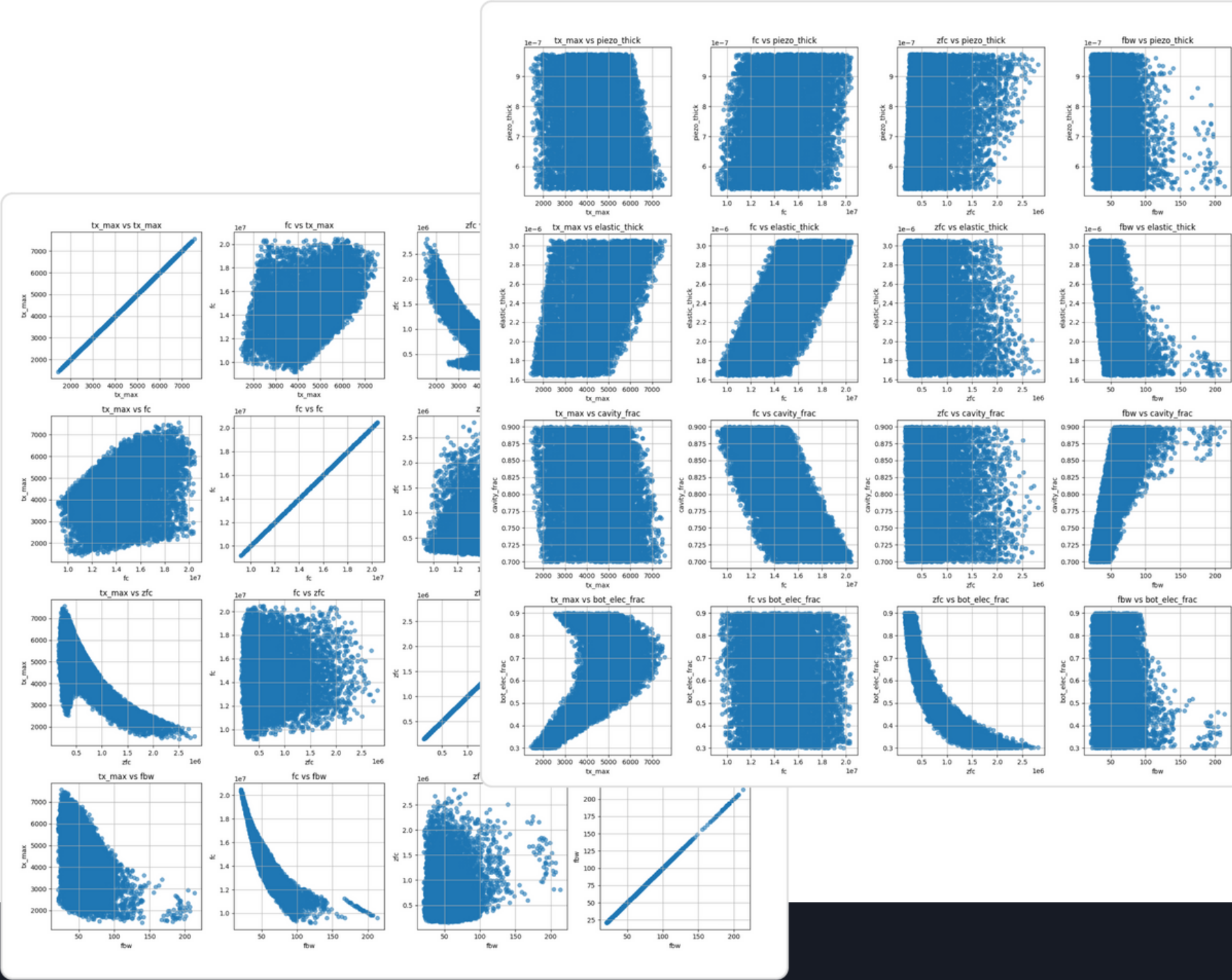


Engineering insights machine

The best source of MultiphysicsAI simulation data



Legacy simulation blocks innovation Quanscient unblocks it

QUANSCIENT

Simulation bottlenecks

<1% of design space explored.

Lack of training data for AI/ML applications

What Quanscient enables

>1000x throughput

→ Full design exploration

AI scale training material in hours

→ Workflows with millions of simulation runs

Engineering for the future

Cloud data for MultiphysicsAI

QUANSCIENT

MultiphysicsAI · 2026

In combination of the best data generation from cloud solver **enables unparalleled capabilities.**

First showcases built and customers onboarded.

- Trains on the world's best simulation data
- Understands context and guides design exploration
- Controls solver usage and AI training recipes

Cloud solver · 2024

Foundation of our platform.

All capabilities are built from this. Adopted by some of the largest R&D organizations globally.

- Strongly coupled multiphysics
- 1000x throughput for simulation exploration
- Proven at large enterprises

The workflow

How MultiphysicsAI works

1. Create proprietary training data

Run up to millions of natively coupled simulations in parallel with Quanscient Allsolve to produce unique multiphysics datasets owned by you.

2. Train physics-aware neural networks

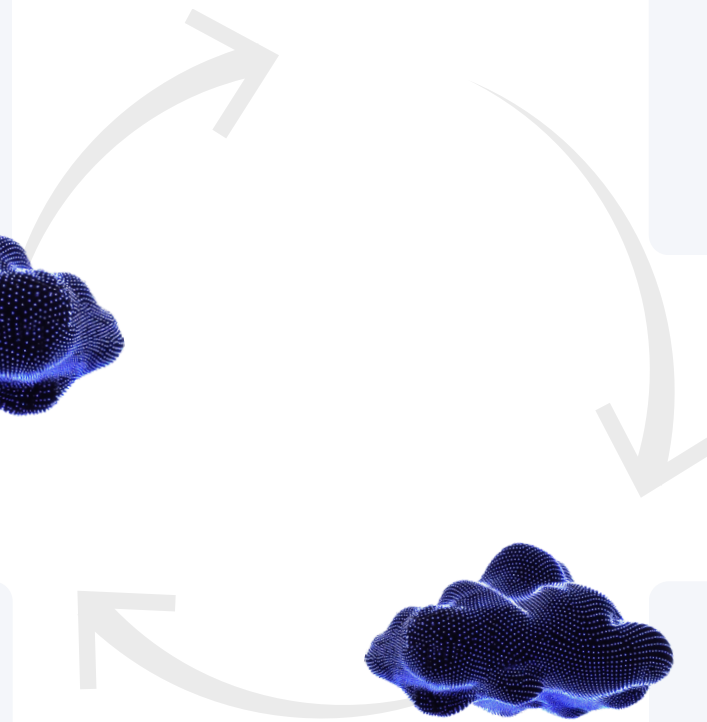
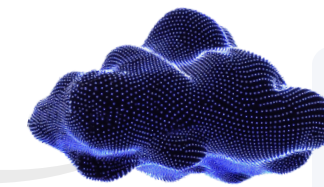
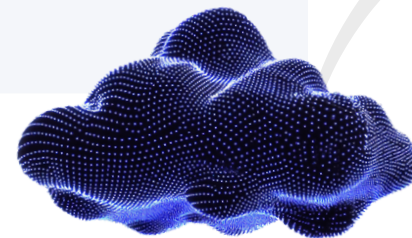
Use that data to train a surrogate that can make hundreds of thousands performance predictions in seconds.

3. Decide with full design-space visibility

The fast model reveals the design landscape, surfaces the few best trade-offs, and shows which options meet your goals—instantly.

4. Verify before you choose

Validate the top options with Allsolve so every decision is grounded in physics.



Optimization and inverse problems

Months of iteration time saved



Use case	Before	With MultiphysicsAI
Piezo material characterization	Slow and difficult to measure required materials	The inverse problem for optimal material parameters solved in milliseconds
PMUT sensitivity and bandwidth optimization	Months of iteration to reach a 'good enough' design	Identified the set of best designs and validated performance improvements in hours
Microspeaker optimization	Slow and costly simulations and prototyping	Identified a better design and validated improved sound performance in hours
Electric Motor Hub optimization	Multiple design loops to tune hub geometry by hand	Real-time model for optimal hub shape
Piezocomposite design	Lengthy iteration to balance sensitivity and bandwidth	Real-time model that identified the best set of designs instantly

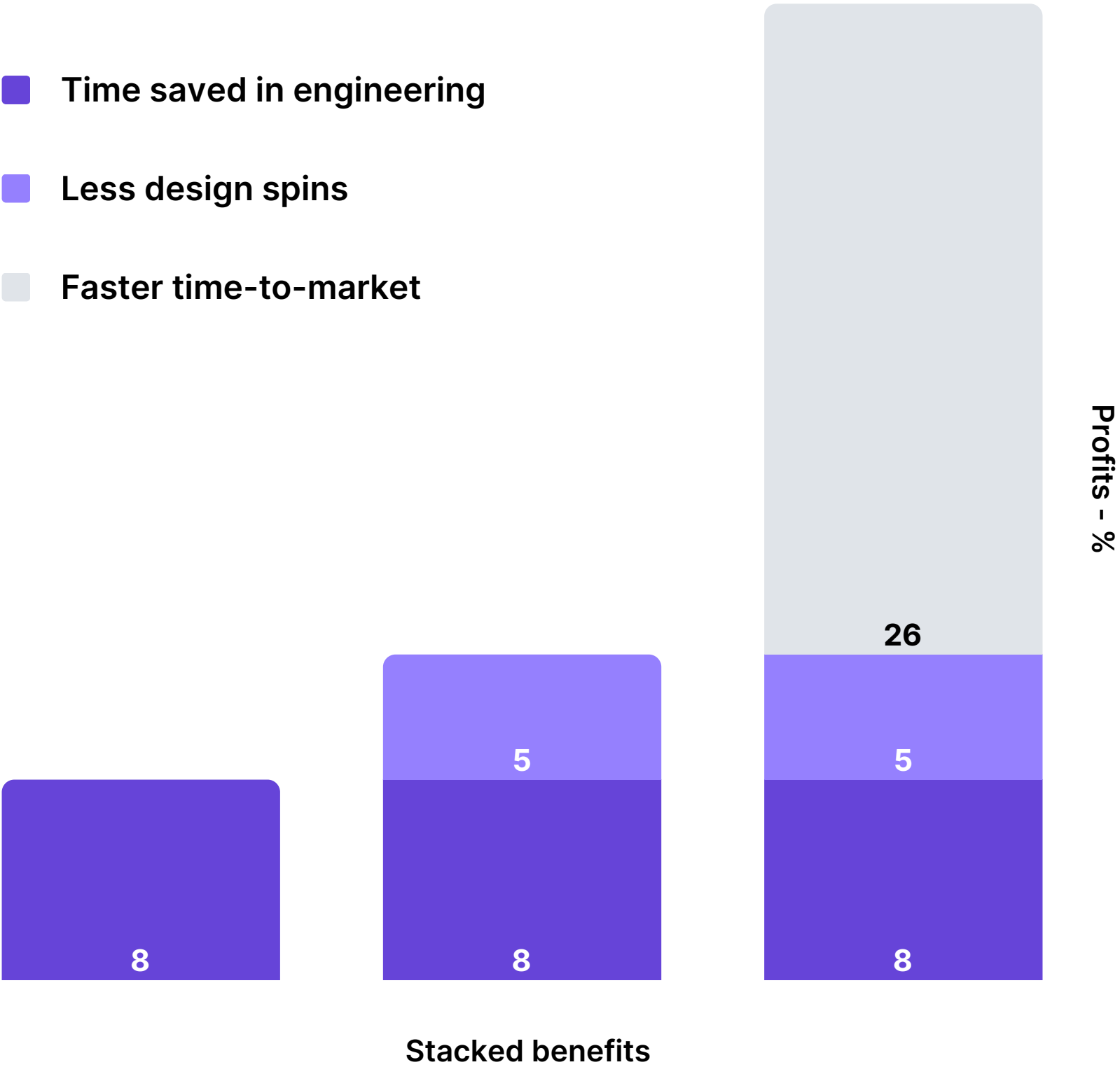
Vision

Accelerate the most
challenging engineering
problems — today and
tomorrow.

QUANSCIENT

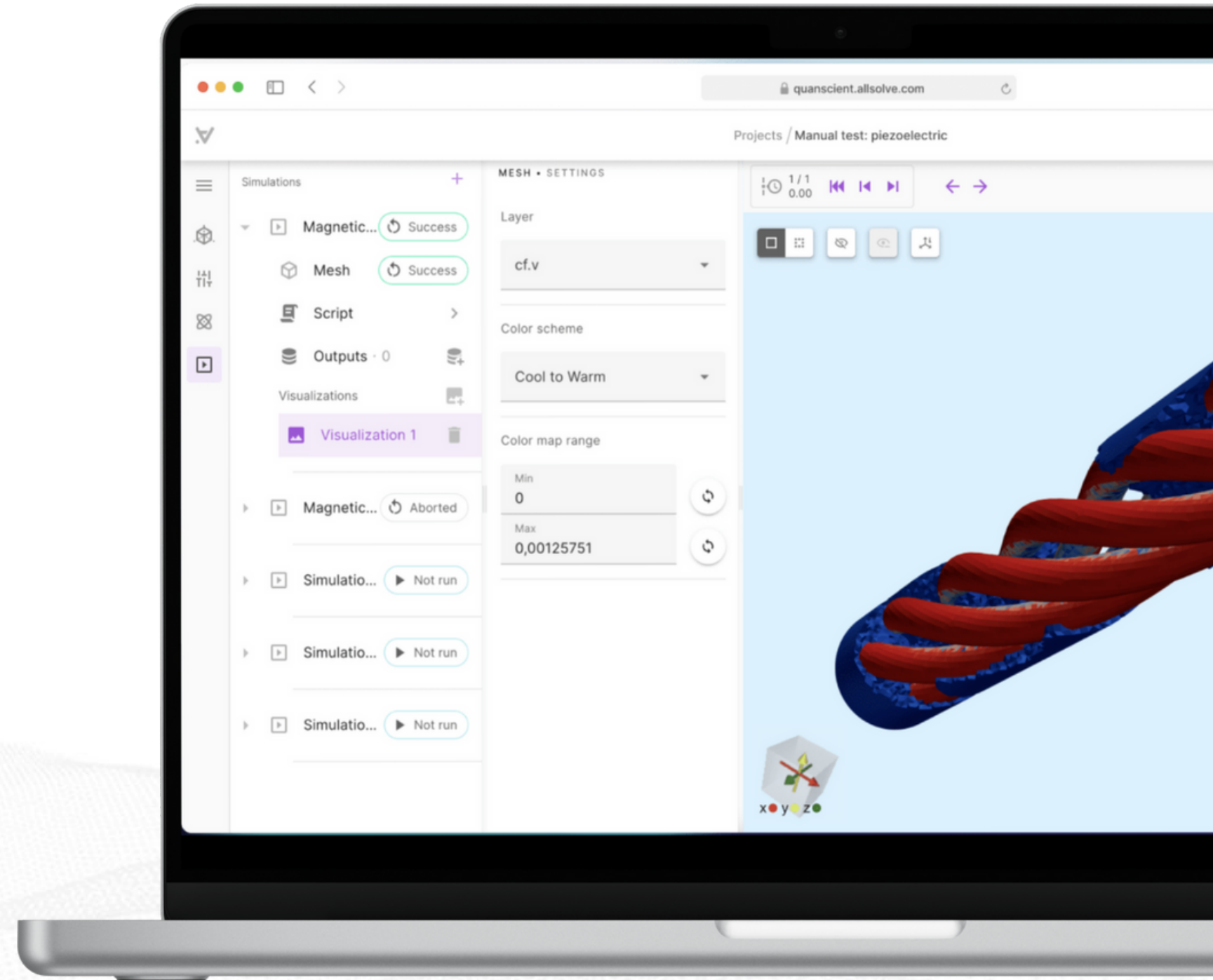
Speed, scale and accuracy
compound profits

- Time saved in engineering
- Less design spins
- Faster time-to-market



AI + Multiphysics: Introducing the new paradigm for engineering simulation

Dr Andrew Tweedie
Co-CTO & Co-Founder



Overview

- Why AI + Multiphysics?
- Allsolve: an engine for multiphysics data
- Training AI tools to solve complex engineering problems
- AI case studies

Why AI?

- As engineers our job is to solve complex inverse problems
 - “Come up with a design that meets this spec!”
- Current simulation tools don’t solve this problem
 - They only tell you what a design will do, not what your best designs might be
 - Often we end up with a single “best” design, with few alternatives
- AI can quickly explore the whole design space
 - Quickly identify the best design candidates
 - Clearly visualise the tradeoffs between different options
 - Verify the a design’s rubustness to manufacturing tolerances

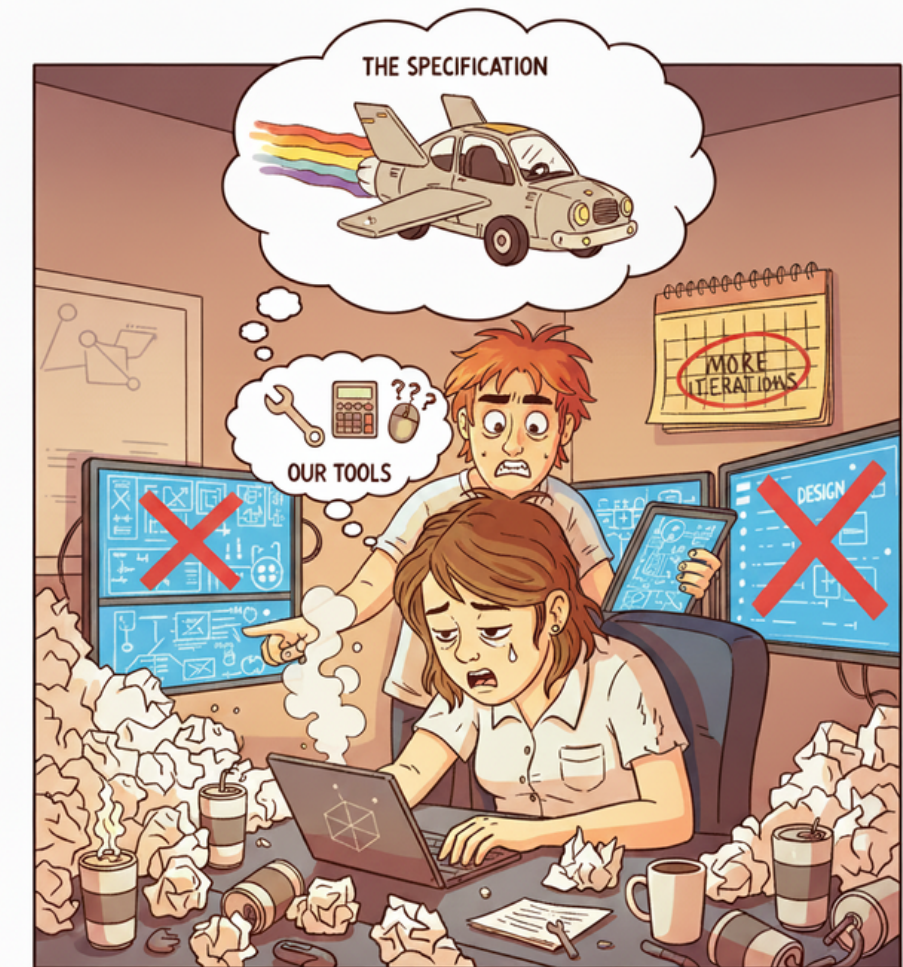
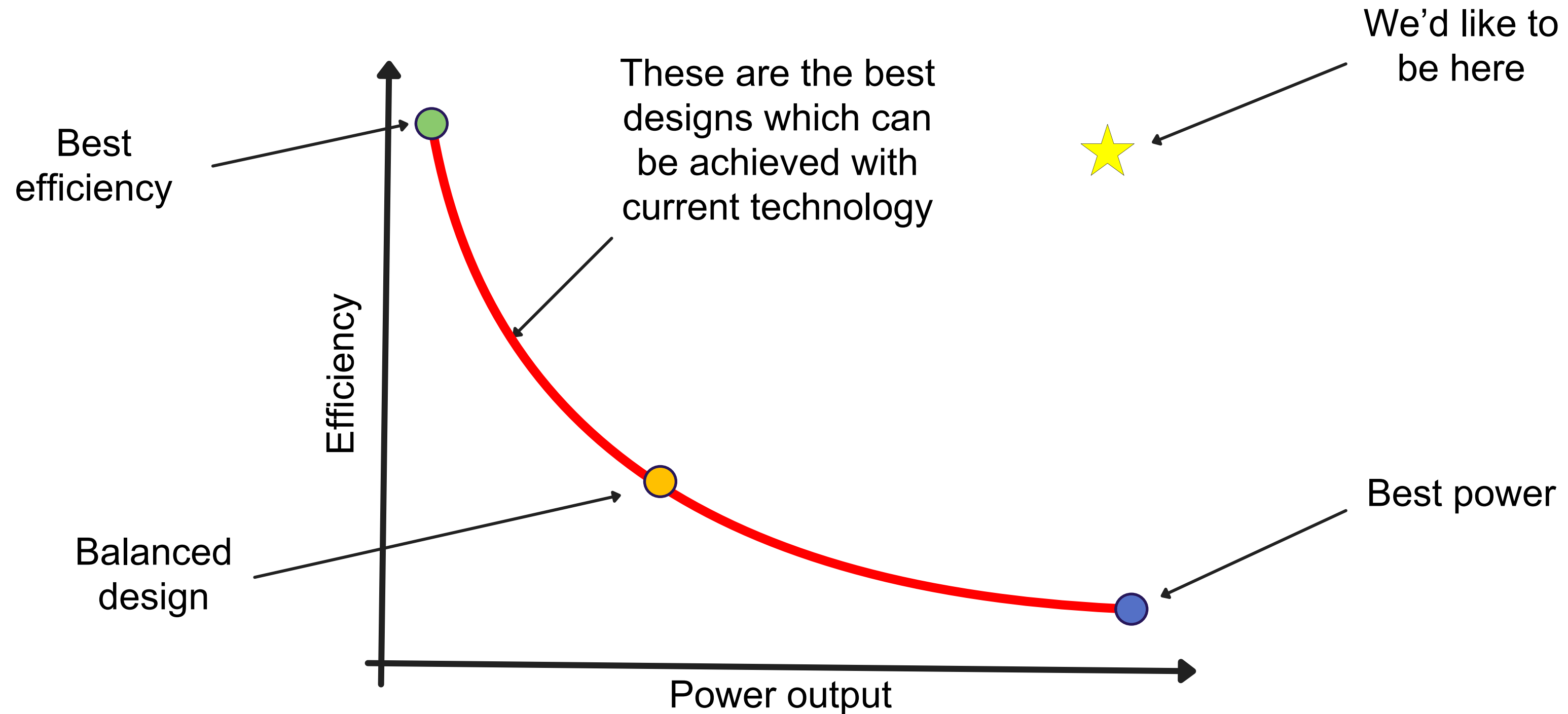


Image courtesy of Gemini

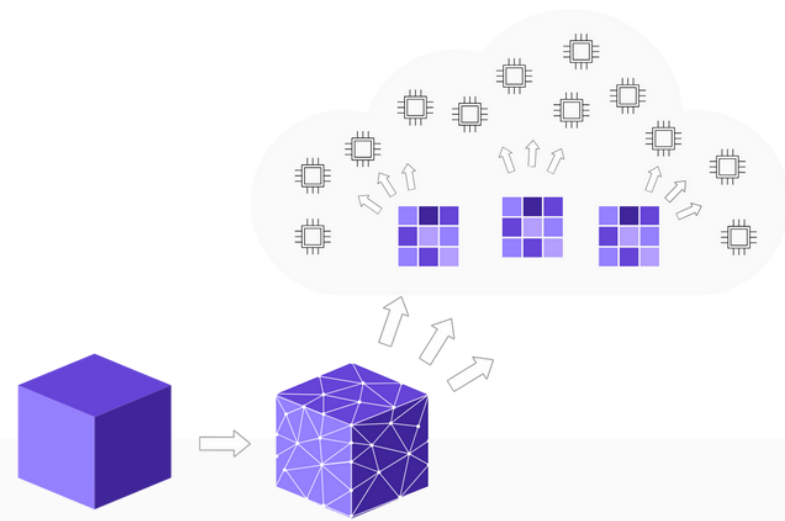
Classic engineering design problem

Performance of an automotive engine



Allsolve provides unparalleled throughput, for multiphysics engineering simulations

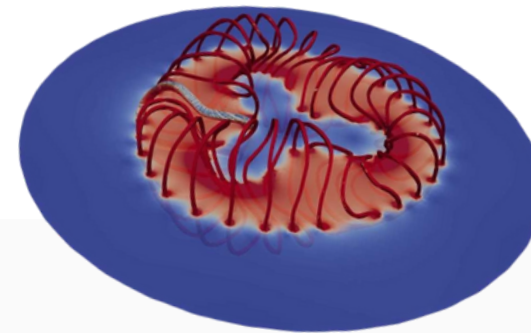
QUANSCIENT



Unparalleled speed

>100x Speedup

Thousands of parallel simulations



Multiphysics solvers

General-purpose multiphysics

Strongly coupled



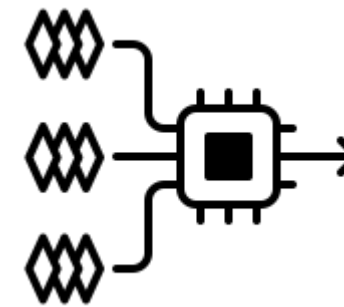
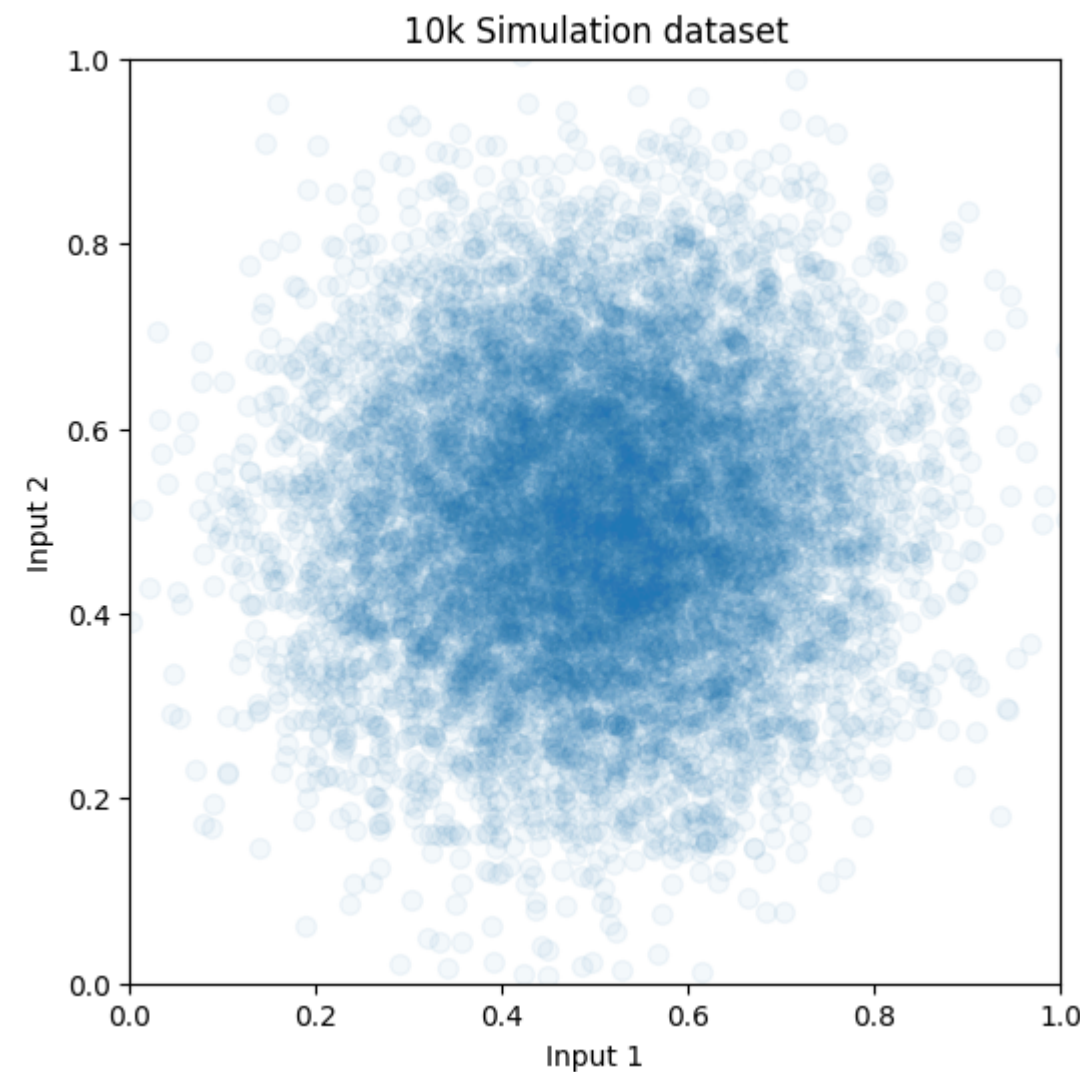
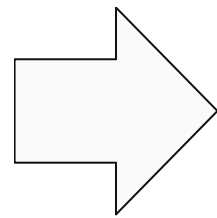
Cloud based

Unlimited hardware

Intuitive browser based UI

Allsolve: the multiphysics data engine

QUANSCIENT

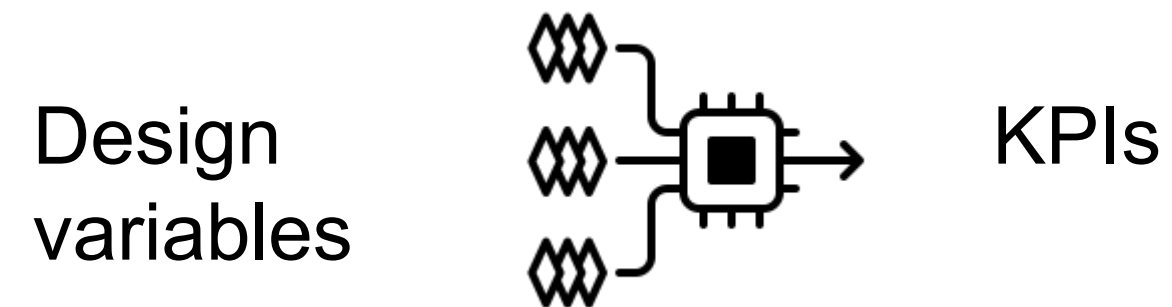


Trained AI model which can
predict device performance

- AI can efficiently “learn” the problem
- It can then be used to make predictions very quickly ($\ll 1$ ms per prediction)

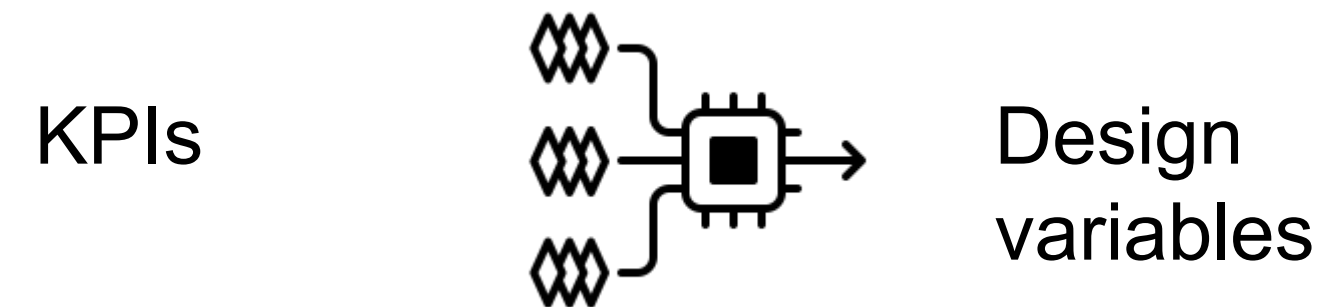
Two approaches to AI training

Forward model



(sometimes called a “digital twin”)

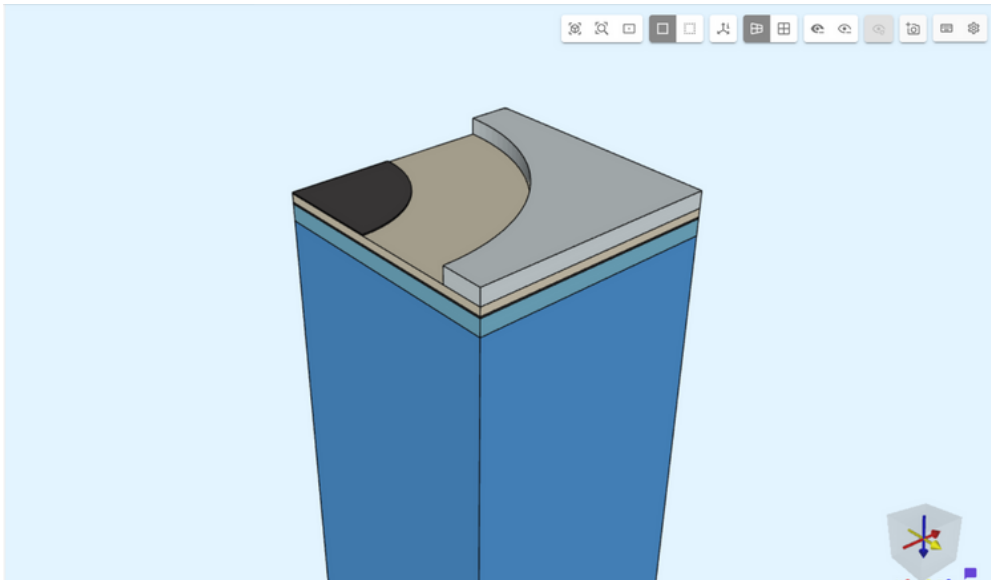
Inverse model



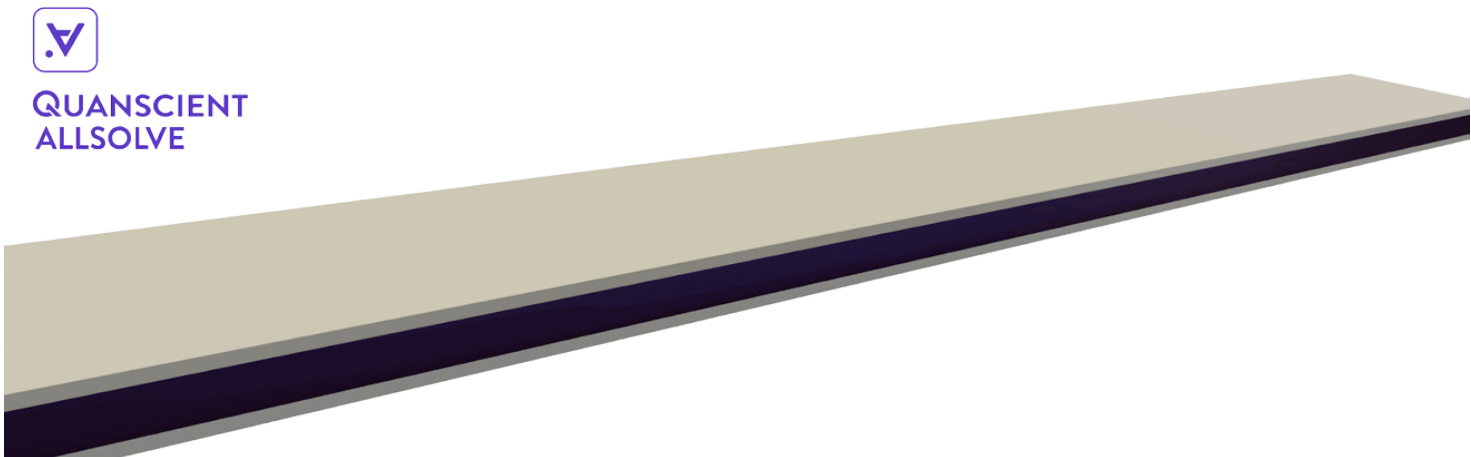
Case studies

MEMS & ultrasound

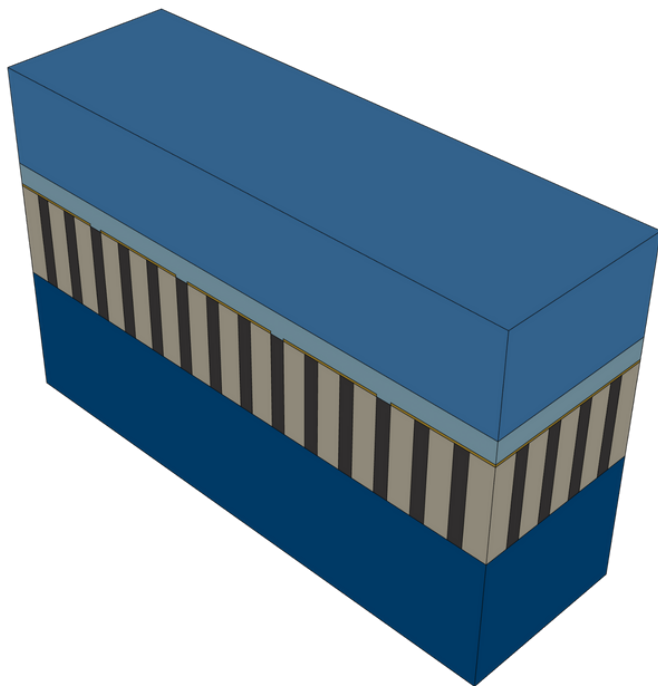
PMUT design optimisation



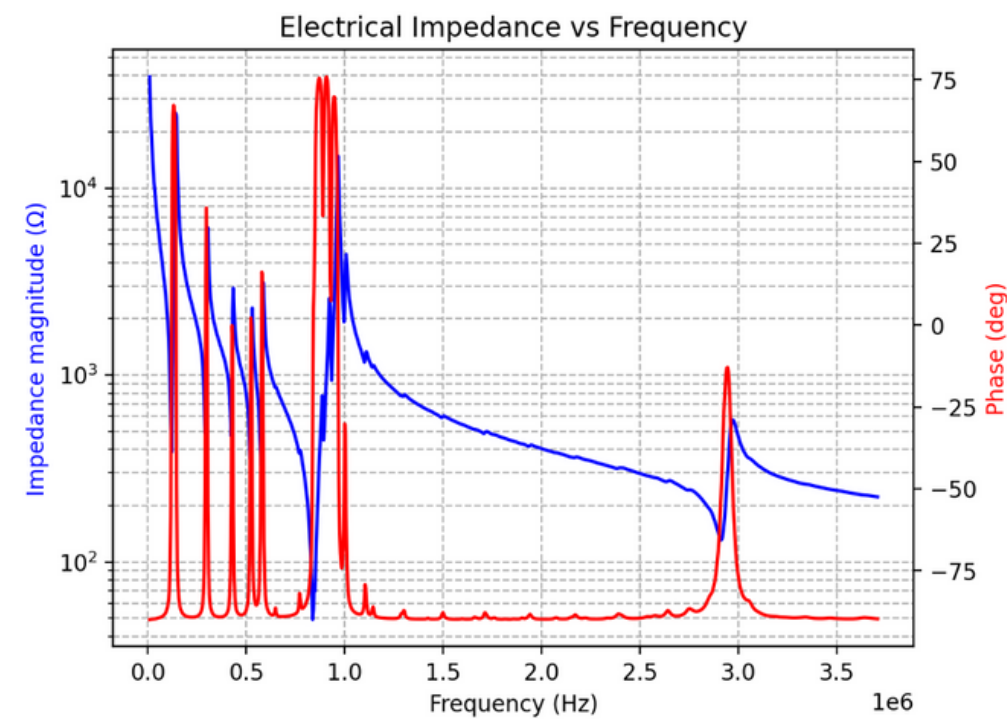
MEMS microspeaker design optimisation



Piezocomposite design optimisation



Piezo material characterization



PMUT design optimisation

Case study



PMUT example

Geometry & physics

QUANSCIENT

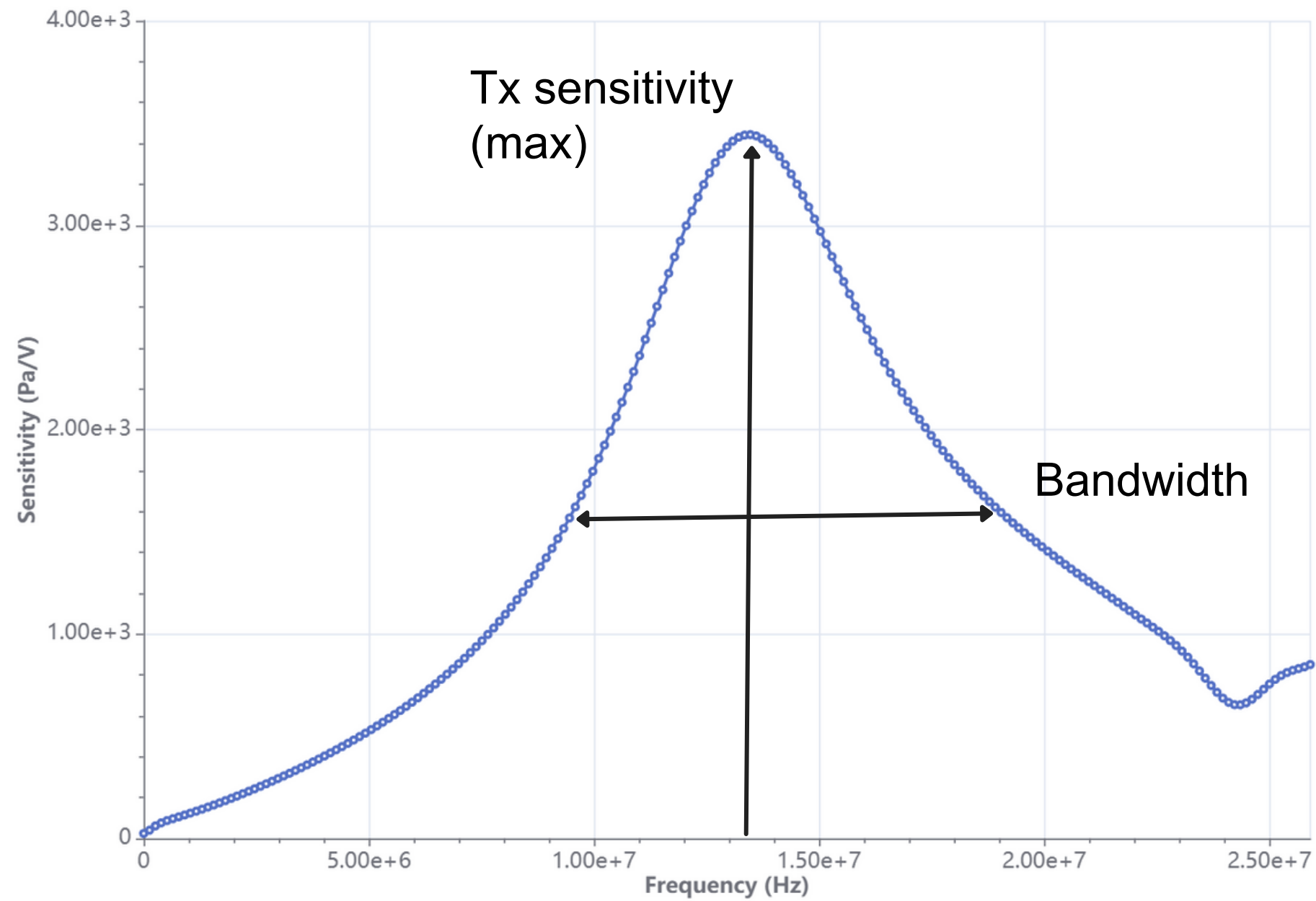
Typical results

PMUT example

QUANSCIENT

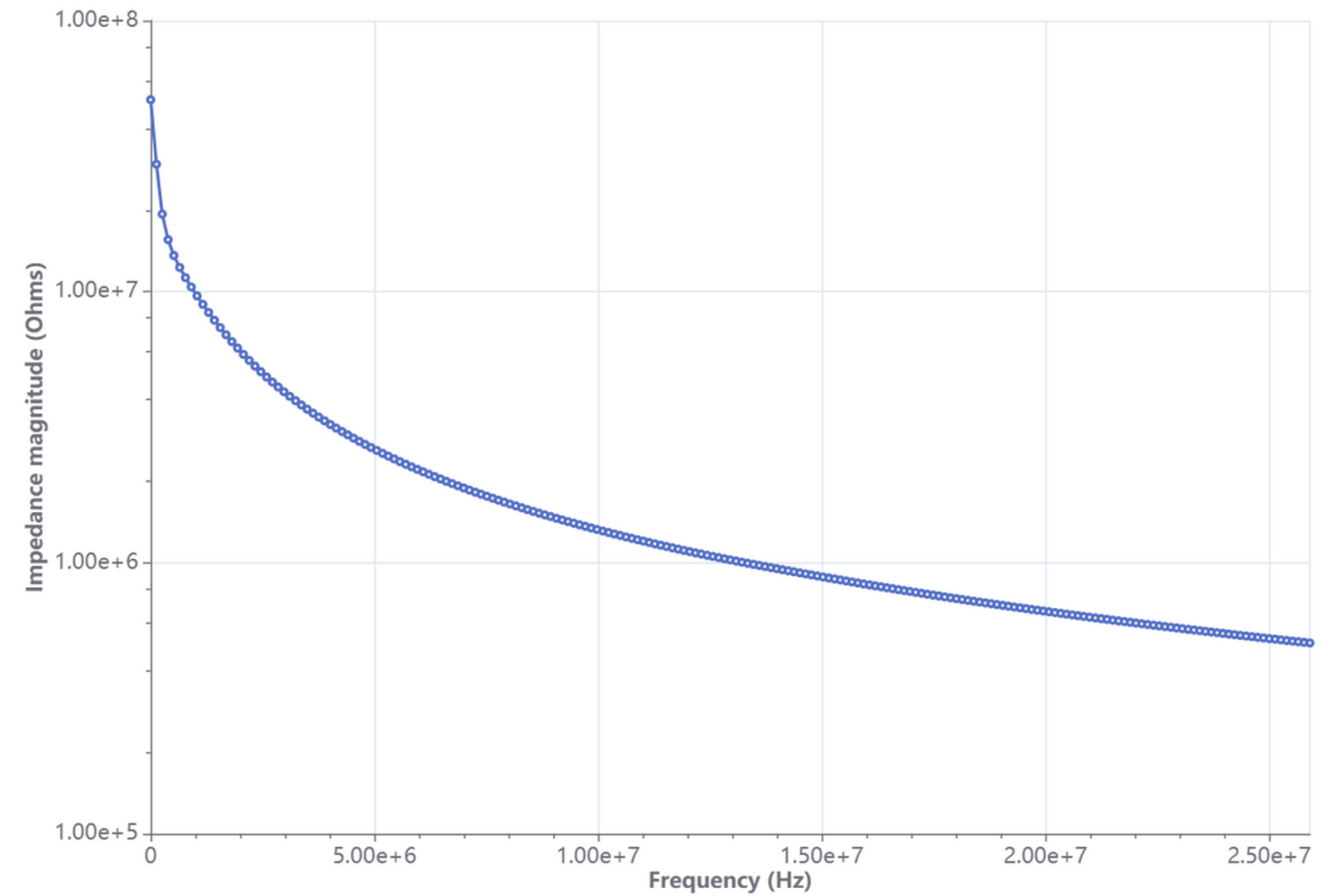
PMUT Unit Cell Tx Sensitivity

○ Txmag



PMUT Unit Cell Impedance Magnitude

○ Zmag



PMUT example

Problem definition

- Design inputs to vary:
 - Elastic layer thickness
 - Piezo layer thickness
 - Cavity radius
 - Bottom electrode radius
- Outputs to study (KPIs):
 - Transmit sensitivity (Pa/V)
 - Centre frequency (Hz)
 - Fractional bandwidth (%)
 - Impedance at resonance (Ohms)

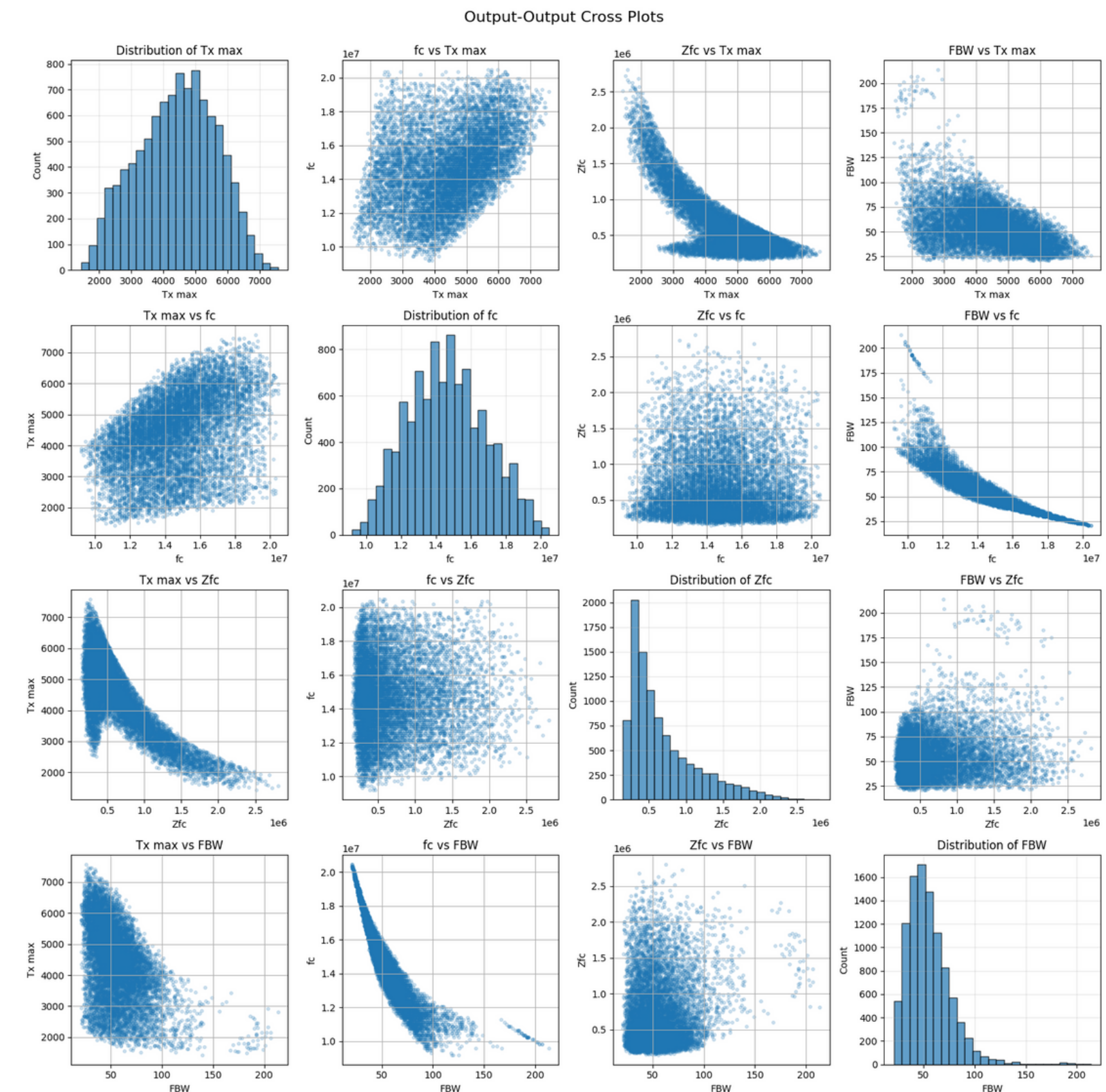
Our goal is to find designs which maximise:

- Sensitivity
- Bandwidth

PMUT example

Simulated training dataset

- Created a dataset of 10k simulations with randomised geometry
 - Each simulation executes in ~5 seconds
 - Calculates all 4 KPIs
- This raw data can provide some insights
 - Which inputs and outputs are linked?
 - Which outputs must be traded off against each other?
- Plotting a correlation matrix can help visualise these relationships

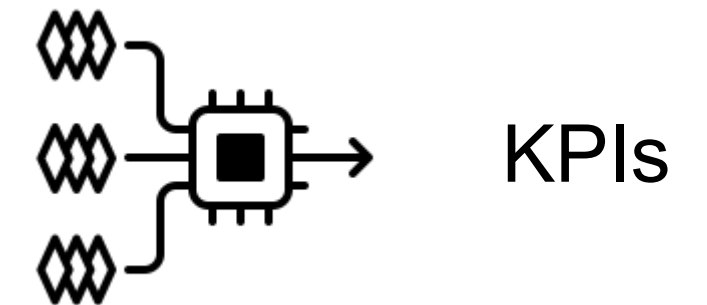


PMUT example

AI training

- Train an AI model on this data to
 - Take dimensions as an input
 - Predict output KPIs
 - i.e. what we would call the “forward model”
- Takes around 5-10 minutes on a GPU
- Resulting AI algorithm is accurate to 1% and executes in $\ll 1$ ms
- So what can we do with this algorithm.....?

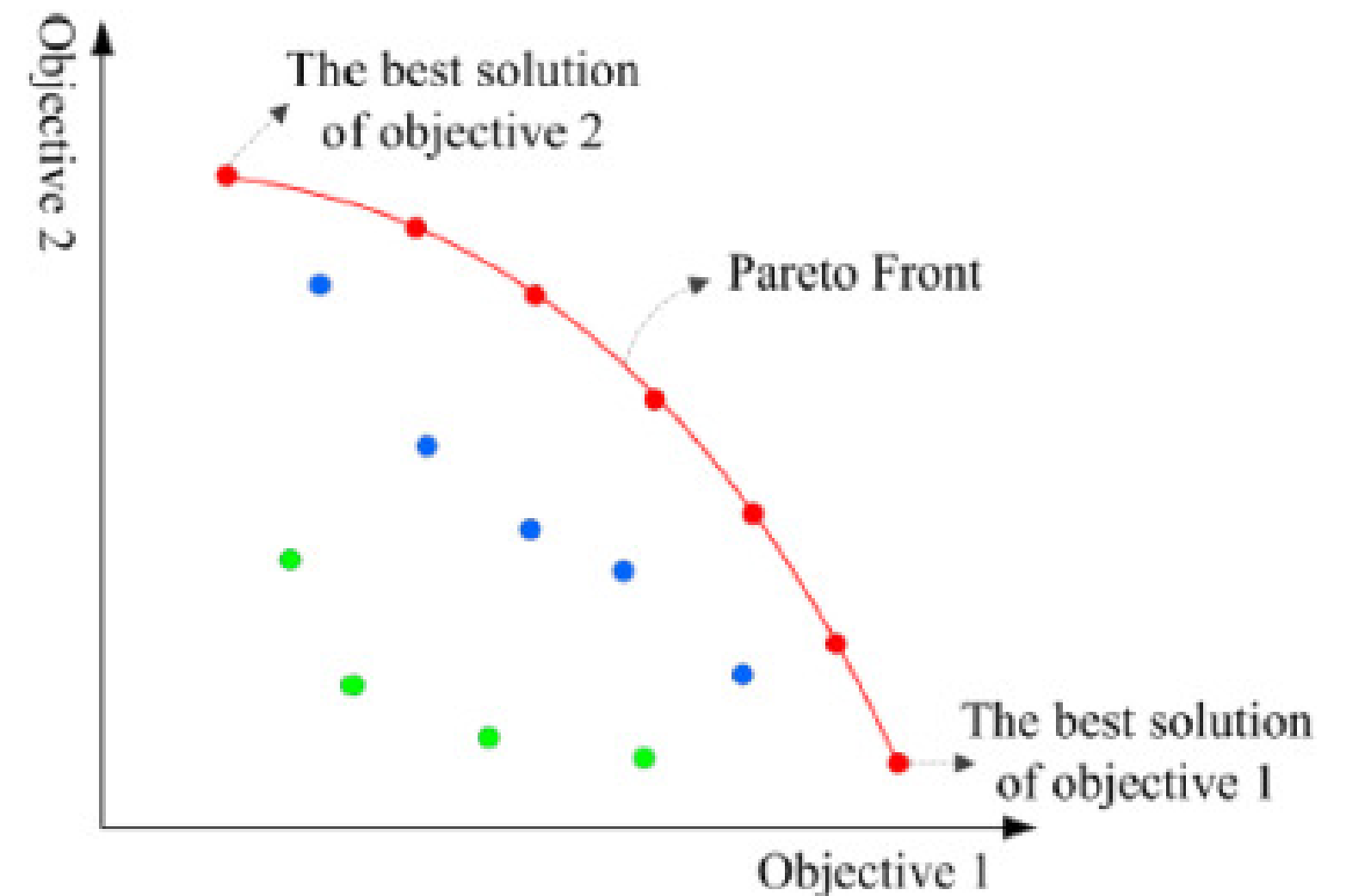
Design
variables



PMUT example

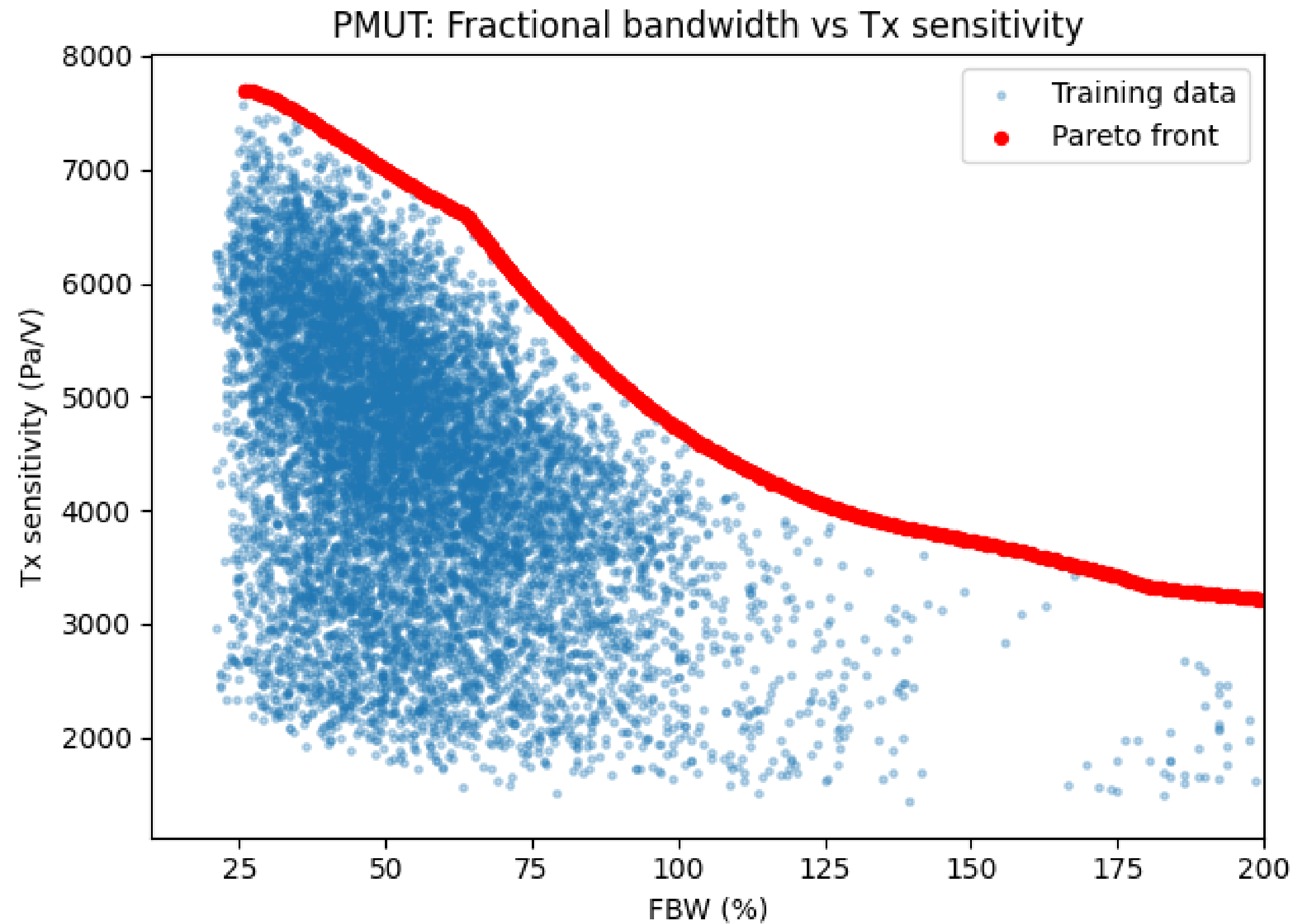
Design exploration

- Goal is to maximise both sensitivity and bandwidth
 - These are typically mutually exclusive
- We can use Pareto front analysis to do this, using the AI algorithm as the forward model
- This can be calculated in seconds



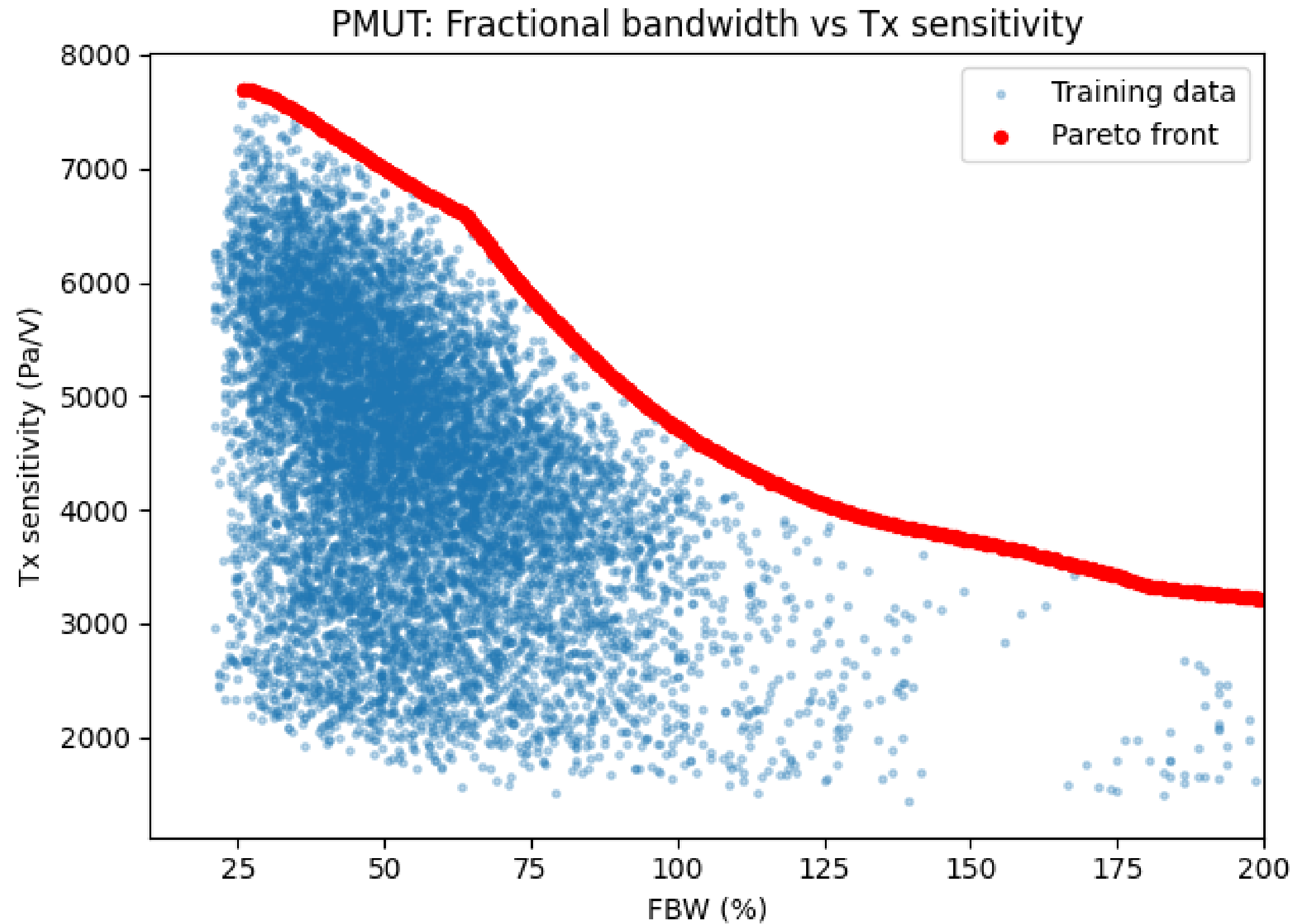
PMUT example

Pareto front



PMUT example

Pareto front

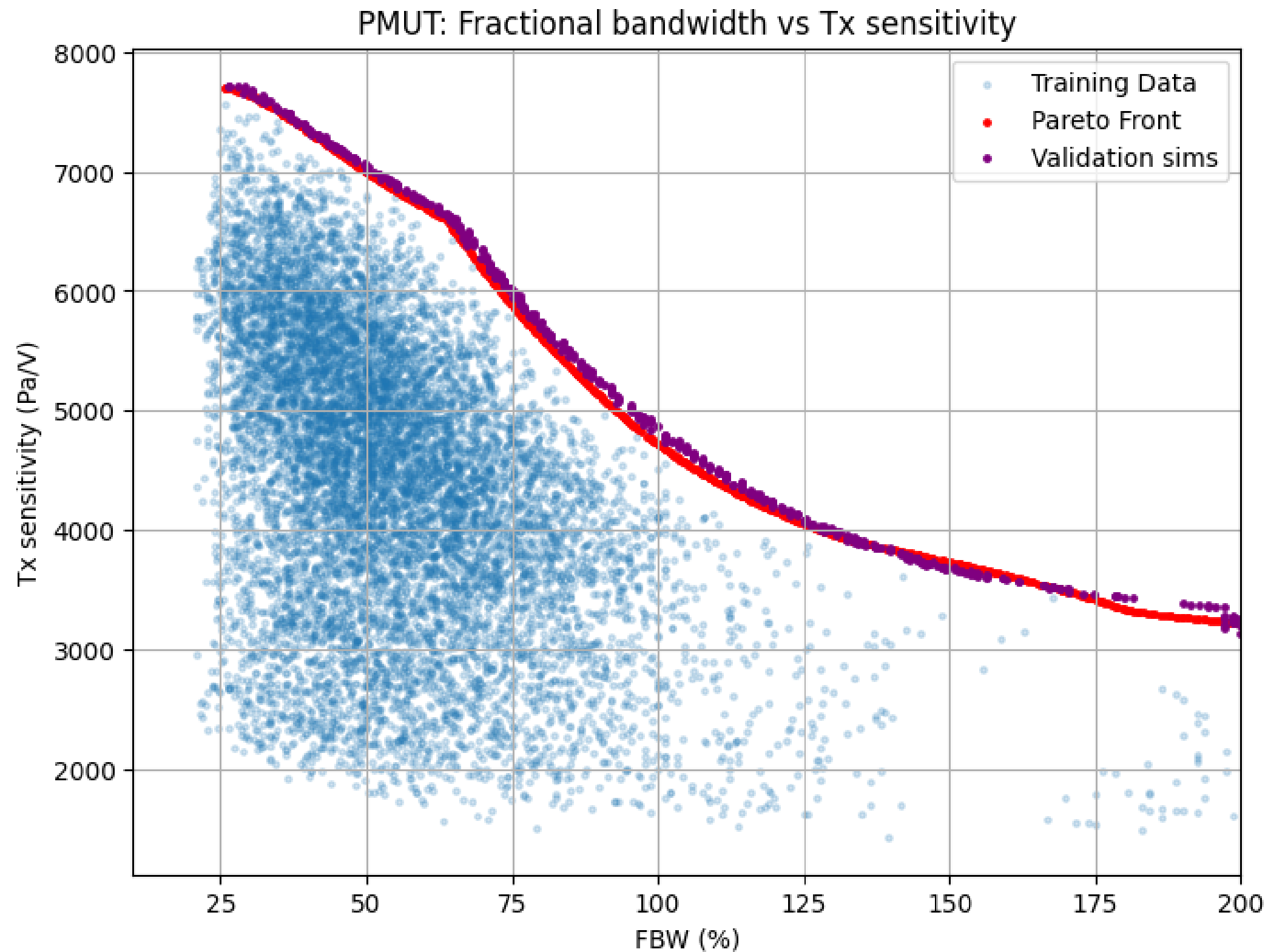


Question:

Are the red dots real designs?

PMUT example

Pareto front with validation sims

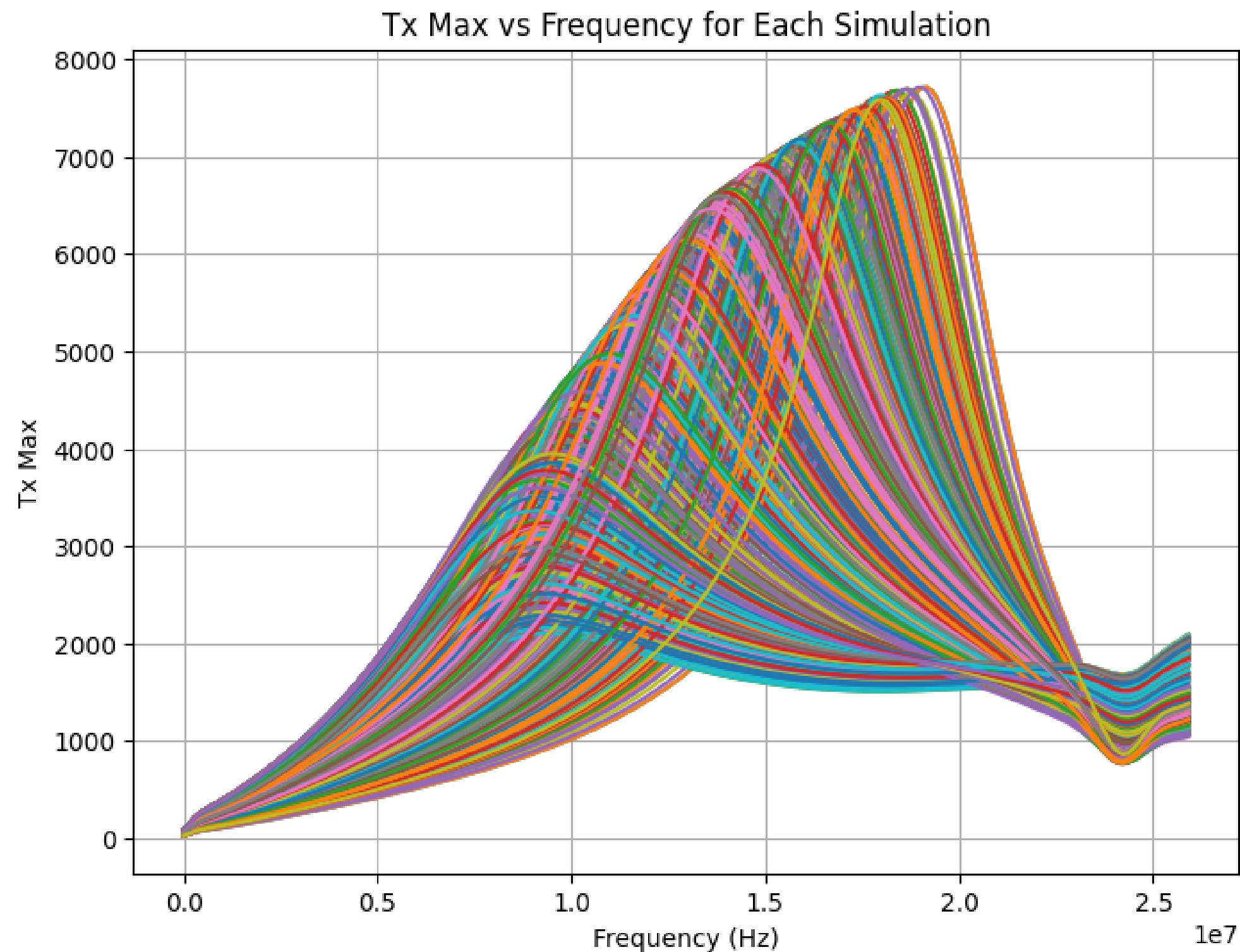


Answer:

Yes, they are!

PMUT example

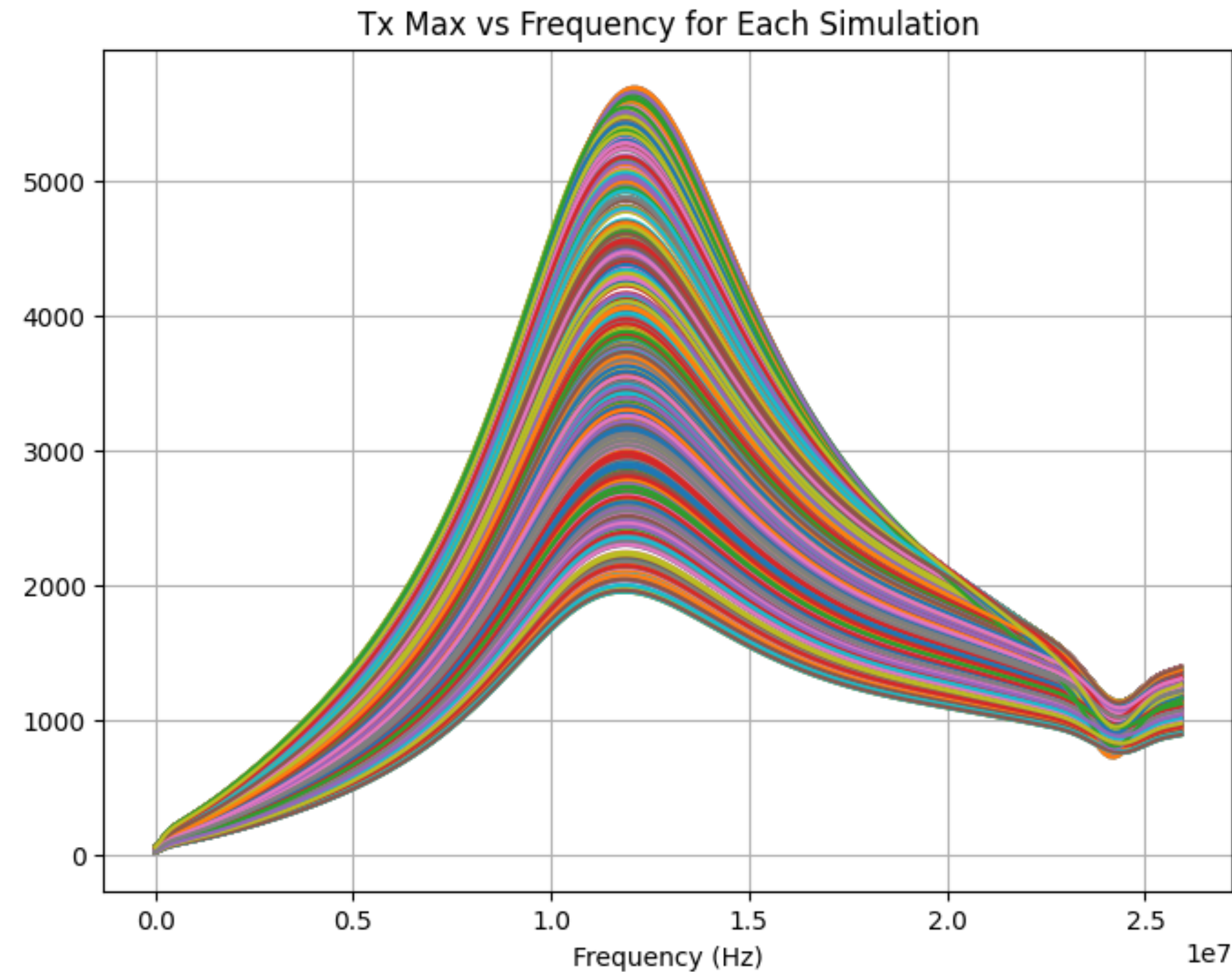
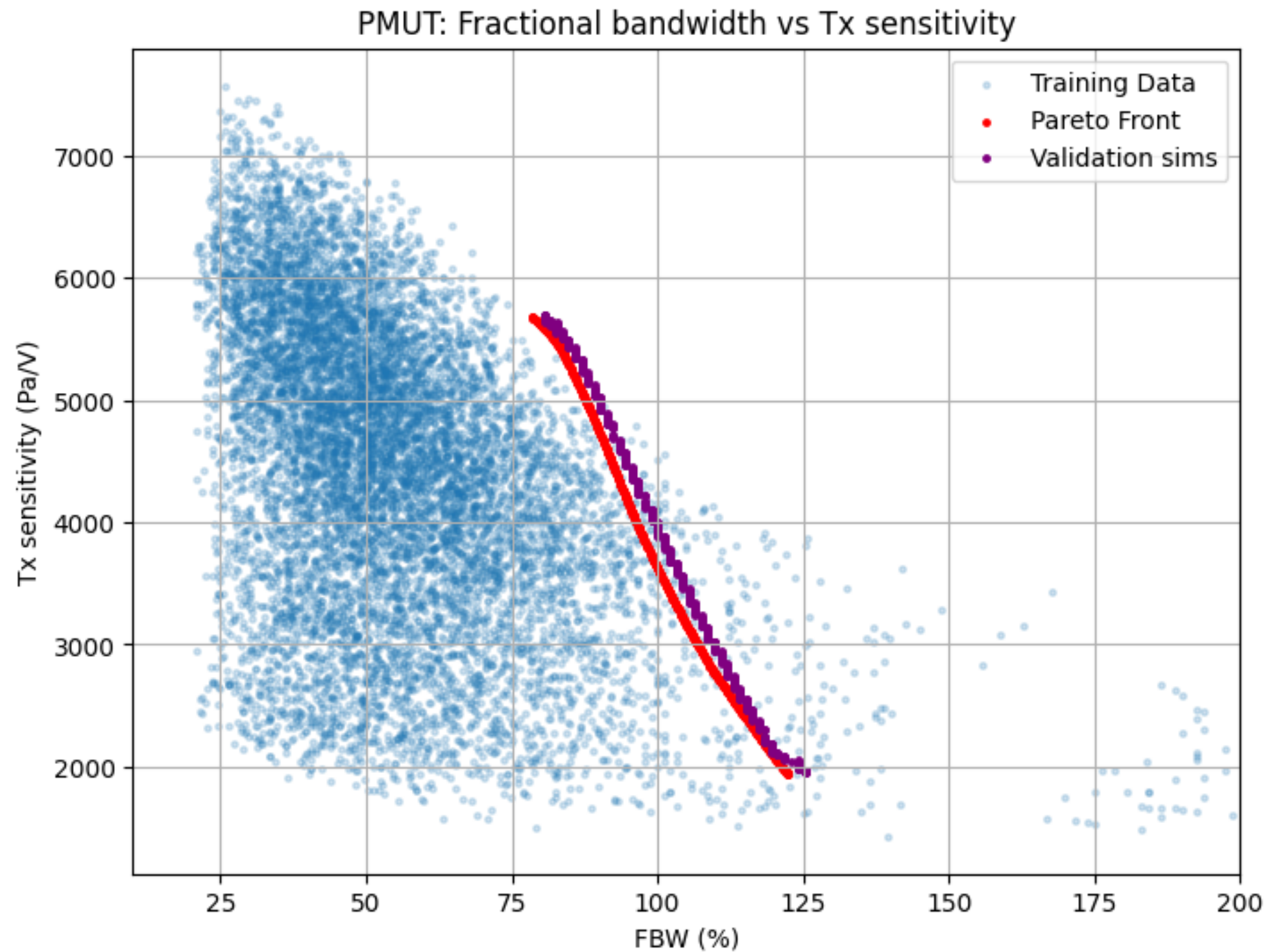
Pareto front raw data



Since we did not constrain frequency the front contains designs with a range of centre frequencies

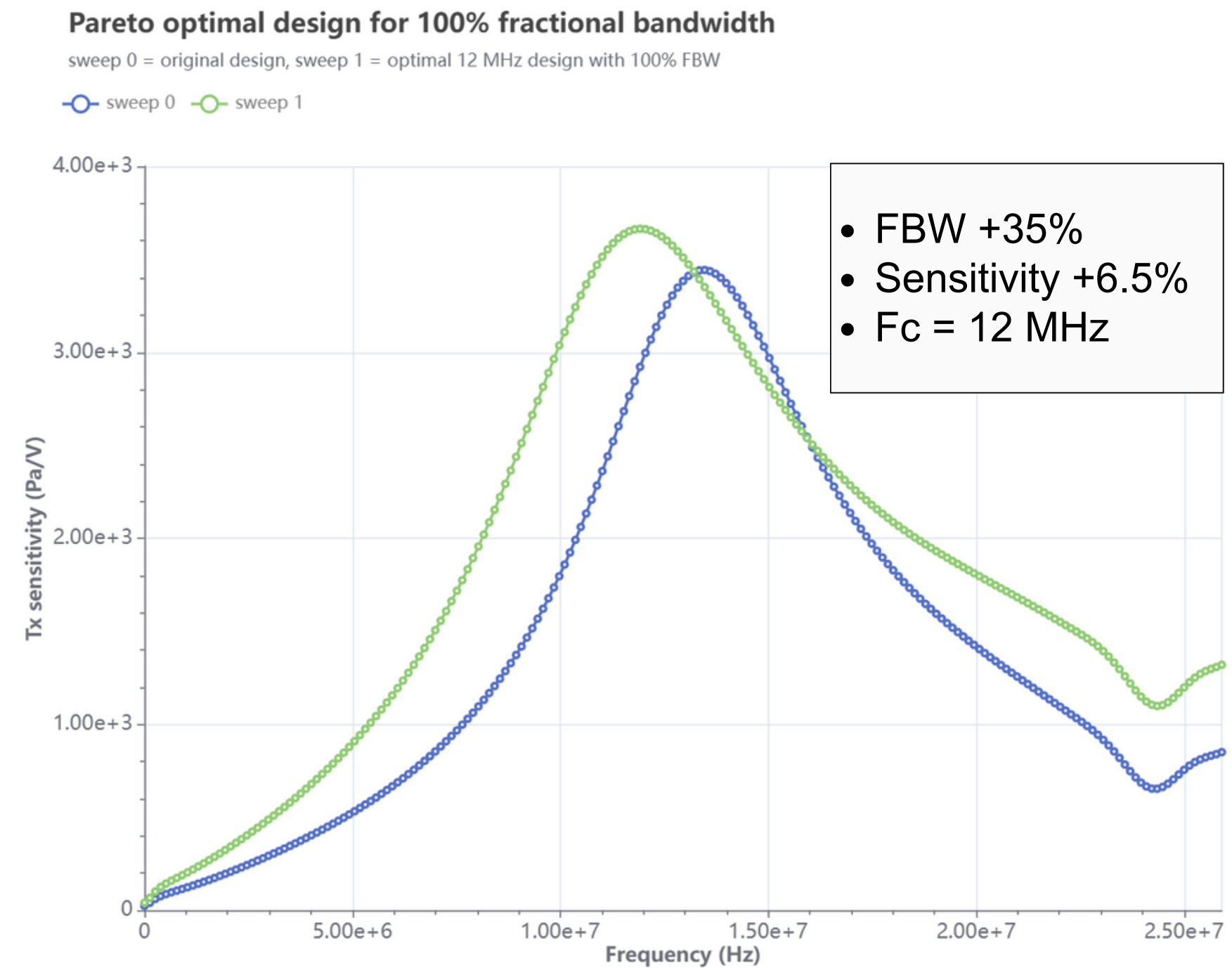
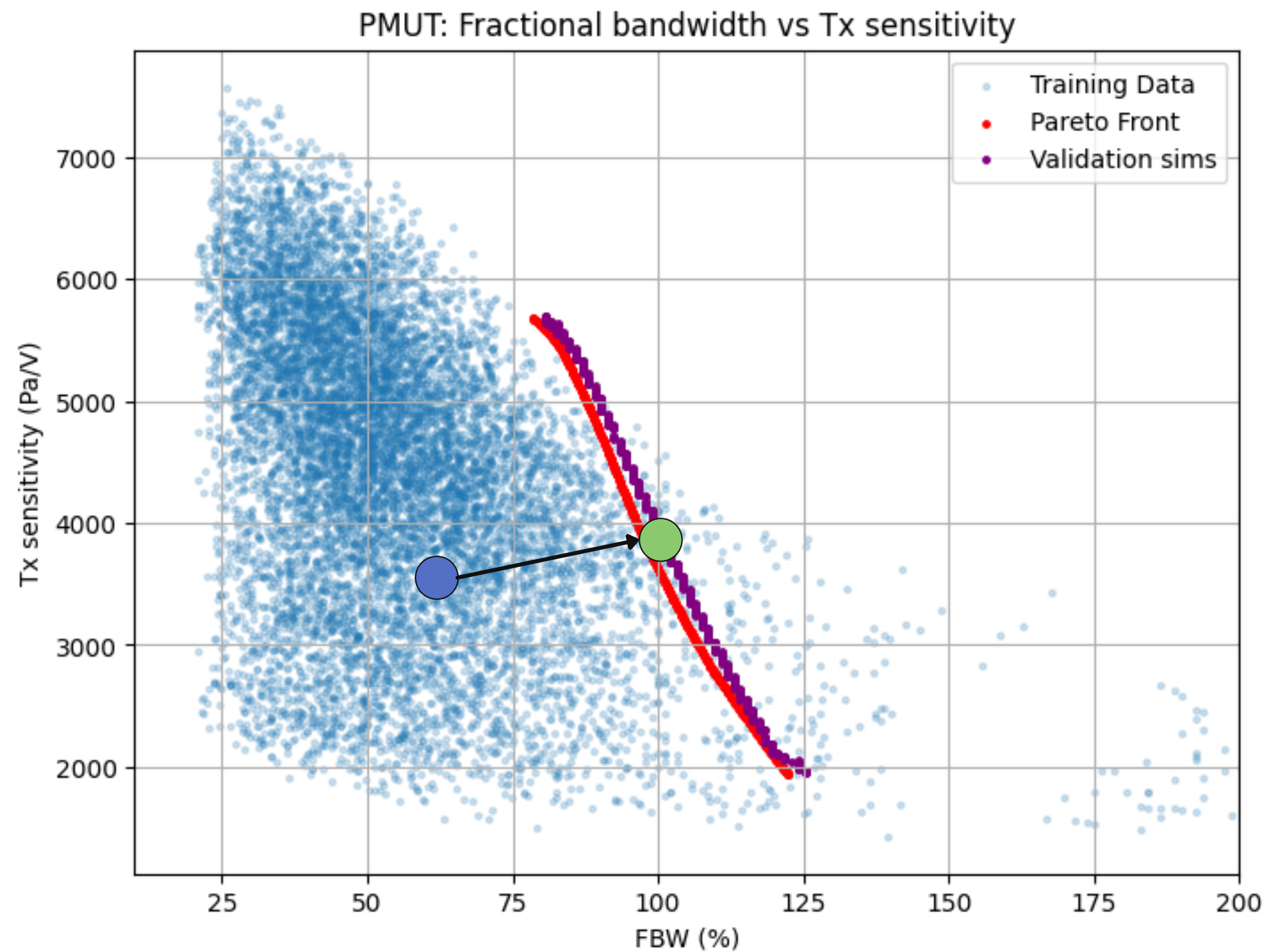
PMUT example

Pareto front with 12 MHz centre frequency constraint



PMUT example

Original design vs Pareto optimal design



MEMS microspeaker design optimisation

Case study



Coulomb-actuated microbeams revisited: experimental and numerical modal decomposition of the saddle-node bifurcation

Anton Melnikov¹, Hermann A. G. Schenk², Jorge M. Monsalve¹, Franziska Wall¹, Michael Stolz^{1,3}, Andreas Mrosk¹, Sergiu Langa¹ and Bert Kaiser¹

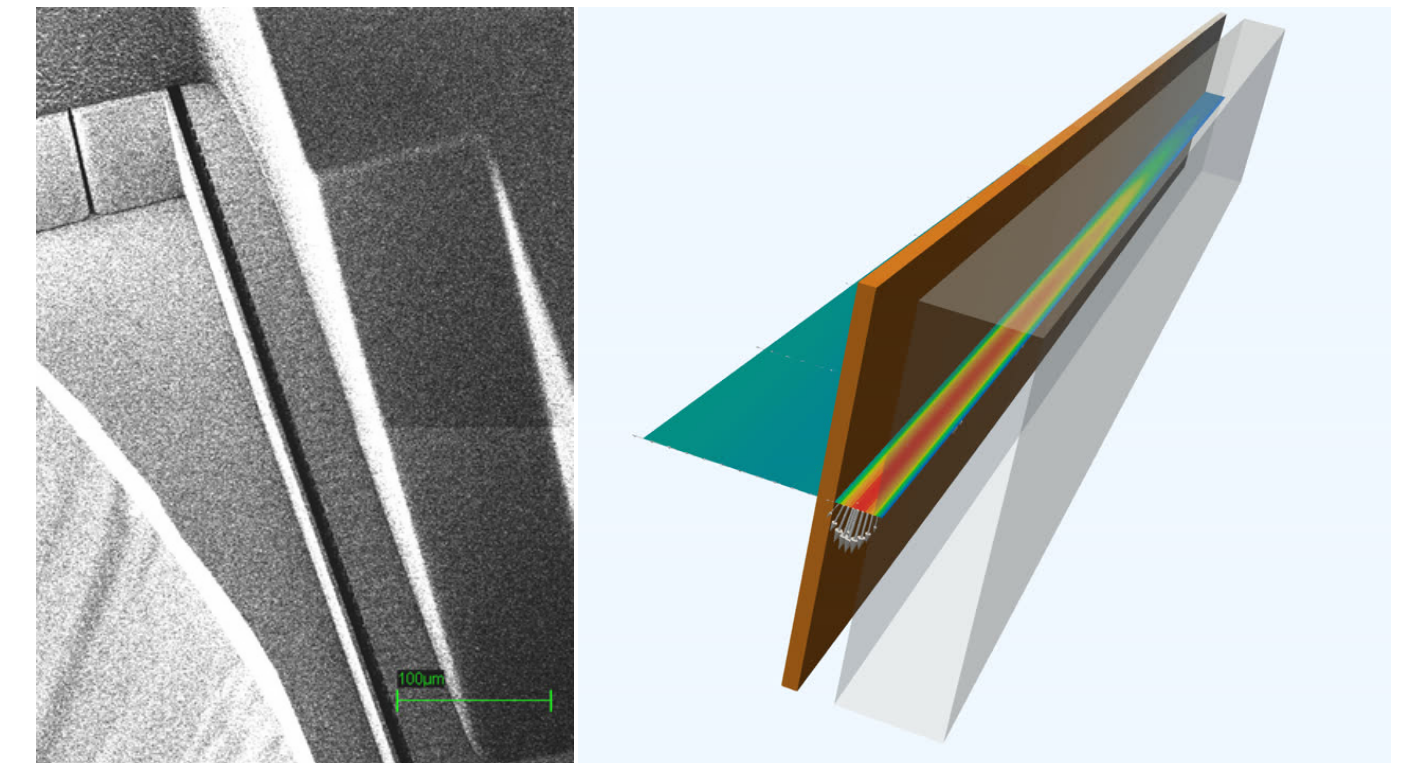
Abstract

Electrostatic micromechanical actuators have numerous applications in science and technology. In many applications, they are operated in a narrow frequency range close to resonance and at a drive voltage of low variation. Recently, new applications, such as microelectromechanical systems (MEMS) microspeakers (μ Speakers), have emerged that require operation over a wide frequency and dynamic range. Simulating the dynamic performance under such circumstances is still highly cumbersome. State-of-the-art finite element analysis struggles with pull-in instability and does not deliver the necessary information about unstable equilibrium states accordingly. Convincing lumped-parameter models amenable to direct physical interpretation are missing. This inhibits the indispensable in-depth analysis of the dynamic stability of such systems. In this paper, we take a major step towards mending the situation. By combining the finite element method (FEM) with an arc-length solver, we obtain the full bifurcation diagram for electrostatic actuators based on prismatic Euler-Bernoulli beams. A subsequent modal analysis then shows that within very narrow error margins, it is exclusively the lowest Euler-Bernoulli eigenmode that dominates the beam physics over the entire relevant drive voltage range. An experiment directly recording the deflection profile of a MEMS microbeam is performed and confirms the numerical findings with astonishing precision. This enables modeling the system using a single spatial degree of freedom.

Melnikov, A., Schenk, H.A.G., Monsalve, J.M. *et al.* Coulomb-actuated microbeams revisited: experimental and numerical modal decomposition of the saddle-node bifurcation. *Microsyst Nanoeng* 7, 41 (2021). <https://doi.org/10.1038/s41378-021-00265-y>

Electrostatic Microspeaker

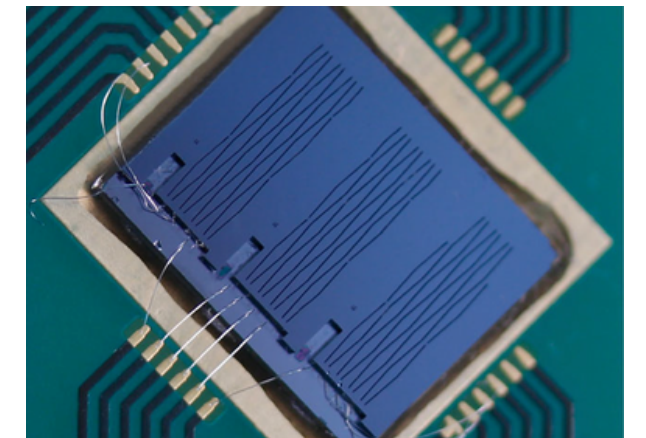
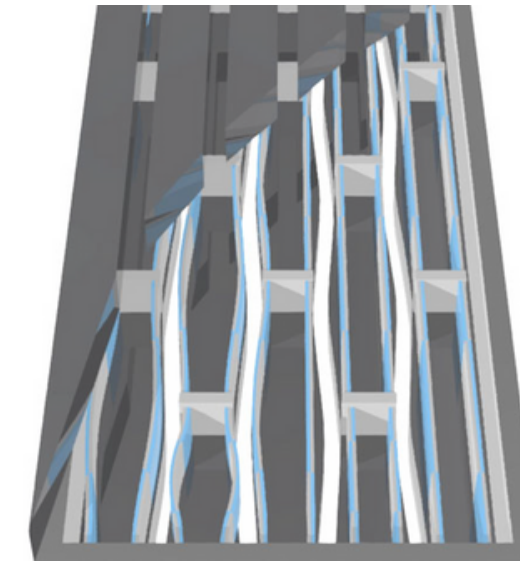
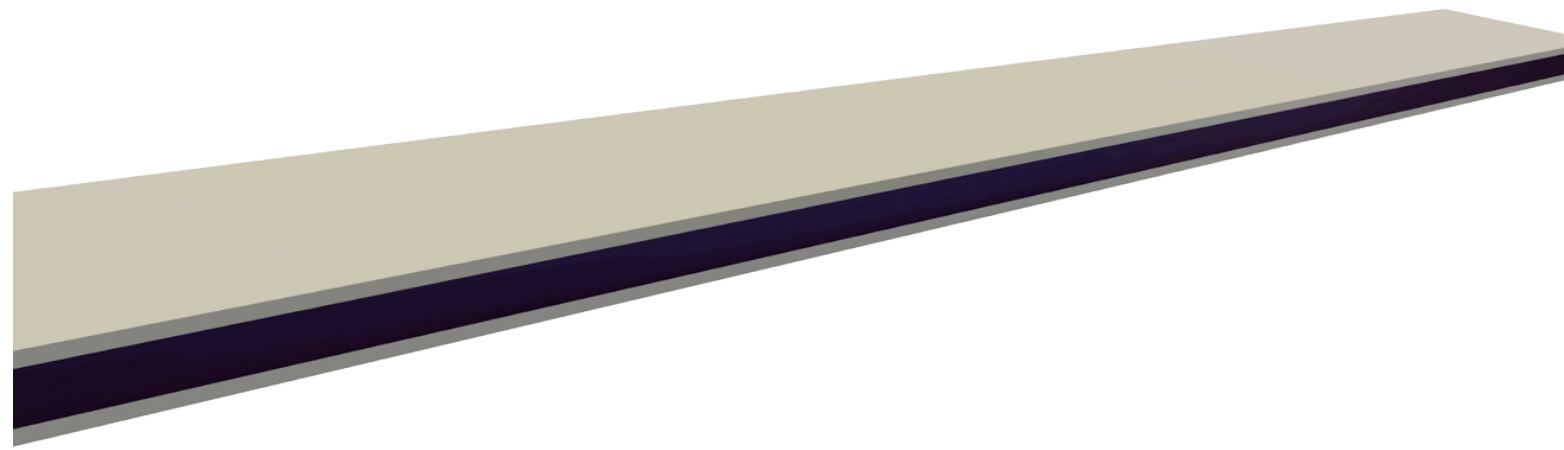
Electrostatically actuated silicon-based microspeakers



MEMS Microspeaker Frequency Domain Simulation

QUANSIENT

Electrostatics + Solid mechanics + Fluid dynamics



192k

DoFs

4

Cores

2

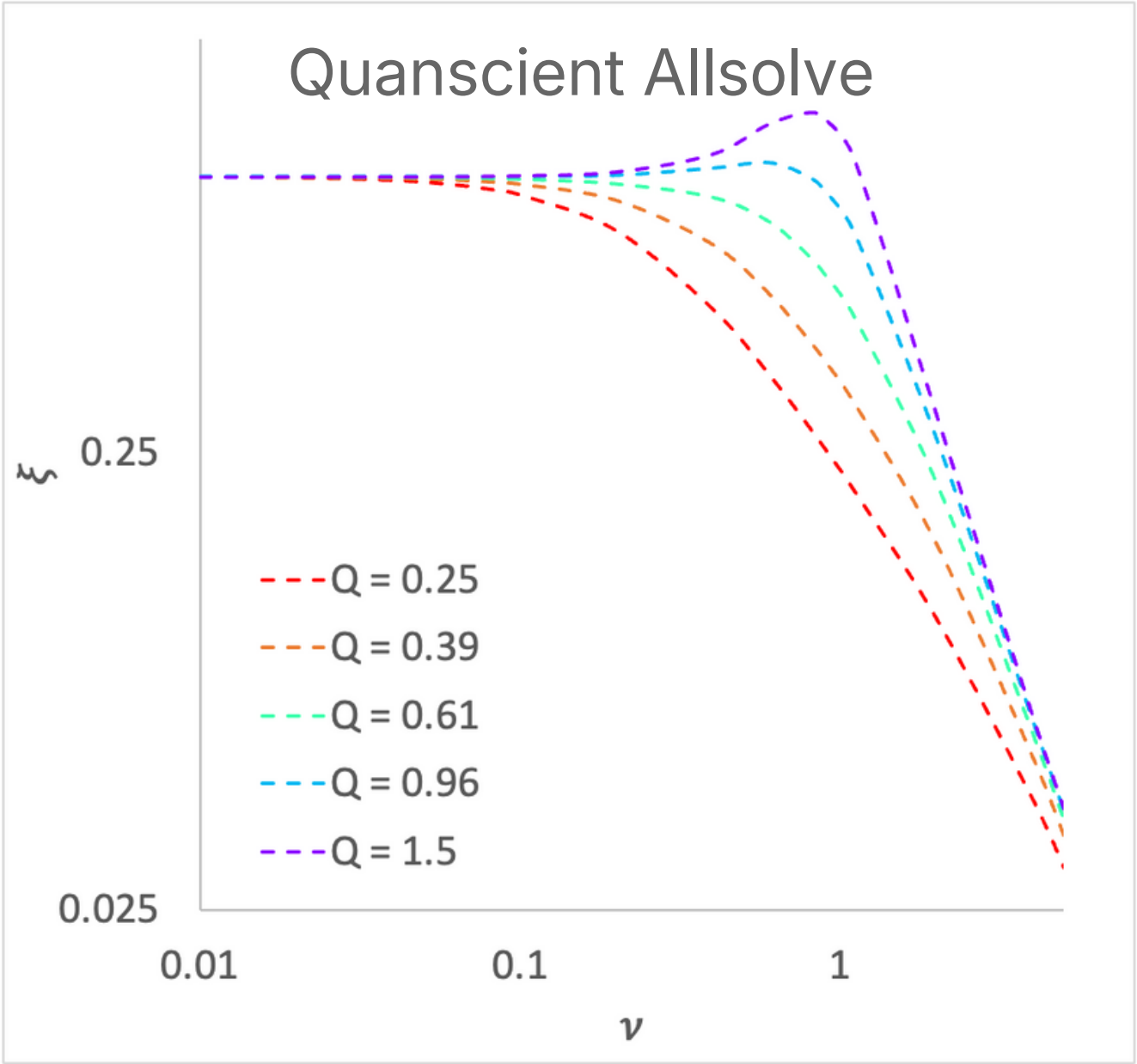
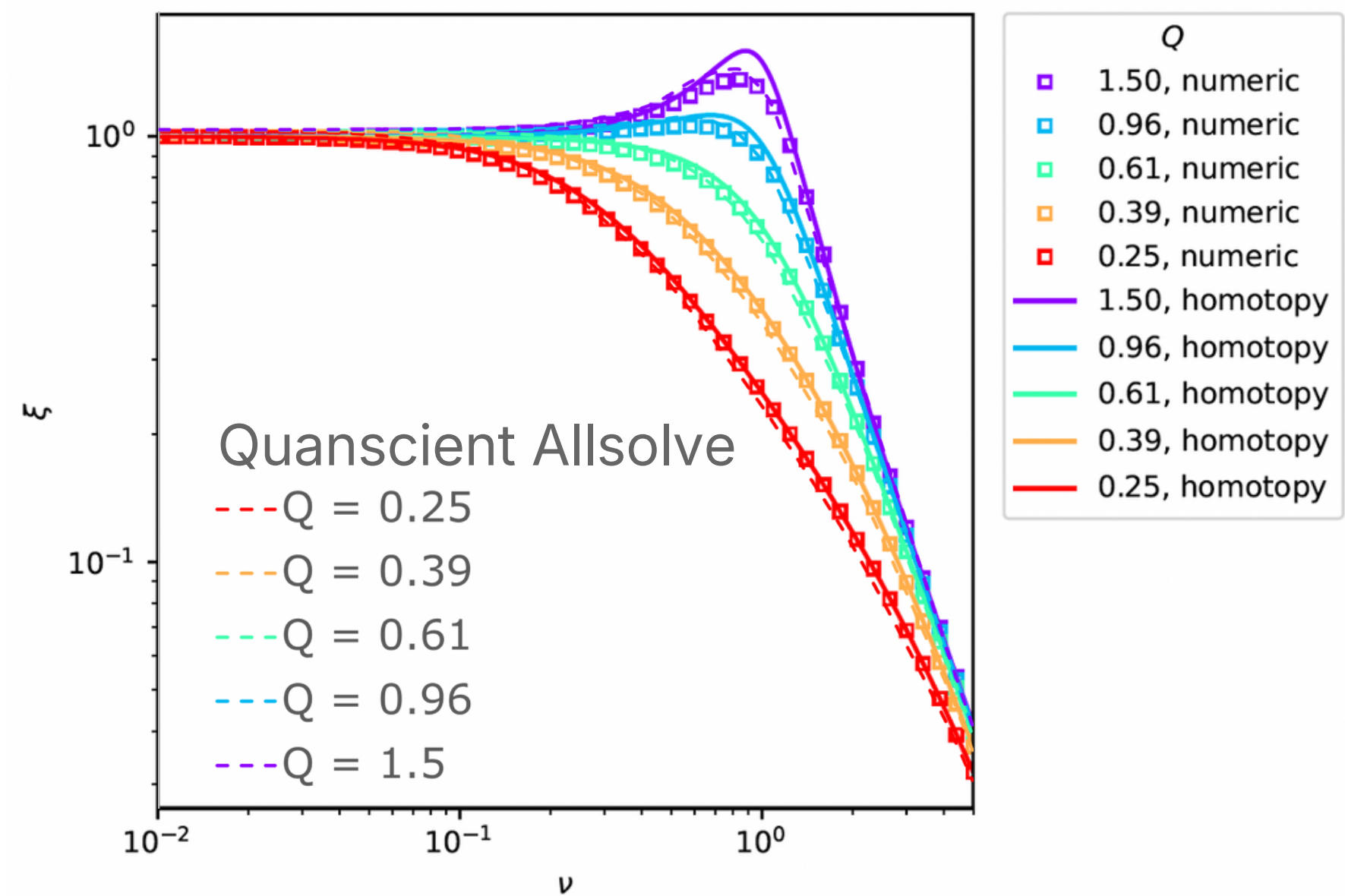
Minutes

100

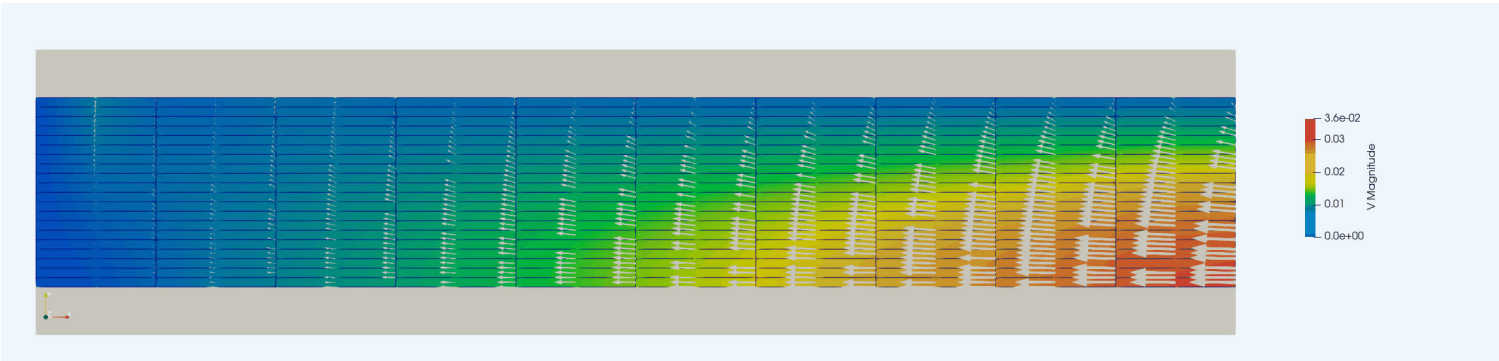
Hz

[1] Kaiser, B. et al. Concept and proof for an all-silicon MEMS micro speaker utilizing air chambers. *Microsyst Nanoeng* 5, 43 (2019). <https://doi.org/10.1038/s41378-019-0095-9>.

Multiharmonic simulation: Navier-Stokes + Linear Elasticity (FSI)



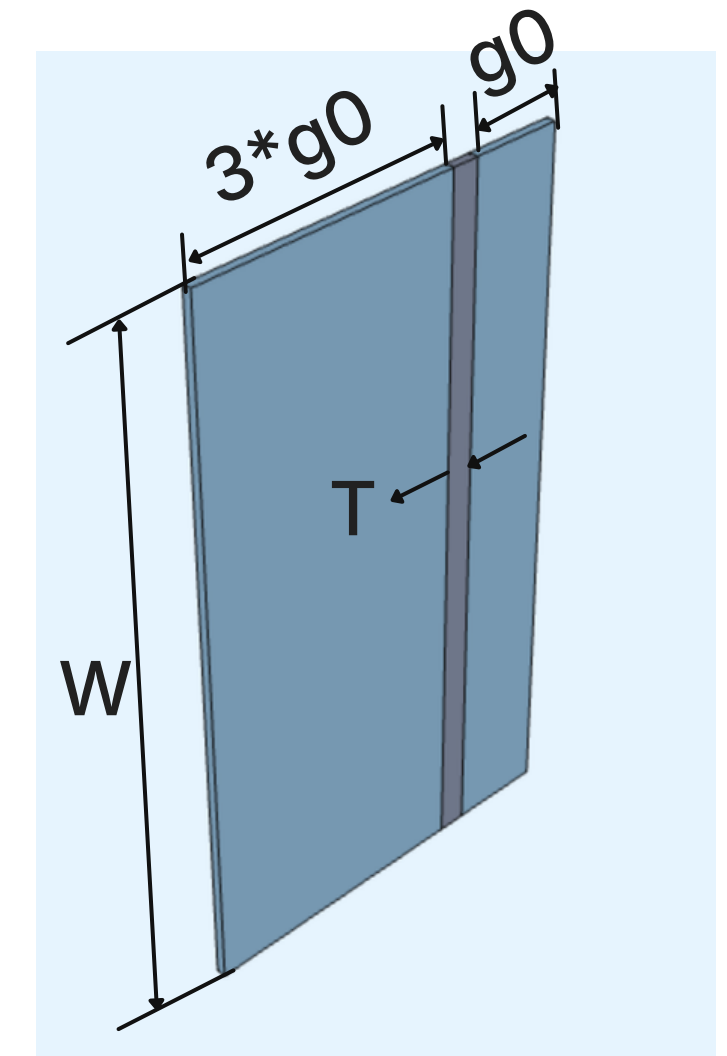
Nonlinear Squeezed-Film Damping Effects:
Comparison with Melnikov et al ICSV 2023



Microspeaker AI Surrogate Model

Optimal design discovery

- **Dataset: 12.5k nonlinear simulations (harmonic balance, ~ 14 Core Hours, ~19 min runtime)**
 - Frequency sweeps over 20Hz-20kHz
 - At a constant driving voltage amplitude of 25 V
 - Parametric sweeps in width (W), thickness (T), and initial gap (g0)
- Design Goal (at a chosen spatial location) at frequency of 1 kHz
 - **Maximize sound pressure level (SPL) in dB**
 - **Minimize total harmonic distortion (%) in pressure field**
- Train an AI surrogate model
- Pareto front analysis for optimal design discovery
 - Use trained surrogate model - runs fast and cheap
 - Find optimum points according to design goal
 - Validate with Allsolve by running interesting designs on the pareto front



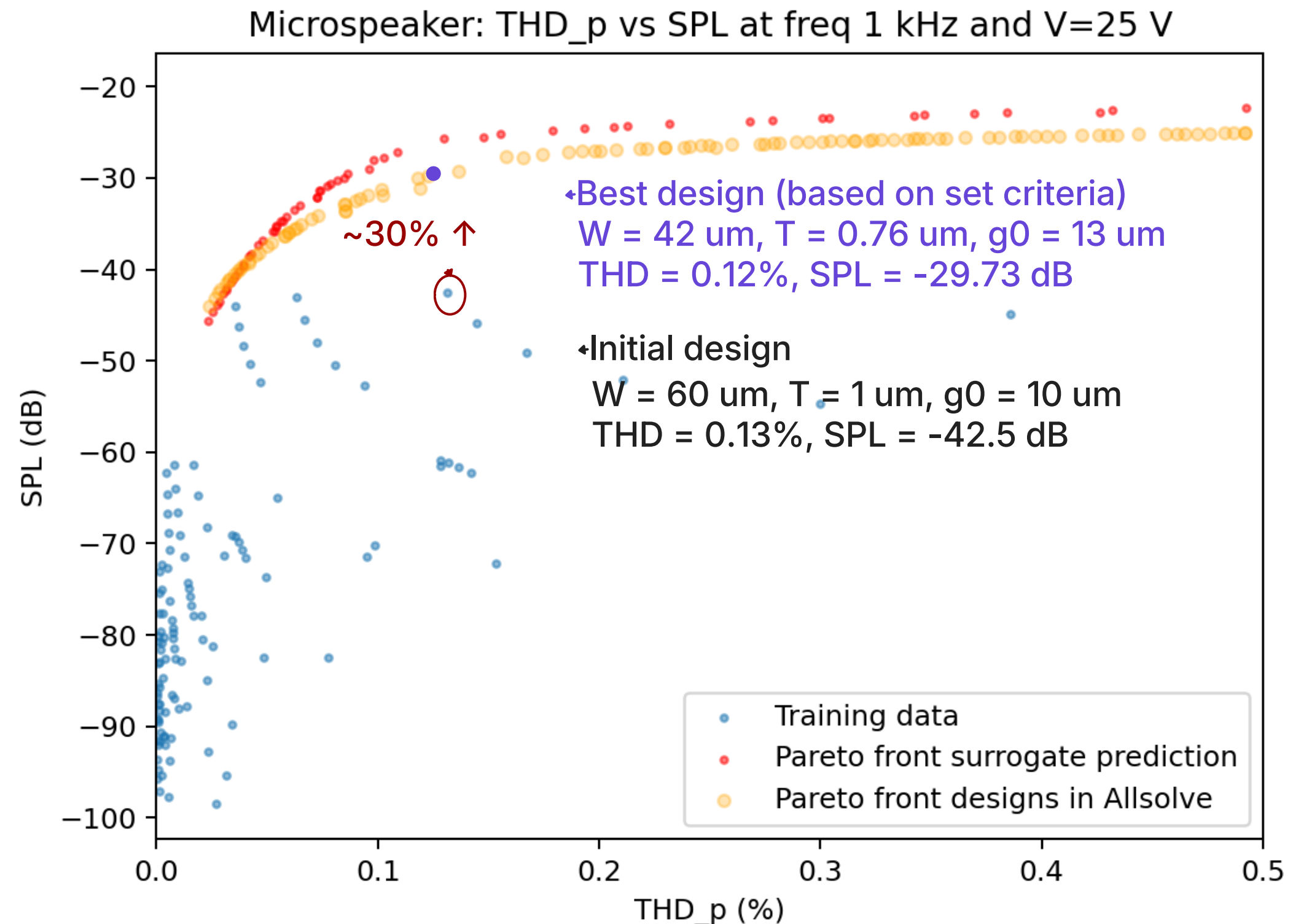
-> Get the best performance out of your design while meeting required specifications

Microspeaker AI Surrogate Model

Pareto front analysis for design discovery

- Best design from parametric data
 - $W = 60 \text{ } \mu\text{m}$, $T = 1 \text{ } \mu\text{m}$, $g_0 = 10 \text{ } \mu\text{m}$
 - THD = 0.13 %
 - SPL = -42.5 dB
- Best design (by performance) after pareto front analysis validated by Allsolve
 - $W = 42 \text{ } \mu\text{m}$, $T = 0.76 \text{ } \mu\text{m}$, $g_0 = 13 \text{ } \mu\text{m}$
 - THD = 0.12%
 - SPL = -29.73 dB

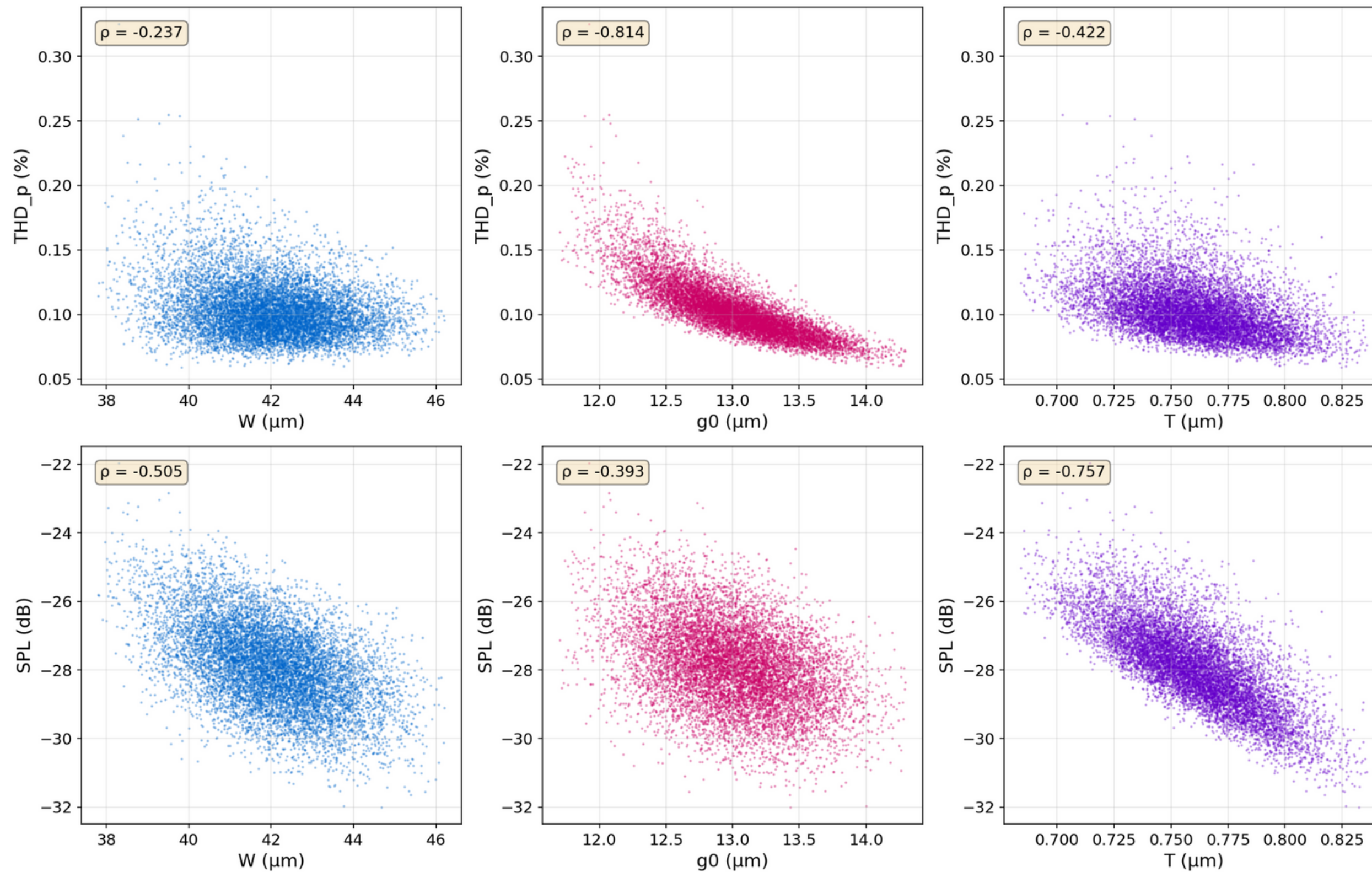
-> Approx. 30% improvement in SPL keeping THD under control



Microspeaker AI Surrogate Model

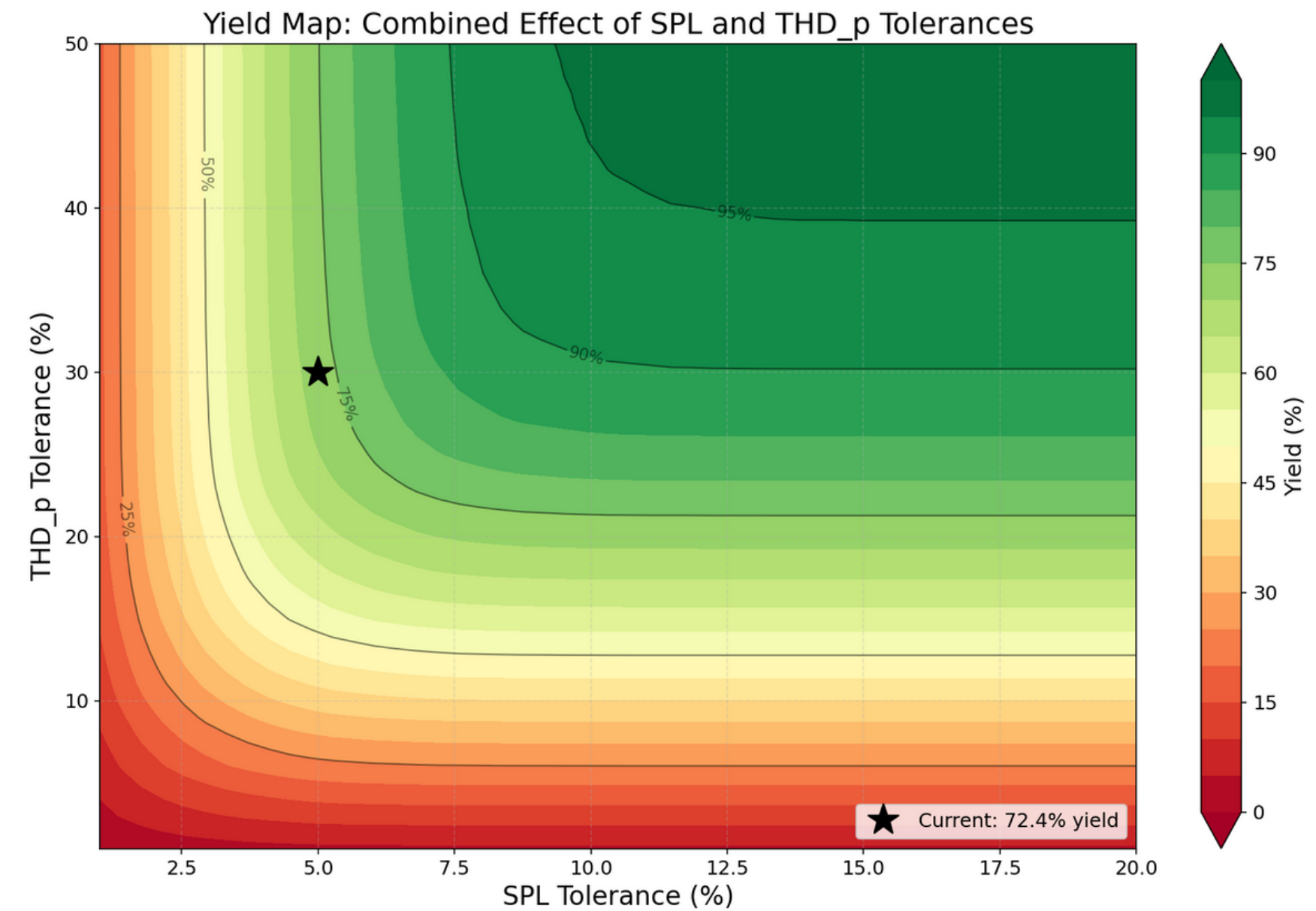
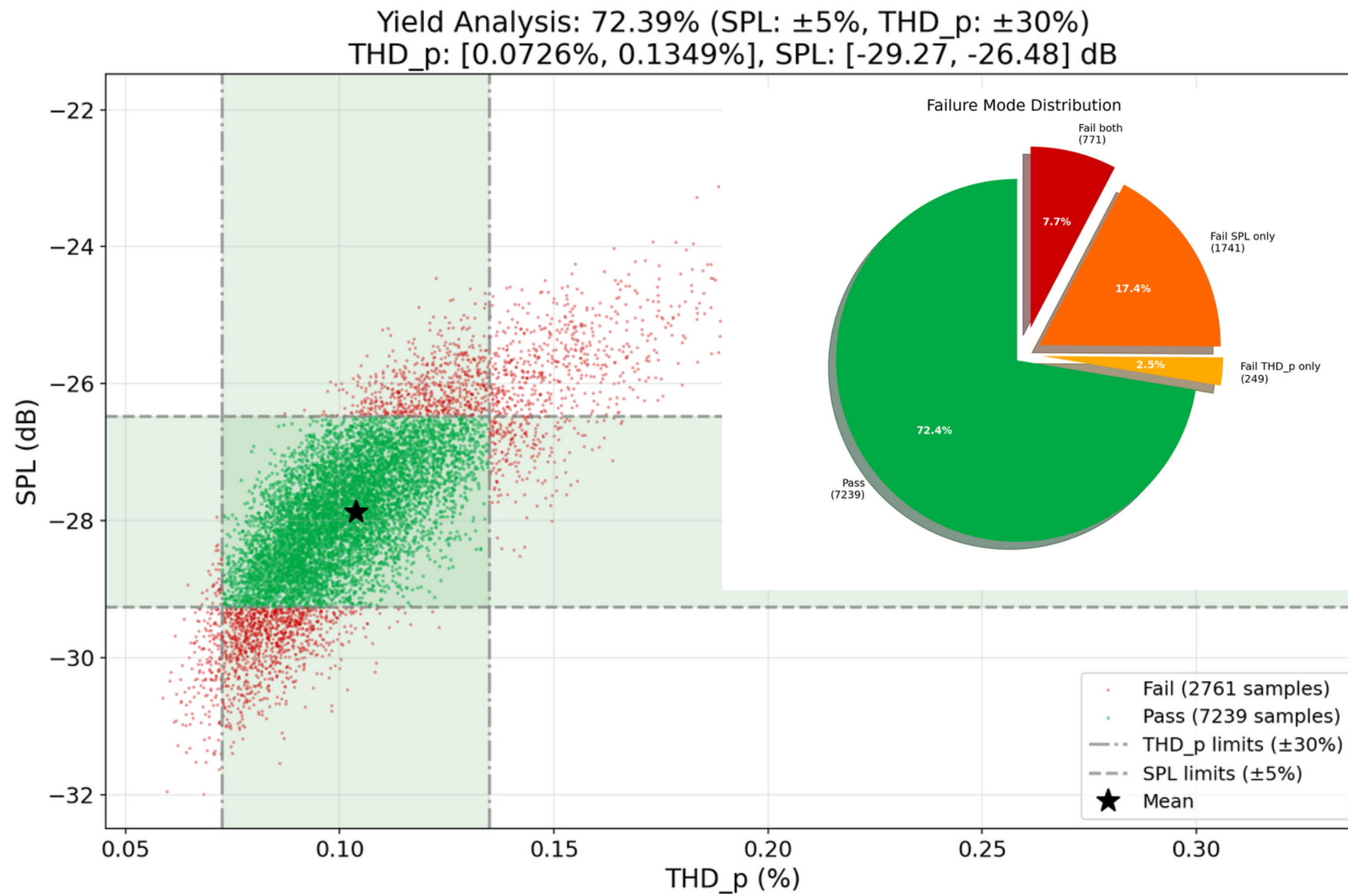
Monte Carlo analysis

Monte Carlo Analysis ($\pm 3\sigma$, 10% of mean) around best design point



Microspeaker AI Surrogate Model Monte Carlo analysis

QUANSCIENT



Piezoelectric material characterisation

Case study



Piezo material characterization

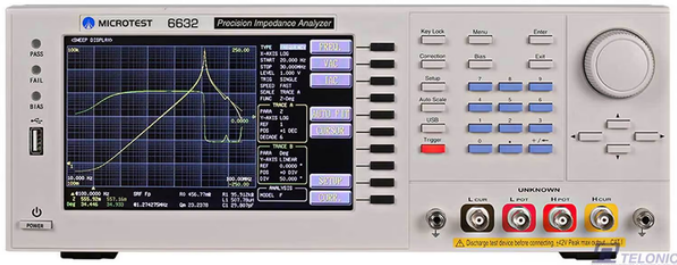
An industry wide problem

- Piezoelectric material properties are challenging to measure
 - Multiple unknown parameters (minimum 12)
 - Typically involves building and measuring multiple test samples
 - This requires expensive equipment, software and expertise
- In practise engineers rely on data from the literature or manufacturers
 - Often inaccurate or outdated
 - Results in poor simulation accuracy
- We have developed an AI based characterization technique based on Allsolve simulation data

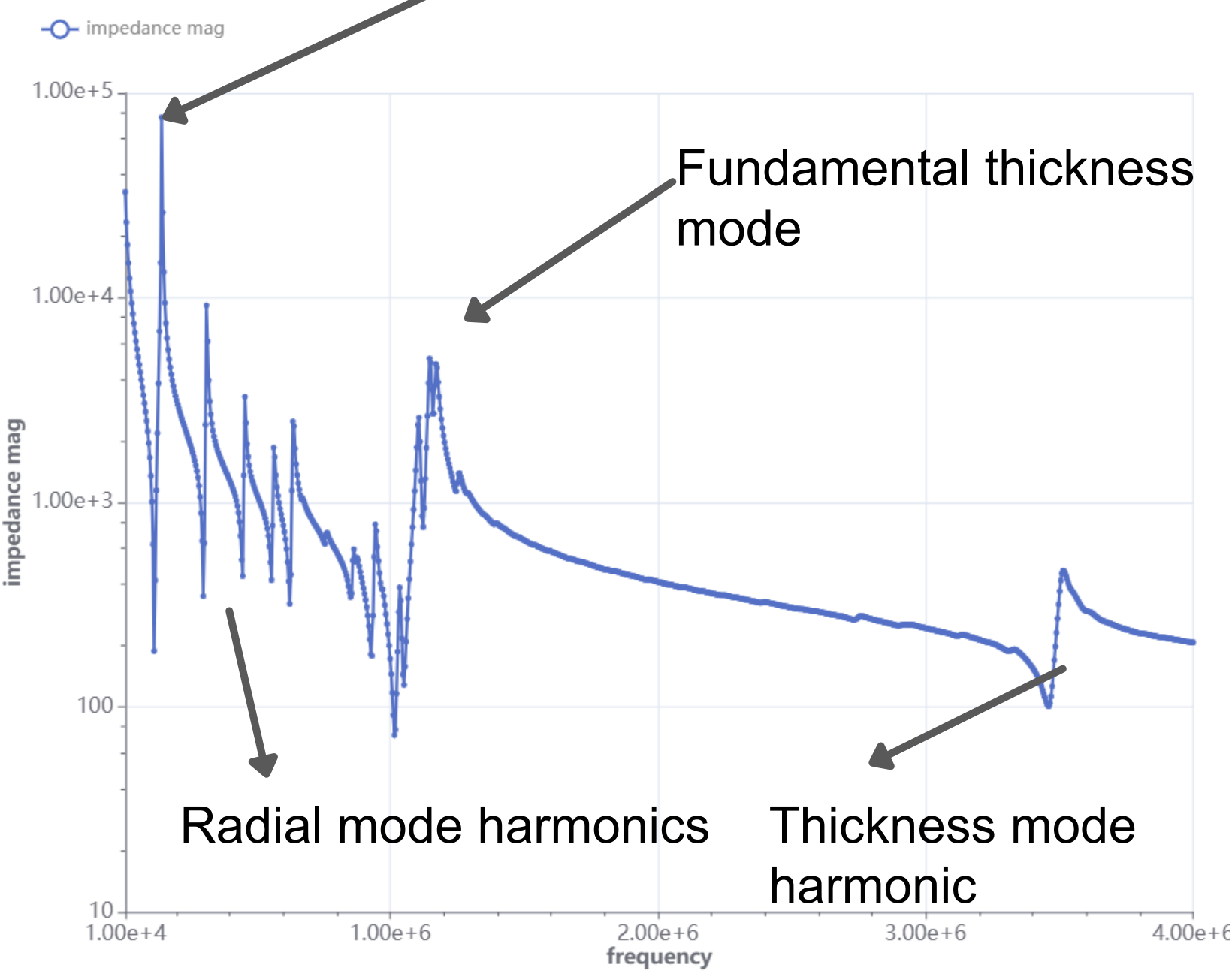
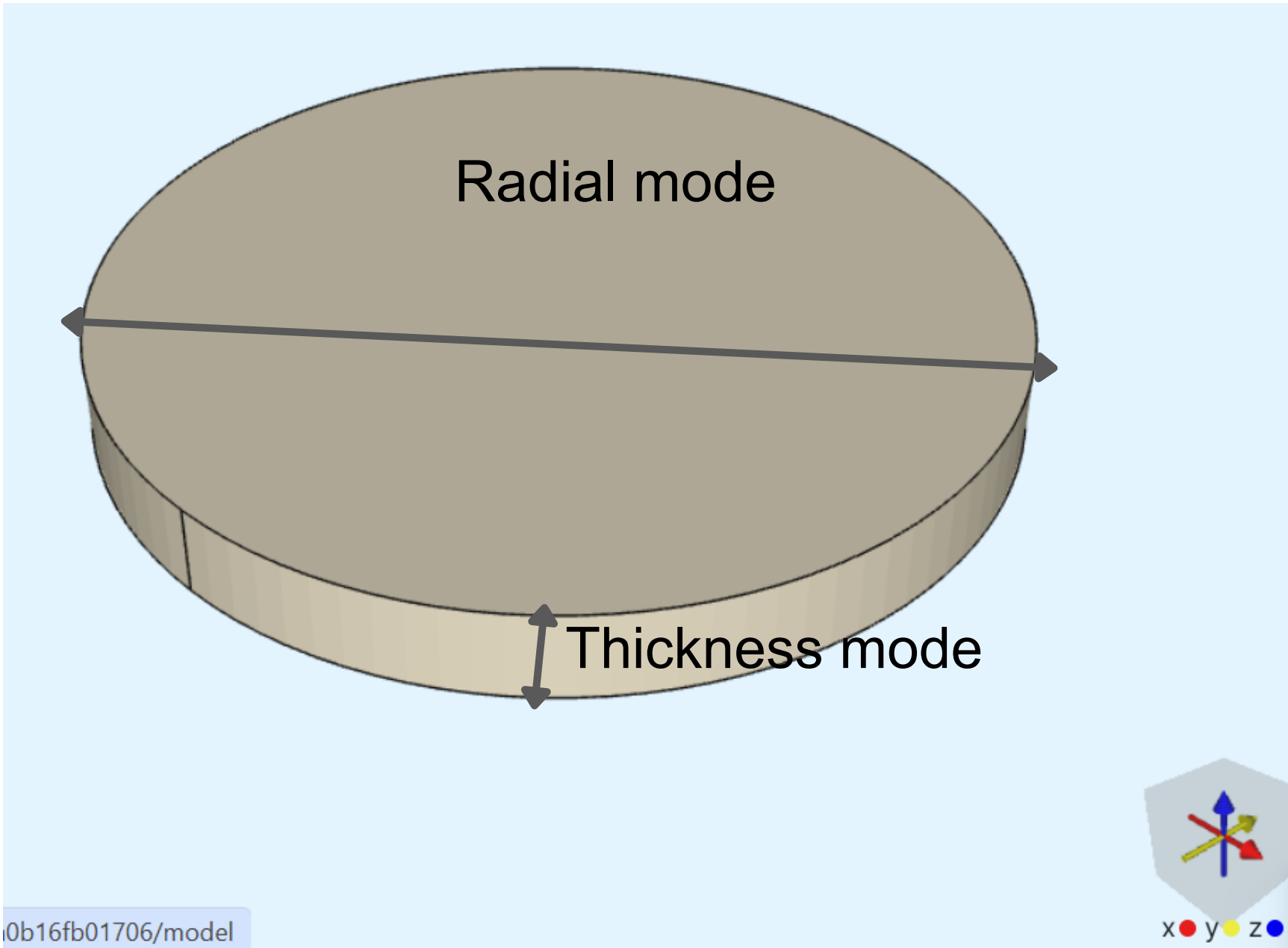
Piezo material characterization

Sample measurements

Impedance analyser



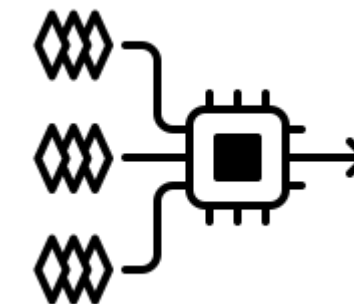
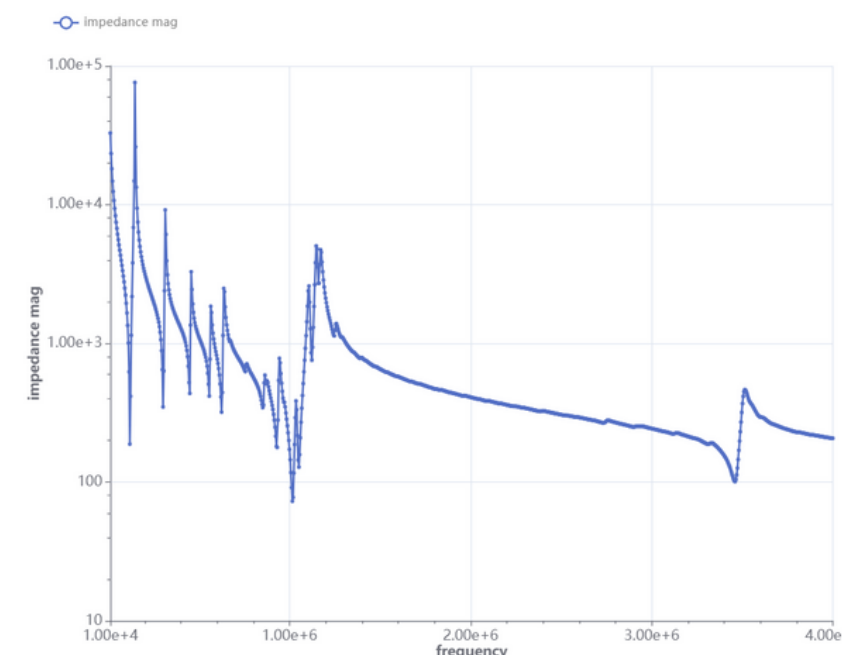
Fundamental radial mode



Piezo material characterization

Training data & AI training

- A dataset of 10k PZT disc simulations was generated in Allsolve
 - Random disc dimensions
 - Random material properties
 - Outputs were electrical impedance magnitude and phase
- An inverse AI model was then trained
 - Inputs
 - Measured electrical impedance spectrum
 - Sample geometry and weight
 - Outputs
 - 8 material properties

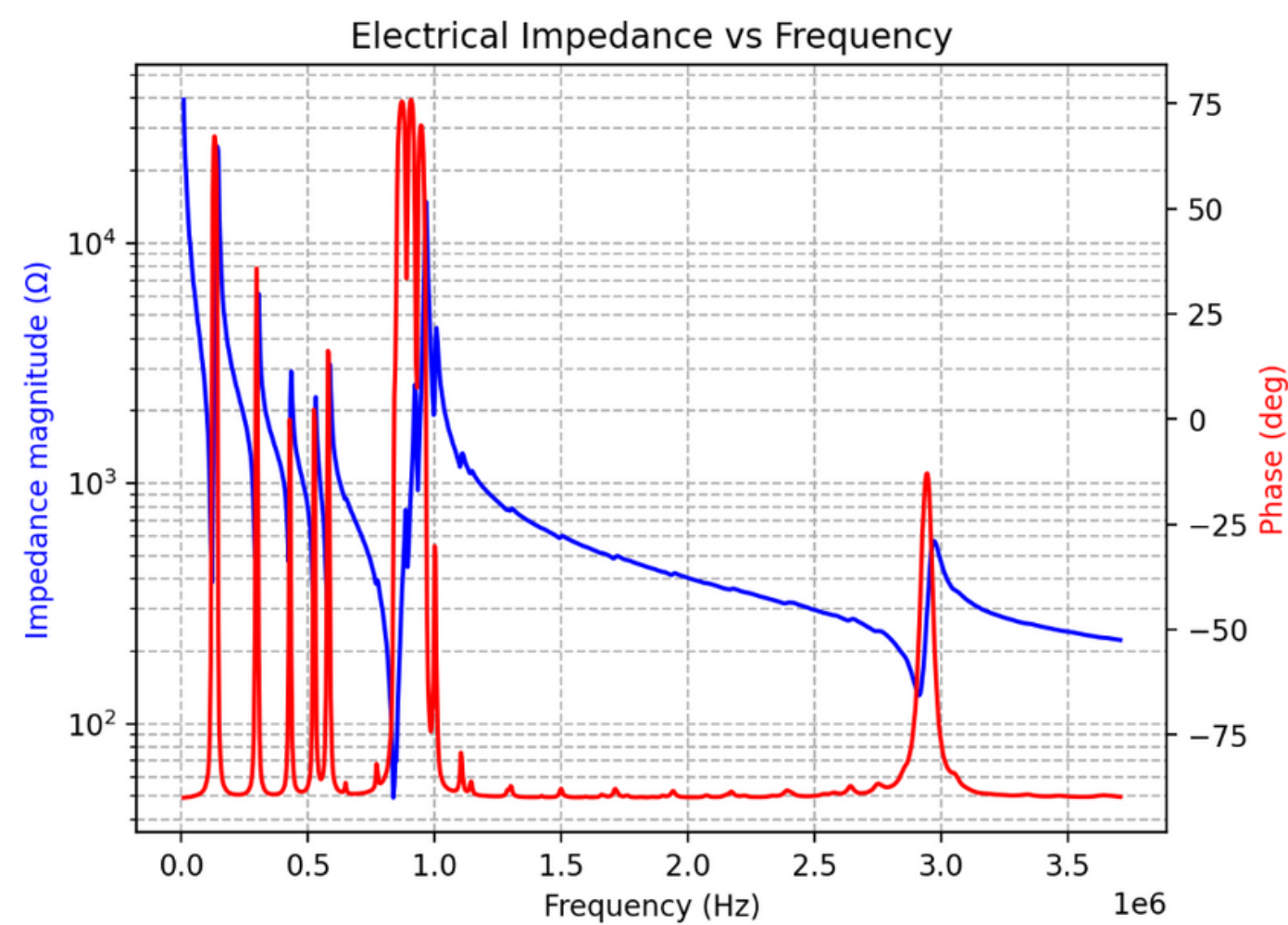


Stiffness matrix
Piezo matrix
Permittivity matrix

Piezo material characterization

Initial testing

AI model input parameters



Disc geometry and density:

Thickness (mm)	Diameter (mm)	Density (kg/m ³)
2.2936	16.089	7927.2754

Note: Thickness, diameter and density are included as inputs to the AI model, based on simple lab measurements.

The piezo properties are predicted purely on these measurements, plus the impedance data.

Run AI model

Run AI Model

Calculating properties...

Calculation completed in 8.97 milliseconds.

Comparison of predicted vs actual properties:

Variable	Predicted	Actual	Error (%)
c11	1.1809e+11	1.1807e+11	0.017
c12	7.9434e+10	7.9437e+10	0.003
c13	7.6400e+10	7.6376e+10	0.031
c33	1.1100e+11	1.1102e+11	0.026
e31	-6.9311e+00	-6.9351e+00	0.058
e33	2.5521e+01	2.5517e+01	0.013
eps33	1.5731e+03	1.5729e+03	0.015
qdamp	9.9305e+01	9.9117e+01	0.190

<0.25% error on simulated data

Piezo material characterization

Beta testing

Piezo property characterization

Previous step

CSV input dataset

Upload CSV file

pzt_disc.csv

CSV file processed successfully.

Disc parameters

Diameter (mm)

21.01

Thickness (mm)

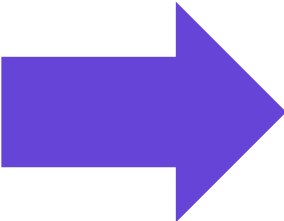
2.35

Weight (g)

5.67

Generate material properties

Cancel



Piezo property characterization

Previous step

Elasticity matrix (Pa)

Elasticity matrix

1.05897623	6.09655111	6.45491179	0	0	0
6.09655111	1.05897623	6.45491179	0	0	0
6.45491179	6.45491179	1.01012070	0	0	0
0	0	0	2.29e10	0	0
0	0	0	0	2.29e10	0
0	0	0	0	0	2.2466056

Switch to expression editor

Add as new material

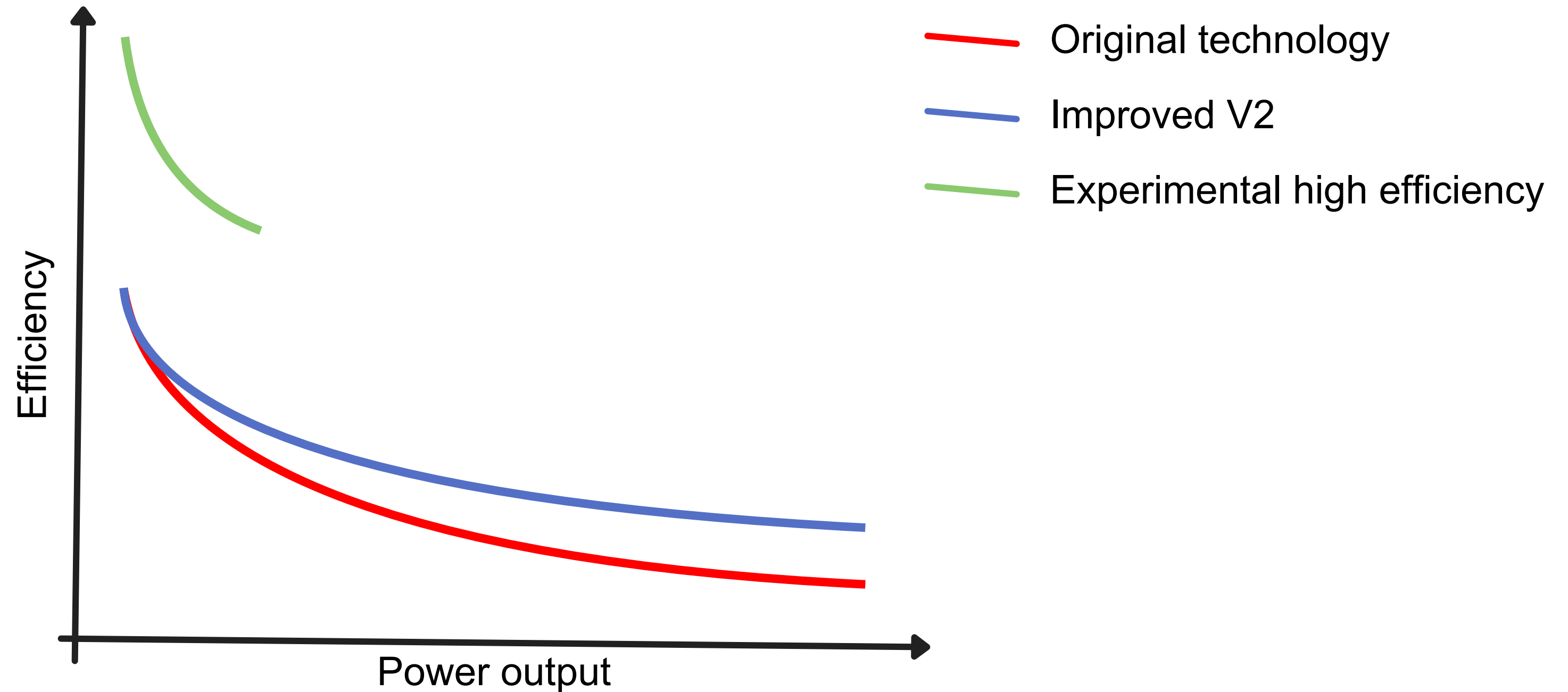
Cancel

Final thoughts



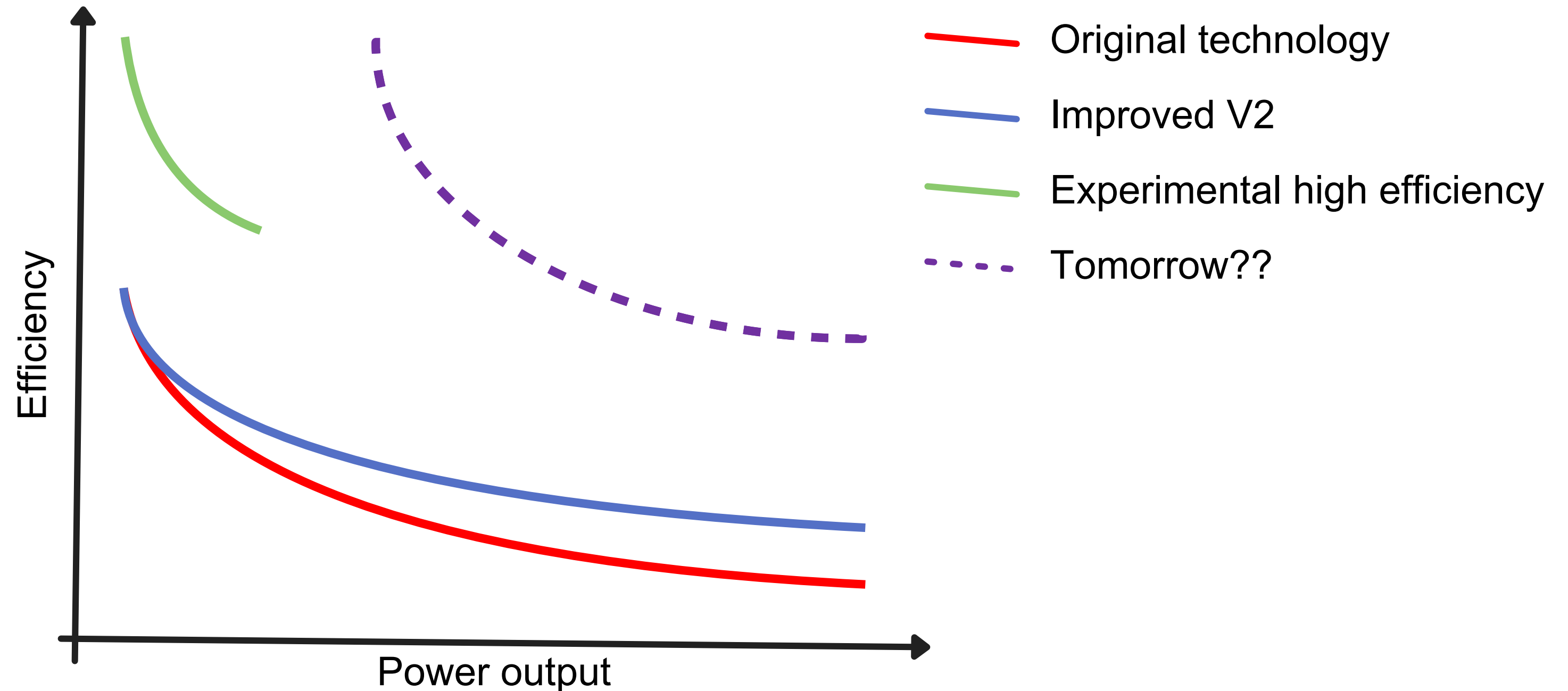
Exploring new design concepts

Our job is to help engineers discover new lines



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Allsolve AI

Key takeaways

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- Allsolve has evolved into an engine for multiphysics data
- We have demonstrated that this data provides a robust platform for AI training
- The resulting AI algorithms can be used to solve challenging inverse problems such as design space exploration and material characterisation

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