IMPLICIT SPACE MAPPING EM-BASED MODELING AND DESIGN EXPLOITING PREASSIGNED PARAMETERS

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Abstract — We introduce the idea of Implicit Space Mapping and show how it relates to the well-known (explicit) Space Mapping between coarse and fine device models. Through comparison a General Space Mapping concept is abstracted. A special, simple case of the novel ISM concept is implemented. It is illustrated on a contrived "cheese cutting problem" and is applied to EM-based microwave modeling and design. We propose to calibrate a suitable coarse model against a fine model (full wave EM simulation) by relaxing certain coarse model preassigned parameters. Our algorithm updates these preassigned parameters through parameter extraction and reoptimizes the mapped coarse model to suggest a new EM design and terminates when relevant stopping criteria are satisfied. We illustrate our approach through an HTS filter example.

I. Introduction

The Space Mapping (SM) concept of using "coarse" models (usually computationally fast circuit-based models) to align with "fine" models (typically CPU intensive full-wave EM simulations) has been exploited by several authors [1]-[8]. Several notable implementations and

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applications of SM have been reported. Pavio presented a companion approach [6]. Snel [7] derived models for RF components. Swanson and Wenzel [8] used SM to optimize mechanical adjustments by iterating between a finite element simulator and circuit simulator. Wu [9] applied SM to design LTCC circuits. Choi *et al.* [10] applied it to magnetic systems, Redhe [11] in vehicle crashworthiness design.

In [1]-[3], a calibration is performed through a mapping between optimizable parameters of the fine model and corresponding parameters of the coarse model such that their responses match. This mapping is iteratively updated. In [4], the coarse model is calibrated against the fine model by adding circuit components to nonadjacent individual coarse model elements. The component values are updated iteratively. The ESMDF algorithm [5] calibrates the coarse model by extracting certain preassigned parameters such that corresponding responses match. It establishes an explicit mapping from optimizable to preassigned parameters.

Our new approach does not establish an explicit mapping: we suggest an indirect approach. In each iteration we extract selected preassigned parameters to match the coarse model with the fine model. With these fixed, we reoptimize the calibrated coarse model. Then we assign its optimized parameters to the fine model. We repeat this process until the fine model response is sufficiently close to the target response. The preassigned parameters, which are updated, calibrate the "mapping". It is a special case of a new concept we call Implicit Space Mapping (ISM).

Examples of preassigned parameters are physical parameters such as dielectric constant in microstrip structures or geometrical parameters such as substrate height. Typically, they are not optimized. As in [5] we allow the preassigned parameters (of the coarse model) to change in some components and keep them intact in others. We implement our technique in Agilent ADS [12].

II. GENERAL SPACE MAPPING TECHNOLOGY

We categorize Space Mapping into (1) the original or explicit SM and (2) Implicit Space Mapping. Both share the concept of "coarse" and "fine" models. Both use an iterative approach to update the mapping and predict the new design.

Explicit Space Mapping

In explicit space mapping, we should be able to draw a clear distinction between a physical coarse model and the mathematical mapping that links it to the fine model as shown in Fig. 1. In each iteration, only the mapping is updated, while the physical coarse model is kept fixed. If the inverse mapping is available at each iteration, then the solution (best current prediction of the fine model) can be evaluated directly. Examples of this type are the original SM [1], Aggressive SM [13], Neural SM [2], etc.

Implicit Space Mapping

Sometimes identifying the mapping is not obvious, as if it is buried within the coarse model. If the "mapping" is integrated with the coarse model, the mapped coarse model becomes a calibrated model or enhanced surrogate as in Fig. 2 (the dashed box). To obtain the next step, the mapped or enhanced coarse model is explicitly optimized. In many cases, the optimal implicit coarse model parameters $\boldsymbol{x}_i^*$ may not be visible. For example, in a circuit simulator such as ADS the electrical length and characteristic impedance are "invisible" parameters of its circuit component library microstrip line model. The mapping may, in that case, not be readily extractable, and the mapped coarse model has to be (re)optimized in order to obtain an "inverse" mapped solution.

These two types of SM are related. Both types iteratively calibrate the mapped model when approaching the fine model solution. If the implicit mapped model is not good enough after the calibration, we may add an explicit mapping between implicit mapped coarse model space and fine model space to align the coarse model and fine model. See Fig. 2. Interestingly, the explicit mapping could be expressed in the form of ISM by using a simple mathematical substitution. We discuss this in Section III.

In general, the space mapping optimization steps can be abstracted as follows.

General Space Mapping Optimization Steps

Step 1 Select a mapping function (linear, nonlinear, neural).

Step 2 Select an approach (implicit, explicit).

Step 3 Optimize the coarse model with respect to design parameters.

Step 4 Apply parameter extraction using Key Preassigned Parameters [5], neuron weights [2], coarse space parameters, etc.

Step 5 If the inverse mapping is easy to obtain, evaluate it here to avoid explicit reoptimization. If not reoptimize the "mapped coarse model" with respect to design parameters.

Step 6 Assign the result of Step 5 to the fine model and simulate it.

Step 7 Terminate if a stopping criterion (e.g., response meets specifications) is satisfied, or else go to Step 4.

III. Implicit Space Mapping (ISM): The Concept

We denote the fine model responses at a point $\boldsymbol{x}_f$ by $\boldsymbol{R}_f(\boldsymbol{x}_f)$. The original design problem is

$$\boldsymbol{x}_f^* = \arg\min_{\boldsymbol{x}_f} U(\boldsymbol{R}_f(\boldsymbol{x}_f)) \tag{1}$$

where U is the objective function and $\boldsymbol{x}_f^*$ is the optimal fine model design. Solving (1) using direct optimization methods may be prohibitive.

We denote by $\boldsymbol{x}_c$ a coarse model point (usually designable parameters), by $\boldsymbol{x}$ a set of other (auxiliary) parameters, for example, preassigned parameters and by $\boldsymbol{x}_i$ a set of implicitly mapped parameters. The corresponding coarse model response vector is $\boldsymbol{R}_c(\boldsymbol{x}_c, \boldsymbol{x})$.

As indicated in Fig. 3, ISM aims at establishing an implicit mapping $\boldsymbol{Q}$ between the spaces $\boldsymbol{x}_f$, $\boldsymbol{x}_c$ and $\boldsymbol{x}$

$$\boldsymbol{Q}(\boldsymbol{x}_f, \boldsymbol{x}_c, \boldsymbol{x}) = \boldsymbol{0} \tag{2}$$

If we include the implicit parameters $\boldsymbol{x}_i$ and simply set

$$\boldsymbol{x}_f = \boldsymbol{x}_c \tag{3}$$

then the mapping can be expressed as

$$\boldsymbol{x}_i = \boldsymbol{P}(\boldsymbol{x}_c, \boldsymbol{x}) \tag{4}$$

such that

$$\boldsymbol{R}_f(\boldsymbol{x}_c) \approx \boldsymbol{R}_c(\boldsymbol{x}_c, \boldsymbol{x}) \tag{5}$$

over a region in the parameter space.

As in Fig. 4, ISM utilizes the mapping to obtain the prediction by solving

$$\boldsymbol{Q}(\boldsymbol{x}_f, \boldsymbol{x}_c^*, \boldsymbol{x}) = \boldsymbol{0} \tag{6}$$

This can be expressed using implicit parameters $\boldsymbol{x}_i$ as

$$\boldsymbol{x}_c^* = \boldsymbol{P}^{-1}(\boldsymbol{x}_i^*, \boldsymbol{x}) \tag{7}$$

where $\boldsymbol{x}_c^*$ is the optimal coarse model solution *for given preassigned parameters* $\boldsymbol{x}$, and

$$\boldsymbol{x}_f = \boldsymbol{x}_c^* \tag{8}$$

This prediction is obtainable by mapped coarse model optimization, because the mapping is usually nonlinear and noninvertible.

In general, ISM optimization obtains a space-mapped design $\bar{\boldsymbol{x}}_f$ whose response approximates an optimized $\boldsymbol{R}_c$ target. $\bar{\boldsymbol{x}}_f$ is a solution of the nonlinear system (2) which is enforced through a Parameter Extraction (PE) (modeling) w.r.t. $\boldsymbol{x}$, and subsequent prediction (optimization) of the next fine model iterate by finding $\boldsymbol{x}_c^*$ for fixed $\boldsymbol{x}$. The first step in all SM-based algorithms obtains an optimal coarse model design $\boldsymbol{x}_c^*$ for given $\boldsymbol{x}$. The corresponding response is denoted by $\boldsymbol{R}_c^*$. In ISM $\boldsymbol{x}_c^*$ depends on the current value of $\boldsymbol{x}$ and will change from iteration to iteration through reoptimization.

For the explicit SM we start with the two models in Fig. 5. The first step for any SM optimization approach is to obtain the optimal solution for the coarse model (Fig. 6). We set the fine model design parameters equal to the optimal solution of the coarse model. The fine model is then evaluated (Fig. 7). Normally the first fine model evaluation does not give the desired response. We adjust $\boldsymbol{x}$ in the given mapping such that the output of the mapping $\boldsymbol{x}_{\mathrm{c}}$ satisfies

$$\boldsymbol{R}_c(\boldsymbol{x}_c) \approx \boldsymbol{R}_f \tag{9}$$

This is the PE procedure (Fig. 8). Now we aim at finding $\boldsymbol{x}_f$ such that the output of the mapping is $\boldsymbol{x}_c^*$, the optimal solution for the coarse model. Here we can obtain $\boldsymbol{x}_f$ by evaluating the inverse mapping. If the inverse mapping is unavailable, optimization is used to predict $\boldsymbol{x}_f$ (Fig. 9). The response for the new $\boldsymbol{x}_f$ is evaluated as shown in Fig. 10 to check if it satisfies the stopping criteria. If not, the algorithm returns to the PE step.

For implicit mapping, the mapping is embedded in the coarse model. The mapping and the coarse model together (mapped coarse model) become the calibrated model or enhanced surrogate. We optimize this model to satisfy the original design specifications. See Fig. 11. We evaluate the fine model at the optimal mapped coarse model point. This is an initial guess (Fig. 12). The preassigned parameters are optimized to perform Parameter Extraction such that the responses of the mapped coarse model match those of the fine model (Fig. 13). We reoptimize (Fig. 14) the calibrated model or enhanced surrogate w.r.t. the coarse model parameters after PE such that they satisfy the original specifications. The solution is a new prediction of the fine model solution. We evaluate the fine model again to verify if it satisfies the specifications. If not, we return to the PE step.

An interesting point that relates the ISM to the explicit mapping is when we set the preassigned parameters

$$\boldsymbol{x} = \Delta \boldsymbol{x}_c \tag{10}$$

where $\Delta \boldsymbol{x}_c$ is the deviation of $\boldsymbol{x}_c$ from $\boldsymbol{x}_c^*$ in PE. The ISM becomes the original SM with the difference shown in Fig. 15 that ISM extracts $\Delta \boldsymbol{x}_c$ rather than $\boldsymbol{x}_c$ in PE. Also for the Neuro Space Mapping [2], if we set

$$\boldsymbol{x} = \boldsymbol{w} \tag{11}$$

where $\boldsymbol{w}$ represents the weights of the neurons, then Neuro Space Mapping is representable by ISM.

Cheese Cutting Illustration

We developed a simple, intuitive physical example to demonstrate ISM. Depicted in Fig. 16, we call it the Cheese Cutting Problem. Our goal is to cut a certain *length* (designable parameter) of cheese to yield a certain *weight* (target "response"). Assume that the density is uniformly unity. We retain in mind ("coarse" model) a regular block (top block in Fig. 16). We will deliver an irregular block ("fine" model) of desired *weight*. The question is how to achieve this using the ISM concept.

Experience suggests a cut corresponding to a regular block and results in the second item in Fig. 16. Weighing it (fine model evaluation) shows that it is too light. We shrink the *width* (preassigned parameter) of the model to match this weight. This corresponds to Parameter

Extraction. We reoptimize the *length* of the model to match our goal. Then we assign the new length to the irregular block. We continue in this manner until the irregular block is close enough to the desired weight (target).

ISM, in this case, is an *indirect* approach. A *direct* approach would extract *length* in the parameter extraction process.

IV. An Algorithm

In Fig. 17 we represent a microwave circuit whose coarse model is decomposed. We catalog the preassigned parameters into two sets as in [5]: Set A of "designated" components and Set B. In Set A, we vary certain preassigned parameters $\boldsymbol{x}$. In Set B, we keep preassigned parameters $\boldsymbol{x}_0 \in \Re^{n_0}$ fixed. We can follow the sensitivity approach of [5] to formally select components for Set A and Set B.

As implied in Fig. 17(b), in each iteration of PE

$$\boldsymbol{x}_c = \boldsymbol{x}_f^{(i)} \tag{12}$$

Notice from Fig. 17(b) that we do not explicitly establish a mapping between the optimizable parameters and the preassigned parameters. This contrasts with [5], where the mapping is explicit (see Fig. 17(c)). Therefore, our proposed approach is easier to implement in commercial microwave simulators.

Parameter Extraction w.r.t $\boldsymbol{x}$ results in $\boldsymbol{x}^{(i)}$. We obtain the next set of coarse model parameters $\boldsymbol{x}_c^{*(i)}$ by optimization. Then we set (prediction)

$$\boldsymbol{x}_f = \boldsymbol{x}_c^{*(i)} \tag{13}$$

where

$$\boldsymbol{x}_c^{*(i)} = \arg\min_{\boldsymbol{x}_c} U(\boldsymbol{R}_c(\boldsymbol{x}_c, \boldsymbol{x}^{(i)})) \tag{14}$$

Summary of the Algorithm

Step 1 Select candidate preassigned parameters $\boldsymbol{x}$ as in [5] or through experience.

Step 2 Set i = 0 and initialize $\boldsymbol{x}^{(0)}$.

Step 3 Obtain the optimal *coarse model* parameters by solving (14).

Step 4 Predict $\boldsymbol{x}_f^{(i)}$ from (13).

Step 5 Simulate the fine model at $\boldsymbol{x}_f^{(i)}$.

Step 6 Terminate if a stopping criterion (e.g., response meets specifications) is satisfied.

Step 7 Calibrate the coarse model by extracting (PE step) the preassigned parameters $\boldsymbol{x}$ (noting (12))

$$\boldsymbol{x}^{(i+1)} = \arg \min_{\boldsymbol{x}} \left\| \boldsymbol{R}_f(\boldsymbol{x}_f^{(i)}) - \boldsymbol{R}_c(\boldsymbol{x}_f^{(i)}, \boldsymbol{x}) \right\| \tag{15}$$

Step 8 Increment i and go to Step 3.

V. HTS Filter Example

We consider the HTS bandpass filter in [14]. The physical structure is shown in Fig. 18(a). Design variables are the lengths of the coupled lines and the separation between them, namely,

$$\boldsymbol{x}_f = [S_1 \ S_2 \ S_3 \ L_1 \ L_2 \ L_3]^T$$

The substrate used is lanthanum aluminate with ε_r= 23.425, H= 20 mil and substrate dielectric loss tangent of 0.00003. The length of the input and output lines is L_0=50 mil and the lines are of width W= 7 mil. We choose ε_r and H as the preassigned parameters of interest, thus $\boldsymbol{x}_0$=[20 mil 23.425]^T. The design specifications are

$$|S_{21}| \leq 0.05 \quad \text{for } \omega \geq 4.099 \text{ GHz and for } \omega \leq 3.967 \text{ GHz}$$

$$|S_{21}| \geq 0.95 \quad \text{for } 4.008 \text{ GHz} \leq \omega \leq 4.058 \text{ GHz}$$

This corresponds to 1.25% bandwidth.

Our Agilent ADS [12] coarse model consists of empirical models for single and coupled microstrip transmission lines, with ideal open stubs. See Fig. 18(b). Set A (Fig. 17) consists of the three coupled microstrip lines. Notice the symmetry in the HTS structure, i.e., coupled lines 5 "CLin5" is identical to "CLin1" and "CLin4" is identical to "CLin2". Here, Set B (Fig. 17) is empty. The preassigned parameter vector is

$$\boldsymbol{x} = [\varepsilon_{r1} \ H_1 \ \varepsilon_{r2} \ H_2 \ \varepsilon_{r3} \ H_3]^T$$

The fine model is simulated by Agilent Momentum [15]. The relevant responses at the initial solution are shown in Fig. 19(a), where we notice severe misalignment. The algorithm requires only 3 iterations (3 fine model simulations). The total time taken is 26 min (one fine model simulation takes approximately 9 min on an Athlon 1100 MHz). Table I shows initial and final designs. Table II shows the variation in the preassigned (coarse model) parameters. Responses at the final iteration are shown in Fig. 19(b).

The Parameter Extraction uses real and imaginary S parameters and the ADS quasi-Newton optimizer, while coarse model optima are obtained by the ADS minimax optimizer.

VI. Conclusions

Based on a general concept, we present an effective technique for microwave circuit modeling and design w.r.t. full-wave EM simulations. We vary preassigned parameters in a coarse model to align it with the EM (fine) model. Since explicit mapping is not involved this "Space Mapping" technique is more easily implemented than [5]. We believe it is the easiest SM technique to implement. The HTS filter design is entirely done by Agilent ADS and Momentum, with no matrices to keep track of. A general space mapping concept is presented which enables us to verify that our implementation is correct and that no redundant steps are used.

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TABLE I
OPTIMIZABLE PARAMETER VALUES OF THE HTS FILTER

Parameter	Initial solution (mil)	Solution reached by the algorithm (mil)
L_1	189.65	187.10
L_2	196.03	191.30
L_3	189.50	186.97
S_1	23.02	22.79
S_2	95.53	93.56
S_3	104.95	104.86

TABLE II
THE INITIAL AND FINAL PREASSIGNED PARAMETERS OF THE CALIBRATED COARSE MODEL OF THE HTS FILTER

Preassigned parameters	Original values	Final iteration
H_1	20 mil	19.80 mil
H_2	20 mil	19.05 mil
H_3	20 mil	19.00 mil
ε_{r1}	23.425	24.404
ε_{r2}	23.425	24.245
ε_{r3}	23.425	24.334

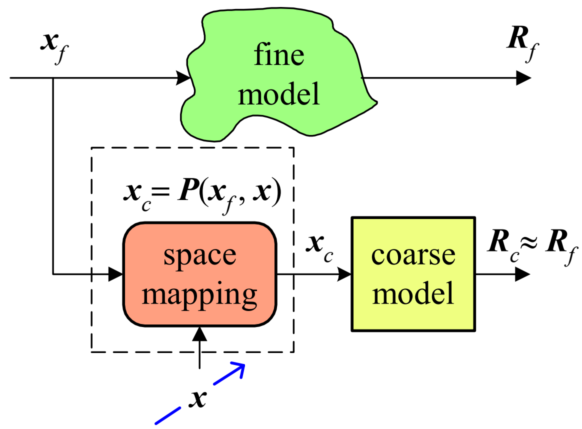


Fig. 1. Illustration of explicit SM.

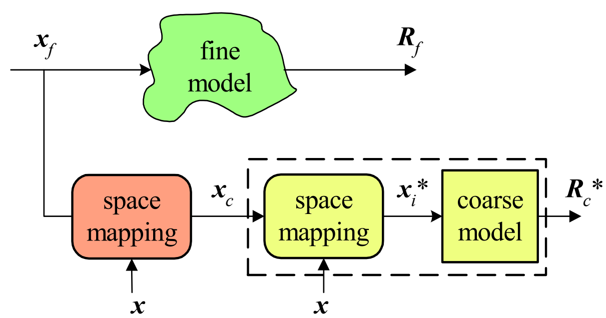


Fig. 2. Illustration of ISM.

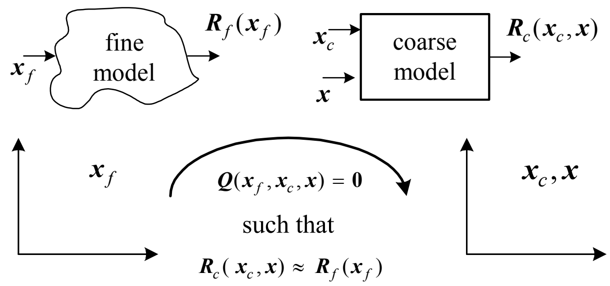


Fig. 3. Illustration of Implicit Space Mapping (ISM)—modeling.

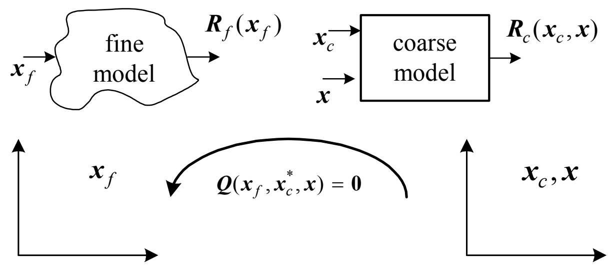


Fig. 4. Illustration of Implicit Space Mapping (ISM)—optimization.

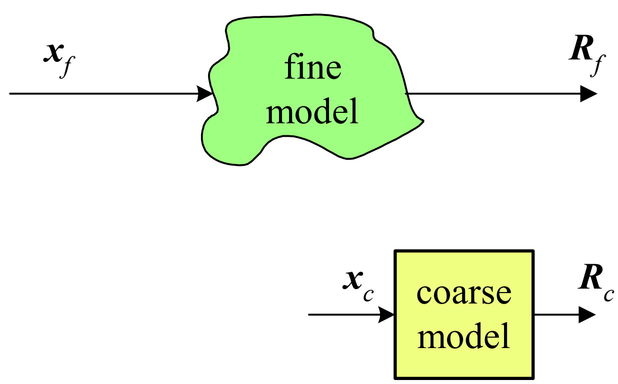


Fig. 5. Explicit mapping—fine and coarse model.

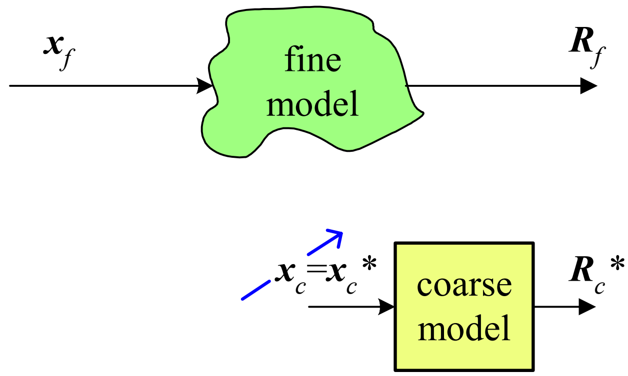


Fig. 6. Explicit mapping—direct optimization of the coarse model.

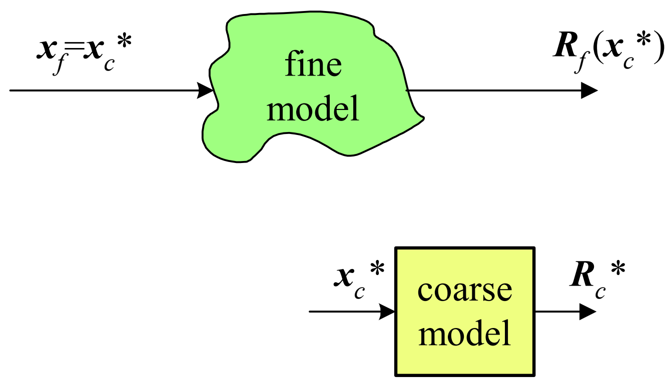


Fig. 7. Explicit mapping—verification of the fine model.

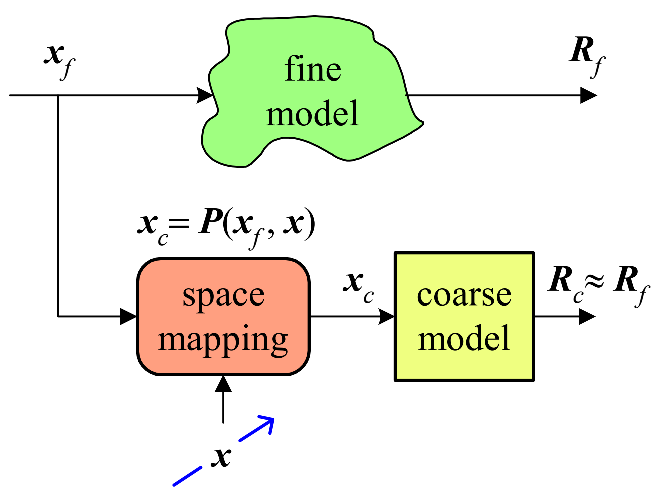


Fig. 8. Explicit mapping—Parameter Extraction.

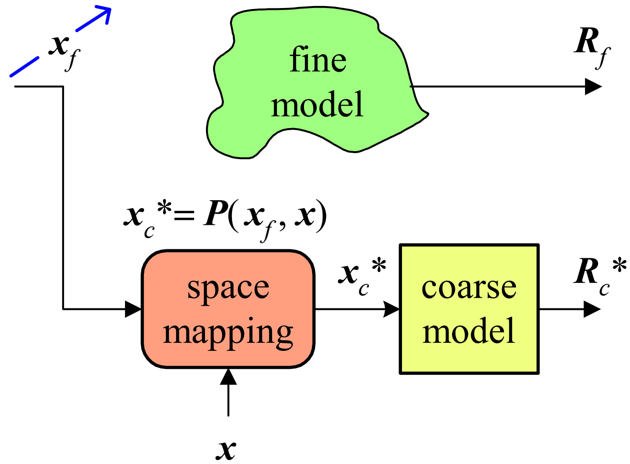


Fig. 9. Explicit mapping—prediction.

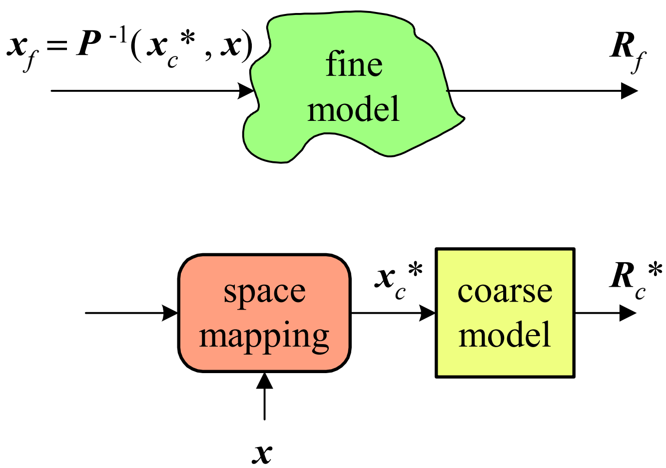


Fig. 10. Explicit mapping—verification of the fine model.

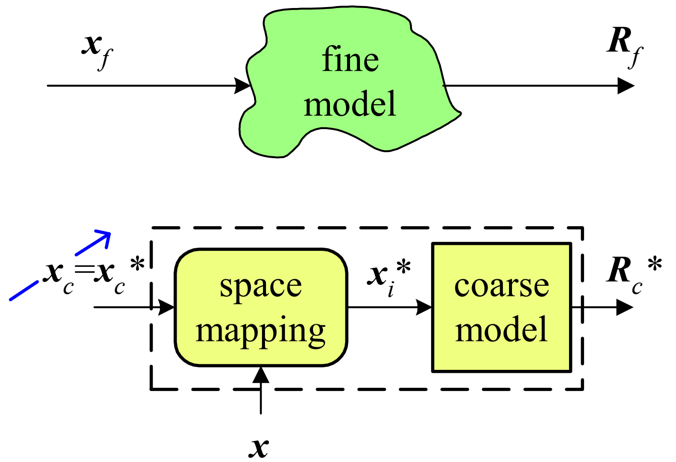


Fig. 11. Implicit mapping—optimization of the mapped coarse model.

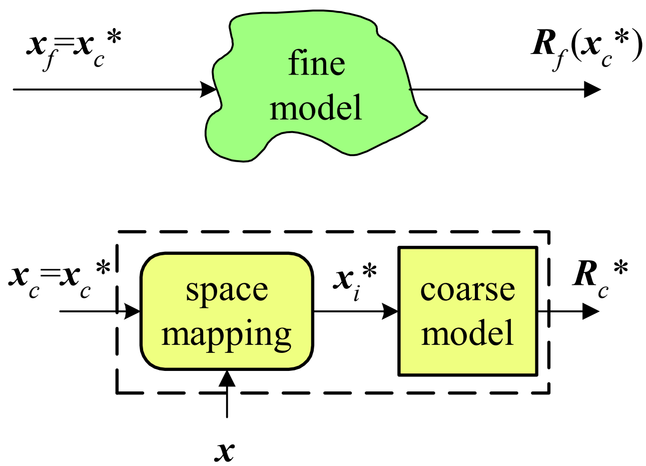


Fig. 12. Implicit mapping—verification of the fine model.

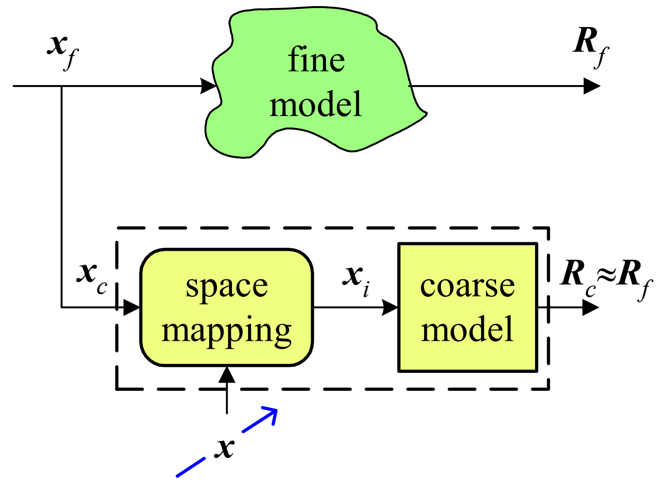


Fig. 13. Implicit mapping—Parameter Extraction w.r.t. preassigned parameters.

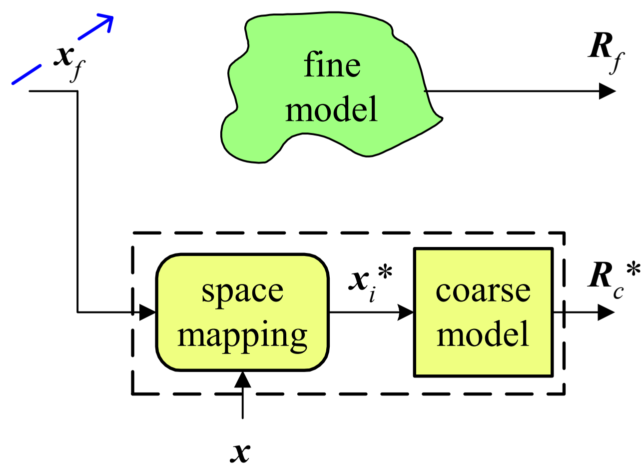


Fig. 14. Implicit mapping—reoptimization (prediction).

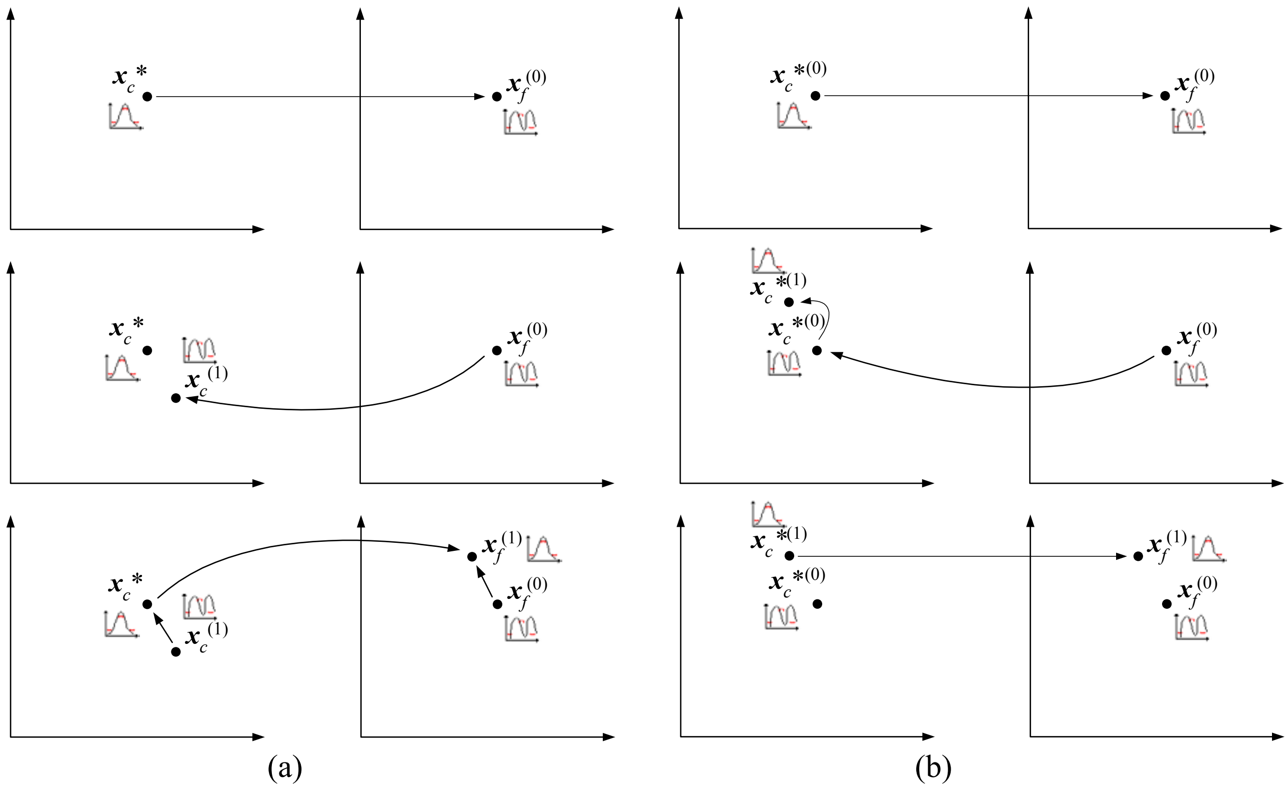


Fig. 15. When we set the preassigned parameters $\boldsymbol{x} = \Delta\boldsymbol{x}_c$, ISM relates to the explicit SM process. (a) The original SM. (b) The ISM process interpreted in the same spaces.

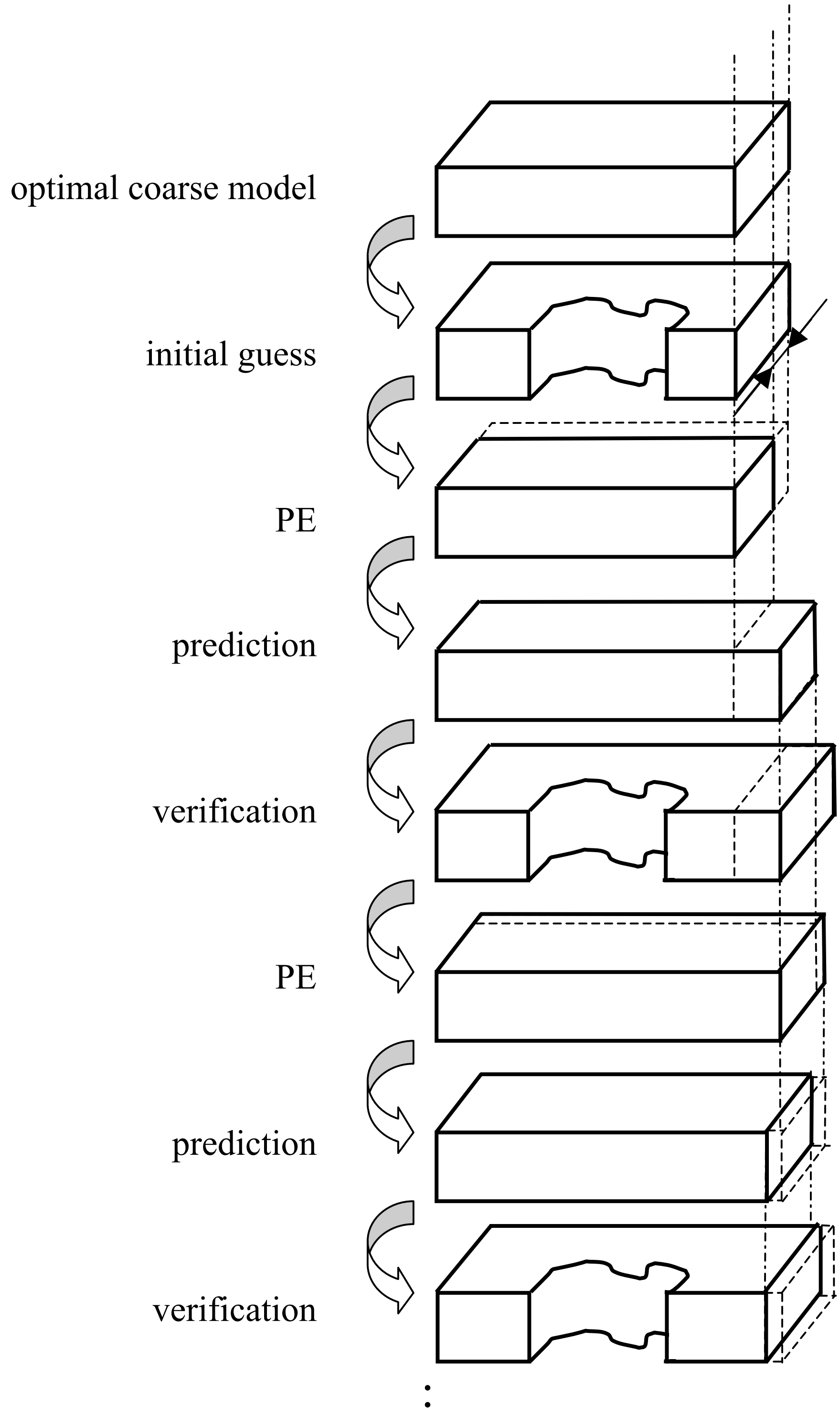


Fig. 16. Cheese Cutting Problem—A demonstration of ISM algorithm.

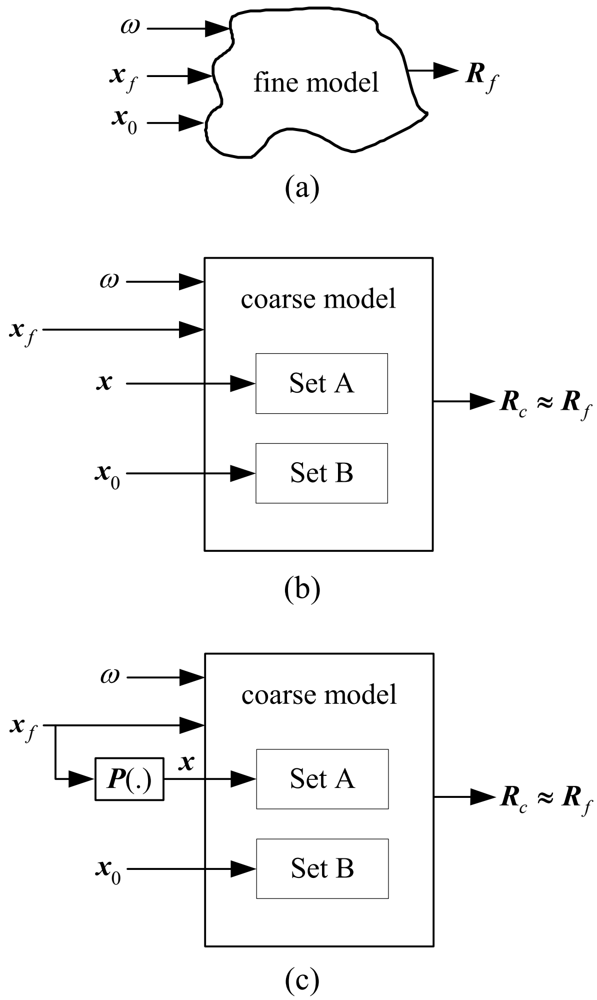
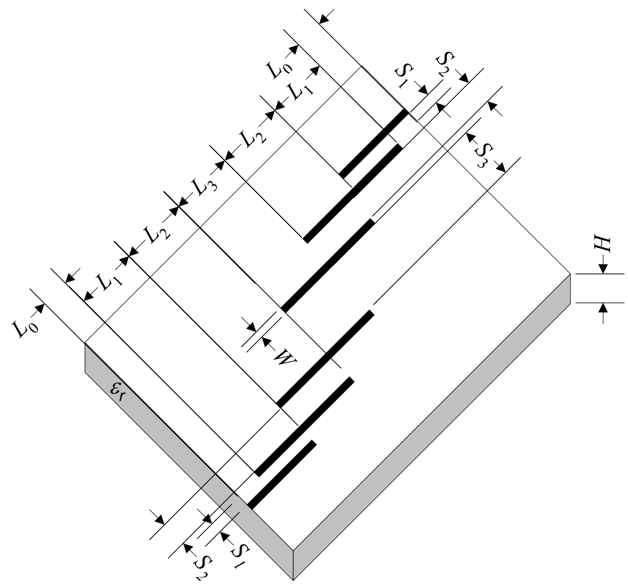
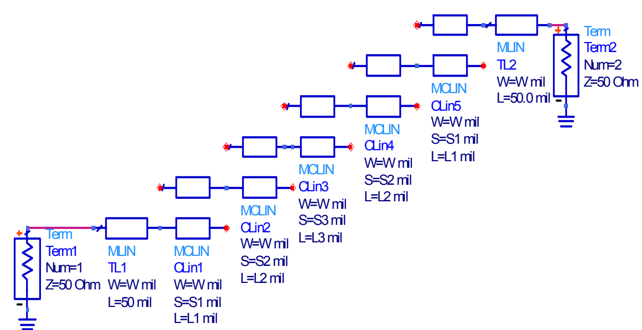


Fig. 17. Calibrating (optimizing) the preassigned parameters $\boldsymbol{x}$ in Set A results in aligning the coarse model (b) or (c) with the fine model (a). In (c) we illustrate the ESMDF approach [5], where $\boldsymbol{P}(\cdot)$ is a mapping from optimizable design parameters to preassigned parameters.

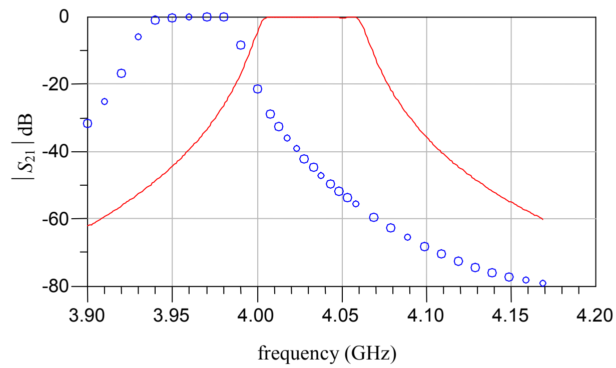


(a)

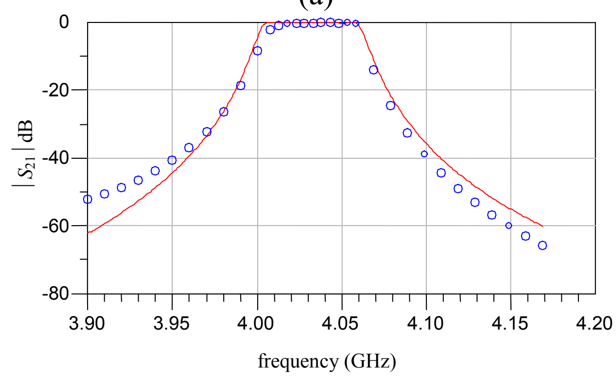


(b)

Fig. 18. The HTS filter [14]: (a) the physical structure and (b) the coarse model as implemented in Agilent ADS [12].



(a)



(b)

Fig. 19. The Momentum fine (○) and optimal coarse ADS model (—) responses at the initial solution (a) and at the final iteration (b).