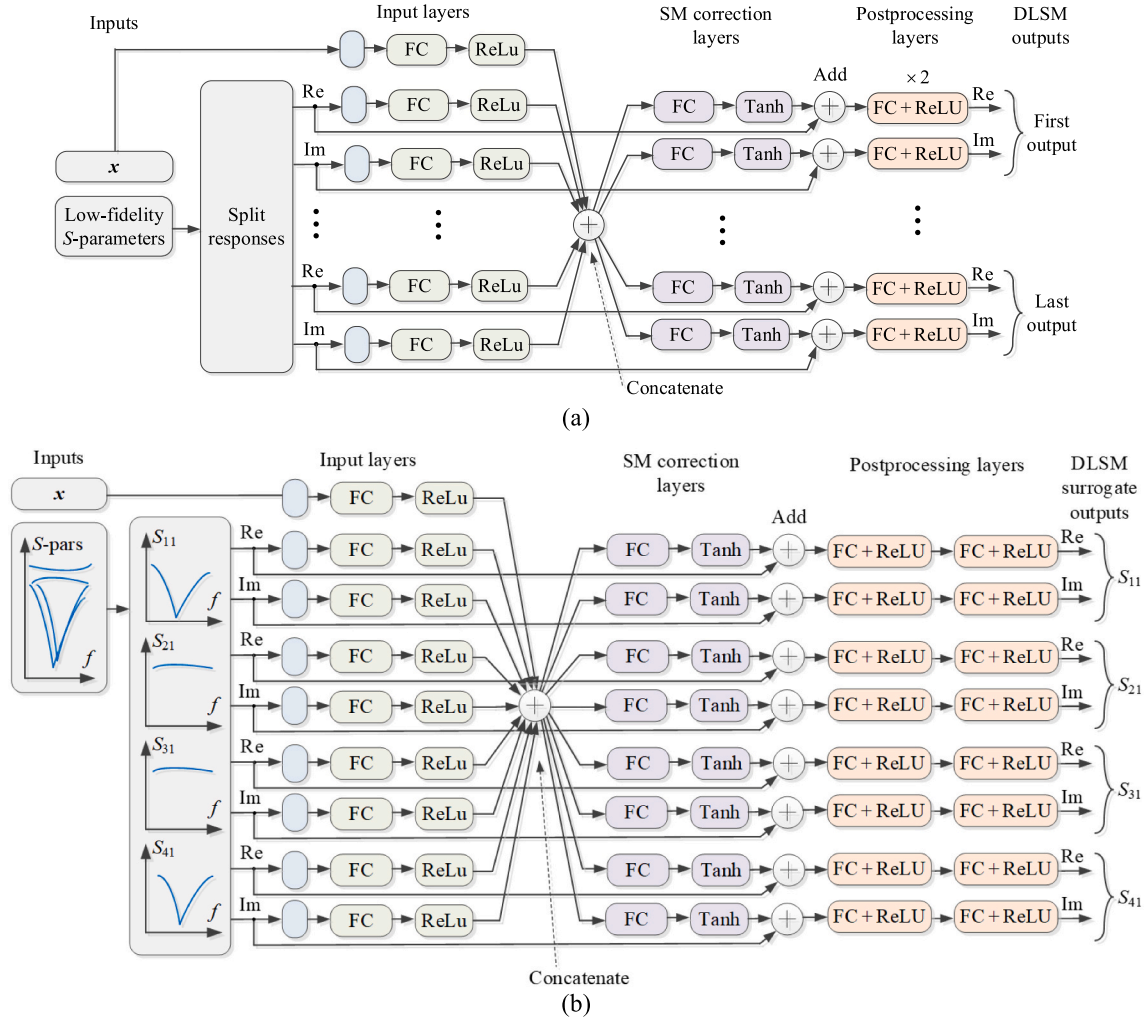


Fig. 2. Deep learning space mapping (DLSM) surrogate. The input responses are fed to the model through input fully connected (FC) layers and concatenated with the pre-processed decision variable vector $\mathbf{x}$. The outputs of the correction layers (FC with tanh() activation) are combined with the input responses fed through residual connections using the summing layers. The corrected characteristics are postprocessed using a stack of FC with ReLU activation. All FC layers contain 512 neurons with the size determined through ablation studies targeting enhancement of generalization performance measured through MSE: (a) generic model, (b) model for a specific arrangement of circuit responses (S_{kl} , $k = 1, 2, 3, 4$, as in microwave coupler).

scenarios (three test circuits, diverse performance specifications).

2. Space mapping optimization with pre-trained DLSM surrogates

This section provides details of the proposed space-mapping (SM) optimization strategy. The problem statement and the outline of EM simulation models are included in Section 2.1. The low-fidelity model correction scheme involving reusable deep learning metamodels is covered in Section 2.2. Iterative model refinement using intermittently acquired high-fidelity data is discussed in Section 2.3. Section 2.4 sums up functioning of the entire framework.

2.1. Parameter tuning: problem formulation

The design objective is to improve the circuit's operation by manipulating the decision variables (typically the device's dimensions), represented as the vector $\mathbf{x} = [x_1 \dots x_n]^T$. The search space X is conventionally a box-constrained domain $[l \ u]$, with l and u representing minimum and maximum parameter limits. The quality of the design is assessed using an objective function $U(\mathbf{x})$, which is monotonic with respect to performance (lower $U(\mathbf{x})$ corresponds to a higher-quality

circuit). The electrical characteristics, in particular S -parameters, are evaluated using the EM simulation model $\mathbf{R}_h(\mathbf{x})$, which is considered high-fidelity. It is set up to ensure sufficient reliability. In practice, $\mathbf{R}_h(\mathbf{x})$ is a tensor consisting of individual responses, e.g., $S_{kl}(\mathbf{x}, f)$, where k and l refer to circuit ports, and $f \in F_S$ stands for frequency, and F_S is the simulation range.

Given the mentioned monotonicity of $U(\mathbf{x})$, the parameter tuning task becomes a minimization problem

$$\mathbf{x}^* = \underset{\mathbf{x} \in X}{\operatorname{argmin}} U(\mathbf{x}) \quad (1)$$

In (1), $\mathbf{x}^*$ is the optimum. If several goals are to be handled, they can be combined [69] or treated as constraints [70]. Here, the latter approach is employed. Multi-objective optimization is out of the scope of this research [71].

The design cases considered in Section 3 pertain to couplers and bandpass filters. Possible formulations of the cost functions are as follows:

- Assuming that a coupler is optimized to enhance impedance matching $|S_{11}|$ and isolation $|S_{41}|$ and to implement power split ratio $K_P = |S_{21}| - |S_{31}|$, both at the center frequency f_0 , the cost function takes the form of

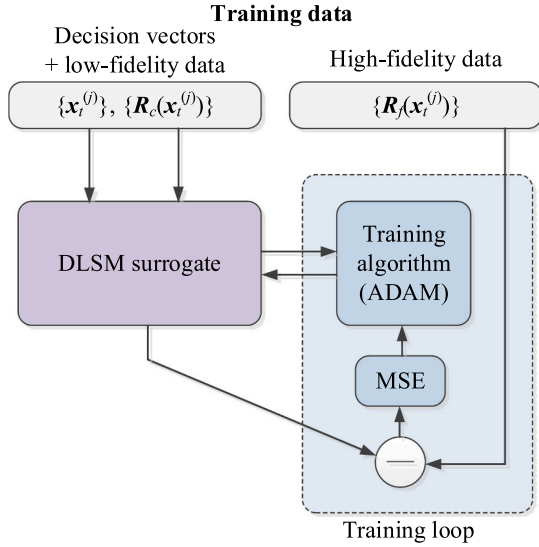


Fig. 3. DSLM model training. The following setup is used: the ADAM algorithm with a maximum of 2000 epochs and the training/validation error in the form of Mean Squared Error (MSE).

$$U(\mathbf{x}) = \max\{|S_{11}(\mathbf{x}f_0)| |S_{41}(\mathbf{x}f_0)|\} + \beta[|S_{21}(\mathbf{x}f_0)| - |S_{31}(\mathbf{x}f_0)| - K_p]^2 \quad (2)$$

where β is a penalty factor. In (3), improving $|S_{11}|$ and $|S_{41}|$ is the primary objective, whereas maintaining an appropriate power division ratio is enforced by the second term.

- Assuming that a bandpass filter is optimized to enhance $|S_{11}|$ within the bandwidth of interest F , the cost function can be written as

$$U(\mathbf{x}) = \max\{f \in F : |S_{11}(\mathbf{x}f)|\} \quad (3)$$

For filters, additional conditions may be imposed (omitted here), e.g., concerning in-band transmission.

To develop a space mapping scheme, we consider an auxiliary low-fidelity model $R_l(\mathbf{x})$, implemented using coarse-discretization EM simulation. For specific responses, we will also employ the notation $S_{kl,h}$ and $S_{kl,l}$. The mesh density for $R_l(\mathbf{x})$ is typically adjusted based on engineering experience to preserve correlations between the models despite their absolute discrepancies. In practice, the simulation time of $R_l(\mathbf{x})$ is two to three times shorter than for $R_h(\mathbf{x})$. An illustration of typical model misalignments for a miniaturized coupler and a broadband filter can be found in Fig. 1.

2.2. Deep learning SM surrogate

The space mapping low-fidelity model enhancement proposed here is a multi-point correction realized using a deep learning surrogate (DLSP) shown in Fig. 2. In space mapping terms, it is a nonlinear output SM parameterized by the decision variables $\mathbf{x}$ and all (concatenated) circuit responses. This arrangement allows for the consideration of interrelations between different responses (e.g., return loss and transmission). The correction is applied separately to the real and imaginary parts of the complex characteristics and is realized using fully connected (FC) layers with tanh() activation.

Network architecture has been established to allow pre-processing of all input responses and the decision variable vector $\mathbf{x}$ using fully connected layers. Their outputs are concatenated to yield comprehensive

1. Input data:
 - Starting point $\mathbf{x}^{(0)}$
 - Initial DLSP surrogate model constructed using the dataset $\{\mathbf{x}^{(j)}\}, j = 1, \dots, N_t$
 - Termination threshold $\varepsilon = 10^{-3}$
2. Set $i = 0$ (iteration index)
3. Simulate the low-fidelity model $R_l(\mathbf{x}^{(0)})$ and DLSP surrogate $R_s(\mathbf{x}^{(0)})$
4. Compute DLSP surrogate Jacobian $J_s(\mathbf{x})$ using FD [74]
5. Build linear model $R_L^{(i)}(\mathbf{x})$ (cf. (6)) using $R_s(\mathbf{x})$ and $J_s(\mathbf{x})$
6. Obtain new candidate solution (cf. (5)):

$$\mathbf{x}^{(i+1)} = \operatorname{argmin}\{\mathbf{x} \in X, \|\mathbf{x} - \mathbf{x}^{(0)}\| \leq r^{(i)} : U_L(\mathbf{x})\}$$
7. Compute gain ratio $\rho = [U(\mathbf{x}^{(i+1)}) - U(\mathbf{x}^{(0)})] / [U_L(\mathbf{x}^{(i+1)}) - U_L(\mathbf{x}^{(0)})]$
8. Update search radius:

$$r^{(i+1)} = 1.5r^{(i)} \text{ if } \rho > 0.75, r^{(i+1)} = r^{(i)}/2 \text{ if } \rho < 0.25, r^{(i+1)} = r^{(i)} \text{ otherwise}$$
9. if $\rho > 0$
 - $i = i + 1$
 - else
 - Go to 6
10. if $i < 3$
 - Compute Jacobian $J_s(\mathbf{x})$ using FD
 - else
 - Update $J_s(\mathbf{x})$ using the Broyden formula [75]
11. if $\|\mathbf{x}^{(i+1)} - \mathbf{x}^{(0)}\| < 100\varepsilon$
 - Evaluate the high-fidelity model $R_h(\mathbf{x}^{(0)})$
 - Add $\mathbf{x}^{(0)}$ to the training dataset $\{\mathbf{x}^{(j)}\}$
 - Compute sample weights w_i as in (2) with $\mathbf{x}_r = \mathbf{x}^{(0)}$
 - Re-train DLSP surrogate (max. epochs = 100)
 - Construct linear model $R_L^{(i)}(\mathbf{x}) = R_h(\mathbf{x}^{(0)}) + J_s(\mathbf{x}^{(0)}) \cdot (\mathbf{x} - \mathbf{x}^{(0)})$
12. if $\|\mathbf{x}^{(i+1)} - \mathbf{x}^{(0)}\| \geq \varepsilon$
 - Go to 6
13. END

Fig. 4. Pseudocode of the space mapping optimization procedure employing the DLSP surrogate.

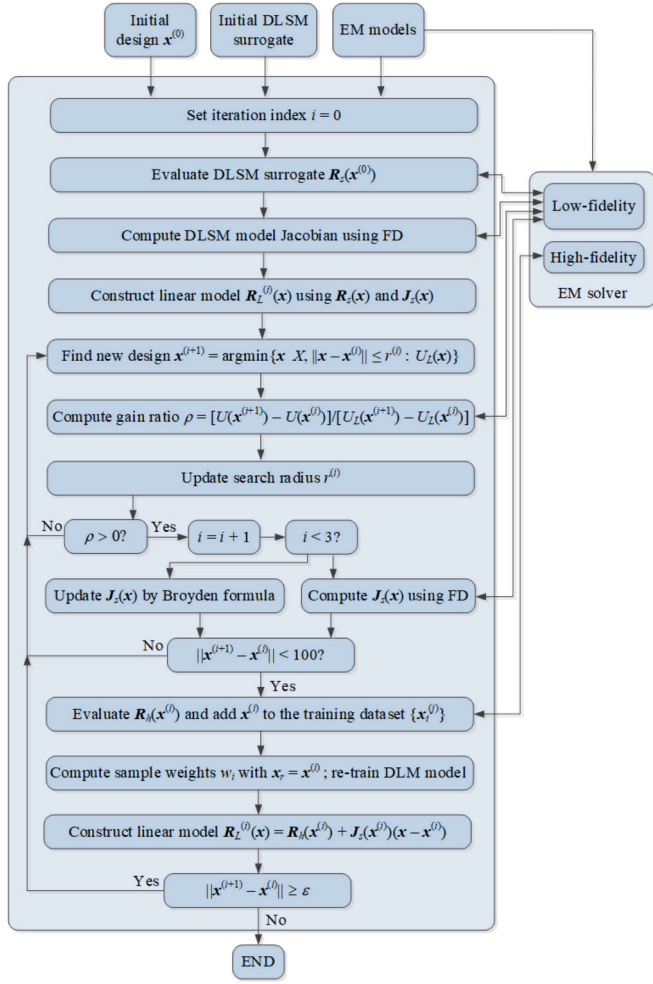


Fig. 5. Flow diagram of the space mapping optimization algorithm employing the DSLM surrogate.

response data for training the correction layers (also FC layers with tanh () activation). The correction is implemented by summing layers with auxiliary residual connections directly feeding the real/imaginary input responses. The corrected characteristics are postprocessed using additional stacks of fully connected layers. Apart from the correction layers, ReLU activation is used throughout. All FC layers contain 512 neurons,

which is a reasonable choice given that the typical response size is between 200 and 300 (the number of evaluation frequencies) and the size the training set is generally kept low. Furthermore, ablation studies were conducted, indicating that the mentioned layer size is the most appropriate for the generalization capability of DSLM, as measured by mean-squared error (MSE).

The DSLM model is built using randomly distributed vectors generated through Latin Hypercube Sampling (LHS) vectors $\{x_t^{(j)}\}$, $j = 1, \dots, N_b$, and the corresponding EM simulation data $R_h(x_t^{(j)})$ and $R_l(x_t^{(j)})$. In our numerical experiments $N_t = 100$. The model is trained using the ADAM algorithm [72], a stochastic gradient descent method. Moreover, a ten-fold cross-validation is employed (i.e., the network is trained using ninety data samples, whereas ten data points are used for testing; the process is conducted ten times while changing the test subset) for model verification. The aggregated responses of the space mapping surrogate will be marked at $R_s(x)$. Fig. 3 illustrates the DSLM model training workflow. The training details are as follows: the maximum number of epochs 2000, initial learning rate 10^{-5} , minibatch size 32, no early stopping, random weight initialization.

In principle, neural-network architectures other than feed-forward networks could also be considered. Still, the results obtained corroborate the suitability of an FF model for correcting the low-fidelity model and its usefulness for design optimization. It should also be emphasized that recurrent networks such as LSTM (Long Short-Term Memory) are not suitable in the considered case, as they are primarily intended for processing sequential or time-dependent data. Whereas the problem considered in this work does not involve such data, because the model input primarily consists of design parameters, while the output is the corresponding EM (corrected) response.

2.3. Intermittent DSLM surrogate refinement using distance-based weighting

At the onset of the optimization run, a pre-trained DSLM metamodel $R_s(x)$ is used in place of $R_h(x)$. Using a pre-trained DSLM model constructed over the entire design space to perform a correction of the low-fidelity EM model permits reducing the computational expenses. This is because the model can be reused for multiple optimization runs with different design specifications. At a certain point, i.e., when approaching convergence (cf. Section 2.4), $R_h(x)$ begins to be referred to, which provides additional high-fidelity data, denoted as $x_h^{(k)}$, $k = 1, \dots, i$. More specifically, $\{x_h^{(k)}\}$ is a subset of the designs encountered along the optimization path, for which both R_h and R_l were evaluated. At the i th iteration, this data is used to augment the initial data set $\{x_t^{(j)}\} \leftarrow \{x_t^{(j)}\} \cup \{x_h^{(j)}\}$. The DSLM surrogate is re-trained using a limited number of

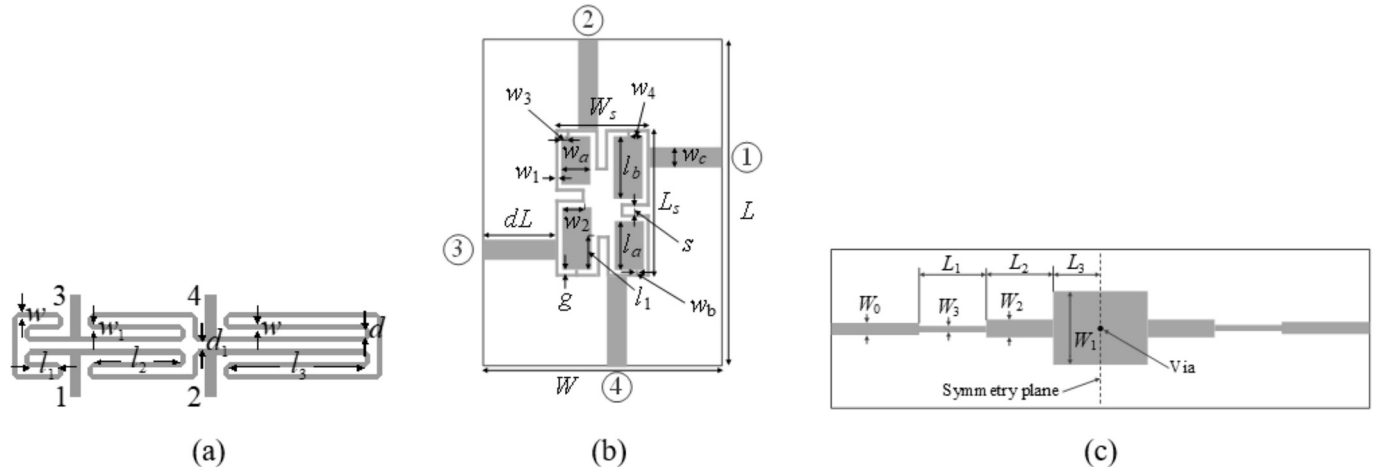


Fig. 6. Verification structures: (a) Circuit I: compact rat race coupler [76], (b) Circuit II: miniaturized branch line coupler [77], (c) Circuit III: broadband filter with stepped-impedance resonators [78].

Parameter	Circuit I	Circuit II	Circuit III
Substrate	RO4003 ($\epsilon_r = 3.38$, $h = 0.81$ mm)	RO4003 ($\epsilon_r = 3.38$, $h = 0.81$ mm)	RO4003 ($\epsilon_r = 3.38$, $h = 0.51$ mm)
Design variables [§] [mm]	$\mathbf{x} = [l_1 \ l_2 \ l_3 \ d \ w \ w_1]^T$	$\mathbf{x} = [g \ l_r \ l_a \ l_b \ w_1 \ w_{2r} \ w_{3r} \ w_{4r} \ w_a \ w_b]^T$	$\mathbf{x} = [L_1 \ L_2 \ L_3 \ W_1 \ W_2 \ W_3]^T$
Other parameters [mm]	$d_1 = d + w - w_1 $, $d = 1.0$, $w_0 = 1.7$, $l_0 = 15$	$L = 2dL + L_s$, $L_s = 4w_1 + 4g + s + l_a + l_b$, $W = 2dL +$ W_s , $W_s = 4w_1 + 4g + s + 2w_a$, $l_1 = l_0/l_r$, $w_2 = w_a w_{2r}$, w_3 $= w_3 w_a$, and $w_4 = w_4 w_a$, $w_c = 1.9$ mm	$W_0 = 0.66$ mm
Simulation frequency range	0.1 GHz to 2.5 GHz	0.1 GHz to 2.5 GHz	2.0 GHz to 14.0 GHz
Parameter space	$\mathbf{l} = [0.5 \ 5.0 \ 5.0 \ 0.2 \ 0.2 \ 0.2]^T$ $\mathbf{u} = [15 \ 30 \ 50.0 \ 2.0 \ 2.0 \ 2.0]^T$	$\mathbf{l} = [0.4 \ 0.6 \ 3.0 \ 9.0 \ 0.6 \ 0.4 \ 0.1 \ 0.6 \ 4.0 \ 0.6]^T$ $\mathbf{u} = [0.5 \ 0.85 \ 6.5 \ 11.0 \ 0.95 \ 0.7 \ 0.4 \ 0.9 \ 5.0 \ 0.7]^T$	$\mathbf{l} = [3.0 \ 3.0 \ 3.0 \ 5.0 \ 0.8 \ 0.3]^T$ $\mathbf{u} = [7.0 \ 7.0 \ 7.0 \ 9.0 \ 1.5 \ 0.8]^T$
High-fidelity model	~180,000 mesh cells, simulation time 120s	~170,000 mesh cells, simulation time 210s	~920,000 mesh cells, simulation time 160s
Low-fidelity model	~40,000 cells, simulation time 45s	~45,000 cells, simulation time 90s	~270,000 cells, simulation time 60s

[§]Dimensions in mm, except relative ones (with subscript r), which are unitless.

Fig. 7. Key parameters of the test circuits of Fig. 6.

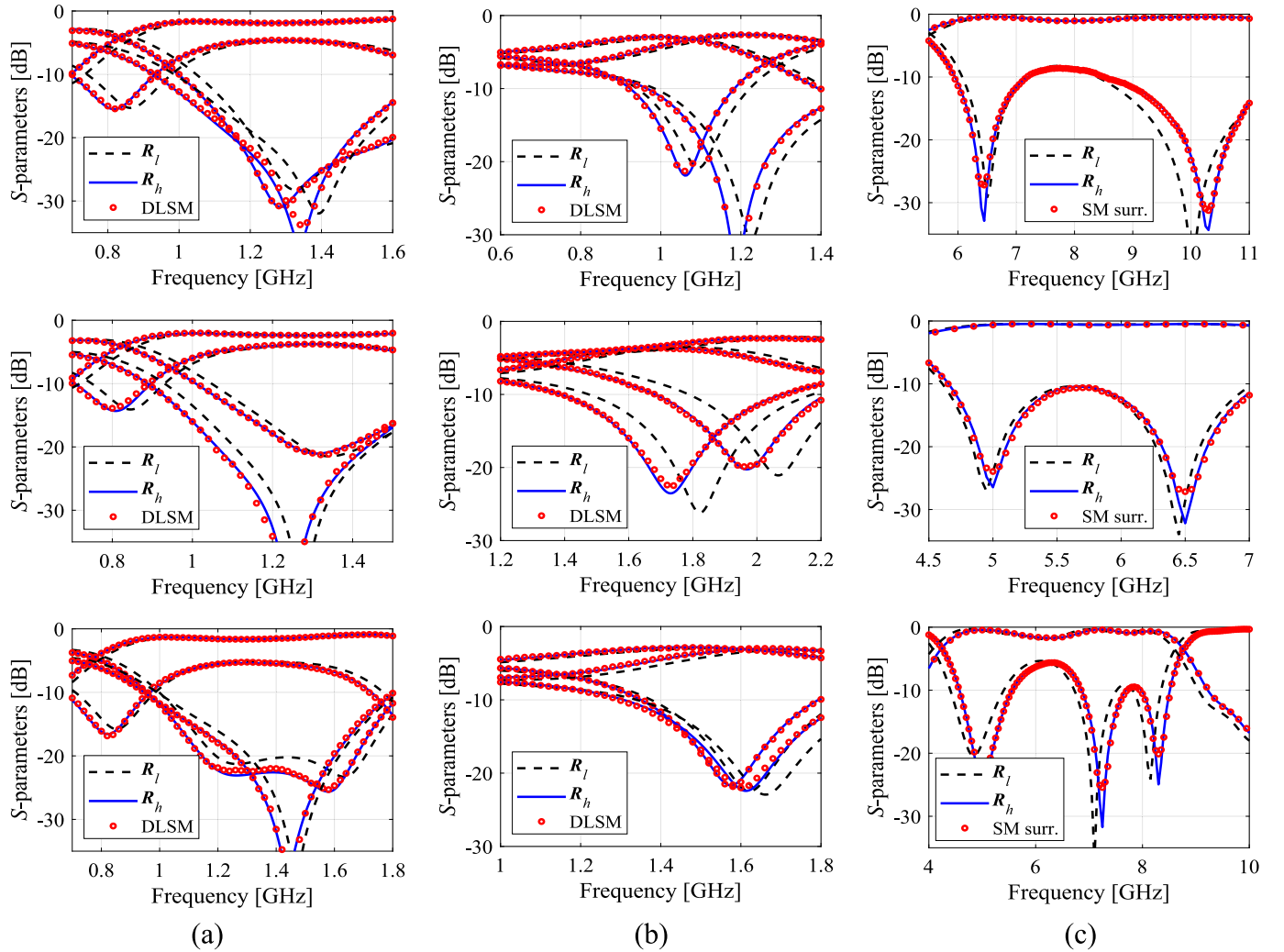


Fig. 8. Typical relationships between low- (R_l) and high-fidelity (R_h) EM models and DLSM surrogate: (a) Circuit I, (b) Circuit II, (c) Circuit III.

epochs (here, 100). To improve the model's precision in the vicinity of the most recent point (here, denoted as $\mathbf{x}_r$), all data samples are assigned weights w_j using a distance-based scheme

$$w_j = \exp\left(-[d_j/D]^2\right), i = 1, \dots, N_t \quad (4)$$

where $d_j = \|\mathbf{x}_r - \mathbf{x}_t^{(j)}\|$ is the distance between $\mathbf{x}_r$ and $\mathbf{x}_t^{(j)}$, and $D = (N_t)^{-1} \sum_j d_j$ is the average distance. This way, the samples closer to $\mathbf{x}_r$ have more impact on the model. Note that the weight assigned to $\mathbf{x}_r$ is one, and w_j decreases while moving away from $\mathbf{x}_r$. As a result, the DLSM

Table 1
Design scenarios for circuits I–III.

Circuit	Design scenario	
	Case	Design targets
I	1	$f_0 = 1.0$ GHz, $K_P = -3$ dB
	2	$f_0 = 1.5$ GHz, $K_P = 0$ dB
	3	$f_0 = 1.8$ GHz, $K_P = -4$ dB
II	1	$f_0 = 1.0$ GHz, $K_P = 0$ dB
	2	$f_0 = 1.5$ GHz, $K_P = 0$ dB
	3	$f_0 = 2.0$ GHz, $K_P = 0$ dB
III	1	$F = [5.8 \ 10.6]$ GHz (upper UWB band)
	2	$F = [8.4 \ 12.4]$ GHz (X-band)
	3	$F = [4.90 \ 7.05]$ GHz (F-band)

surrogate becomes more reliable in the region currently being explored during the search.

2.4. DLSM-based optimization: the algorithm

As this study focuses on local parameter tuning, the utilized optimization engine is the trust-region (TR) algorithm [73], as it is well-suited to implicit constraint handling. Given an initial design $\mathbf{x}^{(0)}$, the TR routine produces approximations $\mathbf{x}^{(i)}$, $i = 1, 2, \dots$, of the optimum $\mathbf{x}^*$ as

$$\mathbf{x}^{(i+1)} = \arg \min_{\mathbf{x} \in X; \|\mathbf{x} - \mathbf{x}^{(i)}\| \leq r^{(i)}} U_L(\mathbf{x}) \quad (5)$$

where the function $U_L(\mathbf{x})$ analytically coincides with $U(\mathbf{x})$ but it is evaluated using a linear model.

$$\mathbf{R}_L^{(i)}(\mathbf{x}) = \mathbf{R}_s(\mathbf{x}^{(i)}) + \mathbf{J}_s(\mathbf{x}^{(i)}) \cdot (\mathbf{x} - \mathbf{x}^{(i)}) \quad (6)$$

The model (6) represents the DLSM surrogate $\mathbf{R}_s(\mathbf{x})$ near the current candidate solution $\mathbf{x}^{(i)}$. The sensitivity matrix $\mathbf{J}_s(\mathbf{x}^{(i)})$ is computed using finite differences (FD) [74] in the first two iterations and the Broyden formula [75] afterwards. The size of the search region $r^{(i)}$ is modified following the conventional TR rules [73]. The DLSM model is retrained locally if a new high-fidelity EM analysis is performed at the current iteration.

Fig. 4 illustrates the pseudocode of our algorithm. Fig. 5 shows the block diagram. As mentioned, after the first two iterations, the Jacobian is updated using the Broyden formula at no extra computational cost (only a single EM simulation at the new candidate design is necessary). When the search process starts converging, i.e., if $\|\mathbf{x}^{(i+1)} - \mathbf{x}^{(i)}\| < 100\epsilon$, we start evaluating the high-resolution model, which serves two purposes: (i) providing more reliable design evaluation, and (ii) enhancing

the DLSM surrogate through model re-training. The re-training process uses distance-based sample weighting to put more emphasis on the region encapsulating the current iteration point, cf. (4). Furthermore, it is limited to 100 epochs. One more change is to replace $\mathbf{R}_s(\mathbf{x}^{(i)})$ by $\mathbf{R}_h(\mathbf{x}^{(i)})$ in the definition of the linear model, maintaining the zero-order consistency of the DLSM model with the high-resolution model.

3. Results

The space mapping algorithm elaborated in Section 2 is verified here using several microstrip structures. Our test cases are outlined in Section 3.1. Section 3.2 outlines the experimental setup, whereas the outcomes and a summary of findings are encapsulated in Section 3.3. Section 3.4 focuses on experimental validation of certain designs that underwent optimization using the presented methodology.

3.1. Test circuits

The circuits used to verify the proposed SM algorithm are illustrated in Fig. 6. Their essential parameters are summarized in Fig. 7, along with the configuration of the high- and low-fidelity computational models. All circuits are designed to be implemented on the RO4003 substrate, which was chosen as a representative and commonly used microwave substrate. Nevertheless, this choice does not affect the general applicability of the proposed approach. The EM analysis is performed using transient solver of CST Microwave Studio. The typical relationships between the EM models and pre-trained DLSM surrogate for all three circuits are illustrated in Fig. 8 (for all considered cases, the relative RMSE error is below 10 %). As shown, despite the differences in the absolute response levels, the low- and high-fidelity models exhibit good correlation across the considered cases, which should be understood as the similarity of misalignments between the low- and high-fidelity models across the domain considered.

3.2. Experimental setup

Circuits I and II are designed to enhance impedance matching and isolation at the intended center frequency f_0 while realizing the assumed power division ratio K_P at f_0 . For Circuit II, $K_P = 0$ dB for all test cases. The merit function is formulated according to Eq. (2). Circuit III is designed for the best $|S_{11}|$ across the assumed bandwidth F . The mathematical form of the cost function is given by Eq. (3). Each circuit is tested under three design scenarios, as listed in Table 1. For each considered design optimization task, the initial design was selected through parametric studies so as to ensure that the optimal solution

Table 2
Optimization results for circuits I–III (Benchmark I).

Circuit	Case	Results (proposed DLSM algorithm)			Results (benchmark I: high-fidelity TR)			Relative acceleration (DLSM versus benchmark I)	
		$U(\mathbf{x}^*)$	Cost ^{&}	Simulation time [min]	$U(\mathbf{x}^*)$	Cost ^{&}	Simulation time [min]	Case-wise	Average
I	1	−30.0	15.5	31.0	−25.7	69	138.0	77.5 %	76.9 %
	2	−38.4	17.7	35.4	−36.7	77	154.0	77.0 %	
	3	−34.0	14.8	29.6	−35.5	62	124.0	76.1 %	
II	1	−20.9	17.3	60.6	−20.	204	714.0	91.5 %	85.8 %
	2	−19.3	20.6	72.1	−21.0	93	325.5	77.8 %	
	3	−19.8	18.0	63.0	−21.6	149	521.5	88.0 %	
III	1	−15.8	15.1	40.3	−16.4	102	272.0	85.2 %	82.0 %
	2	−28.3	16.6	44.3	−29.0	79	210.7	79.0 %	
	3	−26.8	13.4	35.7	−29.1	74	197.3	81.9 %	

& Cost expressed in the number of equivalent high-fidelity EM analyses.

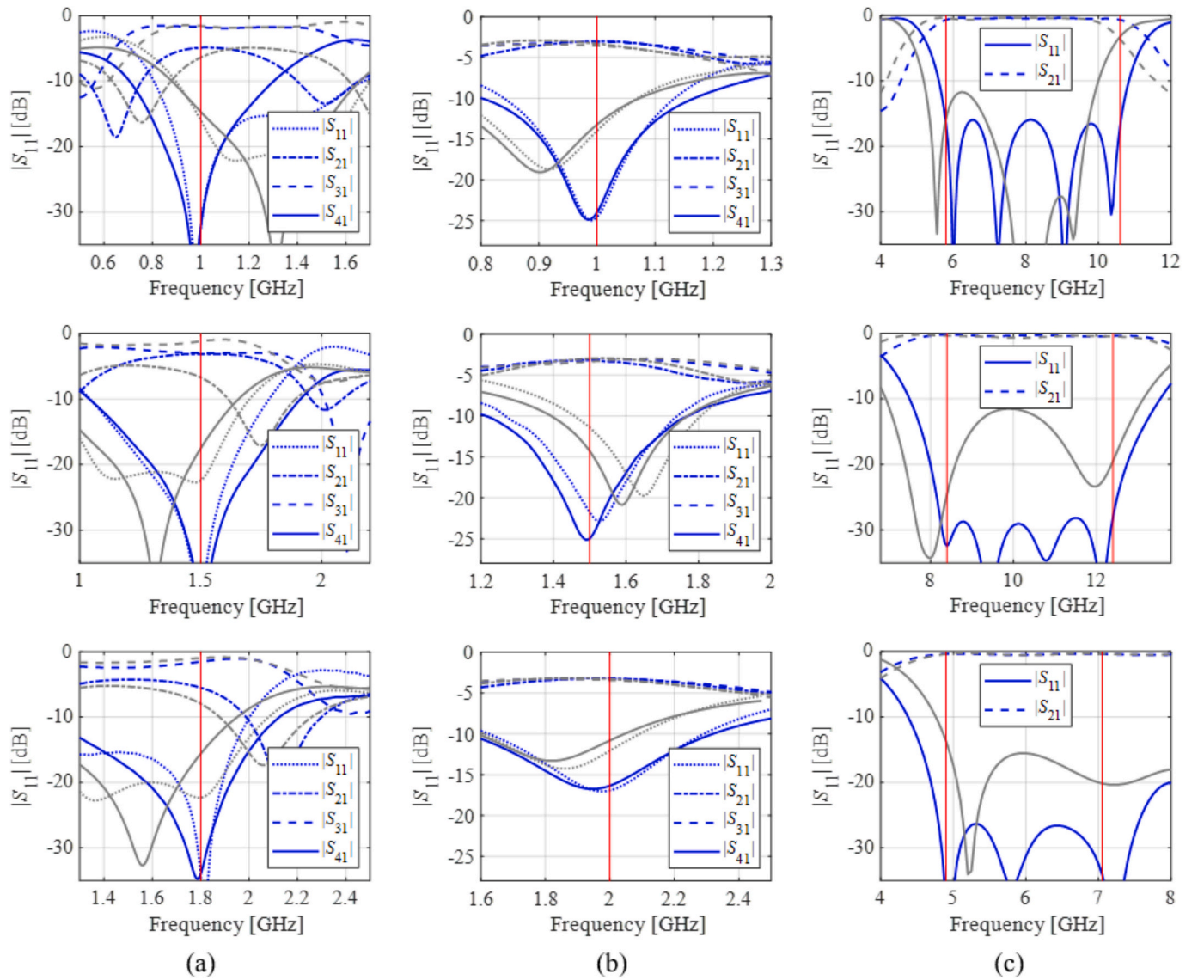


Fig. 9. Optimization results using the developed DSLM procedure: (a) Circuit I, (b) Circuit II, (c) Circuit III. Cases 1–3 are shown from top to bottom. Target center frequencies (or bandwidths for Circuit III) are marked using vertical lines.

Table 3
Optimization results for circuits I–III (Benchmark II).

Circuit	Case	Results (proposed DSLM algorithm)			Results (benchmark II: parametric SM)			Relative acceleration (DSLMS versus benchmark II)	
		$U(x^*)$	Cost ^{&}	Simulation time [min]	$U(x^*)$	Cost ^{&}	Simulation time [min]	Case-wise	Average
I	1	−30.0	15.5	31.0	−24.2	71	142.0	78.2 %	73.8 %
	2	−38.4	17.7	35.4	−33.2	56	112.0	68.4 %	
	3	−34.0	14.8	29.6	−31.8	59	118.0	74.9 %	
II	1	−20.9	17.3	60.6	−21.4	88	308.0	80.3 %	81.8 %
	2	−19.3	20.6	72.1	−17.3	113	395.5	81.8 %	
	3	−19.8	18.0	63.0	−18.2	108	378.0	83.3 %	
III	1	−15.8	15.1	40.3	−15.0	69	184.0	78.1 %	78.6 %
	2	−28.3	16.6	44.3	−25.4	77	205.3	78.4 %	
	3	−26.8	13.4	35.7	−28.3	65	173.3	79.4 %	

[&] Cost expressed in the number of equivalent high-fidelity EM analyses.

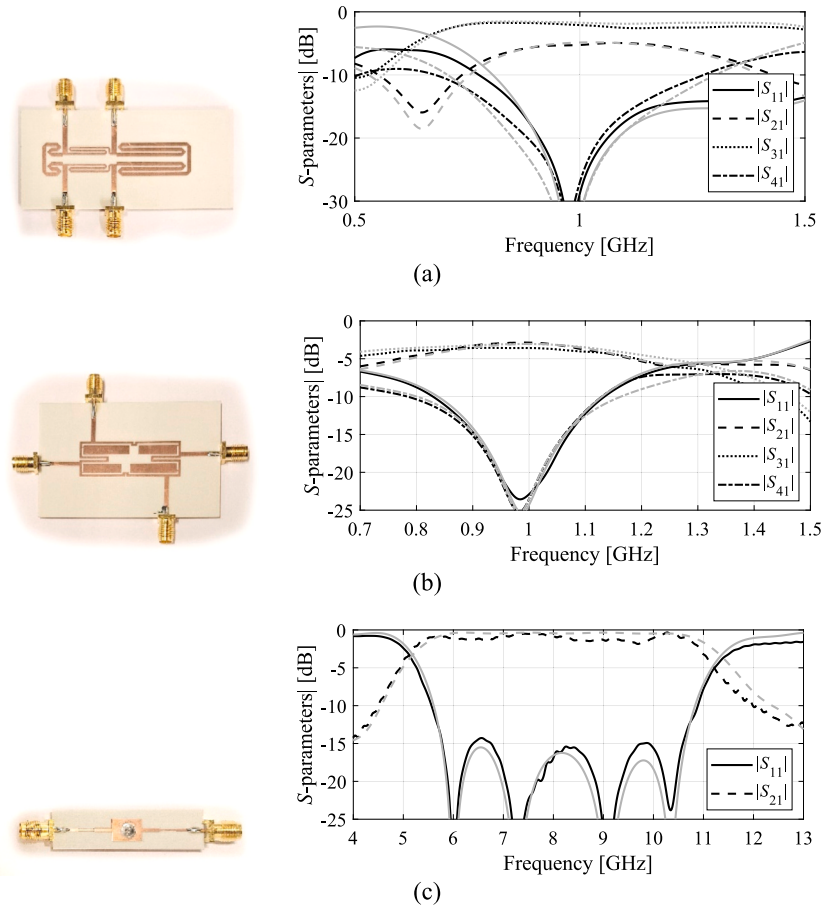


Fig. 10. Experimental validation for the first design scenario (Case 1) of Table 1. The EM-simulated and measured S -parameter characteristics are indicated by gray and black lines, respectively: (a) Circuit I, (b) Circuit II, (c) Circuit III. The photographs of the circuit prototypes are shown as insets.

could be reached using a local optimization algorithm. Furthermore, the implemented DLSM algorithm is benchmarked against the standard (R_h -based) gradient-based search, with the underlying search routine being the TR algorithm [73]. This allows us to verify the computational benefits of DLSM while investigating possible reliability degradation (if any).

3.3. Results

The outcomes for the test cases in Table 1 are presented in Table 2. The data encapsulate the objective function values at the final solutions yielded by the presented DLSM procedure and the benchmark algorithm, as well as the CPU costs. Meanwhile, Fig. 9 illustrates the high-resolution EM-evaluated circuit responses at the starting points and the designs produced by DLSM.

The benchmark algorithm exclusively employs the high-fidelity EM model. The mean cost of DLSM is about 16 high-fidelity EM analyses, compared with about 100 for the benchmark. Consequently, the proposed technique is about six times faster than the baseline procedure. In relative terms, the savings average 82% and range from 77% for Circuit I to 86% for Circuit II. Note that for all circuits R_l is about 2.5 times faster than R_h . Additional acceleration has been obtained by replacing FD with the Broyden formula for Jacobian estimation. The objective function values reported in Table 2 indicate that these mechanisms lead to minor quality degradation for Circuits II and III, which is, however, practically insignificant. For Circuit I, the proposed algorithm outperforms the benchmark in two of three design scenarios.

An additional benchmark (Benchmark II) is a parametric input/output space mapping, which works as follows:

- Low-fidelity model correction at the i th iteration of the optimization process: a combination of input and output space mapping of the form $R_s^{(i)}(\mathbf{x}) = R_l(\mathbf{x} + \mathbf{c}^{(i)}) + \mathbf{d}^{(i)}$, where $\mathbf{c}^{(i)} = \arg\min\{\mathbf{z} : \|R_h(\mathbf{x}^{(i)}) - R_l(\mathbf{x} + \mathbf{z})\|\}$, and $\mathbf{d}^{(i)} = R_h(\mathbf{x}^{(i)}) - R_l(\mathbf{x} + \mathbf{c}^{(i)})$, i.e., the design variable shift is obtained by minimizing the norm-difference between the high-fidelity and input-corrected low-fidelity model, whereas the output SM term is computed to ensure zero-order consistency between the models.
- The parameter extraction process is limited to $2n$ EM simulations, where n is the number of circuit parameters. The parameter extraction and surrogate model optimization process employs the Broyden formula for acceleration.
- The new candidate design is found by optimizing the SM surrogate, i.e., by solving $\mathbf{x}^{(i+1)} = \arg\min\{\mathbf{x} : U(R_s^{(i)}(\mathbf{x}))\}$.

The results are encapsulated in Table 3. It should be emphasized that, because the low-fidelity model is evaluated using coarse-mesh EM analysis, extracting SM parameters is relatively expensive. Consequently, the standard parametric SM cannot compete with the proposed technique, and its operating cost is comparable to conventional gradient-based optimization.

Despite the demonstrated computational benefits, the proposed methodology has certain limitations. Among others, its effectiveness depends on the availability of a reasonably good initial design. Nevertheless, a suitable starting point is often available from earlier design stages, such as topology evolution or parametric studies. Another limitation is the aforementioned requirement for sufficient correlation between the low- and the high-fidelity models. Finally, the proposed

approach belongs to a class of local optimization procedures, and, therefore, does not offer global search capabilities.

3.4. Experimental validation

The designs associated with the first design scenario (Case 1) for all three circuits were prototyped and experimentally validated. Fig. 10 compares the (high-fidelity) EM-evaluated and measured S -parameter characteristics, and only minor discrepancies between them are observed. These misalignments presumably arise from manufacturing and assembly inaccuracies, imperfect VNA calibration, and SMA connector effects. It should be clarified that in this work, the high-fidelity electromagnetic models are assumed to provide reliable representations of the considered structures. Therefore, experimental measurements do not directly validate the proposed optimization methodology; rather, they primarily verify the correspondence between the employed EM models and the fabricated prototypes.

4. Conclusion

This work proposed an innovative strategy for fast design closure of passive microwave devices. Our methodology is a space mapping (SM) algorithm that leverages a reusable deep learning (DL) surrogate constructed to realize multi-point enhancement of the low-resolution EM model. This DLSM correction is applied independently to real and imaginary components of the relevant S -parameter characteristics and trained to account for the interdependence between different responses (return loss, isolation, transmission) and the problem's decision variables. The latter improves the model's versatility and generalization capability. The DLSM model acts as a primary circuit representation within a gradient-based optimization loop. During tuning, the high-resolution model is evaluated sparsely as convergence approaches. The EM samples collected this way are used to retrain the surrogate, focusing on the neighborhood of the current iteration point, which is achieved through distance-based sample weighting. Extensive numerical experiments involving three planar circuits corroborate the high efficacy of our algorithm. The CPU cost equals about 16 high-fidelity EM analyses, which corresponds to more than 80% relative speedup over the baseline (high-fidelity-only) algorithm. Furthermore, considering design scenarios across broad ranges of operating parameters (center frequencies, bandwidths, power division ratios) demonstrated the reusability of the DLSM surrogate and its capability to reliably improve the low-fidelity model over large portions of the decision variable space. The focus of the future work will consist in enhancing the correction quality of the DLSM surrogate by incorporating enhancements that account for typical low- and high-fidelity model misalignments (e.g., frequency shifts).

CRedit authorship contribution statement

Slawomir Koziel: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Anna Pietrenko-Dabrowska:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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