QUANSCIENT

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MultiphysicsAI: Accelerating engineering design with neural surrogates

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Abstract

Quanscient's MultiphysicsAI introduces a new paradigm for simulation-driven engineering. By combining advanced numerical solvers with AI-powered neural surrogates, it enables engineers to automate and accelerate the entire design–simulate–analyze–optimize workflow.

Traditional multiphysics simulations are often computationally demanding and limited by manual design iterations. MultiphysicsAI overcomes these constraints by replacing heavy solver calls with lightweight yet accurate neural models trained on simulation data.

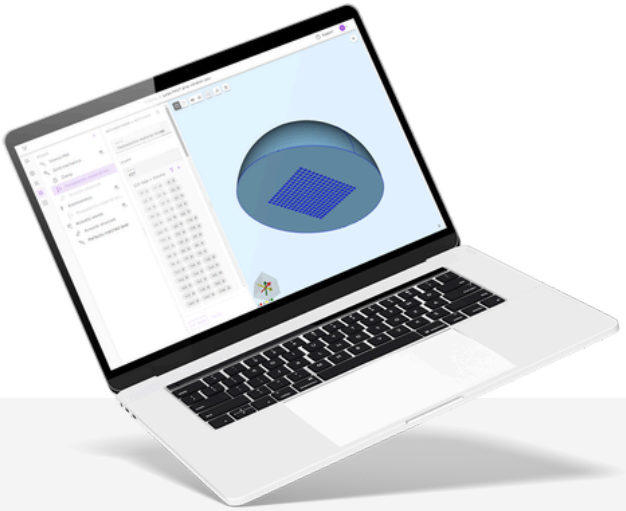
The result is a system that delivers solver-level accuracy at a fraction of the computational cost, enabling rapid optimization, design exploration, and discovery of novel engineering solutions.

Keywords — multiphysics simulation, neural surrogate model, AI, design optimization, computational efficiency, automated simulation, PMUT, microspeaker

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

UK Atomic Energy Authority · Infineon · MIT Massachusetts Institute of Technology · Proxima Fusion · imec · Paul Scherrer Institut PSI

Introduction to MultiphysicsAI

What is MultiphysicsAI?

MultiphysicsAI is Quanscient's proprietary approach to augmenting engineering simulation and design through artificial intelligence. It drastically accelerates both forward and inverse simulations, as well as design optimization, without compromising physical accuracy.

In traditional workflows, a simulation engineer operates within an iterative loop: *design → simulate → analyze → update*. While simulation itself is often automated, the design and analysis phases remain largely manual, heavily dependent on individual expertise. This limitation arises because optimization typically requires running the forward solver millions of times, an approach that quickly becomes computationally infeasible.

MultiphysicsAI solves this challenge by replacing the forward solver with a neural surrogate model, a lightweight, highly accurate neural network trained on high-fidelity simulation data. The surrogate model can be called millions of times at minimal computational cost, allowing full automation of the optimization loop. Once candidate designs are identified, they are verified using the original solver to ensure physical accuracy and eliminate potential AI-induced artifacts.

This end-to-end automation results in massive gains in both speed and accuracy, allowing engineers to focus on creativity and innovation rather than manual iteration.

MultiphysicsAI
5 main stages

1. Problem description

The problem is defined in terms of input variables, such as geometric parameters, material properties, and boundary conditions, and output variables or key performance indicators (KPIs), such as displacement, frequency response, or efficiency. A structured problem description ensures that the surrogate model and optimization process are aligned with engineering objectives.

2. Training data extraction

Simulation data is generated using Quanscient Allsolve, sampling the design space to produce a representative dataset. Sampling methods are selected to cover the relevant range of input parameters comprehensively. A sufficiently diverse dataset is critical to train surrogate models that generalize across the design space rather than interpolating between limited cases.

3. Training

Feedforward neural networks are trained to approximate the mapping from input parameters to output KPIs. Techniques such as regularization and cross-validation are applied to reduce overfitting. The trained models act as surrogates for the original solver, producing results that closely match the solver output while requiring substantially less computational time.

4. Optimization

The trained surrogate is used to evaluate a large number of candidate designs efficiently. Optimization methods, including gradient-based or evolutionary algorithms, are applied to identify configurations that meet the desired performance criteria. The surrogate enables rapid exploration of the design space, with computational requirements orders of magnitude lower than repeated solver evaluations.

5. Verification

Top-performing candidate designs are validated using the original multiphysics solver. This step ensures that the surrogate predictions are physically accurate. Any discrepancies are corrected, and verified designs are suitable for practical implementation or further study.

MultiphysicsAI
Results and conclusion

Results

The workflow has been applied to several engineering problems, including microspeaker and PMUT (Piezoelectric Micromachined Ultrasonic Transducer) design optimization.

In these applications, MultiphysicsAI reduced simulation time substantially compared with conventional approaches, enabling evaluation of a larger number of candidate designs. Optimization using surrogate models identified configurations that were not readily found using manual or conventional iterative methods.

The resulting designs showed measurable improvements in key performance metrics. For PMUT devices, performance gains included higher acoustic output and lower power consumption. Microspeaker designs exhibited improved frequency uniformity and reduced distortion.

The method demonstrates generality across multiple domains, including acoustics, piezoelectric devices, thermal systems, and structural mechanics. Its ability to approximate complex solver responses while allowing extensive exploration of the design space indicates that it can be applied to a wide range of engineering problems.

Conclusion

MultiphysicsAI provides a method for integrating neural surrogate models with conventional multiphysics simulations. It allows for automated exploration of design spaces, reduces computational effort, and maintains agreement with physical laws through solver-based verification.

The approach transforms the workflow from a primarily manual, iterative process into one that is largely automated, enabling evaluation of a larger set of design configurations in a shorter time. Engineers can use the results to make informed decisions and explore configurations that may not be readily accessible using traditional methods.

This framework offers a systematic approach to design optimization and can be applied across multiple engineering domains. It demonstrates that neural surrogates can complement physics-based solvers, providing a balance between computational efficiency and physical fidelity.

Multiphysics AI
Key takeaways

- MultiphysicsAI integrates neural surrogate models with conventional multiphysics solvers to accelerate engineering design workflows.
- Neural surrogates allow rapid evaluation of large numbers of design configurations at minimal computational cost.
- Candidate designs identified by surrogates are verified with full solvers to ensure physical accuracy.
- The approach enables exploration of previously inaccessible regions of the design space.
- Applications in microspeaker and PMUT optimization demonstrated measurable improvements in key performance metrics.
- The framework is generalizable across multiple engineering domains, including acoustics, piezoelectric, thermal, and structural systems.

Get in touch

Learn more and request a demo at
quanscient.com →

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