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System Margining Surrogate-Based Optimization in Post-Silicon Validation

Francisco E. Rangel-Patiño, José L. Chávez-Hurtado, Andres Viveros-Wacher, José E. Rayas-Sánchez, and Nagib Hakim

***Abstract*— There is an increasingly higher number of mixed-signal circuits within microprocessors. A significant portion of them corresponds to high-speed input/output (HSIO) links. Post-silicon validation of HSIO links is critical to provide a release qualification decision. One of the major challenges in HSIO electrical validation is the physical layer (PHY) tuning process, where equalization techniques are typically used to cancel any undesired effect. Current industrial practices for PHY tuning in HSIO links are very time consuming since they require massive lab measurements. On the other hand, surrogate modeling techniques allow to develop an approximation of a system response within a design space of interest. In this paper, we analyze several surrogate modeling methods and design of experiments techniques to identify the best approach to efficiently optimize a receiver equalizer. We evaluate the models performance by comparing with actual measured responses on a real server HSIO link. We then perform a surrogate-based optimization on the best model to obtain the optimal PHY tuning settings of a HSIO link. Our methodology is validated by measuring the real functional eye diagram of the physical system using the optimal surrogate model solution.**

***Index Terms*— DoE, equalization, eye diagram, HSIO, Kriging, neural network, optimization, polynomial, post-silicon validation, surrogate models, receiver, support vector machines.**

I. INTRODUCTION

ONE OF THE MAJOR challenges in computer servers post-silicon electrical validation is the physical layer (PHY) tuning process, where equalization (EQ) techniques are used to cancel undesired effects, including jitter, attenuation, and inter-symbol interference, among others [1]-[3]. PHY tuning in HSIO links is one of the most time-consuming processes in post-silicon validation [4]-[6], since current industrial practices for PHY tuning are typically based on exhaustive testing requiring massive lab measurements, a process that typically takes several weeks to perform.

Accurate direct simulations for PHY tuning in HSIO links are difficult to obtain and computationally very expensive given the complexity of the system involved. On the other hand, surrogate models are scalable mathematical models that can be used as a parameterized approximation of a system response within a design space of interest [7], [8].

In this paper, we develop surrogate models of a high-speed input/output (HSIO) link based on actual measurements of an industrial server post-silicon validation platform. We compare several surrogate modeling methods combined with different design of experiments (DoE) techniques to find the best approach to efficiently simulate the PHY tuning process, verifying the accuracy of the resultant surrogate models by comparing with actual measurements. We next perform a surrogate-based optimization (SBO) with the best surrogate model found to obtain the optimal PHY tuning receiver (Rx) equalizer settings. We finally validate our approach by measuring the actual functional eye diagram on the real system using the optimal settings predicted by the best surrogate.

The present article expands our work in [6] and [9] by incorporating the following aspects: a) we explore several additional surrogate modeling techniques (besides Kriging) to efficiently simulate the PHY equalizer circuitry of the Rx, namely: polynomial-based surrogate modeling (PSM), support vector machines (SVM), generalized regression neural networks (GRNN), and 3-layer perceptron neural networks (3LP ANN); b) we generate the models by using reduced sets of training and testing data exploiting different DoE techniques: Box Behnken (BB); orthogonal arrays (OA), and Sobol; c) we perform a SBO on the best model found to obtain the optimal Rx PHY tuning setting values; d) we evaluate the models performance by comparing with actual measured responses on a real server HSIO link.

This paper aims at assessing several surrogate modeling and DoE techniques to identify the best approach to address a highly relevant industrial challenge: optimizing a receiver equalizer in a measurement-based server HSIO validation platform, focusing on system margining performance. In contrast, [9] considers a simpler, simulation-based HSIO system, with a generic receiver, transmitter, and channel, including the transmitter parameters as optimization variables. Also in contrast, [6] incorporates jitter tolerance in the system performance but it is restricted to only one surrogate modeling approach (Kriging) and one DoE technique (Sobol low discrepancy sequence).

The organization of this paper is as follows: Section II describes the physical system and measurement setup. Section III describes the DOE approaches. Section IV presents the different surrogate modeling techniques and the SBO procedure. Results are discussed in Section V. Finally, Section

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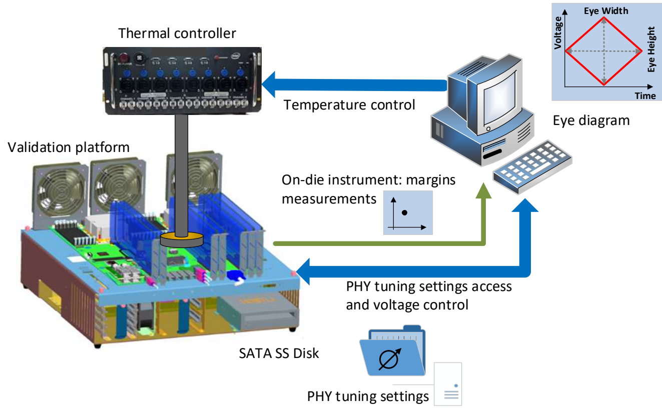

Fig. 1. Test setup: an Intel server post-silicon validation platform.

VI concludes our work.

II. System Description

The system under test is an Intel server post-silicon validation platform in an industrial environment, as shown in Fig. 1. The platform is comprised mainly of a CPU and a platform controller hub (PCH). The PCH is a family of Intel microchips which controls data paths and support functions used in conjunction with the Intel CPU through direct media interface (DMI) [6]. Within the PCH, our methodology was tested on a HSIO link SATA Gen3 [10]. The SATA channel topology is comprised of the Tx driver, the Tx base board transmission lines, several via transitions, an I/O card connector, and 1 m SATA cable used to connect the base board to the device I/O card, as illustrated in Fig. 2. The measurement system is based on an Intel process called system margin validation (SMV) [11], which is a methodology to assess how much margin is in the design relative to silicon characteristics and processes that vary over time, including voltage, temperature, frequency, humidity, and component aging, among other factors. The fundamental process behind the SMV consists of systematically adjusting the corner conditions under which the validation platform operates, then measure the Rx functional eye opening by using on-die design for test (DFT) features until the eye opening has been shrunk to a point where the Rx detects errors or the system fails, as illustrated in Fig. 3.

III. Design of Experiments

A large amount of training and testing data is usually needed to ensure surrogate model accuracy. However, generating large amounts of data is very expensive in the post-silicon validation environment. DoE can be exploited to reduce the dimension of these data sets, ensuring adequate parameter coverage [12]. Here we use DoE to sample the complete design space in an efficient manner by selecting a relatively small number of base points. With k variables and 3 levels for each variable, a full factorial space search requires 3^k experimental runs. We employ three different DoE techniques to explore the desired solution space with a far less number of

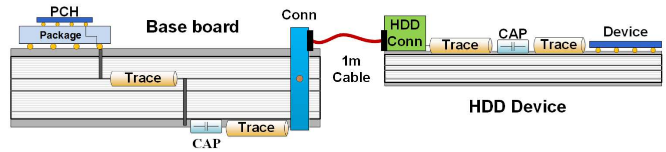

Fig. 2. SATA3 Rx channel topology.

runs: BB, OA, and Sobol. For each technique, we use five input variables that represent Rx PHY parameters, including CTLE (two), VGA (one), and CDR (two) settings, and then we retrieve the eye measurements from the system under test. The samples taken are later used as the training and testing data required for surrogate modeling.

A. Box Behnken (BB)

Response surface methodology (RSM) is a collection of techniques commonly used to obtain the model of a system under study whose response is affected by a set of input variables [13]. RSM helps to find first and second order effects of k variables on the measured outputs. First order effects are easily obtained through two-level full or fractional designs, whereas second order effects are usually captured by spherical designs such as the central composite design [9] that requires up to five levels for each variable (the center points, ±1 and $\pm\alpha$, where $\alpha = k^{1/2}$).

BB is a type of second order RSM design that combines factorial designs with balanced incomplete blocks designs [14]. This characteristic is particularly helpful for variables that are not able to take $k^{1/2}$ values, such as digitally controlled variables, as in our system under test. In this manner, we use only 3 levels for each variable, yielding a total number of 46 experiments. We denote this DoE as BB.

B. Orthogonal Arrays (OA)

OAs are experimental designs identified by $L_N(s^k)$, where N is the number of experimental runs, s is the number of states (or levels) for each variable and k is the number of variables [15]. Their most important feature is that for each variable, all possible levels appear equally often. OAs help to reduce the number of experiments while maintaining the ability to measure the effect of each variable on the output without the need to test all possible combinations.

When $s = 2$, the resulting OA allows to see linear effects. By increasing the value of s, non-linear effects can be assessed. We use an $L_{27}(3^5)$ OA in our work in order to capture non-linear effects in the objective function by only running 27 experiments. We denote this DoE as OA27.

C. Sobol

The most commonly used stochastic sampling algorithm is Monte Carlo. Monte Carlo sampling tends to generate clusters of points, leading to unnecessary samples, as well as leaving gaps in the solution space. One approach to overcome these issues is to use quasi-Monte Carlo methods such as low-discrepancy sequences [16]. The measure of non-uniformity of a sequence of points is known as discrepancy.

We select the Sobol [17] low-discrepancy sequence as the third DoE option to sample the solution space. It is generated

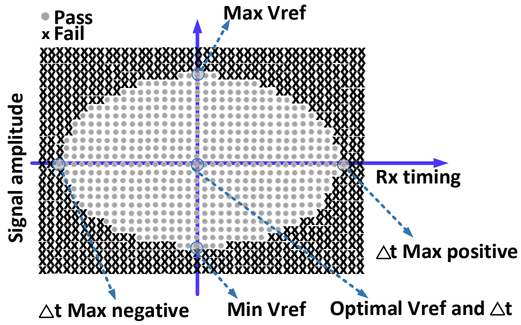

Fig. 3. Functional eye diagram based on system margin validation.

from a set of binary fractions v_i^j of length w bits, where i = 1, 2, …, w and j = 1, 2, …, d is the dimension. The Sobol sequence

$$x_n^j (n = \sum_{i=0}^{w} b_i 2^i , b_i \in \{0,1\}) \tag{1}$$

in dimension j is generated by

$$x_n^j = b_1 v_1^j \oplus b_2 v_2^j \oplus \ldots \oplus b_w v_w^j \tag{2}$$

where operator ⊕ denotes the bitwise XOR operation.

The solution space is better explored as the number of samples increases, at the expense of increasing test time on the real system. Therefore, we use three different Sobol DoE, denoted as Sobol50, Sobol100 and Sobol150, with 50, 100 and 150 samples, respectively.

IV. Surrogate Modeling and Optimization

Surrogate models can be constructed using data from high-reliability models or from measurements, and provide fast approximations of the original system or component at new design points [18]. The surrogates provide fast approximations of the system response, making optimization and sensitivity studies possible. Response surface approximations, neural network techniques, splines, and kriging are examples of methods used to generate surrogates for simulations in the optimization of complex problems [19]. The major benefit of surrogate models is the ability to quickly obtain any number of additional function evaluations without resorting to more expensive numerical models. In this section, several surrogate modeling techniques are explored to construct an efficient surrogate model for PHY equalizer simulation.

A. Surrogate Model Formulation

Let $\boldsymbol{R}_\text{f} \in \Re^m$ represent the actual electrical margining system response, denoted as a fine model response, consisting of the eye width $e_\text{w} \in \Re$ and eye height $e_\text{h} \in \Re$ of the measured functional eye diagram (m = 2) illustrated in Fig. 3,

$$\boldsymbol{R}_\text{f}(\boldsymbol{x},\boldsymbol{\psi},\boldsymbol{\delta}) = \begin{bmatrix} e_\text{w}(\boldsymbol{x},\boldsymbol{\psi},\boldsymbol{\delta}) \\ e_\text{h}(\boldsymbol{x},\boldsymbol{\psi},\boldsymbol{\delta}) \end{bmatrix} \tag{3}$$

The electrical margining system response $\boldsymbol{R}_\text{f}$ depends on the Rx PHY tuning setting values $\boldsymbol{x}$, the operating conditions $\boldsymbol{\psi}$ (voltage and temperature), and the devices $\boldsymbol{\delta}$ (silicon skew and end-point devices).

The surrogate models are trained such that its response is as close as possible to the fine model response for all data in the training set,

$$\boldsymbol{R}_\text{s}(\boldsymbol{x},\boldsymbol{\psi},\boldsymbol{\delta}) \approx \boldsymbol{R}_\text{f}(\boldsymbol{x},\boldsymbol{\psi},\boldsymbol{\delta}) \tag{4}$$

where $\boldsymbol{R}_\text{s} \in \Re^m$ is the response of the surrogate model.

Two sets of data (inputs $\boldsymbol{x}$ and targets $\boldsymbol{R}_\text{f}$) are used to develop the surrogate models: a learning set used to measure the training error, and a testing set used to measure the generalization error during training.

B. Surrogate Modeling Techniques

By using the PHY tuning setting values as inputs and the corresponding eye height and eye width as targets, we exploit five different surrogate modeling techniques: PSM, SVM, Kriging, GRNN, and a 3LP ANN.

PSM is a surrogate modeling technique that has been used to model microwave structures in the frequency domain [20] and also microwave structures subject to multiphysics variations [21]. The surrogate model is implemented by exploiting the multinomial theorem, which allows the algorithm to raise a polynomial to an arbitrary power with all cross terms and no redundancies. A polynomial function is used to represent the behavior of the response around a reference design. The order of the polynomial function is increased until generalization performance deteriorates. A particular advantage of this surrogate model technique relies in the fact that weighting factors are calculated in closed form, achieving a global minimum in the least squares sense and exhibiting a very cheap computational cost. A detail mathematical formulation of PSM is in [20].

GRNN is a special type of ANN that does not require an iterative training procedure [22]. Moreover, the number of neurons in the hidden layers is equal to the number of learning samples [23]. As the number of samples becomes large, this technique exhibits a fast learning and convergence to the optimal regression surface [24]. GRNN uses a special kind of radial basis functions; a detail formulation of GRNN is in [25].

SVM are trained by using the structural risk minimization principle, instead of empirical risk minimization principle used by ANNs models. It allows SVM models to exhibit a good tradeoff between model complexity and generalization capability [26]. The SVM technique solves a constrained quadratic optimization problem, finding a global optimum for the model parameters. The optimization problem is feasible due to the use of kernel functions, being the radial basis function the most employed kernel [27], [28]. A detail formulation of SVM is in [27]. Our implementation exploits the SVM regression available in Matlab, with linear kernel functions and sequential minimal optimization solver (default).

Kriging surrogate modeling is based on space filling experiments, aiming at covering the whole experimental area [29]. Kriging is a kind of kernel-based probabilistic model; it minimizes the prediction variance by exploiting the best linear unbiased estimator of the output value for a given input. If there are not enough function evaluations, the predictions may become inaccurate [29]. A detailed formulation of Kriging is in [29]. Our Kriging implementation exploits the Gaussian process regression available in Matlab, with squared exponential built-in kernel functions (default).

TABLE I

SURROGATE MODELS GENERALIZATION ERROR ε FOR EYE HEIGHT

model	BB	OAL27	Sobol50	Sobol100	Sobol150
PSM	2.77%	8.90%	2.68%	2.05%	0.42%
SVM	6.35%	6.70%	6.69%	6.79%	6.77%
Kriging	3.10%	7.01%	2.74%	1.89%	1.45%
GRNN	7.47%	9.27%	2.86%	2.15%	1.58%
3LPANN	3.33%	7.14%	2.49%	1.96%	1.15%

TABLE II

SURROGATE MODELS GENERALIZATION ERROR ε FOR EYE WIDTH

model	BB	OAL27	Sobol50	Sobol100	Sobol150
PSM	1.66%	2.79%	1.37%	1.23%	0.11%
SVM	3.27%	4.32%	3.43%	3.48 %	3.49%
Kriging	2.71%	5.36%	1.23%	1.28%	0.55%
GRNN	3.82%	4.33%	1.14%	1.04%	0.53%
3LPANN	2.96%	2.59%	1.71%	1.27%	0.56%

The multilayer perceptron (MLP) is a feedforward network and one of the ANN topologies most widely used [30]. They can use different kinds of activation functions with different approximation properties [31], including sigmoidal, hyperbolic tangent, Gaussian, piece-wise linear, etc. In this work, we use hyperbolic tangent activation functions. The number of neurons (h) in the hidden layer depends on the required complexity of the ANN, and its final number is defined based on the ANN generalization performance. In this work, the 3-layer perceptron (3LP) ANN is trained by using Bayesian regularization training [32] available in the MATLAB Neural Network ToolBox. We start training the 3LP ANN with $h = 1$, calculating the corresponding learning and testing errors. We keep increasing the complexity of the ANN (the number of hidden neurons h) until the current testing error is larger than the previous one and the current learning error is smaller than the current testing error [33]. A detailed formulation of ANN is in [34].

SVM, Kriging, and GRNN were implemented using available toolboxes in Matlab (ver. 8.4, R15b) with default parameters. The PSM model was implemented in Matlab based on the procedure presented in [20]. The 3LP ANN was implemented in Matlab as described above.

General reviews of surrogate modeling techniques are available in [7], [35], and [36].

C. Direct Surrogate Model Optimization

According to their generalization performance, we select the best surrogate model found and use it for direct optimization. Following [9], our optimization procedure maximizes the eye diagram by minimizing the following objective function obtained from the best surrogate,

$$u(\boldsymbol{x}) = -[e_{\mathrm{w}}(\boldsymbol{x},\boldsymbol{\psi},\boldsymbol{\delta})][e_{\mathrm{h}}(\boldsymbol{x},\boldsymbol{\psi},\boldsymbol{\delta})] \tag{5}$$

We aim at finding the optimal set of PHY tuning setting values $\boldsymbol{x}^*$ by solving

$$\boldsymbol{x}^* = \arg\min_{\boldsymbol{x}} u(\boldsymbol{x}) \tag{6}$$

Our SBO procedure uses the Nelder-Mead simplex-based method [37] to solve (6). Notice that solving (6) is computationally very efficient since $u(\boldsymbol{x})$ is evaluated from the already available surrogate.

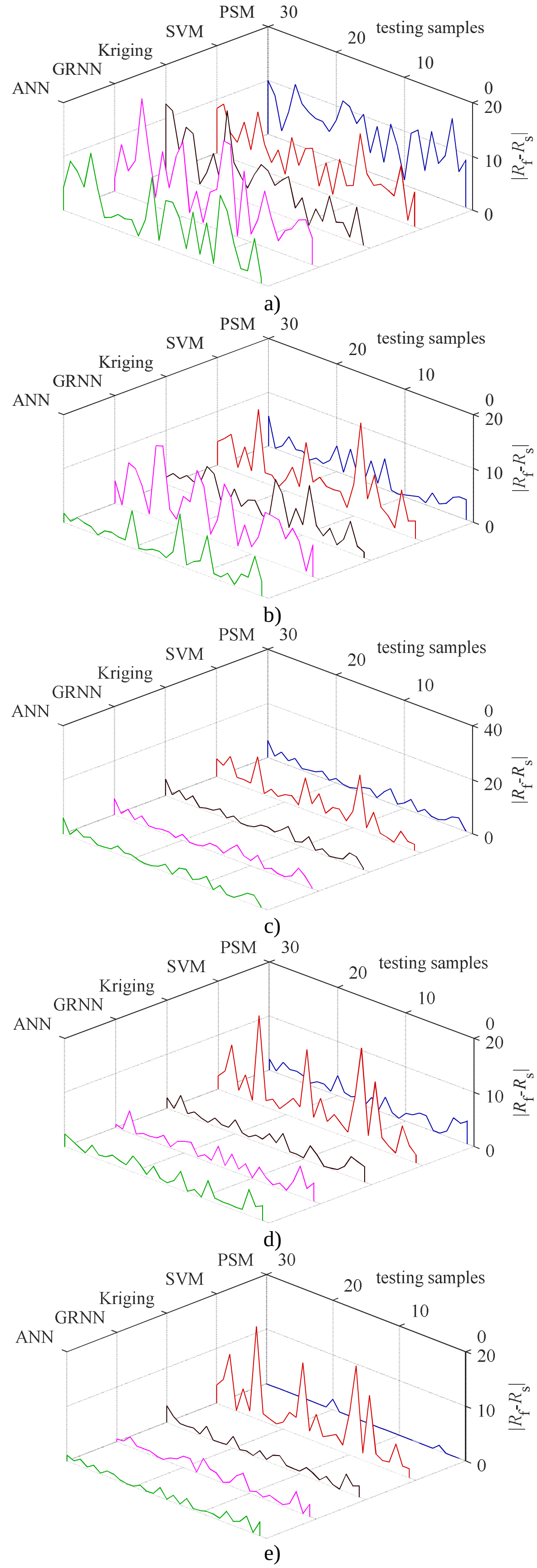

Fig. 4. Surrogate models absolute testing errors for eye height, using: a) OAL27, b) BB, c) Sobol50, d) Sobol100, and e) Sobol150.

V. Results and Comparisons

We first evaluate the accuracy of the obtained surrogate models by comparing with actual measured responses from a SATA Gen3 HSIO link. The average relative error $\boldsymbol{\varepsilon}$ for eye height and eye width at testing base points ($\boldsymbol{x}_{\mathrm{T}}$) not seen during training is calculated as

$$\varepsilon = \frac{\left\| \boldsymbol{R}_{\mathrm{f}}(\boldsymbol{x}_{\mathrm{T}}) - \boldsymbol{R}_{\mathrm{s}}(\boldsymbol{x}_{\mathrm{T}}) \right\|_2}{\left\| \boldsymbol{R}_{\mathrm{f}}(\boldsymbol{x}_{\mathrm{T}}) \right\|_2} \tag{7}$$

In all the modeling cases, we use 30 randomly distributed testing base points not seen during training to measure the generalization performance. Norms in (7) are calculated using these 30 testing base points.

Tables I and II show a summary of the generalization performance, obtained from (7), for the eye height and eye width, comparing the five surrogate models using the five DoE: a) OAL27, b) BB, c) Sobol50, d) Sobol100, and e) Sobol150. It is seen from those tables that, overall, the PSM technique yields the lowest testing average relative errors for both eye measurements when using Sobol150, which is the DoE technique yielding best generalization performance.

Fig. 4 and Fig. 5 show the absolute error at all testing samples for both eye height and eye width, for the five surrogate models using the five DoE techniques. When using OAL27 DoE, it is observed that the SVM model shows the best accuracy for eye height (Fig. 4a), while the 3LP-ANN model provides the best accuracy for eye width (Fig. 5a). When using the BB DoE, the PSM shows the best accuracy for both eye height and width (Figs. 4b and 5b). 3LP-ANN and GRNN models exhibit the best performance when using Sobol50 DoE (Figs. 4c and 5c). When the surrogate models are developed using Sobol100 DoE, the best performance is achieved by Kriging and GRNN models (Figs. 4d and 5d). Finally, it is observed that the PSM technique with Sobol150 DoE yields the best generalization performance (Figs. 4e and 5e), with the lowest average relative testing errors, as confirmed in Tables I and II. From here, we take PSM with Sobol150 as the best surrogate model found.

The actual responses from the best surrogate model found are compared in Figs. 6 and 7 with the fine model response (real measurements), at the same 30 randomly distributed testing base points. It is observed that the PSM model effectively simulates the fine model.

We next perform a SBO with the best PSM surrogate model, as described in Section III.C, to obtain the optimal PHY tuning Rx equalizer settings. Finally, we validate the SBO results by measuring the SATA link Rx inner eye height/width at $\boldsymbol{x}^*$ on the real validation platform with a commercial SATA device. The results, shown in Fig. 8, indicate an improvement of 400% on eye diagram area as compared to the initial PHY tuning settings, demonstrating the high effectiveness of our approach.

The methodology outlined in this paper can be applied to any server silicon that has a similar receiver circuitry with adjustable EQ parameters. Intel works closely with server systems manufacturers to design a reference platform [38], and hence the validation platform we are using is actually a representation of the platforms used by Intel customers.

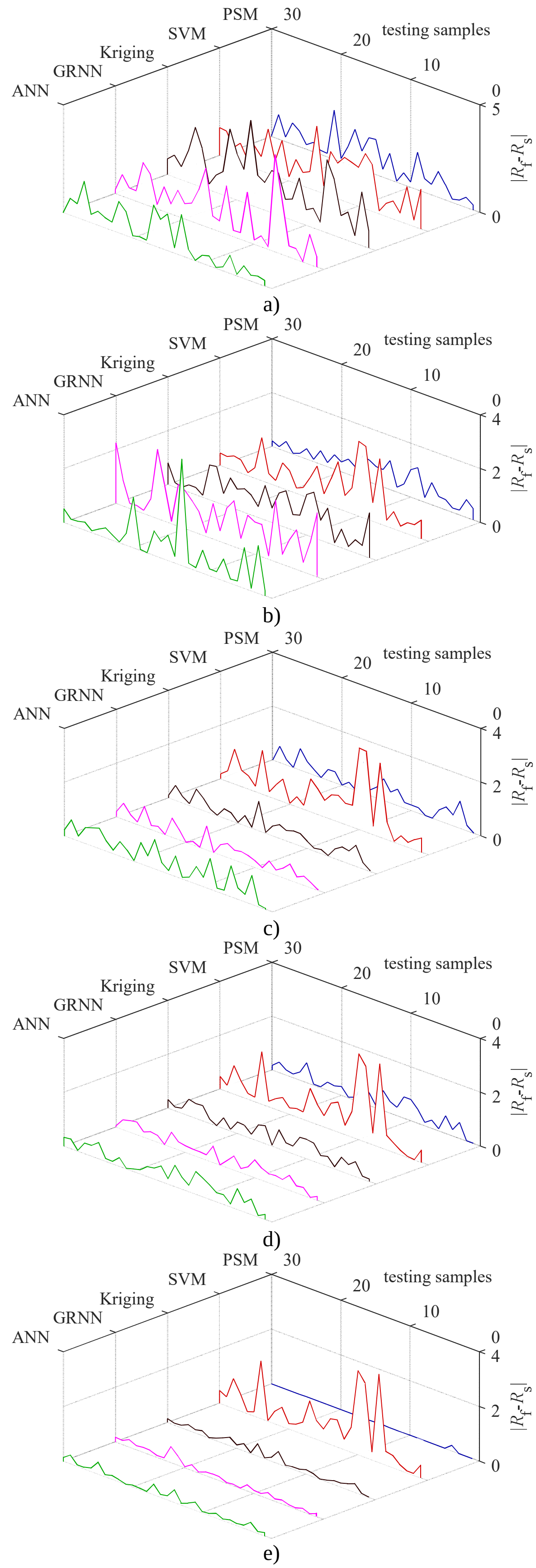

Fig. 5. Surrogate models absolute testing errors for eye width, using: a) OAL27, b) BB, c) Sobol50, d) Sobol100, and e) Sobol150.

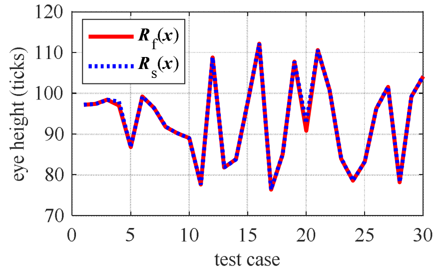

Fig. 6. Comparison between fine model responses and polynomial surrogate model responses at testing base points for the eye height.

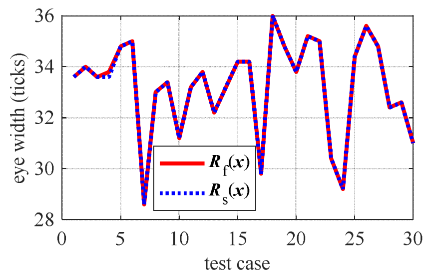

Fig. 7. Comparison between fine model responses and polynomial surrogate model responses at testing base points for the eye width.

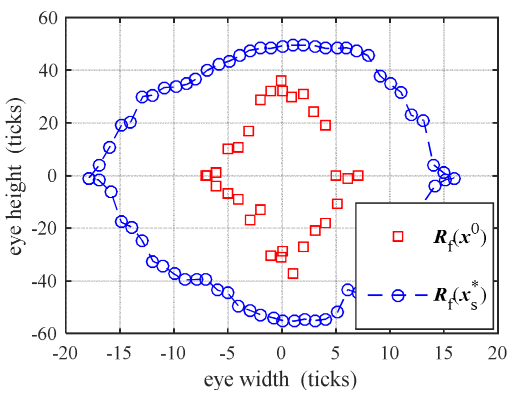

Fig. 8. Comparison between the system fine model responses before and after surrogate-based optimization (square and circle marks, respectively).

VI. Conclusion

We presented several surrogate modeling techniques to find the best approach to simulate the Rx equalization circuitry in an industrial HSIO link. Several surrogate models were trained with different DOE techniques to choose the best sampling approach. All surrogate models were evaluated by comparing with actual measured responses on a real server HSIO link. We selected the best combination of surrogate modeling technique and DOE in terms of accuracy and generalization performance, and applied a surrogate-based optimization to maximize the eye diagram area. The values obtained through our SBO procedure were evaluated by measuring the real functional eye diagram of the physical system, showing a great improvement as compared with the initial margining system performance.

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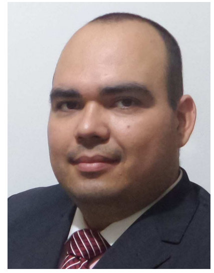

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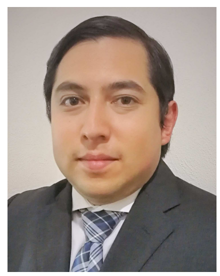

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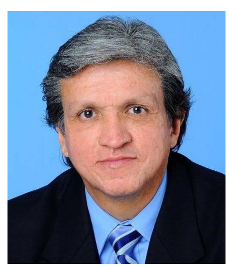

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