High-Speed Link Design Optimization Using Machine Learning SVR-AS Method

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***Abstract*—This paper proposes a novel and fast constrained design optimization method based on support vector regression-active subspace method. The proposed optimization method calculates a linear combination of original design parameters named active variable as a low-dimensional representation of high-dimensional design space to transform the non-linear constraint into a reduced linear constraint for optimization problems, which successfully derives a simplified and mathematically solvable equation. A complex high-speed link with 16-dimensional design parameters is utilized to verify this method and results show that the proposed method can efficiently find the optimal design structures compared to interior-point method.**

I. Introduction

High-dimensional design parameters optimization is one of the most important and challenging problems in the design process of complex high-speed links [1]. Traditional optimization algorithms lead to computational burdens for finding an optimal or relative optimal design due to excessive and repeated link simulation needs. To reduce the computation requirements, surrogate models established by a small amount of simulations or measurements are proposed to replace the link simulations in the optimization routine. Recently, machine learning techniques are also utilized to describes the inverse relationship from desired output to design parameters for efficient parameter optimization. Support vector regression (SVR) can provide the inverse relationship between eye features and geometrical parameters for high-speed links [2], while the combination of deep neural network and symbolic Knowledge Base is used as an intelligent learning architecture for inverse mapping [3].

In this work, we propose a novel and fast constrained design optimization method which uses support vector regression based active subspace (SVR-AS) algorithm [4] to calculate a reduced-dimensional input space of active variables as a linear combination of original design parameters and transforms the non-linear constraint into a linear constraint for optimization simplification. A mathematical formula is provided in this paper from the linear constraint provided by active variable for directly finding the optimal design structure with a specified output and the minimal mean squared distance from the specific design. Numerical results show that compared with interior-point method, SVR-AS based optimization method can successfully and efficiently find the optimal design structures for a complex high-speed link with 16-dimensional design parameters.

978-1-7281-6161-7/20/$31.00

II. Methodology

Let $\boldsymbol{X} = [x_1, ..., x_p]^{\mathrm{T}}$ represent the input p-dimensional normalized design parameter space (e.g. board geometry parameters), Y represents the output of interest (e.g. eye opening), $D = \{(\boldsymbol{X_1}, Y_1), ... (\boldsymbol{X_n}, Y_n)\}$ represents sampling data set, and function h be the non-linear mapping from $\boldsymbol{X}$ to Y. The objective is to find a set of $\boldsymbol{X}$ that is closet to a set of specified numbers (normalized to $x_i = 0$) for desired output. In other words, we want to find the design closest to a prototype design where the eye opening requirements are satisfied. Considering the mean squared distance between $\boldsymbol{X}$ and the nominal numbers, the optimization problem can be expressed as:

$$\begin{aligned} \min \quad & g(\boldsymbol{X}) = \tfrac{1}{p} \sum_{1 \le i \le p} x_i^2, \\ \text{s.t.} \quad & h(\boldsymbol{X}) = Y_0. \end{aligned} \tag{1}$$

A. SVR-AS

SVR-AS method can reduce input design space to a low-dimensional representation from the directions that perturbation on design parameters influence more on outputs. The speed and accuracy of SVR compare favorably with artificial neural networks and stochastic collocation for high-speed link models [5], [6]. SVR predictive function with Gaussian Kernel can be expressed as:

$$f(\boldsymbol{X}) = \sum_{1 \le j \le n} (\hat{\alpha}_j - \alpha_j) \exp\left(\frac{- \|\boldsymbol{X} - \boldsymbol{X}_j\|^2}{2\sigma^2} \right) + b, \tag{2}$$

where $\hat{\alpha}_j$ and α_j are Laplace operator, b is the displacement of hyper-plane and σ is the width of Gaussian Kernel.

A symmetric and positively semi-definite matrix is defined using the gradient of Eq. (2) as:

$$\boldsymbol{Z} = \frac{1}{n} \sum_{1 \le j \le n} \nabla_{\boldsymbol{X}} f(\boldsymbol{X}_j) \left(\nabla_{\boldsymbol{X}} f(\boldsymbol{X}_j) \right)^{\mathrm{T}}, \tag{3}$$

where $\nabla_{\boldsymbol{X}} f(\boldsymbol{X}) = \left[\frac{\partial f}{\partial x_1}, \ldots, \frac{\partial f}{\partial x_p} \right]^{\mathrm{T}}$. After eigendecomposition of $\boldsymbol{Z} = \boldsymbol{W} \boldsymbol{\Lambda} \boldsymbol{W^{-1}}$, let $\boldsymbol{W}_1$ be the partial set of eigenvectors corresponding to the largest q eigenvalues and

$\boldsymbol{y} = \boldsymbol{W}_1^{\mathrm{T}}\boldsymbol{X}$ denotes active variable as a lower-dimensional representation of the input parameters.

B. Design Optimization with Equality Constraints from SVR-AS

SVR-AS provides a sufficient summary plot to illustrate the relationship between active variables and expected output, which can be fitted by polynomial function and then provides the corresponding active variable $\boldsymbol{y}_0$ for desired output Y_0. Eq. (1) can be derived as:

$$\begin{aligned} \min \quad & g(\boldsymbol{X}) = \frac{1}{p}\sum_{1\le i\le p} x_i^2, \\ \text{s.t.} \quad & \phi(\boldsymbol{X}) = \boldsymbol{W}_1^{\mathrm{T}}\boldsymbol{X} - \boldsymbol{y}_0 = 0. \end{aligned} \tag{4}$$

Lagrange multiplier method can be used for optimal problem with constraints. Lagrange function for Eq. (4) can be expressed as:

$$L(\boldsymbol{X}, \boldsymbol{\beta}) = g(\boldsymbol{X}) + \boldsymbol{\beta}\phi(\boldsymbol{X}), \tag{5}$$

where $\boldsymbol{\beta} = [\beta_1, ...\beta_q]$ are the Lagrangian multipliers. The number of multipliers is equal to the number of eigenvectors we choose. The solution of the optimal problem is

$$\begin{cases} \frac{\partial L(\boldsymbol{X},\boldsymbol{\beta})}{\partial \boldsymbol{X}} & = 0 \\ \frac{\partial L(\boldsymbol{X},\boldsymbol{\beta})}{\partial \boldsymbol{\beta}} & = 0 \end{cases}, \tag{6}$$

which can be further derived as

$$\begin{cases} \frac{2}{p}\boldsymbol{X} + \boldsymbol{\beta}\boldsymbol{W}_1^{\mathrm{T}} & = 0 \\ \boldsymbol{W}_1^{\mathrm{T}}\boldsymbol{X} & = \boldsymbol{y}_0 \end{cases}. \tag{7}$$

Thus, the optimal design parameters can be expressed by

$$\boldsymbol{X} = \boldsymbol{W}_1\left(\boldsymbol{W}_1^{\mathrm{T}}\boldsymbol{W}_1\right)^{-1}\boldsymbol{y}_0. \tag{8}$$

III. Optimization Results and Discussion

A. Optimization Example

A chip-to-chip, realistic high-speed link model is considered as a representative example to verify the proposed optimization method. Fig. 1 illustrates the entire model that consists of transmitter, microstrip line, LGA [7], via model, strip line, via model, LGA, microstrip line and receiver. ANSYS Q3D simulator [8] and Keysight ADS [9] are used to simulate eye opening of the high-speed link. The desired output is eye width of eye opening after receiver. Design parameters of transmission lines of this link shown in the Fig. 2 and Table I are considered as the input design space.

B. Results from SVR-AS based Optimization Method

SVR-AS method uses 300 simulated data samples for forward surrogate model training and generates active variable as a reduced-dimensional design space. Since the first eigenvalue is much larger than the others, active variable in this work is defined as a one-dimensional linear combination of 16 design parameters. Fig. 3 shows the sufficient summary plot between active variable and corresponding eye width. A

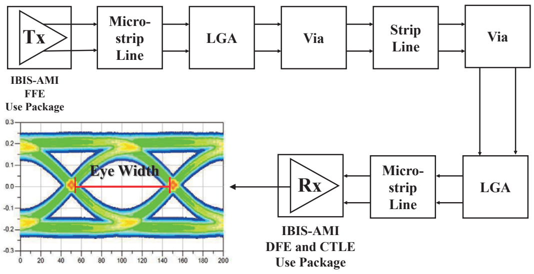

Fig. 1: High-speed link model and eye diagram.

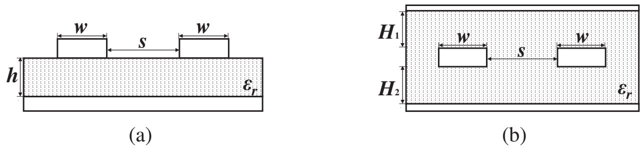

Fig. 2: Geometry of microstrip line and strip line.

second-order polynomial function shown in orange color fits this relationship well with 1.49×10^{-24} mean squared error.

Eq. (8) can be used to calculate the optimal design for desired eye width. In practice, it is common that several design parameters are fixed at specific values and thus not in the set of optimization variables. In this work, we fix $\varepsilon_r = 4.4$. Even for these requirements, a variant of Eq. (8) ($\boldsymbol{X}_{\text{rest}} = \boldsymbol{W}_{\text{rest}}\left(\boldsymbol{W}_{\text{rest}}^{\mathrm{T}}\boldsymbol{W}_{\text{rest}}\right)^{-1}\left(\boldsymbol{y}_0 - \boldsymbol{W}_{\text{set}}^{\mathrm{T}}\boldsymbol{X}_{\text{set}}\right)$) still solves the problem directly. Table I shows the optimal results calculated by SVR-AS based optimization method when eye width $Y_0 = 8 \times 10^{-11}$ sec is required. For this optimal design, simulated eye width is 8×10^{-11} sec as required and the mean squared distance from nominal number is 0.003 for normalized design parameters. SVR-AS based optimization method only needs 0.0014 sec to calculate the optimal results on an AMD Ryzen Threadripper 1950X 16-Core Processor without additional simulations or surrogate model predictions.

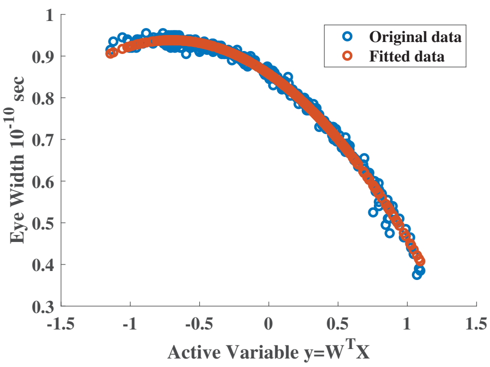

Fig. 3: Sufficient summary plot and its fitted function.

TABLE I

DESIGN SPACE AND OPTIMAL RESULTS OF THE HIGH-SPEED LINK

	Parameter	Specified design	Range	Optimal results from SVR-AS based optimization method	Optimal results from interior-point method with SVR model	Unit
Tx microstrip line	ε_r	4.4	3.6-5.2	4.4	4.4	/
	w	5	4.5-5.5	4.9996	4.9995	mil
	s	8	7.2-8.8	8.0011	8.0008	mil
	h	4	3.7-4.3	3.9999	4.0003	mil
	l	11	2-20	11.0920	11.0108	mm
Strip line	ε_r	4.4	3.6-5.2	4.4	4.4	/
	w	5	4.5-5.5	4.9977	4.9980	mil
	s	8	7.2-8.8	7.9975	7.9984	mil
	H_1	8	7.2-8.8	7.9999	8.0000	mil
	H_2	8	7.2-8.8	7.9952	7.9952	mil
	l	275	50-500	323.8759	327.2000	mm
Rx microstrip line	ε_r	4.4	3.6-5.2	4.4	4.4	/
	w	5	4.5-5.5	4.9997	4.9995	mil
	s	8	7.2-8.8	7.9994	8.0000	mil
	h	4	3.7-4.3	3.9996	3.9994	mil
	l	11	2-20	11.0521	11.0630	mm
Simulated eye width				80	80	ps
Eye width evaluations of optimization process				/	693	/
Computation time of optimization process				0.0014	7.69	sec
Mean squared distance from nominal design				0.0030	0.0034	/

C. Comparison and Discussion

Traditionally, interior-point method can solve non-linear constrained minimization problem through a sequence of approximation problems. In this example, interior-point method needs 38 iterations and 693 function evaluations to solve Eq. (1). Eye width is evaluated by SVR predictive model in this paper. Jointly calling ANSYS Q3D Extractor and Keysight ADS can also be used in the optimization stage to replace surrogate model. The optimal results are shown in Table I and the corresponding simulated eye width result is also 8×10^{-11} sec. The mean squared distance from nominal design is 0.0034 for normalized design parameters, which is larger than the result from SVR-AS based optimization method.

Results from Table I illustrate the comparison between SVR-AS method and interior-point method. SVR-AS optimization method can calculate the optimal results accurately with extremely low computation cost after the SVR predictive model is established. However, interior-point algorithm calls SVR predictive model repeatedly during the iterations. Also it is worth mentioning that SVR-AS based optimization method can quickly calculate lots of different settings that satisfies different specific requirements (in this paper, we keep $\varepsilon_r = 4.4$).

IV. CONCLUSION

In this paper, SVR-AS based optimization method is proposed for fast design optimization of complex high-speed link model. SVR-AS based optimization method utilizes the sufficient summary plot calculated by SVR-AS algorithm to successfully transform the complex non-linear constraint optimization into a linear equality constraint minimization problem and provides a directly solvable function for the optimal results calculation. Compared with interior-point method, a traditional non-linear constrained minimization algorithm, the proposed method has an extremely low computation cost and a better optimal result. Results show that SVR-AS based optimization method is promising for high-speed link pre-design.

ACKNOWLEDGMENT

Hanzhi Ma was supported by the Scientific Project Foundation of Zhejiang Lab under Grant No. 2020KC0AB01. Xu Chen was supported by the National Science Foundation under Grant No. CNS 16-24811 - Center for Advanced Electronics through Machine Learning (CAEML).

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