A Probabilistic Gaussian Process Regression Approach to Uncertainty Quantification in Electromagnetic Compatibility Investigations

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Uncertainty quantification (UQ) is of paramount importance in various aspects of the design of cable harnesses and in the evaluation of their performance. Unknown wave parameters of external disturbances and/or uncertainty in the conductor location stochastically impact, e.g., radiated susceptibility and crosstalk. In this contribution, we propose an effective approach, based on Gaussian process regression (GPR) [1], to the uncertainty quantification of cable bundles.

GPR is a nonparametric technique belonging to the class of supervised machine learning algorithms. It allows to construct a surrogate model of the outputs of interest as a function of selected design variables or uncertain physical parameters. The GPR model is trained using a limited amount of data samples computed for some (random) configurations of these parameters. Compared to alternative methods, GPR also provides an indication of the prediction uncertainty. Therefore, in an UQ framework, it allows estimating confidence bounds of the predicted statistics, including average responses, output variance, and probability distributions, as illustrated in Fig. 1 for the probability density function of a crosstalk voltage.

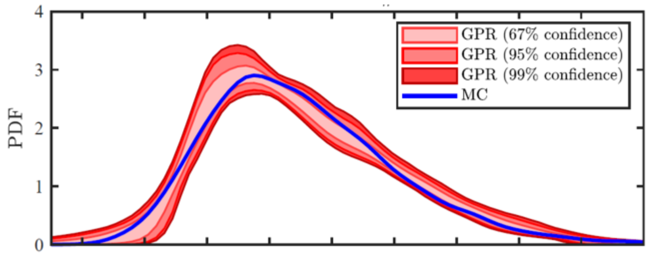

Figure 1. Prediction of the probablity distribution of a crosstalk voltage (blue line, estimated with Monte Carlo) with the inclusion of confidence bounds (red areas).

Another advantage of GPR is its natural capability of dealing with large input dimensionalities and large variations of the outputs, thanks to the fact that the form of the model is not predetermined, but it is rather learned from data. The combination with principal components analysis (PCA) allows to effectively deal with data at multiple frequencies, by exploiting the inherent correlation of the output at different frequency points. Specifically, the frequency-dependent data is compressed to a reduced dataset, for which a limited number of GPR models can be feasibly trained. Statistical information for the original output space is then recovered.

The present contribution will showcase a few applications of relevance in electromagnetic compatibility investigations.

1. C. E. Rasmussen and C. K. I. Williams, *Gaussian Processes for Machine Learning*. Cambridge, MA, USA: MIT Press, 2006.