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ACTIVE LEARNING FOR EFFECTIVE ELECTROMAGNETIC COMPATIBILITY PREDICTION: LSBOOST ACTIVE LEARNING APPROACHES

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Résumé: In this paper, we develop an active learning (AL) strategy within electromagnetic compatibility (EMC) prediction frameworks to reduce experimentation and simulation costs while maintaining high model accuracy. Traditional EMC prediction relies on extensive measurement campaigns or computationally intensive simulations to characterize conducted or radiated emissions. To overcome these limitations, we develop in this paper an active learning-based LSBoost ensemble model with a deep learning (DL) architecture for efficient EMC behavior prediction. The AL-LSBoost approach iteratively selects the most informative data points to train the model, reducing the required dataset by up to 60% compared to random sampling, while preserving predictive fidelity. The results show that the proposed active LSBoost model achieves accuracy with significantly lower computational costs and better interpretability and rapidity. This study highlights the potential of ensemble techniques based on active learning as a robust and data-efficient alternative to deep neural approaches for EMC prediction and virtual prototyping.

I. INTRODUCTION

Predicting electromagnetic compatibility (EMC) plays a crucial role in ensuring the reliable operation of modern electronic systems [1-2]. As circuits become faster and more integrated, conducted and radiated emissions [3-4] become increasingly complex to model and control. Conventional approaches rely heavily on full-wave simulations or extensive measurement campaigns carried out in controlled environments such as anechoic chambers, which is both time-consuming and expensive. In this context, data-driven modelling has emerged as an effective alternative, using machine learning (ML) [5] and deep learning (DL) methods to predict emission levels or coupling effects from measured or simulated data. However, one of the main challenges of ML-based EMC prediction lies in the need for large and well-distributed training datasets to achieve acceptable accuracy. Generating such datasets through high-fidelity electromagnetic experiments or simulations remains expensive and often impractical. Active learning (AL) offers a promising strategy to solve this problem by allowing the model to adaptively select the most informative samples for learning, thus minimizing the number of measurements required while maintaining high predictive performance integrated with ensemble methods

such as least squares boosting (LSBoost), machine learning offers increased robustness, interpretability and generalization capacity compared to deep development (DL) architectures [6].

This article proposes an active learning-based LSBoost model for EMC prediction trained on a dataset. The effectiveness of this method lies in its accuracy, convergence speed, computational efficiency, and data requirements. The results demonstrate that the proposed AL-LSBoost approach achieves competitive prediction accuracy while requiring less labeled data and a reduced computational load, making it an ideal candidate for virtual EMC testing and rapid system prototyping.

The remainder of the article is organized as follows: Section II, presents the theoretical background of active learning. Section III, describes the proposed framework and the dataset generation process. Section IV, presents the results of the proposed AL-LSBoost method. Section V, concludes with the prospects for integrating active learning into CEM test automation and digital twin development.

II. STUDIED CIRCUIT AND DATASET COLLECTION

II.1. Studied circuit

The studied circuit in this work (Figure 1) is a buck converter, used as a measurement bench for electromagnetic analysis. This converter, based on a single-switch topology (MOSFET), converts a DC input voltage to a lower regulated output voltage.

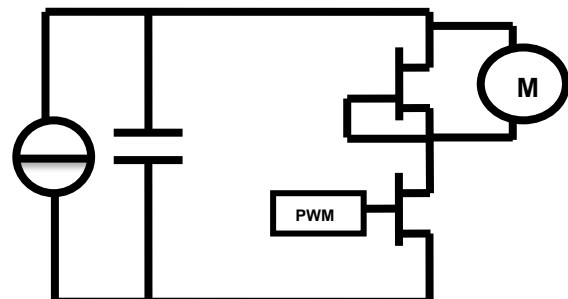


Figure 1: Studied circuit

Their construction is simple, yet they serve a wide range of devices, making them easy to construct, model and use electronically. To quantify the effects of circuit parameters: Power supply, load current, switching frequency, Duty cycle, Component choice, PCB layout,

Filter capacitance and Gate resistance on the EMI we design à 10 PCB for this buck converter and we measure for each parameter variation common and differential mode. After that we reorganize our dataset to use in model training.

Figure 2 present the EMC measurement bench based on using the CISPR25.



Figure 2. EMC measurement bench

In the CISPR 25 standard in which test methods and limits of electromagnetic compatibility (EMC) performance for vehicles electronic equipment are described, therein defined methods are used for conducting electromagnetic interference (EMI) measurements. The setup of the measurement incorporates a line impedance stabilization network (LISN) that allows maintaining controlled impedance and shields the device under test from the external interferences. Emissions are captured at the terminals of the device under test (DUT) that is connected to the LISN, and both common and differential interference signals at the output are measured. The appendix includes a standard procedure of emission measurement that enables the fulfillment of automotive EMC regulations and assessment of the DUT's emissions on other devices installed in an automobile.

Electromagnetic compatibility measurements performed in an anechoic chamber are highly expensive and time-consuming, especially when multiple design parameters are involved. In this work, each parameter was varied three times, which would lead to a prohibitive experimental cost if relying solely on measurements. Therefore, a virtual prototype of the buck converter was developed using OrCAD/PSpice, including all relevant parasitic effects [1]. The simulated results show an excellent agreement with the experimental measurements. As a result, both measured and simulated data were combined to construct the training database, providing a reliable and cost-effective dataset for the proposed active learning framework.

II.2. Data set collection

Based on both measurement and simulation results, the dataset was constructed following a controlled parameter variation strategy. At each iteration, only one parameter among those mentioned above was varied over 20 discrete values, while all other parameters were kept fixed. This approach ensures a structured and well-balanced exploration of the design space while limiting the number of required measurements and simulations. Table I

summarizes the database construction process for the power supply under study.

Table 1. Data base construction of power supply

Parameter 1 (V)	V _{MC} (dBμV)	V _{MD} (dBμV)
P1_Val_1	Data_1V _{MC_1}	Data_1V _{MD_1}
P1_Val_2		
P1_Val_18	Data_1V _{MC_18}	Data_1V _{MD_18}
P1_Val_19	Data_1V _{MC_19}	Data_1V _{MD_19}
P1_Val_20	Data_1V _{MC_20}	Data_1V _{MD_20}

We repeat the same simulation procedure for the others parameters, varying one parameter at a time while keeping all others fixed for the 20 values.

Table II show the data base construction for load current

Table 2. Data base construction of load current

Parameter 2 (A)	V _{MC} (dBμV)	V _{MD} (dBμV)
P2_Val1	Data_2V _{MC_1}	Data_2V _{MD_1}
P2_Val2		
P2_Val18	Data_2V _{MC_18}	Data_2V _{MD_18}
P2_Val19	Data_2V _{MC_19}	Data_2V _{MD_19}
P2_Val20	Data_2V _{MC_20}	Data_2V _{MD_20}

After varying all parameters that influence conducted electromagnetic interference, we proceed the construction of our data base.

In table III we present the data base matrix form.

Table 3. Data base matrix

Input parameters				Output parameters		
P1	P2	P3	P8	F	VMC	VMD
Variable	Fixed					
Fixed	Variable	Fixed				
Fixed		Variable	Fixed			
Fixed				Variable		

After data base construction we proceed the prediction using MATLAB software.

III. PROPOSED METHODE

After constructing the database and implementing the proposed methodology in MATLAB, the framework was tested and validated using randomly selected combinations of input parameters. For each combination, the corresponding common-mode (VMC) and differential-mode (VMD) emissions were simulated in parallel, allowing a direct comparison between predicted and reference results to assess the accuracy of the proposed approach. The overall workflow of the proposed methodology is summarized in Fig.3. It includes data normalization, output preprocessing, active learning initialization, and an iterative learning loop in which the most informative samples are automatically selected based on model uncertainty. Within this framework, an

innovative combination of Active Learning (AL) and LSBoost is proposed for electromagnetic compatibility (EMC) prediction. AL plays a central role by iteratively identifying the most uncertain operating points through the variance among ensemble trees and selecting them for annotation. This strategy significantly reduces the number of required samples while maintaining or even improving predictive accuracy. Consequently, the resulting LSBoost-based model is able to simultaneously predict both common-mode and differential-mode emission levels with high accuracy and reduced computational cost.

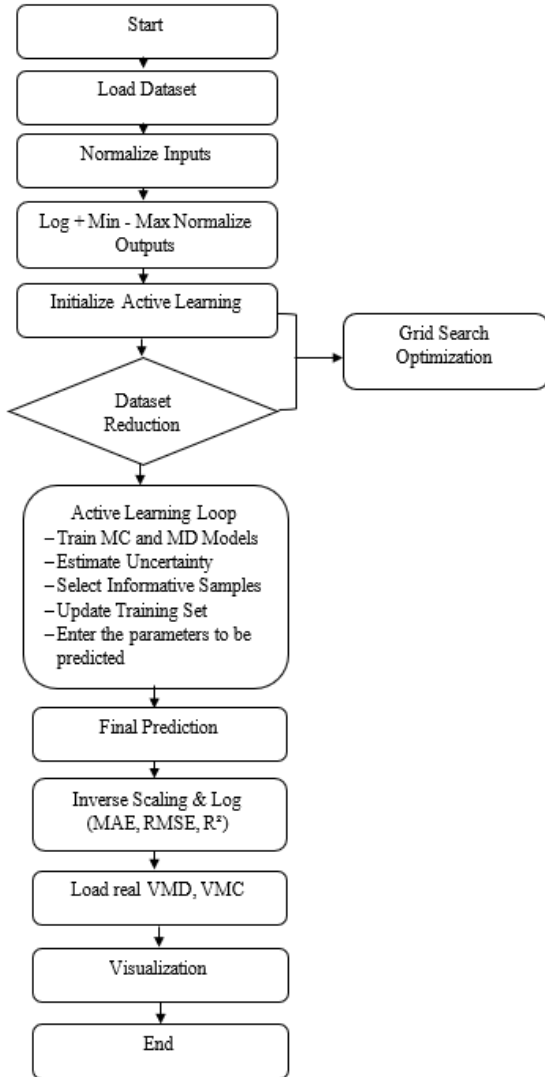


Figure 3: Flowchart of active learning program

IV. RESULT AND DISCUSSION

To evaluate the performance of our proposed method we calculate the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Coefficient of Determination (R^2).

Figures 1 and 2 illustrate the real and predicted values for both common and differential mode voltage.

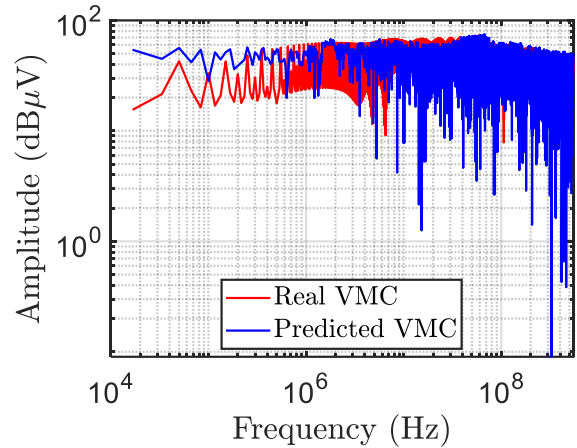


Figure 4. Predicted and Real FFT of common mode voltage

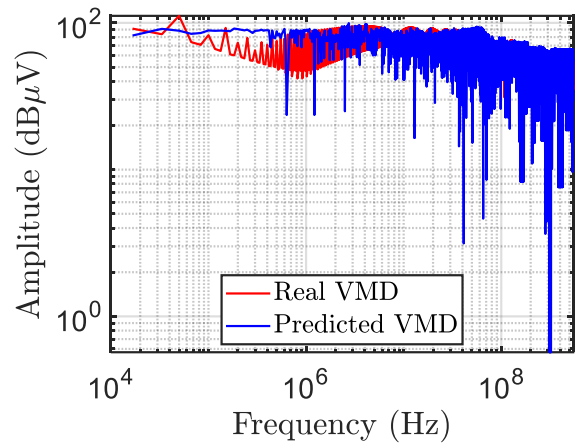


Figure 5. Predicted and Real FFT of differential mode voltage

The results obtained show that the model exhibits good predictive capabilities, particularly for the differential component (VMD) with an R^2 of 0.9654, indicating excellent correlation between predicted and measured values. The RMSE of 7.29 and the MAE of 12.78 confirm a low mean error and limited dispersion of predictions around the actual values, as is the case for the VMC. Overall, these results validate the suitability of the proposed learning framework for EMC prediction with a reasonable computation time (60.42 s).

The principle of Active Learning is based on an iterative and selective approach to learning: unlike traditional methods where all the data is labeled from the outset, this approach begins with a small labeled subset, for example, 500 samples. The model is first trained on this restricted set, then it actively identifies the most informative points to annotate among the unlabeled data, according to an uncertainty criterion (such as the variance of the trees or the dispersion of the predictions). Thus, only a fraction of the data is actually labeled, while the remaining data is used to guide the learning process. The goal is to reduce the number of annotations required while maintaining high model accuracy. In practice, this method is particularly advantageous when obtaining labels is costly, such as in experimental EMC measurements, medical imaging, or

any other field requiring complex measurement or labeling campaigns.

To assess the effectiveness and robustness of the proposed approach, the algorithm was tested on several representative cases covering different operating conditions, as summarized in Table 4.

Table 4. Tested parameters

	Case 1	Case 2	Case 3	Case 4
Input voltage	48	48	48	24
Load current	0.5	5.25	0.5	10
Switching frequency KHz	50	50	500	50
Duty cycle %	50	50	50	50
Component choice	IRF730	IRF730	IRF730	IRF730
PCB layout	fixed	fixed	fixed	fixed
Filter capacitance μF	22	22	22	22
Gate resistor	8	8	2	2

a - Case 1

Figures 6 and 7 illustrate a comparison between the predicted and measured common-mode (VMC) and differential-mode (VMD) voltages.

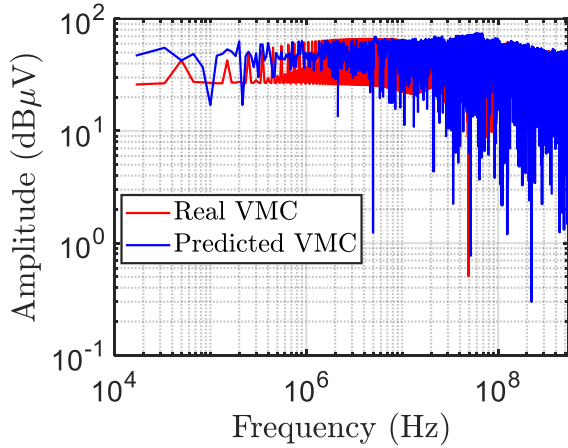


Figure 6. Predicted and Real FFT of common mode voltage

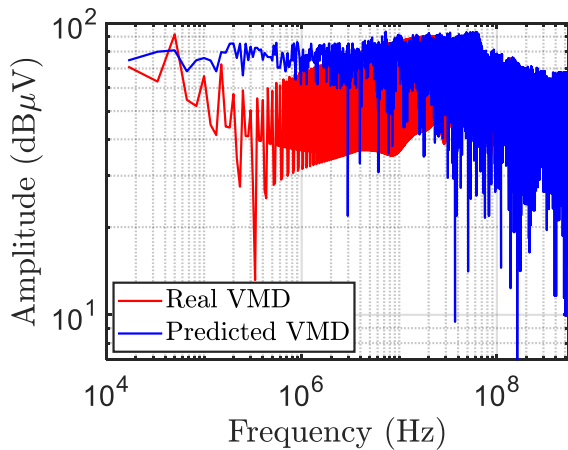


Figure 7. Predicted and Real FFT of differential mode voltage

b - Case 2

Figures 8 and 9 show the predicted and measured common-mode (VMC) and differential-mode (VMD) voltages.

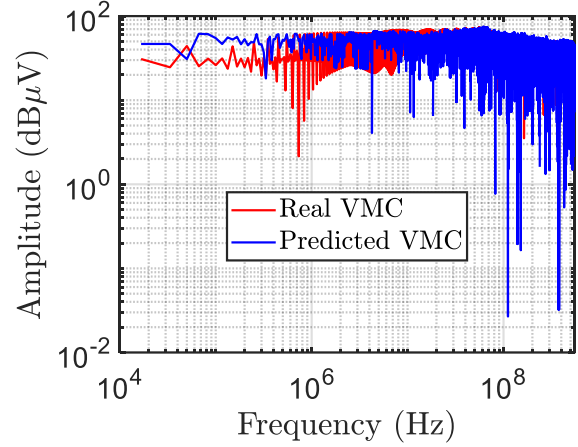


Figure 8. Predicted and Real FFT of common mode voltage

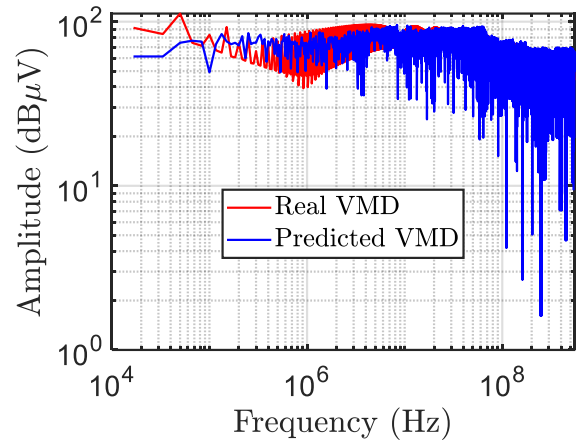


Figure 9. Predicted and Real FFT of differential mode voltage

c - Case 3

Figures 10 and 12 compare the predicted and measured common-mode (VMC) and differential-mode (VMD) voltages, demonstrating the effectiveness of the proposed Active Learning-based approach.

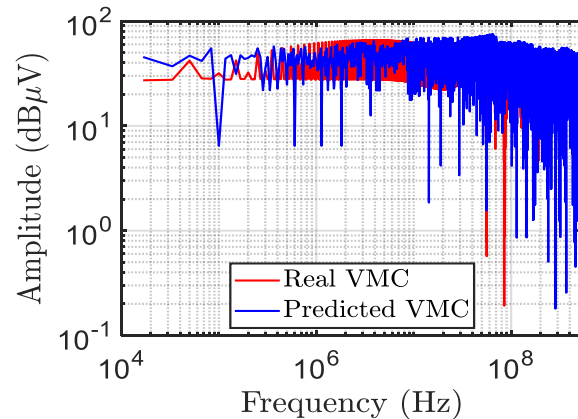


Figure 10. Predicted and Real FFT of common mode voltage

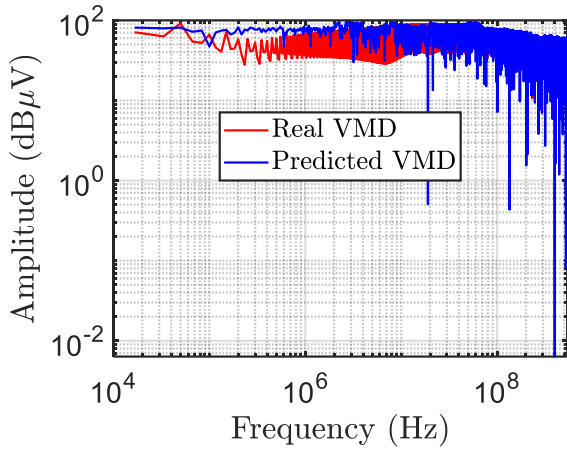


Figure 11. Predicted and Real FFT of differential mode voltage

d - Case 4

Figures 12 and 13 present the comparison between the predicted and measured common-mode (VMC) and differential-mode (VMD) voltages.

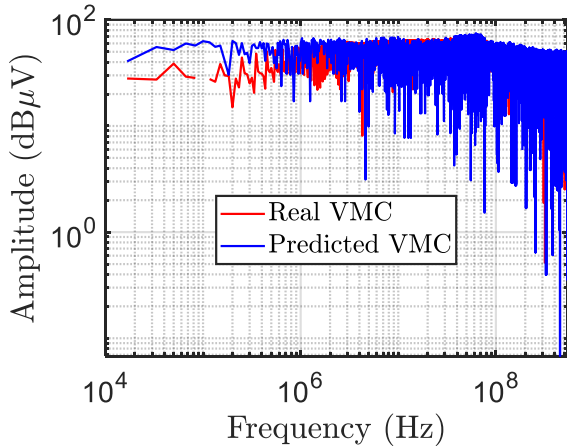


Figure 12. Predicted and Real FFT of common mode voltage

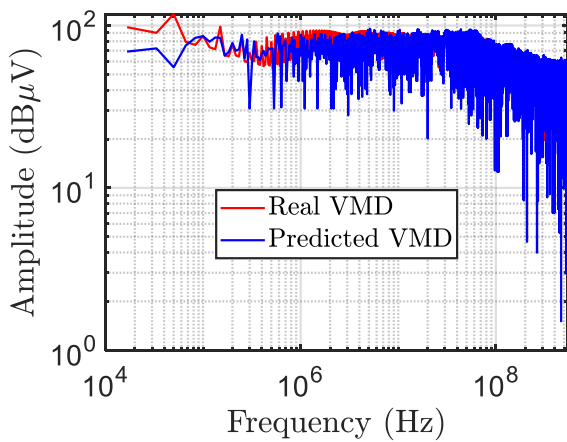


Figure 13. Predicted and Real FFT of differential mode voltage

Table 5. Performance Metrics for the Four Test Cases

Case	Mode	MAE (dBμV)	RMSE (dBμV)	R ²	Simulation times (s)
1	VMC	17.07	13.73	0.92	183.57
	VMD	16.29	13.36	0.93	
2	VMC	12.00	8.82	0.89	97.72
	VMD	12.27	6.18	0.98	
3	VMC	15.84	16.65	0.97	187.30
	VMD	17.73	14.28	0.95	
4	VMC	11.44	7.08	0.95	164.70
	VMD	11.40	5.82	0.94	

Although the improved KNN approach presented in [1] demonstrates strong predictive performance through feature normalization and distance-weighted averaging, it remains inherently dependent on a large, fully populated training dataset. Consequently, the computational burden associated with data generation and model validation remains significant. In particular, the reported simulation times range from 1451 s to 1807 s for different test cases, highlighting the high cost of conventional passive learning strategies. In contrast, the proposed Active Learning framework selectively enriches the training database by iteratively querying only the most informative samples. As a result, comparable or improved prediction accuracy is achieved with a significantly reduced number of training samples, leading to a drastic reduction in computational time. Specifically, the total simulation time is reduced to 60.2 s using Active Learning, representing more than a 95% decrease compared to the KNN-based approach. These results clearly demonstrate that Active Learning is more suitable for EMC prediction problems, where data acquisition and simulation costs are critical constraints.

V. CONCLUSION

This article presents a study on the use of the active learning technique AL LSBoost for predicting electromagnetic compatibility (EMC) behavior, focusing on conducted emission phenomena. The results demonstrate that integrating active learning (AL) into the learning process significantly reduces the amount of data required to achieve high prediction accuracy, thus lowering the overall cost of EMC characterization and simulation. Compared to classical deep neural networks, the proposed AL-LSBoost approach achieves comparable or even superior accuracy, while offering better interpretability, faster convergence, and reduced computational requirements.

These results suggest that ensemble models based on active learning can be powerful tools for virtual EMC testing, enabling adaptive measurement planning and intelligent data acquisition. Future work will focus on extending this methodology to predict multi-source electromagnetic interference, co-simulating at the circuit level with finite element solvers, and integrating Bayesian optimization to improve uncertainty quantification and model robustness. Ultimately, this approach paves the way for autonomous and data-efficient EMC design frameworks, bridging the gap between numerical modeling and experimental validation.

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