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#### **REFERENCES**



# **Towards Machine Learning for Acoustic Resonance Technology**

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The simplified geometry of the wind sensor, illustrated in Fig.1, is imported in COMSOL Multiphysics® with the LiveLink™ *for* SolidWorks®. The computational domain is set up following an optimization study outlined in reference [1]. The model is validated against experimental data, comparing the normalised pressure magnitude on the receiving transducer with the voltage signal measured in a real sensor. After the validation, the model is used to conduct a Design of Experiments, exploiting the functionality of COMSOL Multiphysics, varying 10 geometrical parameters in their tolerances intervals. The DoE is then used to train a Deep Neural Network (DNN), optimizing the number of points needed in the DoE, the learning rate, the duration of the training, i.e. the number of epochs, and the structure of the DNN. The DNN is then compared with the FE simulations to uncover the hyperparameters set that leads to the best compromise of computational cost and accuracy of the predictions.

1. A. Jimenez-Garcia and G. C. Diwan, "A comparison of acoustic solvers for FT ultrasonic wind," in 54th Spanish Congress on Acoustics, Cuenca, 2023.



Implementation of Machine Learning algorithms allows to speed-up simulations improving the understanding of how geometrical tolerances affect the acoustic resonance technology in FT wind sensors.

FT wind sensors measure wind speed and direction using an acoustic field superimposed on a flow field in an acoustic resonator equipped with three piezoelectric transducers. The study proposed here focuses on the acoustic resonance technology of a simplified wind sensor geometry, and how it is affected by geometrical tolerances. In particular, it will explore the advantages of using machine learning algorithms to save computational costs without compromising the accuracy and

> FIGURE 2. Mean Squared Error (MSE) of DNN predictions compared to FE simulations when the number of DoE points increases (top-left); DNN predictions when different numbers of epochs are used for training (top-right); comparison of the descent of the loss function when the learning rate is set to 5x10<sup>-3</sup> (bottom-left) and 5x10<sup>-3</sup> (bottom-right).

reliability of the results. The outcome of this analysis is to optimize the number of points needed in the Design of Experiments (DoE) table, the structure of the Deep Neural Network (DNN), the learning rate used, and the duration of the DNN training. The results will focus on the comparison between the surrogate modeling and FE simulations in terms of accuracy, reliability, and computational time.



#### **Abstract**

## **Methodology**

FIGURE 1. Simplified geometry of FT wind sensor (on the left); validation of FE simulation through the comparison with experimental data (on the right)

This study demonstrated that by using Machine Learning, a tool can be developed to analyse the effect of tolerances on acoustic resonance wind sensor geometry in just over 24 hours, compared to the six months required to capture these interactions using Finite Elements simulations.

This research focused on the optimisation of the hyperparameters of a Deep Neural Network, unveiling the effects of dimensions of the dataset used for the training, length of the training (number of epochs), learning rate and structure of the network. Once the set of hyperparameters was finalised, the DNN predictions proved to be equally good at representing a specific test case. A real functioning sensor was measured using a Coordinate Measuring Machine (CMM), and it was replicated in a COMSOL Multiphysics FE simulation with the same dimensions. The same geometrical dimensions were also used as inputs of the DNN and the same level of agreement with the experimental data was reached by the simulation results and the DNN predictions, proving the capabilities of the tool.

### **Results**

