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Selecting Surrogate-Based Modeling Techniques for Power Integrity Analysis

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***Abstract* — In recent years, extensive usage of simulated power integrity (PI) models to predict the behavior of power delivery networks (PDN) on a chip has become more relevant. Predicting adequate performance against power consumption can yield to either cheap or costly design solutions. Since PI simulations including high-frequency effects are becoming more and more computationally complex and expensive, it is critical to develop reliable and fast models to understand system's behavior to accelerate decision making during design stages. Hence, metamodeling techniques can help to overcome this challenge. In this work, a comparative study between different surrogate modeling techniques as applied to PI analysis is described. We model and analyze a PDN that includes two different power domains and a combination of remote sense resistors for communication and storage CPU applications. We aim at developing reliable and fast coarse models to make trade off decisions while complying with voltage levels and power consumption requirements.**

***Index Terms* — DoE, fitting algorithms, neural networks, polynomial surrogate modeling, power delivery network, power integrity, support vector machines, surrogate model.**

I. Introduction

The usage and implementation of metamodels, so called surrogate based models, has been well explored in signal integrity applications such as high speed I/O simulation [1] and validation to come up with reasonable equalization tuning knobs and maximizing eye's opening [2], as well as, for antennas and high-speed filter design applications [3], [4], or study of fault and tolerance analyses [5], [6].

Power integrity (PI) has important effects on RF and signal integrity design, since transmitted data on high-speed interconnects can be severely deteriorated if the power sources that feed the RF circuitry and buffers is noisy or at improper voltage levels.

The usage of surrogate models for PI applications has not been widely exploited yet. An example of its usage is described in [7], where machine learning (ML) techniques, based on Bayesian optimization (BO), are used to come up with a black box system where integrated voltage regulators (IVR) and embedded package inductors (EPI) are co-simulated to design a robust PI solution.

This paper focuses on the study of different surrogate-based modeling techniques, including response surface modeling (RSM) [8], polynomial surrogate modeling exploiting the multinomial theorem (PSM) [4], and support vector machines (SVM) [6], [9], to build parametrized black box models for power integrity applications.

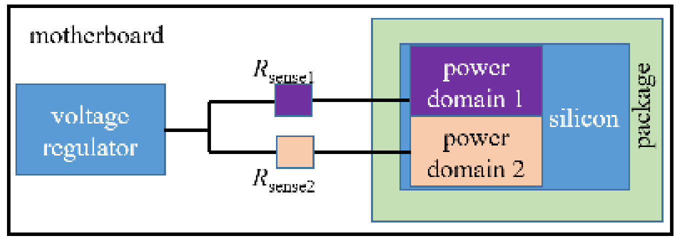

Fig. 1. Illustration of the PDN under study, with a single VR and two remote sense resistors for two different power domains at silicon

Our paper is organized as follows. In Section II, we describe the PI application under study. Section III briefly reviews the surrogate-based modeling techniques used. In Section IV, we compare the performance of the surrogate models developed and identify the best approach. Finally, we state our conclusions and indicate some future work.

II. Power Delivery Network Under Study

The power delivery network (PDN) under study corresponds to a monolithic CPU processor for communication and storage applications. It requires sharing two power domains with a single voltage regulator (VR). However, these two power domains operate with different current and power magnitudes at silicon level, requiring an implementation of a dual remote sensing feedback scheme at silicon level, as illustrated in Fig. 1.

Since it is required that both power domains meet their own minimum voltage (V_{min}) and power consumption (P_D) specifications, we need to find optimal sense resistors (R_{sense}) to ensure the right operation at the silicon. To achieve this, engineers typically rely on their expert knowledge to try suitable combinations of R_{sense} and maximum current (I_{max}), collecting both P_D and V_{min} and selecting the combination that best achieves design specifications; this can be a very time consuming process.

III. Developing Metamodels for PI Applications

As mentioned before, sweeping iteratively several current and resistance values is very time consuming from simulation and post-processing perspective (fine model). It is desirable to develop a fast surrogate (coarse) model that behaves similarly to our fine model. Then, we can formulate a general surrogate coarse model function:

$$f_c(\boldsymbol{x}) = f_f(\boldsymbol{x}) + \varepsilon \tag{1}$$

where $\boldsymbol{x} \in \Re^k$ contains the design variables or model parameters, in this case $\boldsymbol{x} = [R_{sense1}\ R_{sense2}\ I_{max1}\ I_{max2}]^T$, $f_c(\boldsymbol{x})$ and $f_f(\boldsymbol{x})$ are the coarse and fine model functions, respectively, for each PDN response of interest, and ε represents the inherent error due to the approximate method employed to obtain our coarse but fast model.

We consider three surrogate modeling techniques: response surface methods (RSM), polynomial surrogate modeling (PSM), and support vector machines (SVM). It should be noted that for each of these methods, we employed the same formulation to create our training data set denoted by:

$$b = 2^k + (2k) + n_c \tag{2}$$

where b is the number of combinations to be evaluated, k is the number of variables of interest, 2^k is the number of scenarios evaluated at high and low corners, $2k$ corresponds to the number scenarios evaluated at each corner plus a given deviation α, and n_c is the number of center points.

Table I illustrates our DoE input data used to train and assess the three surrogate-based modeling techniques. Notice that the training region of interest is quite large, especially for the sensing resistors.

TABLE I
DoE TRAINING DATA SET CONSIDERING CORNER CASES

R_{sense1}	R_{sense2}	I_{max1}	I_{max2}
85	15	2.2	12
50	50	1.55	20
50	50	0.63	20
85	85	2.2	28
15	85	0.9	12
85	85	0.9	12
15	15	0.9	28
15	15	0.9	12
50	50	1.55	8.68
85	15	0.9	12
15	15	2.2	12
0.50	50	1.55	20
15	85	2.2	28
85	85	0.9	28
85	15	2.2	28
50	50	1.55	31.31
99.49	50	1.55	20
85	85	2.2	12
15	15	2.2	28
50	50	2.46	20
50	99.49	1.55	20
15	85	0.9	28
85	15	0.9	28
50	50	1.55	20
50	0.50	1.55	20
15	85	2.2	12

A. Surrogate Model Based on Response Surface Methods

RSM methods are obtained from first and second order polynomial regression equations, whose coefficients are given by the wellness of the fitness response [8]:

$$f_c(\boldsymbol{x}) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + \varepsilon \tag{3}$$

$$f_c(\boldsymbol{x}) = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_i x_i^2 + \sum\sum_{i<j} \beta_{ij} x_i x_j + \varepsilon \tag{4}$$

where (3) is the general first order regression model formulation, and (4) corresponds to the second order regression model formulation. The coefficients found after performing the RSM analysis are in vector $\boldsymbol{\beta}$.

B. Surrogate Model Based on Polynomial Models

As described in [4], polynomial based surrogate models (PSM) are similar to RSM methods. However, one of its advantages is that it is not restricted up to second order polynomial formulations. A general formulation for this method applying the multinomial theorem [4] is given by:

$$f_c(\boldsymbol{x}) = f_c^{n-1}(\boldsymbol{x}) + \boldsymbol{w}^{nT} \boldsymbol{q}^n(\boldsymbol{x}) \tag{5}$$

where $f_c^{n-1}(\boldsymbol{x})$ is the function of the previous polynomial coarse model function evaluated at $n-1$ order, $\boldsymbol{w}^{nT}$ is the transpose vector of the weighting factors and $\boldsymbol{q}^n(\boldsymbol{x})$ contains the n–th order multinomial terms.

C. Surrogate Model Based on Support Vector Machines

Due to its availability in Matlab® [9] and their easy usage, support vector machines (SVM) becomes a suitable mechanism to compare against the above described methods. SVM makes available machine learning techniques particularly tailored for approximating and classifying data.

IV. Performance and Selection of Surrogate Model

We are exploring three different methods to generate surrogate models based on a PDN with a single VR, aiming to find a remote sense recipe that allows two different power rails to perform adequately. From our DoE input data (Table I), each R_{sense} is constrained in two corners, where the maximum is 85 Ω and the minimum is 15 Ω. Since we are handling two different power domains, for the case of the current we have I_{max1} constrained from 0.9 A to 2.2 A, and I_{max2} constrained from 12 A to 28 A. The remaining values for all variables are defined by the center points and maximum and minimum deviations given by α, as seen in Table I.

Time domain simulations were carried out in HSPICE[1] simulator to collect the system responses $\boldsymbol{R}_f$ in specific time windows, being $\boldsymbol{R}_f = [P_{D1}\ P_{D2}\ V_{min1}\ V_{min2}]^T$. Using $\boldsymbol{R}_f$ as target and $\boldsymbol{x}$ as input, we implemented in Matlab[2] the three surrogate modeling methods described previously to generate our coarse models. Figures 2 and 3 show a comparison of the fine and coarse model responses when using SVM, both normalized due to Intel's confidentiality constraints.

To compare the performance and quality of each surrogate model, we tested their responses against HSPICE results. As figures of merit, we calculate the errors for each P_D and V_{min} measurement to verify which method gave us closer results

[1] Hspui for Windows, G-2012.06, Synopsys®, 690 East Middlefield Road, Mountain View, CA 94043.

[2] MATLAB, Version R2015a, The MathWorks, Inc., 3 Apple Hill Drive, Natick MA 01760-2098, 2006.

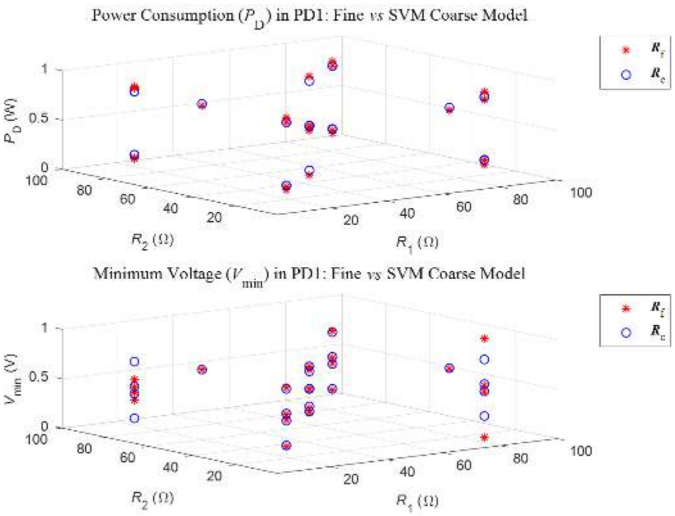

Fig. 2. Normalized scattered plot for P_D and V_{min} from power domain 1 sweeping R_{sense1} and R_{sense2}. A comparison between fine model response (star) and coarse model response using SVM (circle).

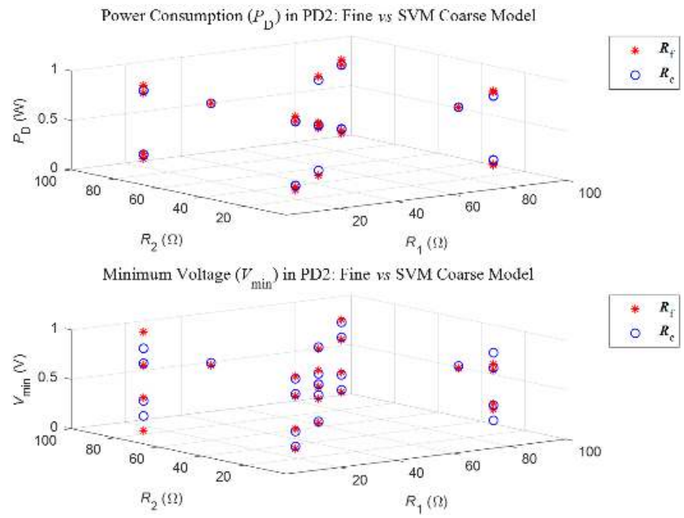

Fig. 3. Normalized scattered plot for P_D and V_{min} from power domain 2 sweeping R_{sense1} and R_{sense2}. A comparison between fine model response (star) and coarse model response using SVM (circle).

(see Table II). The errors were calculated using Frobenius norm ($\|\boldsymbol{E}\|_F$) as well as the maximum relative error (e_r).

From Table II, it is seen that SVM yields the lowest error overall, since it generalizes better. PSM exhibits a quite poor performance. An explanation of this very low performance of PSM lies in the size of the training region, which as mentioned in Section III, is very large, along with the reduced amount of training data. This is consistent with prior research: as it was discussed in [4], PSM has best performance when the size of the region of interest is small. On the other hand, RSM shows a similar (slightly better) performance to PSM. From here, we select the SVM surrogate modeling method to develop our fast coarse model to approximate the behavior of the system.

V. Conclusion

We analyzed in this paper a power delivery network with two power domains sharing a single voltage regulator solution. It was implemented using a dual sense resistor scheme to ensure the right performance of the silicon and meet minimum voltage and power requirements. We designed a DoE training data set, considering corner cases, and collected corresponding responses from high-fidelity HSPICE simulations. From the three different surrogate-based methods employed, support vector machines proved to be the best option to use due to the size of the modeling region of interest and the limited amount of data. Further research work will include a space mapping-based design optimization procedure exploiting the available coarse model to get the best design PI recipe.

TABLE II
SUMMARY OF ERRORS USING DIFFERENT COARSE SURROGATE MODELS FOR TWO POWER DOMAINS

measurement	$\|\boldsymbol{E}\|_{FRSM}$	$\|\boldsymbol{E}\|_{FSVM}$	$\|\boldsymbol{E}\|_{FPSM}$	e_{rRSM} (%)	e_{rSVM} (%)	e_{rPSM} (%)
P_{D1}	0.67	0.18	0.47	46.47	44.25	61.87
P_{D2}	0.53	0.17	0.49	37.53	41.28	61.11
V_{min1}	0.58	0.41	1.49	2.97	2.62	65.13
V_{min2}	1.01	0.30	1.20	4.15	3.59	65.33

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