Introduction to SimAl

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The Problems

- Spending hours/days for simulation
- Worried of wrong results
- Less time for innovation

A Brief History of Deep Learning

Deep Learning has roots dating back to the 1940s through early neural network research.

Machine Learning breakthroughs over the following decades set the stage for modern Deep Learning.

Accessible computing power now drives a new era of rapid innovation.

Deep Learning is transforming industries worldwide, from healthcare to finance and beyond.

Language (LLM) Time **Image Deep Learning** Series (Stable (RNN) Diffusion) **Physics**

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Standard DeepLearning models

Going from CFD (Computational Fluid Dynamics) to DeepLearning models

PointNet++

Flexible for data points), but lose relationship between points.

GNN

Capture local relationships and interactions, but slower and hard to scale.

3D CNN

Captures local spatial features, but lose geometry precision.

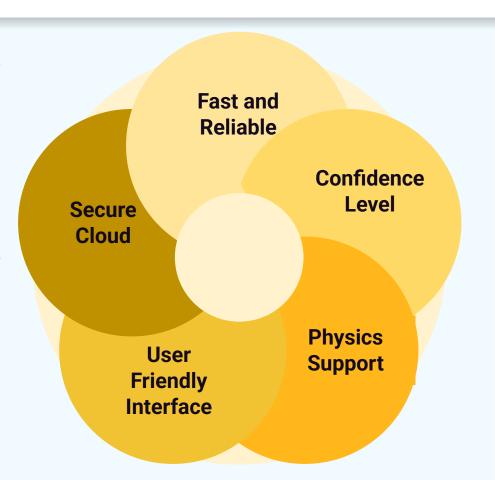
SimAl

Tailored for CAE needs and overcomes the limitations of other options.

What is SimAl?

SimAl leverages Deep Learning models to approximate physics simulation results.

- Trains on volumetric or surface simulation data through transfer learning.
- Outputs pressure, velocity, or similar fields from 3D inputs.



SimAl

Cloud-enabled generative artificial intelligence platform

	SimAl	Normal CAE	Other DL models
Fast Iteration	\odot	8	\odot
Automatic optimization	\odot	8	⊘
Reliable	\odot	\bigcirc	8
User Friendly Interface	\odot	\odot	\otimes
In two clicks	\odot	⊘	8
No DL knowledge	\odot	_	\otimes

Use Case: optimize a design to reduce drag

Spoiler Design Optimization

Objective: The user wants to minimize drag by adjusting spoiler shape/position.

CFD is too slow. SimAl gives near-instant predictions, but optimization is still manual.

Optimization strategies:

Manual try and error

- Slow
- Imprecise
- Custom

Grid search

- Test all possibilities
- Inefficient
- Time Consuming

SimAl approaches

It is now quick to run simulations. Using SHAP/Grad-CAM, we can understand why a certain shape performs better.

- **Bayesian net:** build a surrogate model, iteratively test best candidates.
- Reinforcement Learning: train an agent to learn best designs.
- Genetic Algorithm: inspired from biology; evolve a population of spoiler shapes over time.

Note: gradient based optimization is difficult as geometry is discrete

Bayesian optimization for drag reduction

What is Bayesian Optimization?

A smart, adaptive search algorithm that learns how SimAI responds to spoiler designs and suggests the next best configuration — no gradients required.

It builds a surrogate model: a fast, approximate function that mimics SimAI's drag predictions and helps decide which designs are worth testing.

Why use it with SimAl?

- Balances exploration (trying new ideas) and exploitation (refining promising ones)
- Easy to integrate with SimAl's prediction API
- Works with continuous, bounded parameters

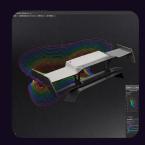
Example parameters

- spoiler_angle ∈ [5°, 25°]
- spoiler_width ∈ [0.8, 1.2]
- spoiler_height ∈ [0.05, 0.20]

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Proposed workflow

- Define parameters (e.g., spoiler angle, width, position)
- 2. Initial Designs
- Run the Model → Predict Drags through PySimAI
- 4. Use Bayesian optimizer (use scikit optimize)
- 5. Propose new geometry
- 6. Iterate to minimize drag



The results

- Predictions are fast to iterate
- Suggest better shapes
- Reduce drag
- Satisfy stress constraints
- Explore large design spaces without simulating each design



At the end, drag decreases significantly automatically in a small amount of time.

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See more on SimAl

- Fast and reliable data-driven insights
- Intuitive and simple workflow
- Flexible deployment options
- Expansive design space exploration

