Design of High-Speed Links via a Machine Learning Surrogate Model for the Inverse Problem

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***Abstract*—This paper presents an alternative approach for the design of high-speed link based on a preliminary version of a surrogate model for the inverse problem. Specifically, given the overall structure of the link, our goal is to build an accurate and fast-to-evaluate model for the estimation of the geometrical parameters of its interconnect starting from the desired eye diagram characteristics. The modeling scheme proposed in this paper relies on a powerful machine learning regression technique such as the least-squares support vector machine (LS-SVM) which is used to provide an accurate relationship among the desired eye features and the geometrical parameters of the link interconnect. The proposed model is built from a set of training samples generated by a parametric simulation of the link through the full-computational model. The feasibility and the accuracy of the proposed modeling scheme are then investigated by comparing its predictions with the corresponding results provided by the full-computational model on 250 unseen samples.**

***Index Terms*—High-speed link, inverse problem, Machine Learning, least-squares support vector machine.**

I. Introduction

Nowadays, due to the high level of integration and chip density, the design of high-speed channel is other than being straightforward [1]. Usually, complex optimization algorithms are adopted to guide the designer to find out the optimal configuration of the link parameters (e.g., the geometrical parameters of the interconnects, the materials, etc.) in order to achieve the desired link performances (e.g., the desired eye-diagram characteristics) [2].

Optimization algorithms are used to efficiently explore the design parameter space by minimizing the number of calls to the full-computational model. For the case of high-speed links, such full-computational model consists of the implementation of the high-speed link within a commercial solver, thus providing synthetically (i.e., through simulations) an accurate and reliable estimation of the link output variables for any configuration of the input design parameters. To achieve good accuracy, the channel simulation with the full-computational model is usually computationally expensive, especially for complex structures. In order to speed up the optimization process, several modeling techniques (e.g., [3], [4] and the references therein) have been developed in the last decades with the aim of providing fast and accurate alternatives to the full-computational model.

All the aforementioned models, including the full-computational model, are referred as *forward mapping* $\mathcal{M}$, since they provide a non-linear relationship which maps the input design parameters $\mathbf{x}$ into the corresponding outputs of interest $\mathbf{y}$, such that:

$$\mathbf{y} = \mathcal{M}(\mathbf{x}), \tag{1}$$

where $\mathbf{x} \in \mathcal{X} \subset \mathbb{R}^d$ represents a vector collecting d design parameters and $\mathbf{y} \in \mathcal{Y} \subset \mathbb{R}^u$ is a vector collecting u output variables.

This paper focuses on a different approach for tackling the optimization problem in high-speed link based on the inverse problem formulation. The inverse problem approach proceeds in the opposite direction with respect to the standard forward mapping model usually adopted for the optimization purposes. Specifically, a model $\mathcal{M}^{-1}$ for the inverse problem allows finding the configuration of the input parameters $\mathbf{x}$ starting from the information on the required set of outputs $\mathbf{y}$ such that:

$$\mathbf{x} = \mathcal{M}^{-1}(\mathbf{y}). \tag{2}$$

It is ought to remark that the inverse problem is usually ill-posed, in the sense that a unique solution is not generally available, since we deal with a one-to-many mapping (i.e., for given value of the desired outputs $\mathbf{y}$ we can find more than one configuration of the input parameters $\mathbf{x}$) [5]–[7].

In this paper, the inverse problem in (2) will be applied to estimate the optimal configuration of the geometrical parameters of a high-speed link starting from the desired eye diagram characteristics calculated at the receiver stage, without using any optimization algorithm. Since the optimization is implicitly done in the parameter space during the model training. Different from [5]–[7], in which the inverse problem has been addressed via a neural network formulation, the proposed modeling scheme relies on the least-squares support vector machine (LS-SVM) regression [8], [9]. The resulting surrogate model is built from a set of training samples provided by the full-computational model and allows predicting directly the geometry of the link interconnect.

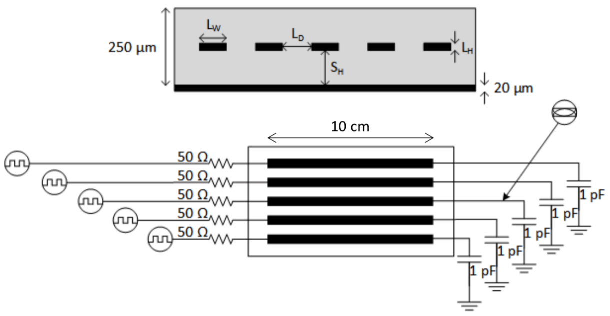

Fig. 1. Schematic of the high-speed link considered in this paper for the generation of the inverse model for the optimal design of the embedded microstrip.

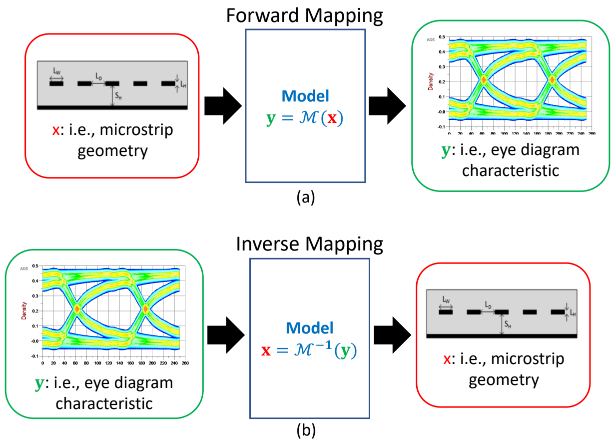

Fig. 2. Graphical interpretation of the high-speed link design tackled in this paper: panel (a) presents the standard forward mapping, (i.e., the full-computational model is used to derive input data), while panel (b) show the inverse problem mapping for the design. See the text for more details.

II. Proposed Model for the Inverse Problem & Results

Let us consider the high-speed link in Fig. 1. It consists of a five-channel bus operating at a data rate of 1 Gbps. The channel is driven by five single ended drivers and terminated by five receivers, modeled by their internal capacitance taking the value of 1 pF. Each of the drivers has been fed by a random bit stream at data rate of 1 Gbps with a rise/fall time of 100 ps with high and low voltage levels $V_H = 1$ V, and $V_L = 0$ V, respectively.

The link consists of an embedded microstrip structure with five coupled lines of length 10 cm. The traces and the ground plane are made of copper and the substrate is made of FR4 with $\epsilon_r = 4.3$ and thickness $250\,\mu$m. The ground plane thickness is set to $20\,\mu$m. Moreover, the traces width L_W, separation L_D, thickness L_H and their distance with respect to the ground plane S_H (see inset of Fig. 1 for additional details) have been considered as design parameters spanning over the following intervals: $L_W \in [70, 210]\,\mu$m, $L_D \in [75, 225]\,\mu$m, $L_H \in [15, 45]\,\mu$m and $S_H \in [50, 150]\,\mu$m.

The full computation model is obtained via simulations in HSPICE. Moreover, the embedded microstrip lines are modeled in HSPICE via the W-element, by using the frequency dependent per unit length (p.u.l) parameters estimated via the 2D extractor of the solver, for any value of the four geometrical parameters. Specifically, 8 characteristics of the eye diagram can be derived, i.e., the mean value of both the high and low logic levels, the eye diagram width and height, the average rise/fall time, the root mean square value of the jitter and the level crossing time point.

A graphical interpretation of the advocated computational procedure is outlined in Fig. 2(a), where the full-computational model $\mathbf{y} = \mathcal{M}(\mathbf{x})$ provides a forward mapping between the design parameter space $\mathbf{x} \in \mathcal{X} \subset \mathbb{R}^4$ (i.e., the 4 geometrical parameters of the embedded microstrip) and the corresponding simulation outputs $\mathbf{y} \in \mathcal{Y} \subset \mathbb{R}^8$ (i.e., the 8 eye diagram characteristics). However, the goal of this paper is to build an accurate and efficient model for the inverse mapping $\mathbf{x} = \mathcal{M}^{-1}(\mathbf{y})$ depicted in Fig. 2(b), which provides as output the geometrical parameters $\mathbf{x}$ of the embedded microstrip, needed to obtain the desired eye diagram characteristics $\mathbf{y}$. To this aim, the full-computational model has been used to generate a set of L training samples $\{\mathbf{x}_i, \mathbf{y}_i\}_{i=1}^{L}$, where $\mathbf{y}_i = \mathcal{M}(\mathbf{x}_i)$. Such samples are required to train the proposed surrogate model for the inverse problem, which we build via the LS-SVM regression with radial basis function (RBF) [8], [9], i.e.,

$$x_i = \mathcal{M}_i^{-1}(\mathbf{y}) \approx \tilde{\mathcal{M}}_{i,LS-SVM}^{-1}(\mathbf{y}), \tag{3}$$

for $i = 1, \ldots, 4$.

The surrogate model for the above inverse problem has been trained with an increasing number of training samples $L = 300$ and 500. The accuracy of the resulting models has been first investigated through the scatter plots of Fig. 3. The plots compare predictions of the geometrical parameters estimated by the proposed LS-SVM-based surrogare model for the inverse problem with the corresponding results of the full-computational model, for 250 validation samples. The plots highlight the good accuracy of two considered models, since the points are very close to the dashed black line representing the perfect correlation between the model and the reference samples. However, such kind of validation provides the worst-case scenario for the accuracy of the proposed surrogate model for the inverse model, since it is not able of accounting for the one-to-many behavior of the inverse model mapping.

To overcome the above limitation, a second validation is presented in Fig. 4. In this case, the scatter plots are computed by comparing 250 values of the desired eye-diagram characteristics: the mean high logic level, height, width and jitter with the corresponding results obtained with the full-computational model by using the geometrical configurations optimized by the proposed surrogate model. For this second unbiased validation, the results show the excellent accuracy of the proposed model for the inverse problem.

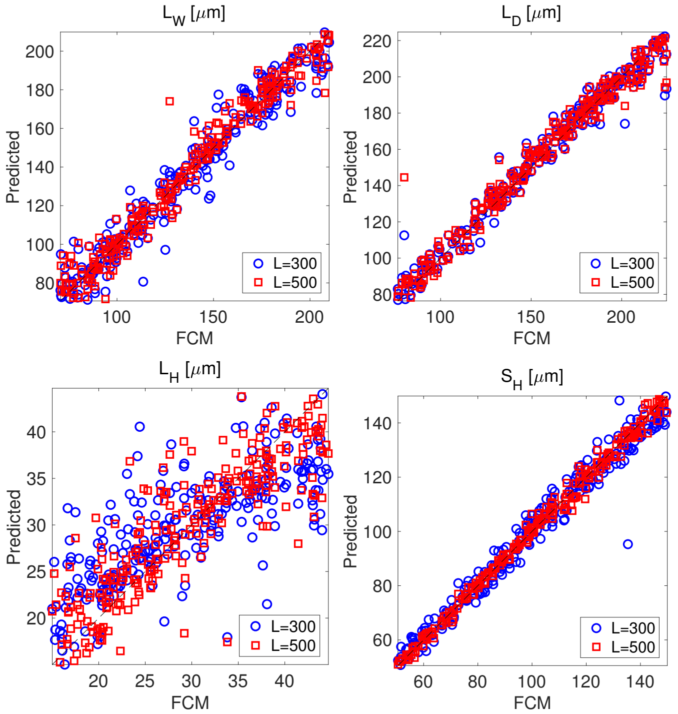

Fig. 3. Scatter plots comparing the geometrical parameters of the embedded microstrip structure of the link in Fig. 1 calculated via the full-computational model (FCM) for 250 validation samples with the corresponding ones predicted by the proposed surrogate model based on the LS-SVM regression built with $L = 300$ and 500 training samples.

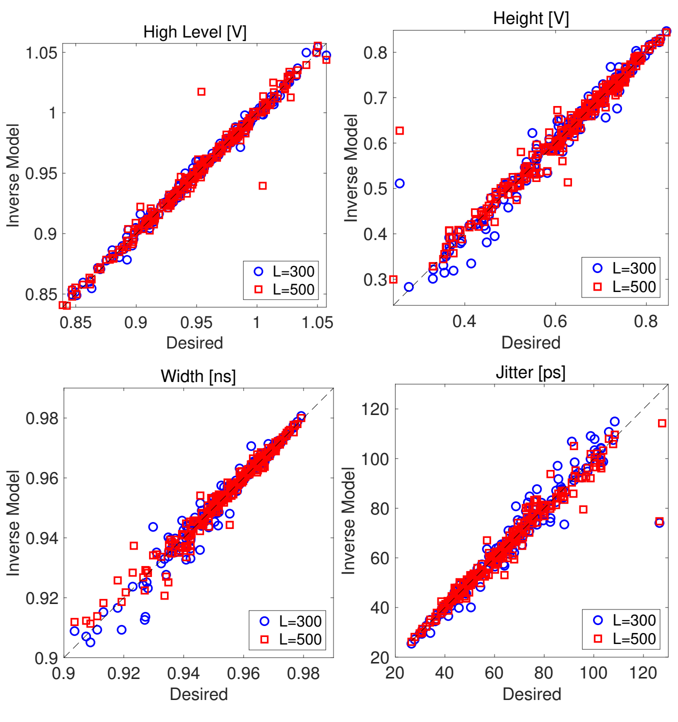

Fig. 4. Second validation providing the correlation between the desired values of the eye-diagram: high level, height, width and jitter with the corresponding ones obtained by simulating the FCM starting from the geometrical parameters of the embedded microstrip line optimized via proposed the surrogate model of the inverse problem for 250 unseen samples. The model is built with $L = 300$ and 500 samples.

III. Conclusions & Future Works

This paper focuses on the development of a surrogate model for the inverse problem based on the LS-SVM regression. The model is trained with a limited number of training samples provided by the results of a parametric simulation of the link based on the full-computational model. The resulting model allows providing the geometrical parameters of the embedded microstrip interconnects starting from the desired eye diagram characteristics without using any optimization algorithm, thus providing a valuable resource during the design phase of the channel.

Nevertheless, there are at least two open issues that should be carefully investigated in future research. Although several techniques for the selection of the training samples have been devised for the standard case of forward mapping, additional efforts are needed to adapt such methods to the case of the inverse mapping, especially with the aim of reducing the number of training samples. Also, since in general the inverse model results from an ill-posed problem having more than one solution, a large number of information data on the desired output $\mathbf{y}$ must be used in order to get an accurate prediction of the design parameters $\mathbf{x}$ (e.g., we are using 8 eye diagram characteristic descriptors). The definition of such excessive characteristics of the model may be cumbersome in realistic applications.

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