Towards Machine Learning for Acoustic Resonance Technology

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Elisabetta Merico[1*] and Antonio Jimenez-Garcia[2]

[1]Graduate Multiphysics Engineer, FT Technologies Ltd, Sunbury House, London, UK
[2]Principal Research Engineer, FT Technologies Ltd, Sunbury House, London, UK
*elisabetta.merico@fttechnologes.com

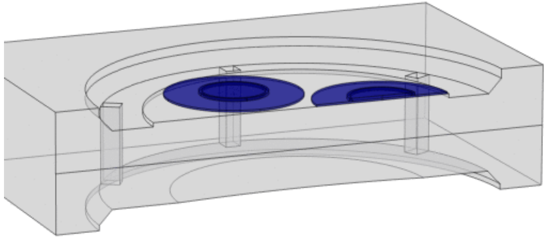
Agenda

- Introduction to FT Technologies
- Objectives of this Study
- Results of the Study
  - Validation of COMSOL Model
  - Hyperparameter Optimisation
- Conclusions

FT742 Flat Front [1]

Introduction to FT Technologies

- Ultrasonic wind sensor that measures speed, direction, and temperature using acoustic resonance technology (Acu-Res® [2])
- Operating range from 0 to 90 m/s and -40°C to 85°C



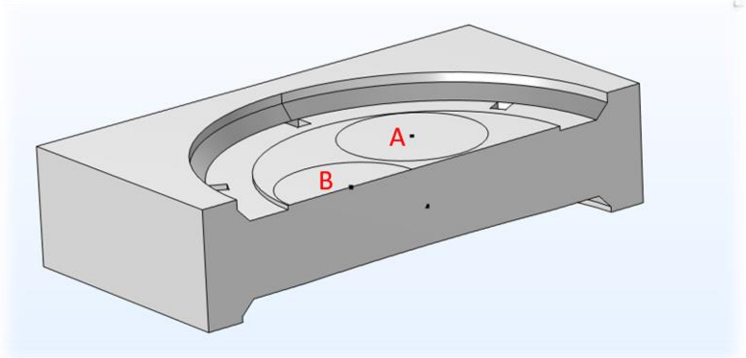
Objectives and Steps of the Study

- AIM: Comparison of Finite Elements (FE) simulations in COMSOL Multiphysics® and the new Surrogate Modelling functionality introduced in v6.2, with hyperparameter optimisation of a DNN to represent acoustic resonance technology

- STEPS:
  - Create and validate against experimental data an FE model in COMSOL Multiphysics® of the sensor resonator in the frequency domain, exploiting the Acoustic module and the LiveLink for SolidWorks®
  - Generate a Design of Experiment (DoE), varying 10 geometrical parameters
  - Use the DoE to train a DNN, optimising its hyperparameters through the comparison with the Finite Elements simulations

Step 1.a: FE Model Definition

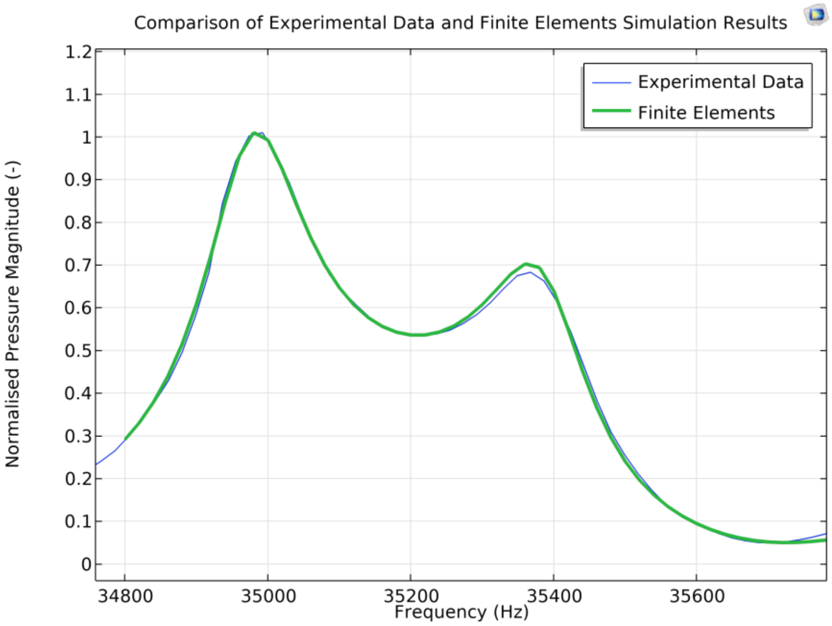
- Import a simplified geometry through the LiveLink for SolidWorks® (it will be needed later for the DoE)
- Define computational domain encompassing half the resonator area and extending half the maximum[3] wavelength outside of it
- Impose appropriate boundary conditions:
  - Impedance matching at the extremes of the domain to avoid reflections
  - Sound hard boundary in the middle plane to simulate a symmetry plane
  - Wall with optimised absorption coefficient on the edges of the resonator cavity
  - Constant amplitude of the normal velocity on transducer B to simulate its behaviour



Computational Domain encompassing half the resonator area, with transmitting transducer B and receiving transducer A

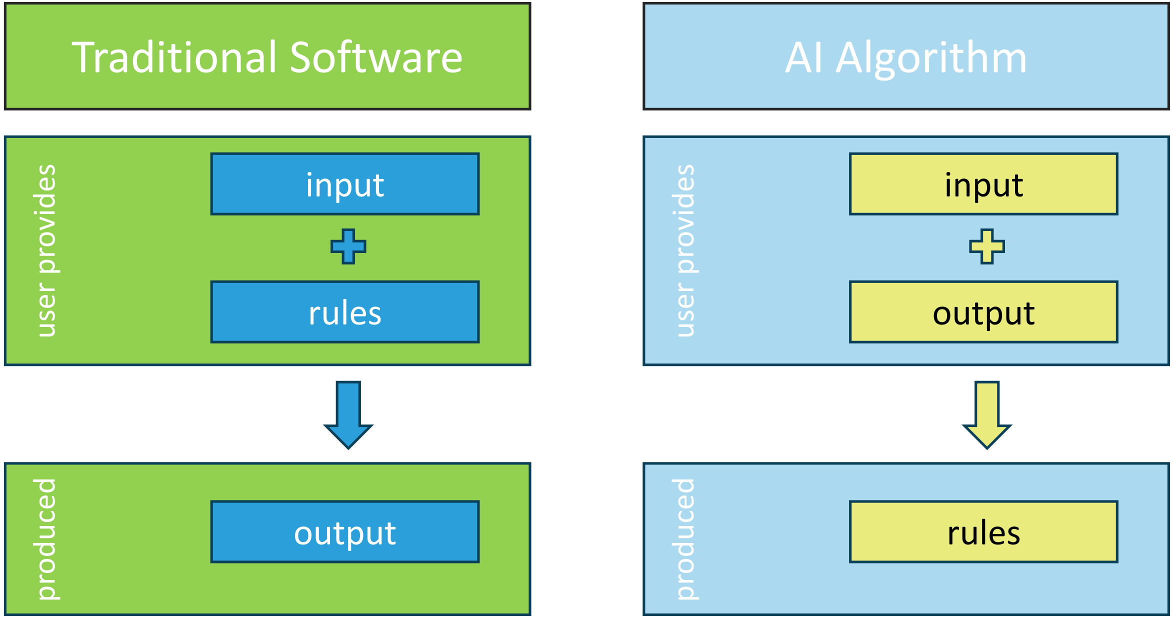
Step 1.b: FE Model Validation

- Measure the dimensions of a real sensor on a coordinate measuring machine (CMM) and recreate an exact model in COMSOL
- Compare the signal received by transducer A in the real sensor with the average pressure on the surface of transducer A in the simulation across the frequency range of interest



FE simulation validation against experimental data

Traditional Software vs AI



PROs

- It can adapt easily
- It can handle complex problem
- We don’t need to fully know the physics

CONs

- Often obscure
- It can produce unexpected results

Step 3: Build DNN and Compare Results with FE

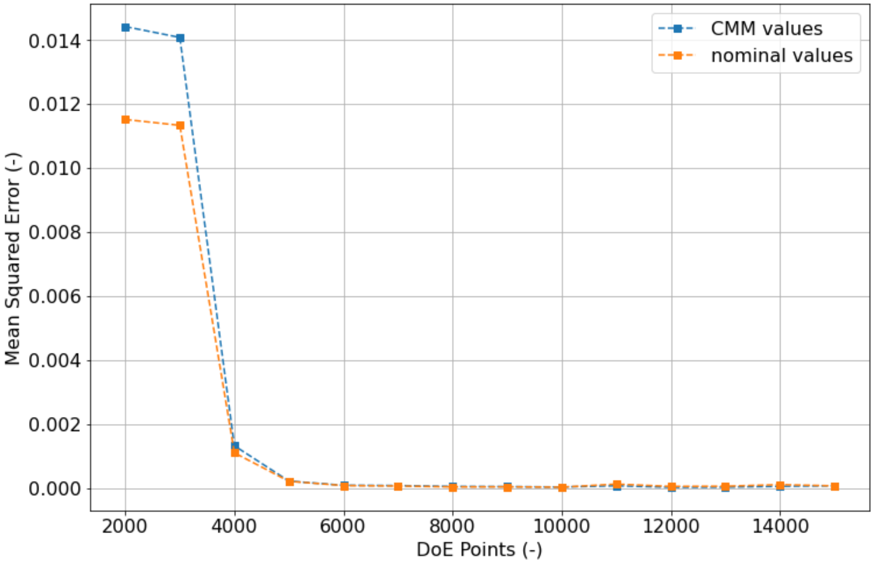
a) Number of points in DoE needed

b) Optimal Learning Rate

c) Number of Epochs (duration of the training):

d) Layer Structure

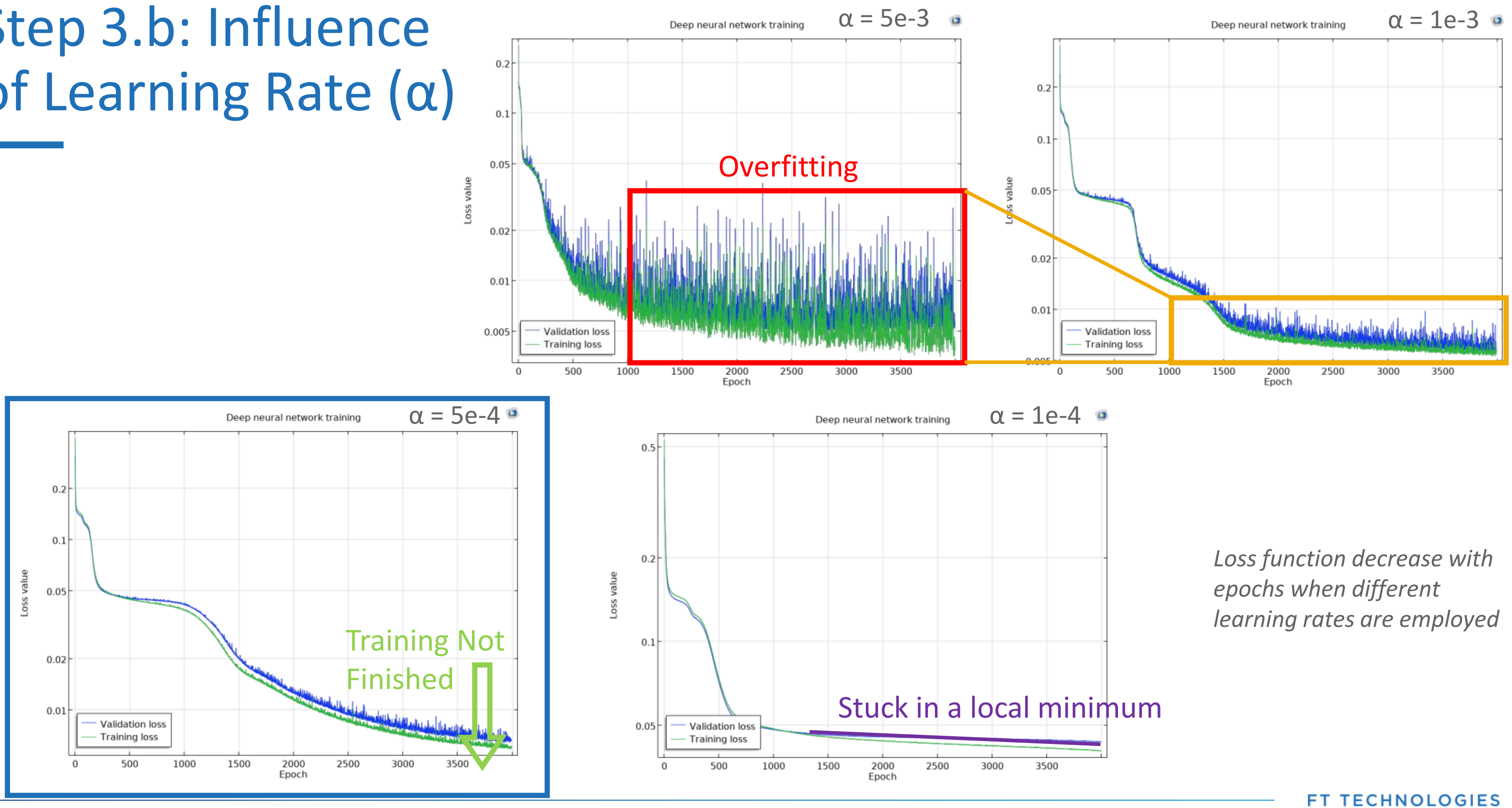
Step 3.a: Effects of the Number of DoE points



MSE between DNN predictions and FE simulation results for nominal and CMM values, increasing the number of points in the DoE

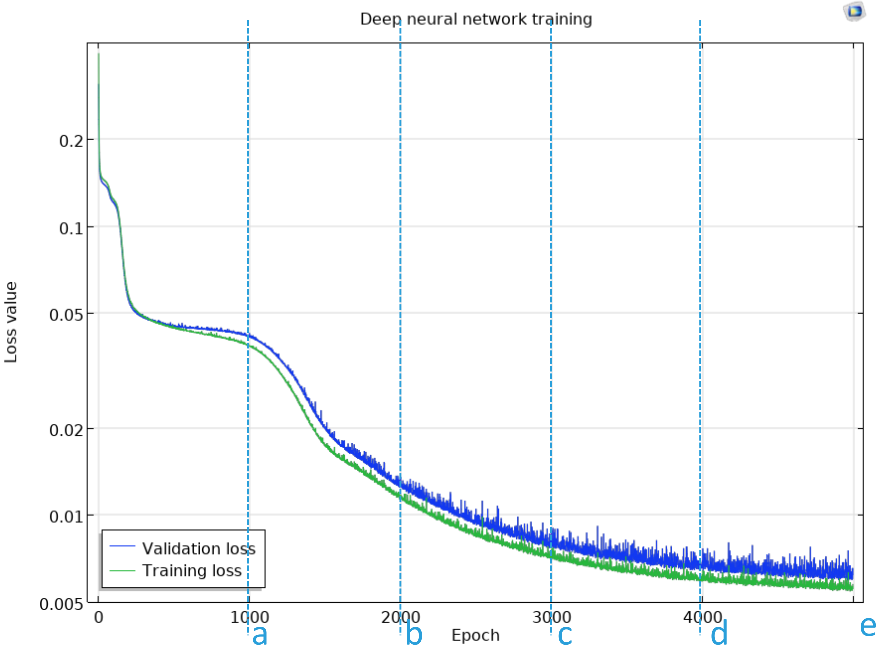
Increasing the number of points used to build the DoE greatly improves the accuracy of the DNN predictions, plateauing if more than 6000 points are used, both when compared with the nominal values and with the CMM scanned values

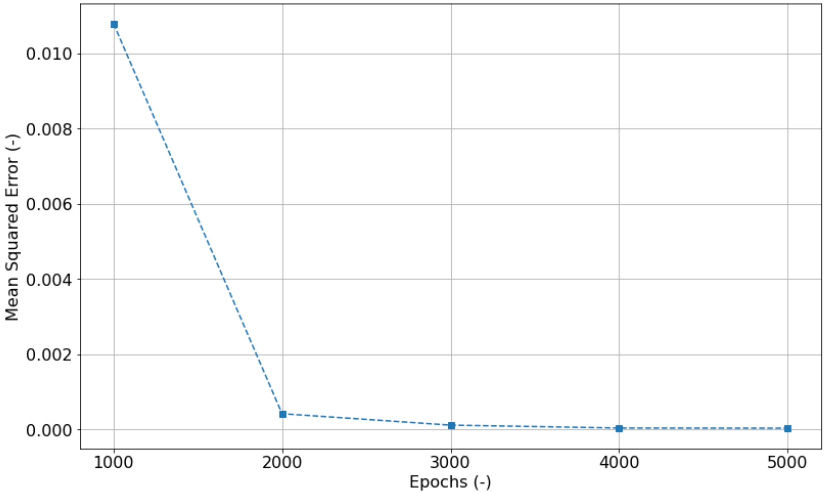
Step 3.b: Influence of Learning Rate (α)



Loss function decrease with epochs when different learning rates are employed

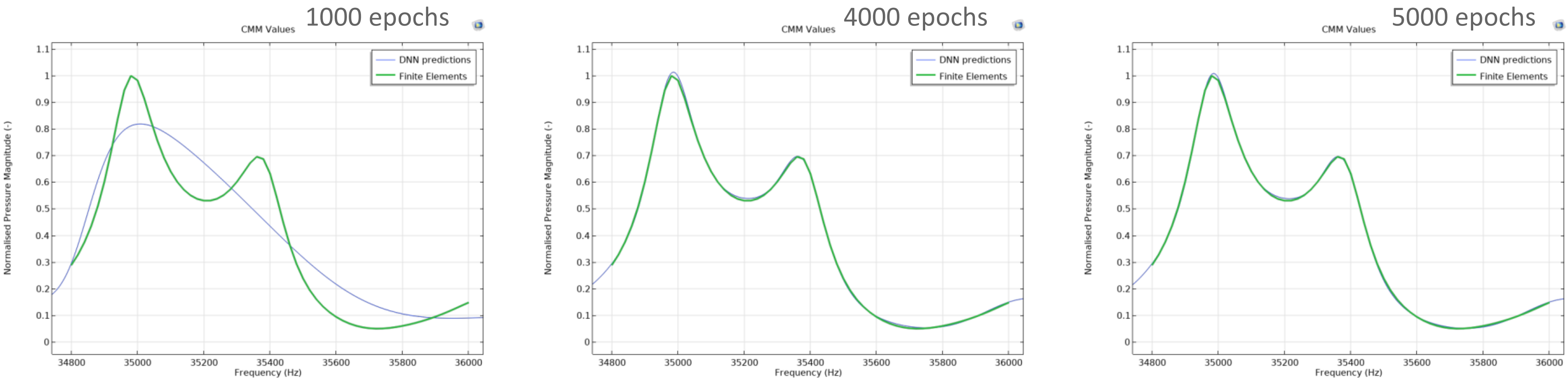
Step 3.c: Effects of the Duration of the Training





The longer the training, the smaller the loss function is allowed to get; however, comparing the DNN predictions with FE simulation results shows that the improvement after 4000 epochs is negligible

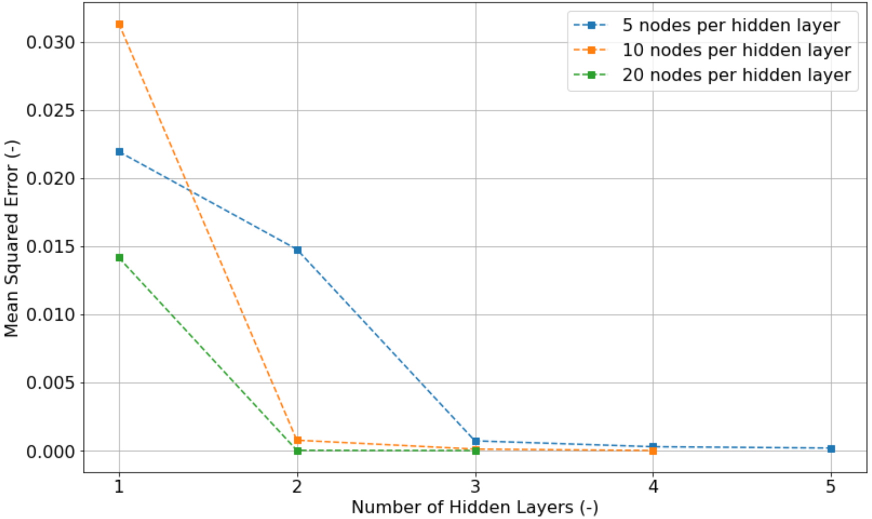
Step 3.c: Effects of the Duration of the Training

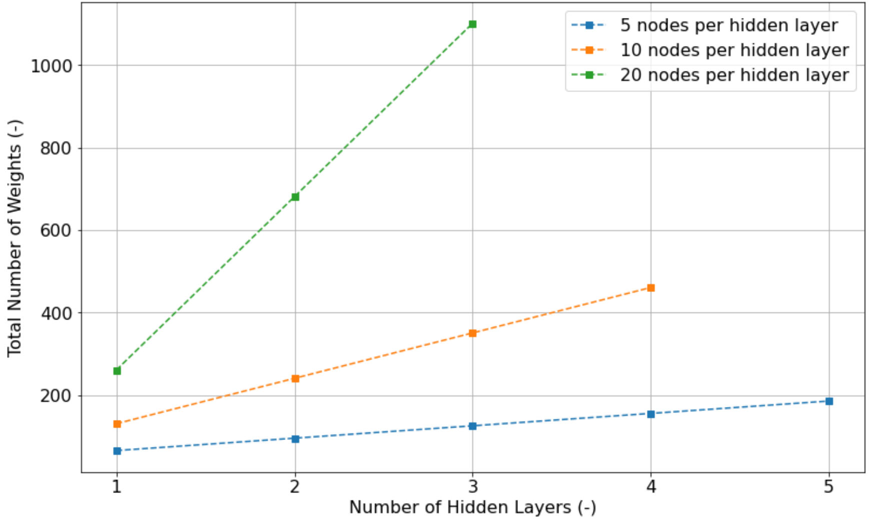


Comparison of the DNN predictions with FE simulations when CMM values are considered for an increasing number of epochs for the training

When the Deep Neural Network is allowed more epochs for the training the loss error decreases, leading to a higher accuracy of the predictions

Step 3.d: Influence of the Layer Structure





Increasing the number of layers more complex features and non-linearities of the function can captured by the DNN

A wide network greatly increases the number of weights needed, causing a longer and more computationally expensive training of the DNN

Conclusions

- Optimised DNN hyperparameters:
  - DoE points: 6000
  - Learning Rate (α): 5e-4
  - Epochs to train for: 4000
  - Wider shallow layer structure
- Computational Time Comparison:
  - With FE simulations:
    - 4 mins/simulation
    - 3^{10} simulations needed
    - 236,196 mins ≈ half a year
  - With ML:
    - 14.5s per point in DoE
    - 6000 points needed
    - 24 hrs 10 mins

References

[1] FT Technologies website, https://fttechnologies.com/ , last accessed 19/09/2024

[2] S. Kapartis "Anemometer employing standing wave normal to fluid flow and travelling wave normal to standing wave." U.S. Patent No. 5,877,416. 2 Mar. 1999

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

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