A Multi-Output Active Learning Method for the Uncertainty Quantification of PCB Lines

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This summary outlines recent developments by the Torino "Elettronica" unit in the field of compact modeling techniques for design and optimization of electronic systems. The proposed methodology leverages kernel-based learning to build accurate behavioral models, with a specific focus on reducing model complexity through data-driven compression strategies.

Nowadays, the need for smarter strategies to perform both design and optimization of electronic systems, along with their uncertainty quantification (UQ), is rapidly increasing. Gaussian process (GP) models were proven to be particularly successful due to their capability of associating confidence bounds to model predictions. One of the most critical steps in the achievement of a good model is the selection of the training data, which should be as small as possible. In this work, a new active learning (AL) strategy tailored to the effective augmentation of the training dataset of multi-output GP surrogates is presented and investigated. The algorithm, starting from the already obtained insights on this topic, relies on the predictive variance of the output mean, focusing this time on the overall time/frequency domain. To make the computation efficient, both the concepts of principal component analysis (PCA) compression and Cholesky factorization are exploited.

The proposed technique is applied to the UQ of the insertion loss of a microstrip line with a discontinuity in the ground plane. The stochastic input parameters are the location and the length of the slot in the ground plane, while the magnitude of S_{21}, analyzed with CST Studio Suite® for a frequency sweep spanning from dc to 10 GHz, is considered as the output. The GP model is trained in MATLAB® using the Statistics and Machine Learning Toolbox™ toolbox and its accuracy is assessed based on the means of both the relative errors on the variance and the RMSE between observations and predictions at each frequency point.

The outputs of the resulting metrics are shown in Fig. 1 and 2, highlighting the comparison between the proposed stochastic strategy and the traditional deterministic method, which relies on the predictive variance of the model predictions. Numerical tests in [1] demonstrate that the proposed method outperforms the traditional one, as it provides faster convergence and tighter confidence bounds as the number of iterations (i.e., added samples) increases. These results confirm the advantage of using a more probabilistic algorithm instead of a deterministic one when dealing with stochastically distributed data.

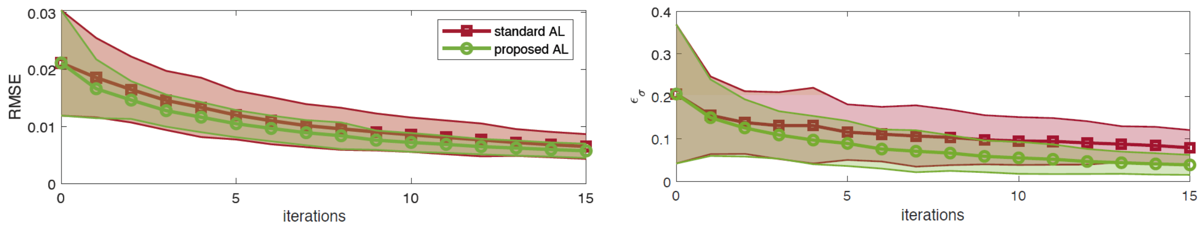

Fig.1. $RMSE$ (top) and ϵ_σ (bottom) over 50 runs as the iterations increase. Red: standard AL; green: proposed AL.

[1] M. Cusano et al., "A Multi-Output Active Learning Method for the Uncertainty Quantification of PCB Lines", Proc. 29th IEEE Workshop on Signal and Power Integrity, Gaeta, Italy, May 11-14, 2025.