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Comparison of Surrogate Modeling Approaches for Estimation of EMI Filter Insertion Loss

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***Abstract*—The increasing application of silicon carbide and gallium nitride transistors decreases the size of power electronic systems because of faster switching and clock times. However, both increase the electromagnetic emission, causing additional cost for the design of EMI filters. Finding a joint optimum requires long computation time. Meta modeling techniques reduce the computation time by approximating physical models with a simple mathematical equivalent function, generated from training data. If the physical models are computationally expensive, it is important to identify particularly efficient methods. We compare the surrogate modeling techniques of Kriging, Polynomial Chaos Expansion, Polynomial Chaos Kriging and Wideband Kriging. We find that Wideband Kriging is most accurate, but also has the most excessive model generation time.**

***Index Terms*—Meta model, Surrogate model, Kriging, Polynomial Chaos, Polynomial Chaos Kriging, EMI/EMC, EMI filter, wideband Kriging, Silicon Carbide, Gallium Nitride.**

I. Introduction

DC-DC converters are an integral part of any electronic system for power distribution and are the primary source of electromagnetic interference (EMI). The electronic system design for electromagnetic compatibility involves using an EMI filter with a DC-DC converter to reduce the conducted emissions. Analysis of filter performance at the design stage is crucial to achieve an optimum filter in terms of volume and performance. However, the parasitics of components, printed circuit board (PCB), and mutual coupling between the components alter the actual performance of the EMI filter in the manufactured product. To this effect, different methodologies based on equivalent circuit models, electromagnetic models, and artificial neural networks are proposed to model EMI filters in the literature. Modeling using equivalent circuit models / 3D modeling methods is time-consuming because of the broad frequency range of operation of EMI filters.

The surrogate model / meta model approach has gained importance to avoid excessive computation times by fast mathematical approximations such as kriging or polynomial chaos expansion [1]. In [2], a so-called wideband kriging (WBK) based surrogate model is used to carry out the optimization of a common mode choke. The authors extended the WBK to estimate Common Mode (CM) emissions of a power system combined with EMI filter [6]. Owing to multiple ways of obtaining the surrogate models, this paper compares different surrogate modeling approaches for estimating EMI filter performance using UQLAB uncertainty Quantification framework [3].

The rest of the paper is structured as follows. Section II describes the brief details of different surrogate models. Section III explains the design of the EMI filter model used to compare the different types of surrogate models. Section IV compares the results of various surrogate models in predicting the EMI filter response. Section V concludes this paper.

II. Surrogate Modeling Techniques

A. Kriging

Kriging or Gaussian Process modeling is well-known for scalar predictions based on a number of n training samples. Consider a set of n training data, $\boldsymbol{X} = \{\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \cdots, \boldsymbol{x}^{(n)}\}^T$, where each $\boldsymbol{x} = \{x_1, x_2, \cdots, x_k\}$ with corresponding output $\boldsymbol{y} = \{y^{(1)}, y^{(2)}, \cdots, y^{(n)}\}^T$. Using this training data, we like to predict new responses $\tilde{y}$ given any new input vector $\tilde{\boldsymbol{x}}$. A Kriging meta model provides the prediction based on assumption that the vector formed by the prediction at x, i.e., $\hat{y}(x)$ and the true model responses y, have a joint Gaussian distribution defined by [3] [4]

$$\begin{pmatrix} \hat{y}(x) \\ y(x) \end{pmatrix} \sim \mathcal{N}_{n+1}\left(\begin{pmatrix} f^T(x)\beta \\ F\beta \end{pmatrix}, \boldsymbol{\sigma}^2 \begin{pmatrix} 1 & r^T(x) \\ r(x) & R \end{pmatrix}\right) \quad (1)$$

where F is the observation (design) matrix of the Kriging metamodel trend given as $F_{ij} = f_j(x^{(i)})$. The vector $r(x)$ describes the cross-correlations between the prediction point x and each of the observations. The matrix R is the correlation matrix with elements. With a Gaussian correlation, the output function predicted for unknown input is given as [4]

$$\hat{y}(x) = f(x)^T\hat{\beta} + \tilde{r}(x)^T\tilde{R}^{-1}(y - F\hat{\beta}). \quad (2)$$

B. Polynomial Chaos Expansion (PCE)

For given n training samples $\boldsymbol{X}$ with corresponding output $\boldsymbol{y}$, a polynomial approximation of scalar valued function $\hat{y}(x)$ of order m can be written as

$$\hat{y}(x) = \sum w_i \boldsymbol{\chi_i}(x) \quad (3)$$

where $\boldsymbol{\chi}(x)$ represents multivariate polynomials orthonormal w.r.t the input distribution of the x and w_i indicates corresponding coefficients [4].

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C. Polynomial Chaos-Kriging (PCK)

Kriging interpolates the local variations of a function, whereas PCE approximates the global behaviour of Y. Polynomial Chaos-Kriging (PCK) is a method obtained by combining these two techniques to realize a more accurate meta model [4]. The predictor $\hat{y}(x)$ is

$$\hat{y}(x) = \sum w_i \boldsymbol{\chi_i}(x) + \sigma^2 Z(x, \omega) \tag{4}$$

where first term relates to PCE and second term relates to a stationary Gaussian process.

D. Wideband Kriging (WBK)

Wideband Kriging (WBK) operates, instead of a vector of n normal distributed training data samples as in kriging, with training tuples $\{\mathbf{y}_l\}$, $l = 1, \ldots, n$ which are vectors of size p with p denoting the number of frequency samples of the data. This is because, in EMC computation, we easily obtain dense information along the frequency axes for a given set of design parameters using frequency-domain simulation. WBK leverages this information to improve scalar kriging. The Gaussian Process on which the broadband Kriging is based is a random matrix $\mathbf{Y} \in \mathbb{R}^{p\times n}$ distributed as $\mathbf{Y}^T \sim \mathcal{N}(\boldsymbol{\mu}\mathbf{1}^T, \boldsymbol{\sigma}^2 \otimes \boldsymbol{\Psi})$ where $\boldsymbol{\mu}\mathbf{1}^T$ is the mean value matrix, $\boldsymbol{\sigma}$ the diagonal matrix composed of the variances σ_i, $\boldsymbol{\Psi}$ the correlation matrix and $\otimes$ denotes the Kronecker product. The final broadband predictor of a frequency response is [6]

$$\hat{\mathbf{y}} = \boldsymbol{\mu} + \psi^T \boldsymbol{\Psi}^{-1}(\mathbf{Y} - \boldsymbol{\mu}\mathbf{1}^T)^T \tag{5}$$

III. Model of the EMI Filter

The filter topology chosen is C-L-C, i.e. there are capacitance's mounted before and after a common mode choke with inductance L_{CM} and parasitic parallel capacitance C_{LCM}. A schematic of the EMI filter connected in CISPR 25 setup for measurement of CM emissions is shown in Fig. 1. The EMI filter is characterized by its Insertion Loss (IL) which is defined as

$$\mathrm{IL(dB)} = 20 \log \left(\frac{U_{CM,w/Filter}}{U_{CM,w/oFilter}} \right) \tag{6}$$

where $U_{CM,w/Filter}$, $U_{CM,w/oFilter}$ denote the CM voltage with filter (as in Fig. 1) and without filter, respectively.

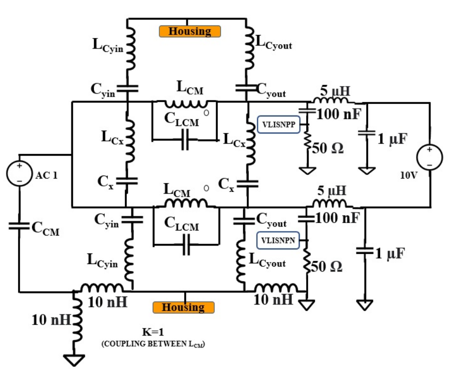

Fig. 1. Schematic of the EMI filter and measurement of $U_{CM,w/Filter}$

To equip the system with a realistic CM source impedance, we add in series to the voltage source a common mode capacitance (C_{CM}) varying in the same range as that of the CM parasitic capacitance C_{CM} of a DC-DC converter. The voltage $U_{CM,w/oFilter}$ is calculated by removing the filter from this setup. This model is needed to take include the effect of the source impedance. We note that the filter's attenuation is a function of the source and load impedance's. The load impedance is given by the two LISNs and is constant. The source impedance is the CM capacitance. The C_y capacitance's of the EMI filter are also connected to the housing (noted as a node in Fig. 1) which is connected via a ground strap to the table.

In total, the IL of the filter has seven design parameters, namely the common mode inductance L_{CM} of the common mode choke, its equivalent parallel capacitance (C_{LCM}), the values of the CY capacitors (C_{yin} and C_{yout}), their parasitic inductance (L_{Cyin} and L_{Cyout}), and the common mode capacitance C_{CM}.

IV. Comparison of Surrogate Techniques

A. Building of Surrogate models

The range of filter parameters used for training the surrogate models is as given in Tab. I.UQLAB framework software obtains PCK, PCE, and Kriging(K) default surrogate models. Models are generated for different sizes of input training sets of 250x1, 500x1, and 1000x1 vectors and corresponding output (IL) vectors of length 250x1, 500x1, and 1000x1, respectively. Accordingly, wideband Kriging prediction modeling of the filter uses a training set of length $p = 62$ frequency and $n = 250/500/1000$. MATLAB calls LTSpice to generate the training set required as input for the EMI filter modeling. The Random Latin Hypercube (RLH) sampling method selects training data from the design space mentioned earlier. This takes $\approx$ 17 sec to obtain one filter response for given input design parameters, with an i3 processor 8 GB RAM laptop.

TABLE I
EMI Filter design parameter ranges

Name	Range	Function
L_{CM}	1 μH – 50 μH	CM choke inductance
C_{CM}	0.2 pF – 200 pF	CM parasitic capacitance
C_{LCM}	0.1 pF – 50 pF	Parallel Capacitance of CM choke inductance
C_{yin}	2.2 nF – 100 nF	Cy capacitance-Input side
L_{Cyin}	4.7 nH–25 nH	Cyin parasitic inductance
C_{yout}	22 nF – 1000 nF	Cy capacitance-Output side
L_{Cyout}	4.7 nH–25 nH	Cyout parasitic inductance

B. Comparison of Models

A comparison of different models w.r.t actual IL is carried out using MATLAB and LTSpice simulation. Fig (2) and Fig (3) show a comparison between the predicted models and the actual LTSpice IL when trained for 500 points and 1000 points, respectively, for design parameter values of L_{CM} =20 μH, C_{LCM}= 20 pF, C_{yin} = 50 nF, L_{Cyin}= 10 nH, C_{yout} = 500 nF, L_{Cyout}= 10 nH and C_{CM} = 20 pF.

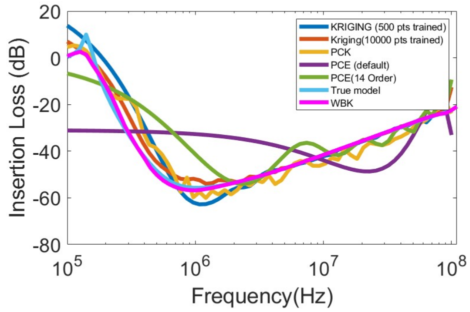

Fig. 2. Typical IL prediction of different models (500 training points)

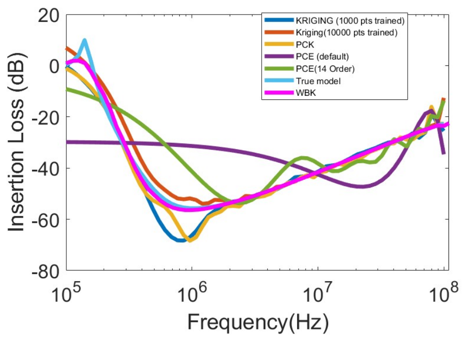

Fig. 3. Typical IL prediction of different models (1000 training points)

C. Quantification of Error

Quantifying the error between the predicted model output and actual IL from LTSpice is done using Normalized Root Mean Square Error (NRMSE). Predicted models built using 500 training points are verified at 10 different testing samples by varying the design parameters using the MATLAB RLH function. The NRMSE for same is shown in Fig. 4. It can be seen that PCE with default polynomial in UQLAB deviates the most. We believe this is because, contrary to what is mentioned in the [1], we only train on individual, random single frequency points to achieve a single metamodel for the entire frequency range. Detailed comparison between the other models w.r.t training samples and training time is shown in Table II. The results indicate that WBK provides the most accurate prediction for a given set of training samples. This accuracy comes at the cost of an excessive training time required to estimate the model hyperparameters at $p = 62$ frequency samples. It takes 12.7 hours to train Kriging on points equal to the total number of points in WBK, i.e. 15500 (equivalent to 250x62 points in WBK), with a resulting average NRMSE of 0.06, which is comparable to WBK's average NRMSE. Training Kriging on 10,000 points takes 12380 seconds to build a model with an NRMSE of 0.07, which is more than the WBK prediction for 250x62 points. PCK gives a similar average NRMSE of 0.08 with 1000 training points in 107 seconds as in Table II. The PCK and kriging methods are used from an existing toolbox. WBK is implemented by us in MATLAB and the code can be optimized for speed.

V. Conclusion

This study briefly reviews the applicability of viable surrogate modeling options to effectively and accurately model the IL of the EMI filter. The effect of the number of training points on training time and accuracy is highlighted. It is seen that WBK provides the most accurate prediction, but at the cost of long training time. For applications that require less accurate prediction, Kriging and PCK methods provide a viable solution with less training time.

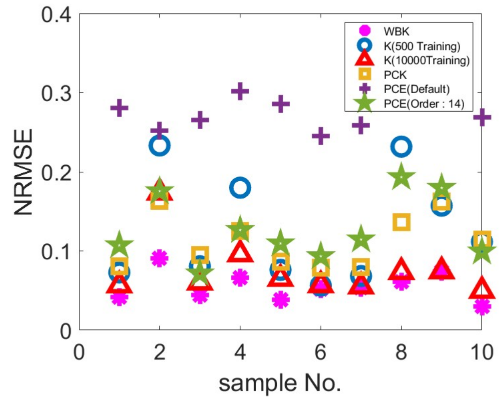

Fig. 4. NRMSE at 10 test samples (Model generated from 500 points)

TABLE II
Comparison of surrogate models

Method	Model building time (sec)	Avg. NRMSE (at 10 points)	Training Samples
Kriging	5.37	0.133	250
	18.01	0.1268	500
	59.88	0.0749	1000
	12387	0.076	10000
	45720	0.06	15500
WBK	3600	0.062	250x62 ($n \times p$)
	14400	0.0552	500x62
	36000	0.0472	1000x62
PCK	7.06	0.1383	250
	19.16	0.1123	500
	107.9	0.0837	1000

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