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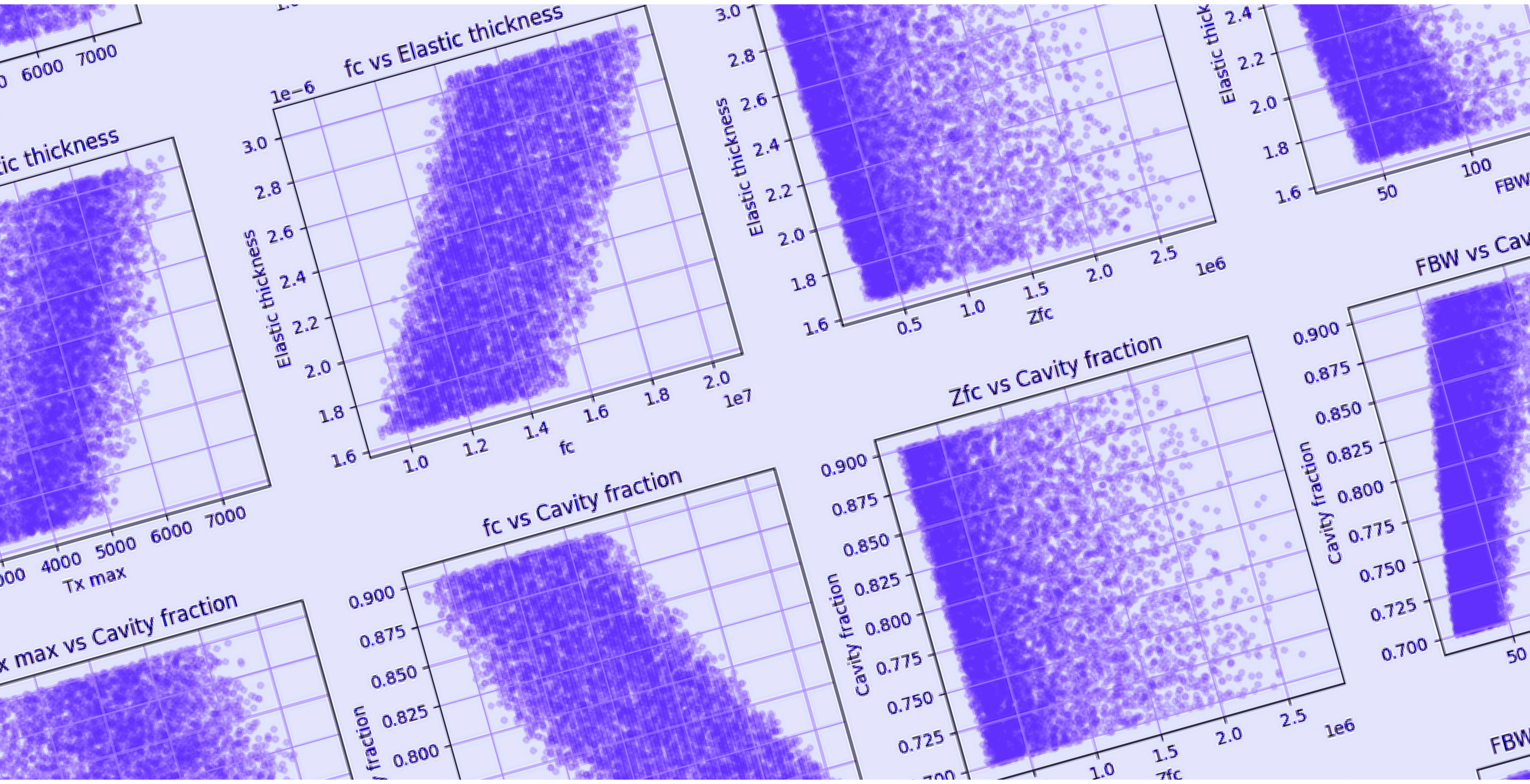

White Paper | November 2025

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Quanscient MultiphysicsAI for PMUT design

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Abstract

This white paper presents the Quanscient MultiphysicsAI workflow for Piezoelectric Micromachined Ultrasonic Transducer (PMUT) design. The approach unites large-scale multiphysics simulation with an AI surrogate model to accelerate design space exploration and reveal performance trade-offs.
A dataset of 10,000 large-scale Finite Element Method (FEM) simulations was generated by randomly sampling four geometric design parameters. A forward AI surrogate was trained to predict four key performance indicators (KPIs); transmit sensitivity, center frequency, fractional bandwidth (FBW), and electrical impedance at resonance. The trained model achieved approximately 1% mean prediction error and sub-millisecond evaluation time, enabling rapid exploration of the design space. As an example, it allows the Pareto front for this multi-objective problem to be calculated in seconds.

Validated results demonstrate physically realizable PMUT designs that simultaneously increase fractional bandwidth and sensitivity while maintaining a target centre frequency.

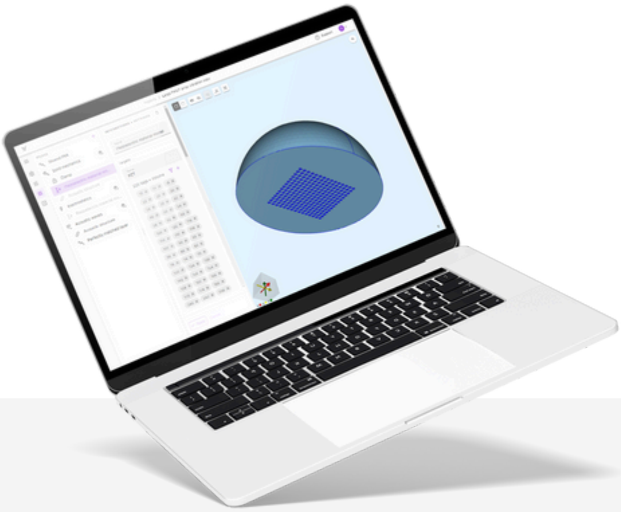
The workflow replaces manual, iterative design loops with transparent, data-driven exploration, empowering engineers to navigate performance trade-offs efficiently and confidently.

Keywords — AI; multiphysics; FEM (Finite Element Method); cloud simulation; design exploration; ai surrogate model; inverse design; pareto front

Introduction to Quanscient Allsolve

The cloud-based multiphysics simulation platform Quanscient Allsolve was used for all simulations featured in the webinar.

Learn more at quanscient.com ⟶



Quanscient Allsolve

- A cloud-based FEM platform for fast and scalable multiphysics simulations
- Developed by Quanscient, founded in 2021 in Tampere, Finland
- Enables fully coupled multiphysics simulations across all core physics domains

Trusted in both industry and academia

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Introduction to MultiphysicsAI for PMUT design

PMUTs are critical components in biomedical imaging, and a variety of other sensing applications. Two key performance metrics are their sensitivity and bandwidth, which govern image quality, and resolution.

Traditional design workflows rely on sequential simulation–build–test cycles. These cycles are labor-intensive and offer limited visibility into global design space. Engineers typically iterate locally, exploring only a few design variations at a time.

MultiphysicsAI addresses this challenge by combining scalable multiphysics simulation with AI. The framework transforms conventional forward modeling, predicting how a given design behaves, into inverse design, systematically identifying which designs best satisfy performance goals.

Challenges in PMUT design

Inverse design gap: Conventional solvers answer the forward problem, “what does this design do?”, rather than the inverse problem, “which designs meet the target specification?” MultiphysicsAI bridges this gap.

Trade-offs: PMUT design involves balancing sensitivity and bandwidth, which are inherently conflicting objectives, as improving one degrades the other.

Scale and throughput: Large-scale multiphysics simulations are computationally expensive, and traditional parameter sweeps are infeasible at scale.

Frequency targeting: Design adjustments that improve bandwidth often shift the center frequency. Meeting strict targets (e.g., a specified centre frequency) complicates manual optimization.

Verification and trust: AI-generated optima must be validated through physical simulations to ensure that they represent realizable designs rather than numerical artifacts.

Introduction to MultiphysicsAI for PMUT design

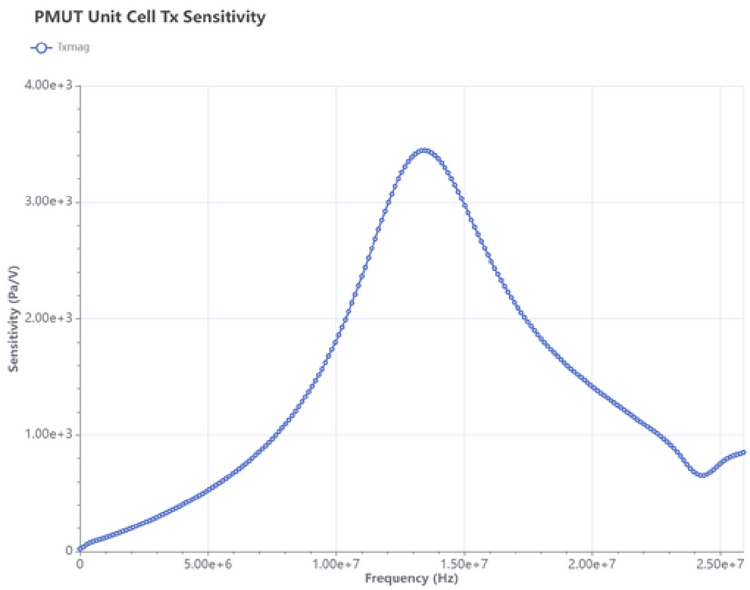
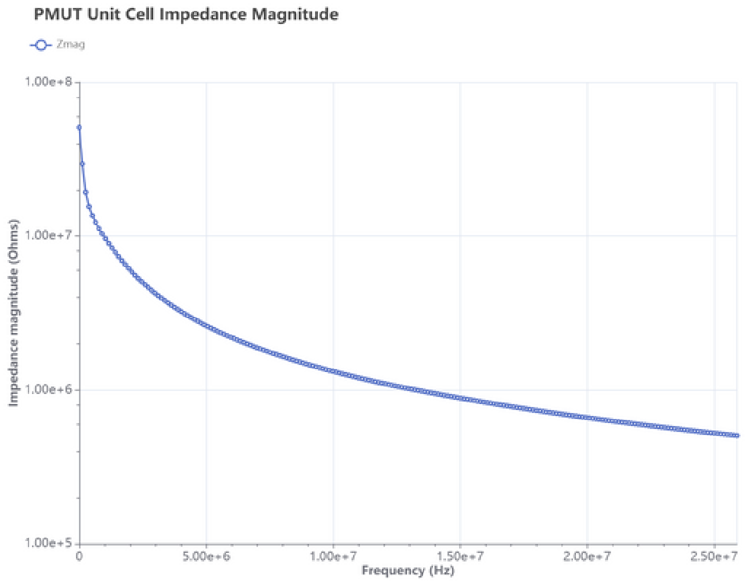


Fig. 1: PMUT example typical results



Motivation for the simulation

Engineers require methods to explore thousands of design options efficiently. High-throughput, multiphysics simulation can be used to generate a rich dataset, which can be used to train AI surrogate models. These AI surrogates can in turn be used to create near-instant predictions of device performance for new configurations.

Quanscient Allsolve enables running thousands of parallelized multiphysics simulations in the cloud. This makes Allsolve an ideal platform for developing AI models that provide instantaneous predictions and enable interactive, interpretable design optimization.

MultiphysicsAI
Methods and models

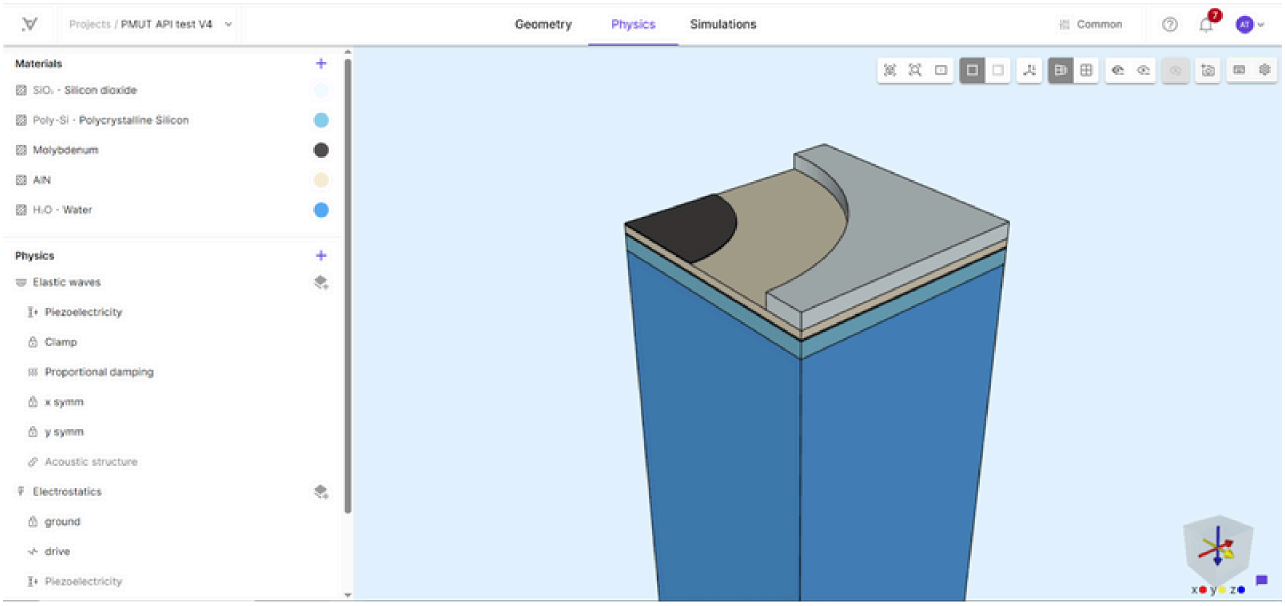


Fig. 2: PMUT example geometry

Model description

A circular PMUT was modeled using coupled piezoelectric–structural–acoustic FEM physics, with quarter-symmetry for efficiency. The problem was solved in the time domain, and the output waveforms were then transformed to the frequency domain and used to generate transmit sensitivity and electrical impedance responses.

Design parameters

Four geometry variables define the design space:

1. Elastic membrane thickness
2. Piezo layer thickness
3. Cavity radius
4. Bottom-electrode radius

Simulation dataset

- 10,000 randomized geometries generated and simulated in Quanscient Allsolve
- Runtime: ≈ 5 s per job, all parallelized
- Outputs: transmit sensitivity, center frequency, FBW, impedance

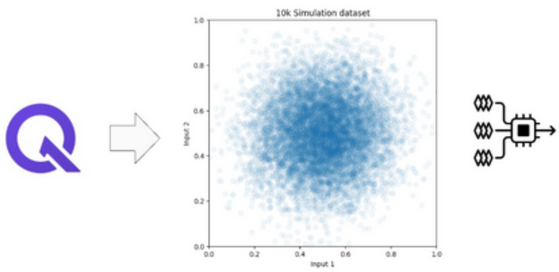


Fig. 3: Allsolve can generate large datasets for training AI models

MultiphysicsAI
Methods and models

Surrogate modelling

A forward surrogate was trained (geometry → KPIs) using the dataset.

- Training time ≈ 10 min (GPU)
- Mean prediction error ≈ 1 %
- Inference time ≪ 1 ms

Plotting a correlation matrix confirms intuitive dependencies, e.g., cavity radius strongly influences bandwidth, electrode radius affects impedance.

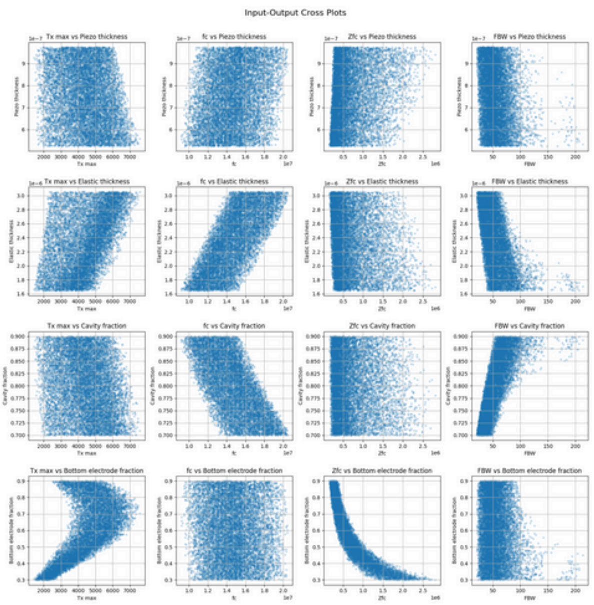


Fig. 4: Input-output cross correlation plot

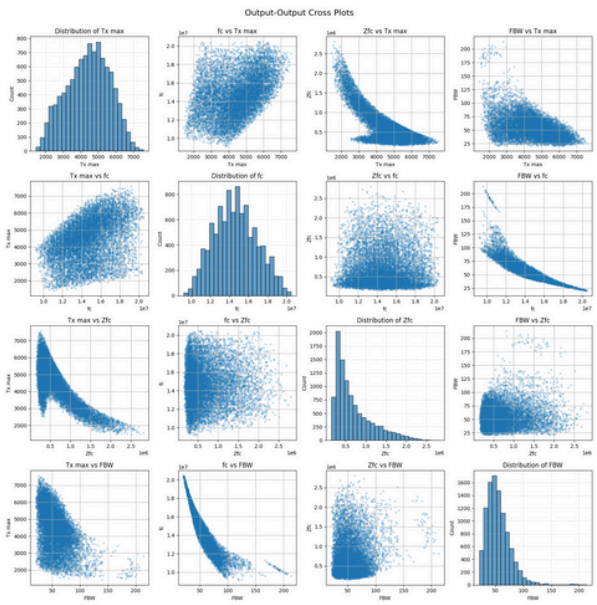


Fig. 5: Output-output cross correlation plot

MultiphysicsAI
Methods and models

AI surrogate model training

The neural surrogate model maps problem-specific parameters, elastic membrane thickness, piezoelectric layer thickness, cavity radius, and bottom-electrode radius, to key performance indicators (KPIs): transmit sensitivity, center frequency, fractional bandwidth (FBW), and impedance. The model architecture is a deep residual feedforward neural network with Swish activations, featuring adjustable hidden dimensions and a configurable number of residual blocks

We split the dataset into 80% training and 20% validation subsets. All inputs and outputs are normalized using statistics computed from the training set. The network is trained using the Adam optimizer with an initial learning rate of 1×10^{-3}, which is reduced by a factor of 4 every 1000 epochs. We use mean absolute error (MAE) as the loss function, as it offers a balanced compromise between minimizing root-mean-square error and relative percentage error.

Throughout training, we monitor validation performance and save the model checkpoint that achieves the lowest validation loss.

To determine the optimal architecture, we perform an initial neural architecture search that progressively increases model complexity. The search selects the simplest architecture that meets predefined validation criteria during a short preliminary training run. This chosen architecture is then trained fully with the procedure described above.

At inference time, inputs are normalized using the training-set statistics, passed through the network, and the predicted KPIs are denormalized using the corresponding output statistics.

MultiphysicsAI
Methods and models

Optimization and validation

In multi-objective optimization, the Pareto front is the set of all Pareto efficient solutions. In essence, it represents the set of the best possible performing designs, as in order to improve one objective we necessarily need to degrade others. Searching for these solutions is typically a lengthy process as it's highly iterative and often involves >100,000 FEM simulations. However, in this work the AI surrogate model was used to accelerate this process, allowing the Pareto front to be calculated in a matter of seconds. Once this Pareto front is calculated, Allsolve can be used to quickly validate its predictions. This provides engineers with confidence that the designs identified are indeed realistic.

One of the main benefits of using an AI surrogate is that the Pareto front analysis can be quickly rerun with different parameters. These can include:

- Changes to the range over which input parameters can be varied
  - For example, to consider process restrictions
- Constraints on one or more of the output KPIs
  - For example to constrain the operating frequency to a specified value

Final design selections can then be based on the desired performance balance, along with merits such as manufacturability, electronics matching.

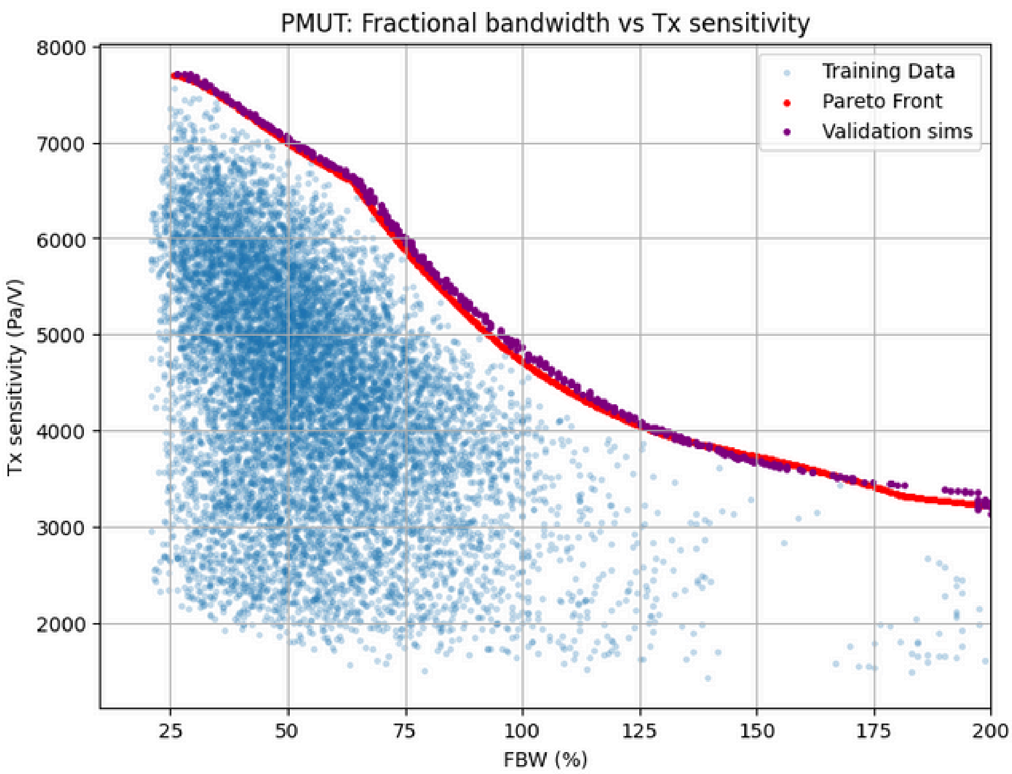


Fig. 6: Plot of the design space showing the tradeoff between the two main KPIs, including training data, AI generated Pareto front and validation simulations.

MultiphysicsAI
Results and discussion

Design-space insights

The Pareto front was calculated for the two main KPIs: transmit sensitivity and fractional bandwidth. The 600 designs along the Pareto front were then simulated in Quanscient Allsolve, confirming that they are indeed valid designs. The scatter plot below shows the 10,000 simulations from the training set, along with the AI predicted Pareto front and the validation simulations.

Results show that despite the large size and random distribution of the training data set, the Pareto front has identified better designs at every point in the space. Furthermore, the validations confirm that the AI surrogate is accurately predicting performance at the extremities of the design space.

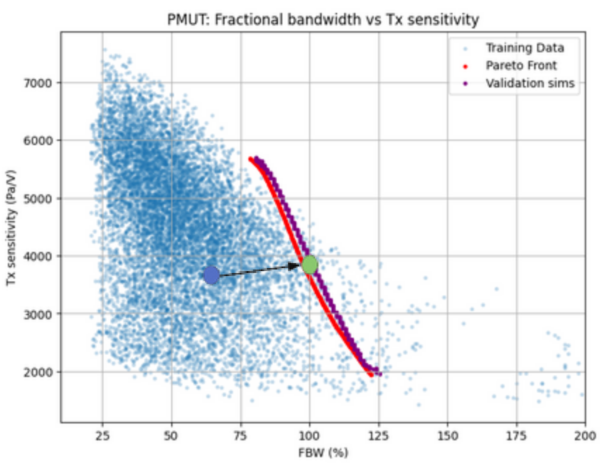
Surrogate accuracy

Parity plots indicate ≈ 1 % mean deviation between surrogate predictions and FEM outputs across all KPIs. The model delivers near-instant evaluation, enabling engineers to explore thousands of alternatives interactively.

Frequency-constrained optimization

Most ultrasonic sensors are designed with a specific centre frequency in mind. By applying a 12 MHz constraint to the centre frequency KPI and a new Pareto front can be generated which contains only designs centred at this frequency. Furthermore, the AI surrogate allows this to be calculated within seconds.

Verified simulations show:
- FBW increase: ~65 % → ~100 %
- Sensitivity improvement: +2–3 dB re 1 Pa/V
- Center frequency stability: 12 MHz ± 0.2 %



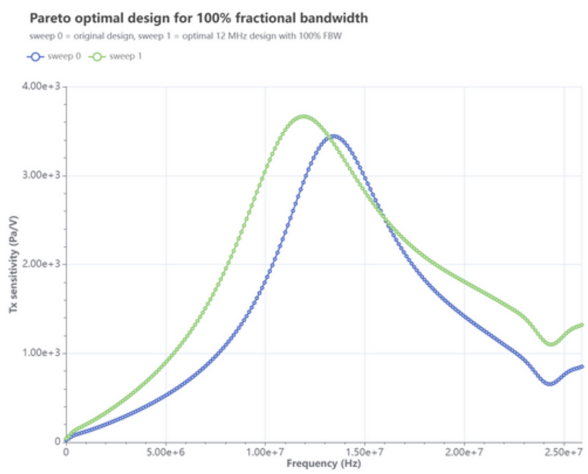


Fig. 7: Design space with Pareto front and validation simulations constrained to 12 MHz (left). Initial design vs final design (right, blue initial, green final).

Benefits of MultiphysicsAI

The Quanscient MultiphysicsAI workflow delivers several tangible advantages for PMUT designers.

- It provides dramatic speed gains. Multi-objective optimization that previously required days of manual simulation and tuning can now be completed within seconds.
- It offers full transparency. Instead of a single black-box optimum, engineers can visualize the entire performance envelope and directly inspect trade-offs between sensitivity, bandwidth, and frequency.
- As new design concepts are explored they can be directly compared, not just for a single design, but across the entire Pareto front.
- The approach ensures confidence and physical fidelity, as all AI-predicted optima are verified through complete Allsolve finite-element simulations, confirming that the results correspond to realizable devices.
- The workflow demonstrates strong scalability. The same framework can be extended to alternative geometries, material systems, or other multiphysics problems, establishing a generalizable foundation for data-driven engineering design.

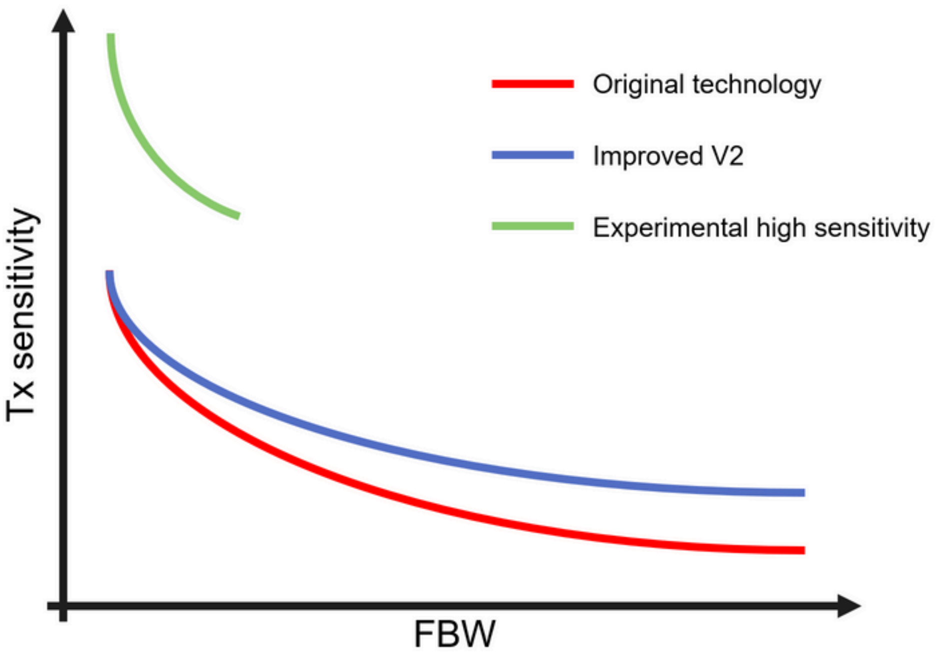


Fig. 8: Pareto fronts for multiple technology generations, showing relative strengths and weaknesses.

MultiphysicsAI
Conclusion

Quanscient MultiphysicsAI workflow unites high-throughput multiphysics simulation with accurate AI surrogate modeling to accelerate inverse design. It transforms PMUT development from a slow, local search into a fast, global exploration, reducing days of manual iteration to seconds of guided, data-driven analysis.

By combining physics-based simulation and machine learning, the workflow uncovers the achievable frontier between sensitivity and bandwidth, supports strict frequency targets, and delivers validated design candidates with full physical verification through Allsolve. Early results demonstrate significant improvements in fractional bandwidth and measurable gains in sensitivity, all achieved with minimal engineering overhead.

Beyond this PMUT case study, the same MultiphysicsAI framework generalizes to other device geometries, material stacks, and design objectives, providing a scalable path toward broader adoption across complex multiphysics engineering domains.

MultiphysicsAI
Key takeaways

- **Unified workflow:** Quanscient MultiphysicsAI integrates high-performance multiphysics simulation with AI to accelerate inverse design.
- **Validated accuracy:** AI-generated results are verified through Allsolve simulations, ensuring confidence and physical fidelity.
- **Data-driven insight:** Thousands of simulations and a highly accurate surrogate enable near-instant exploration of design trade-offs.
- **Rapid iteration:** Multi-objective optimization and frequency-specific design can be completed in seconds instead of days.
- **Transparency and control:** Engineers gain clear visibility into feasible performance boundaries and maintain full control over design choices.
- **Scalable framework:** The same approach extends to other devices, materials, and physics domains, paving the way for future quantum-enhanced workflows.

Get in touch

Learn more and request a demo at
quanscient.com →

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