Using AI/ML to Accelerate Engineering Simulations for Asset Design and Optimization

SPE Gulf Coast Section
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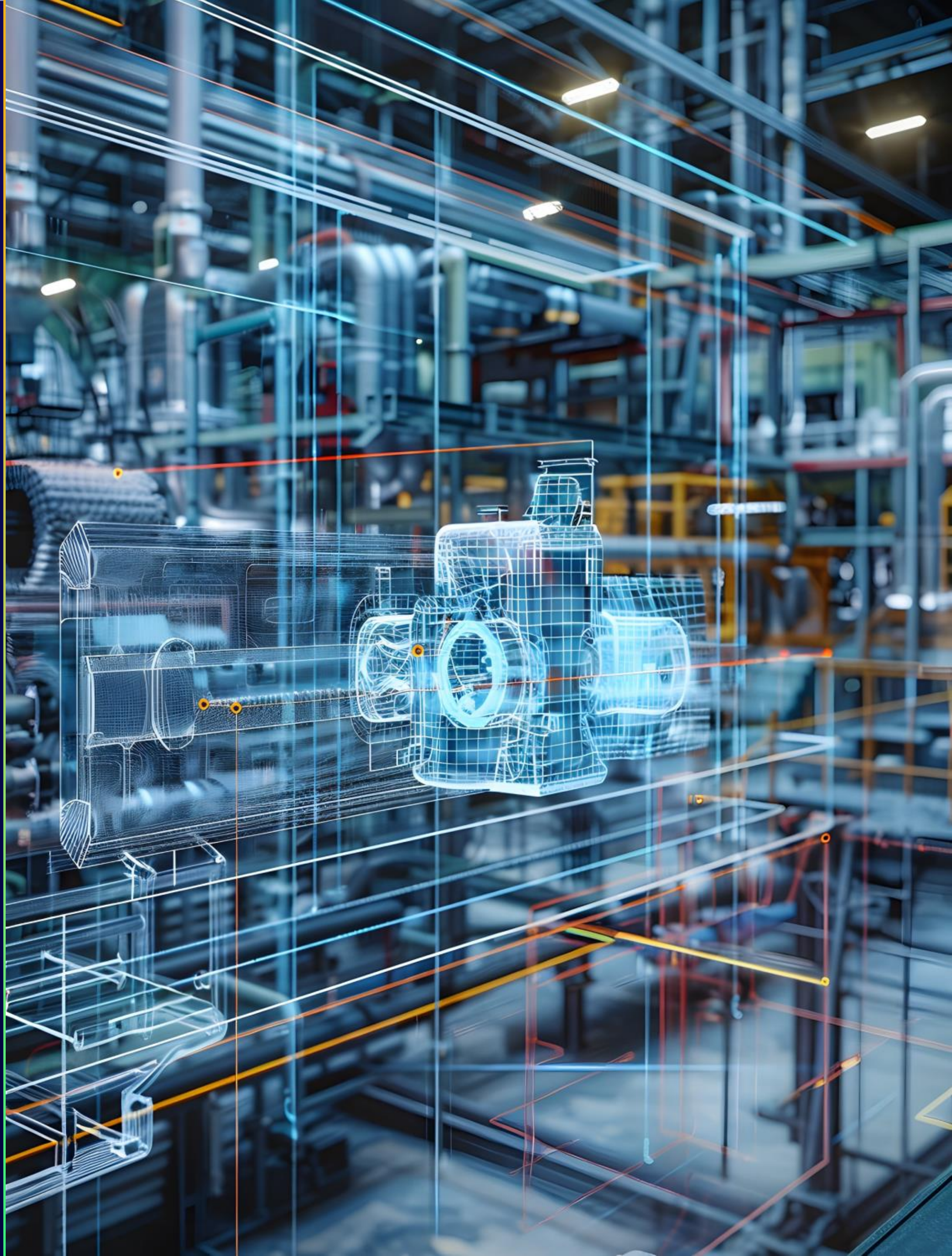
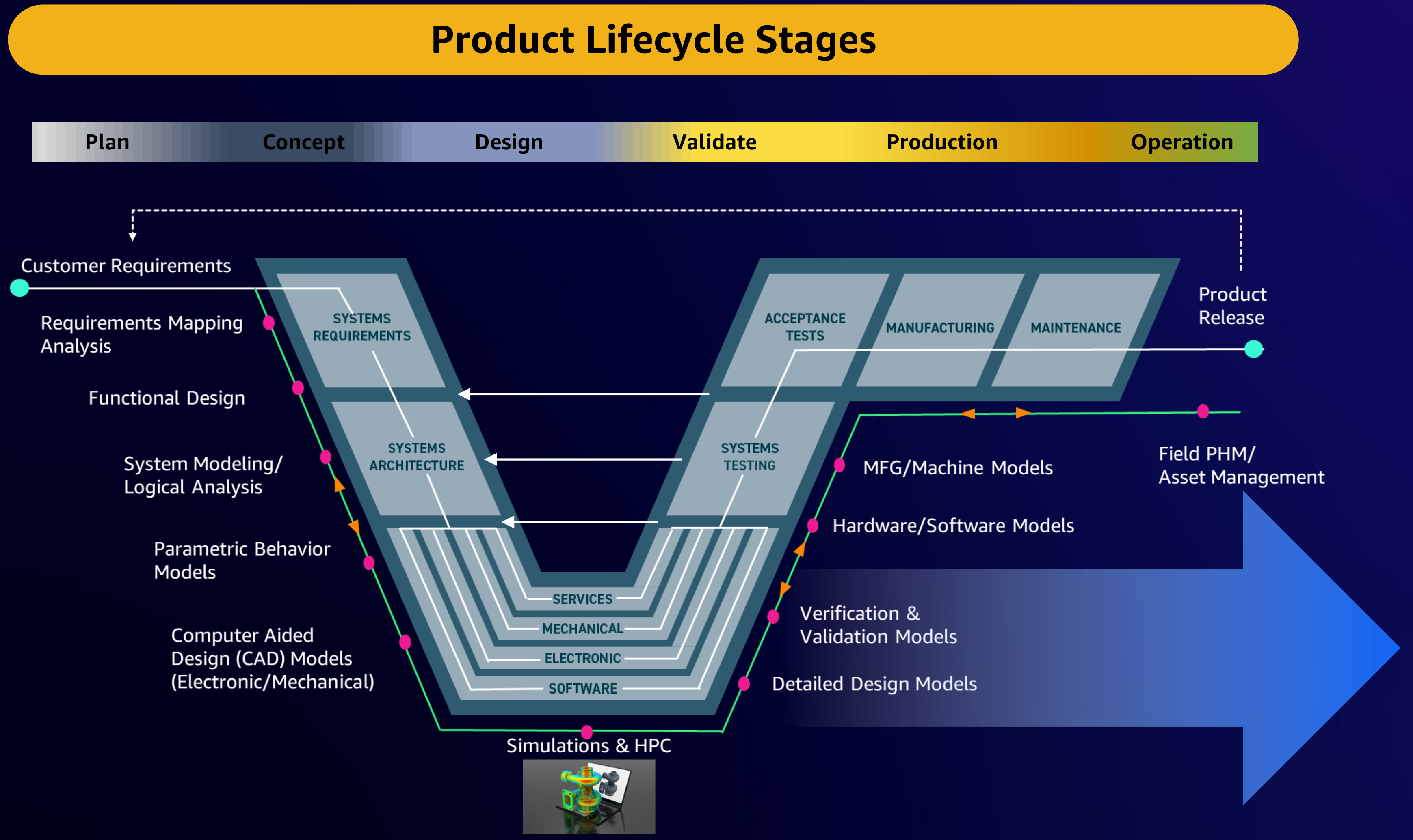
Agenda

- Background and Challenges
- AI/ML for Engineering Simulations
- Applications & Demonstrations
- Next Steps



Product Lifecycle: Design, Development & Operations

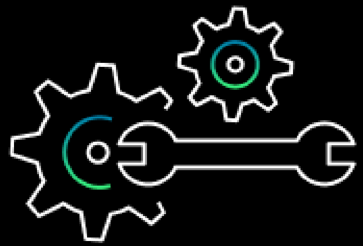


Optimal asset design needs to cover large trade space studies consistent with the requirements

Challenges in traditional design space exploration

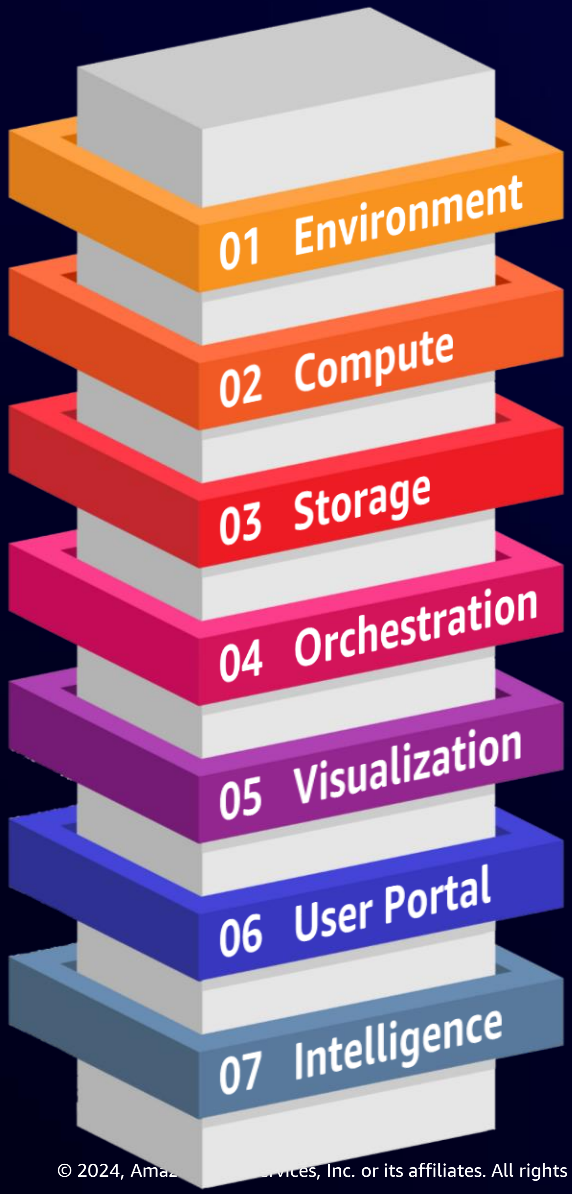
Can't explore sufficient design iterations to find an optimal performance

Time-consuming and costly to run high fidelity physics-based simulations



Leverage existing data for simulation intelligence

AWS Engineering Simulation Tech Stack



1. ENVIRONMENT

VPC, VPN, AWS DIRECTCONNECT, SUBNETS, GATEWAYS, COST MANAGEMENT, GOVERNANCE

2. COMPUTE

COMPUTE INSTANCES, AWS NITRO, ELASTIC FABRIC ADAPTER

3. STORAGE

AMAZON FSX, AMAZON EBS, AMAZON S3, AMAZON EFS

4. ORCHESTRATION

AWS PARALLELCLUSTER, BATCH

5. VISUALIZATION

AWS NICE DCV

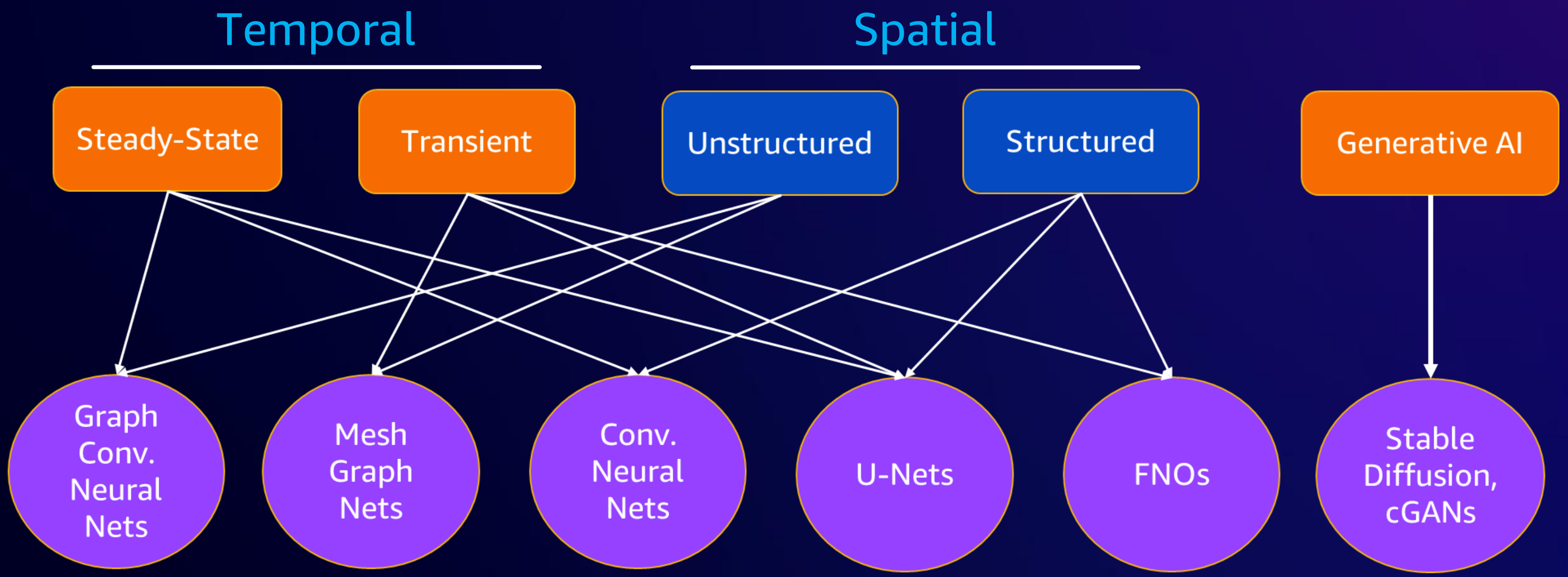
6. USER PORTAL

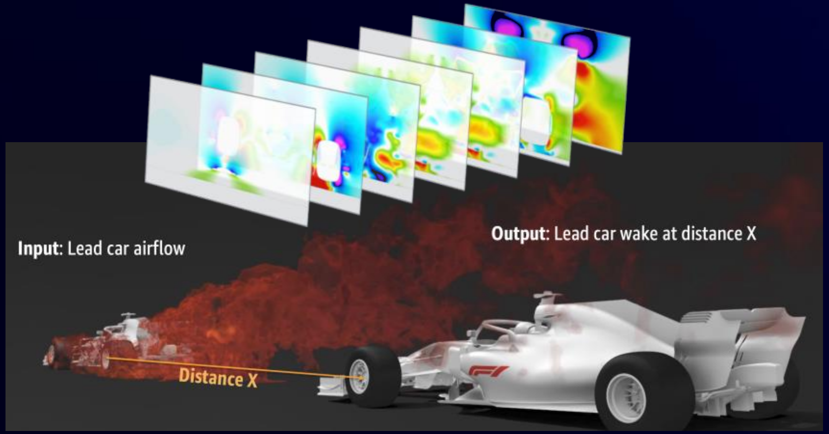
AWS RESEARCH AND ENGINEERING STUDIO

7. AI/ML

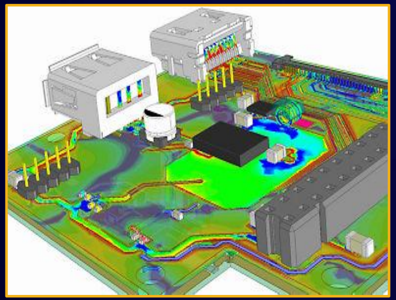
AI/ML – UNET, MESHGRAPHNET, PHYSICS INFORMED NEURAL NETWORKS (PINN)
GenAI – DIFFUSION TRANSFORMER LLMs

Overview – AI/ML Techniques and Applications

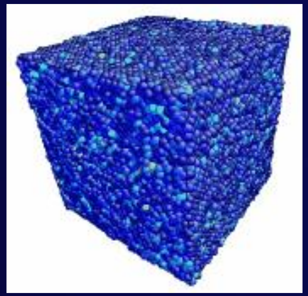




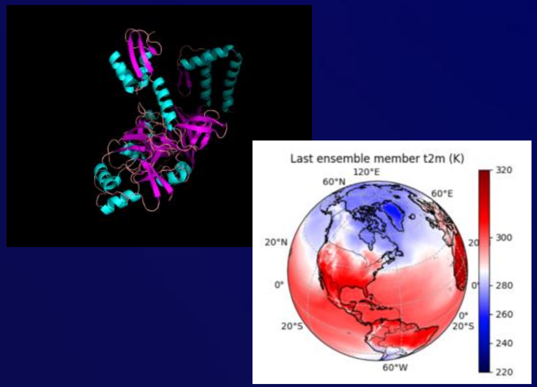
Fluid Dynamics



Structural, Thermal

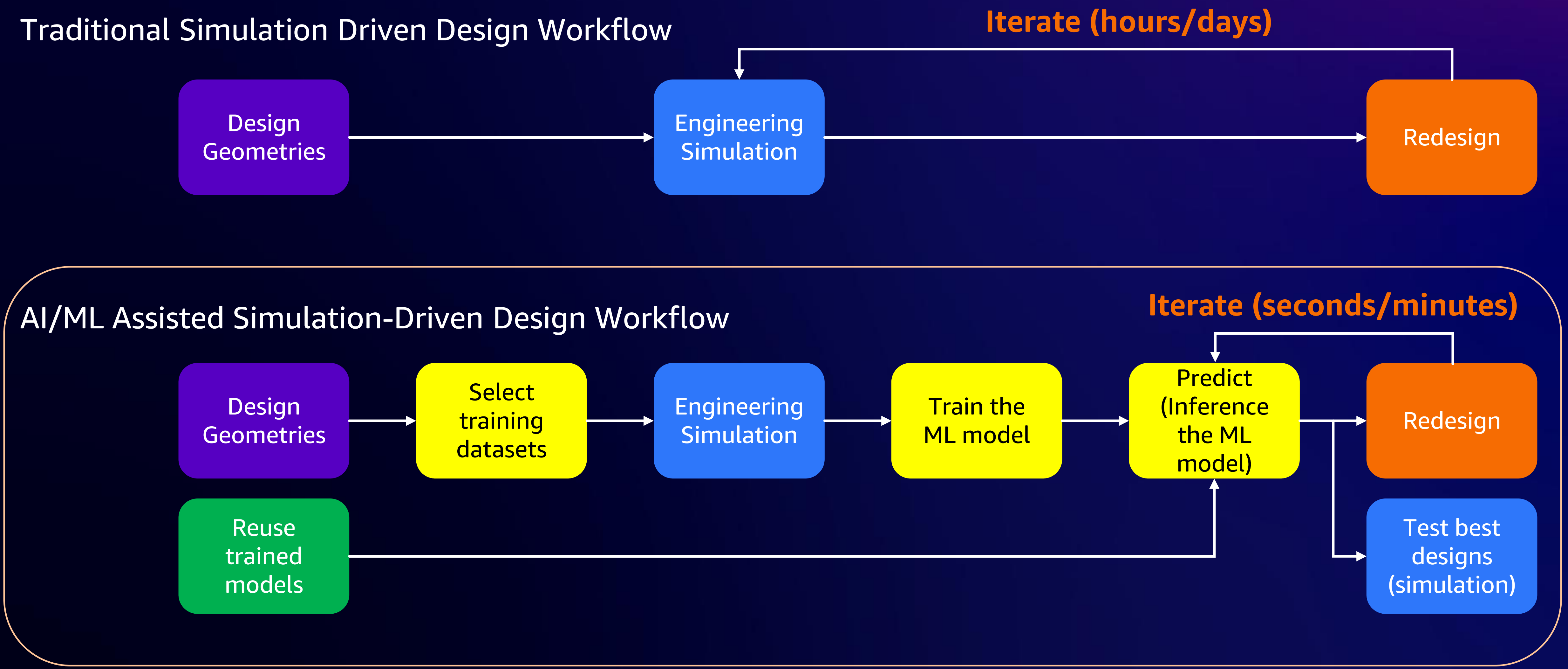


Materials



Drug Discovery, Weather

AI/ML for Engineering Simulation Workflows



Asset Design: Fluid Injection Application

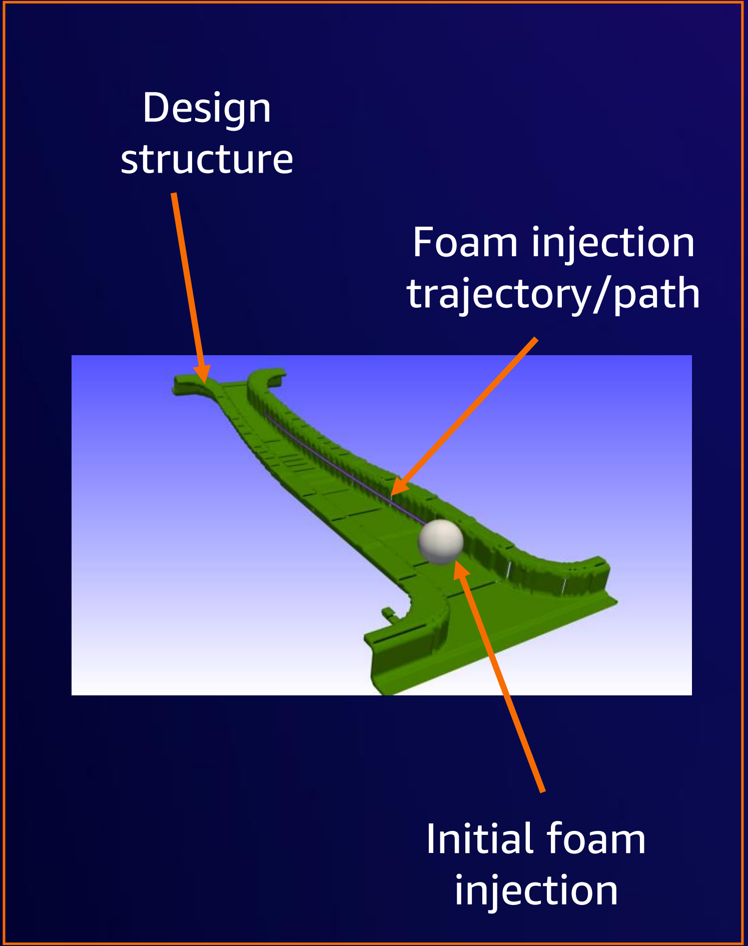
ML ASSISTED TRANSIENT SIMULATIONS

Scenario: Foam injection use case involves injecting a liquid which hardens into a foam to provide structural strength for panels.

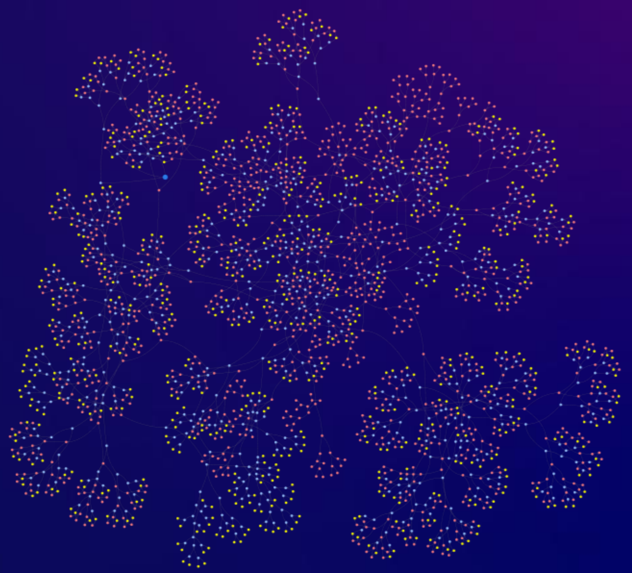
Challenge: Find optimal injection trajectory to maximize contact surface and minimize void formation and foam wastage

Approach: Optimize the foam injection path to maximize foam volume using a genetic algorithm

Outcome: reduced total amount of foam injected by 8% while maximizing contact surface to 15%

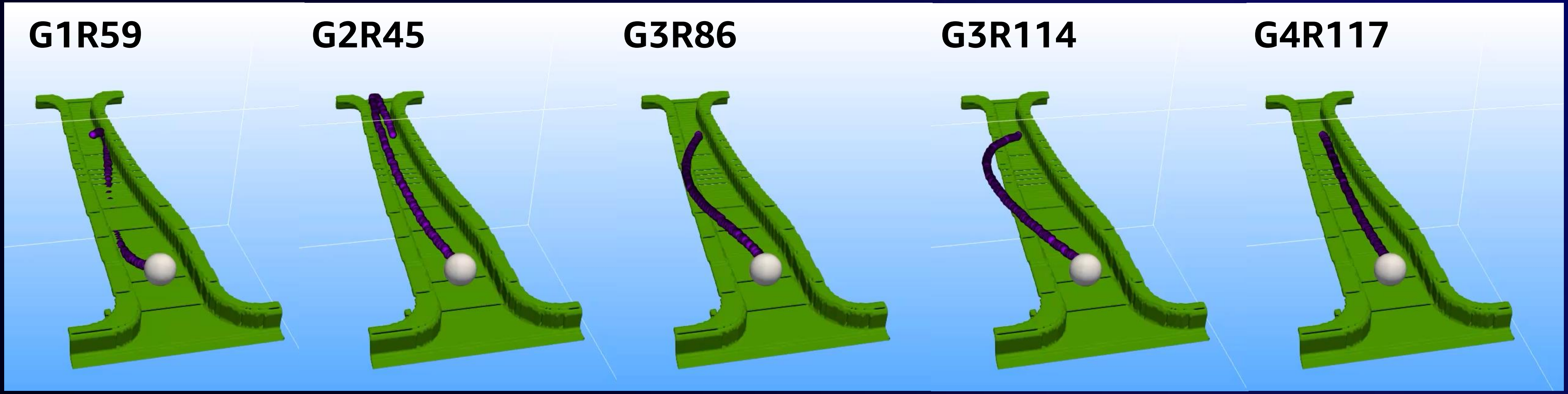


Asset Design & Optimization: Fluid Injection

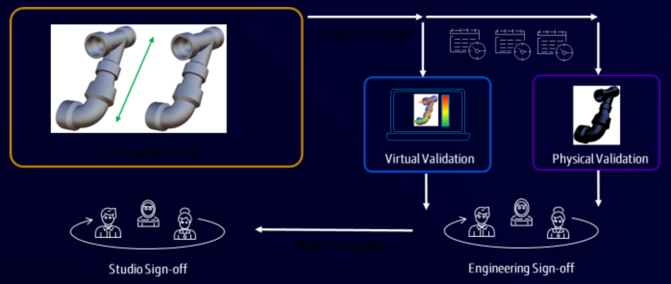


Simulation Optimization Details

- 10 design iterations, each with 128 simulations (1280 foam growth simulations)
- Best of 128 was used to seed next design iteration (Genetic Algorithm)
- Structured grid 16.7M cell count
- Runtime per simulation (9-11.5 min: ~5min simulation, ~5-6min post-processing)

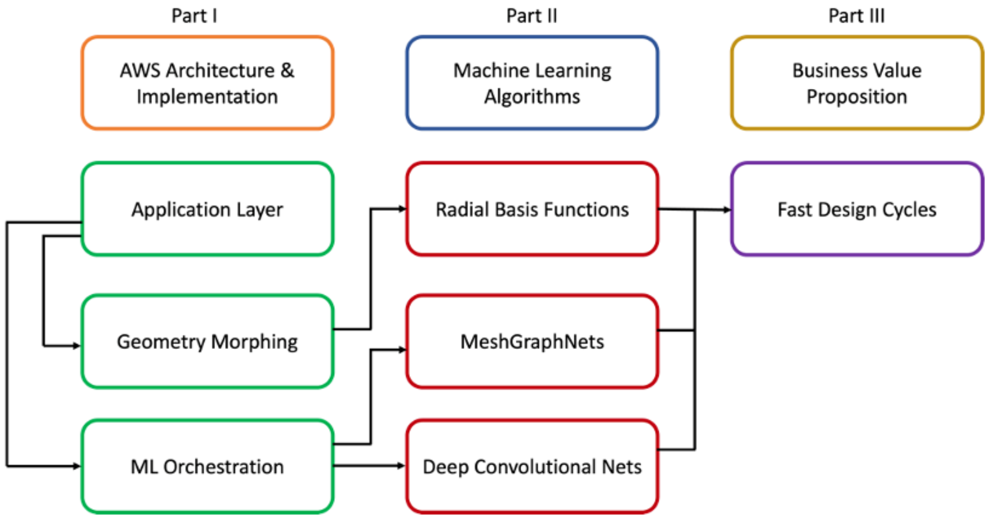


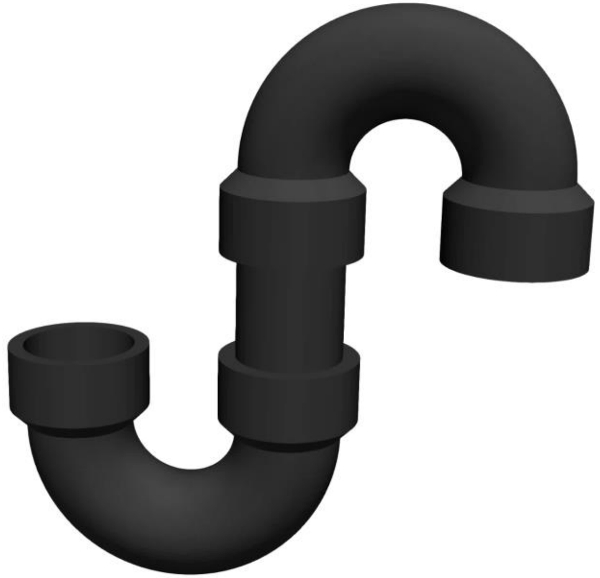
AI Driven Design

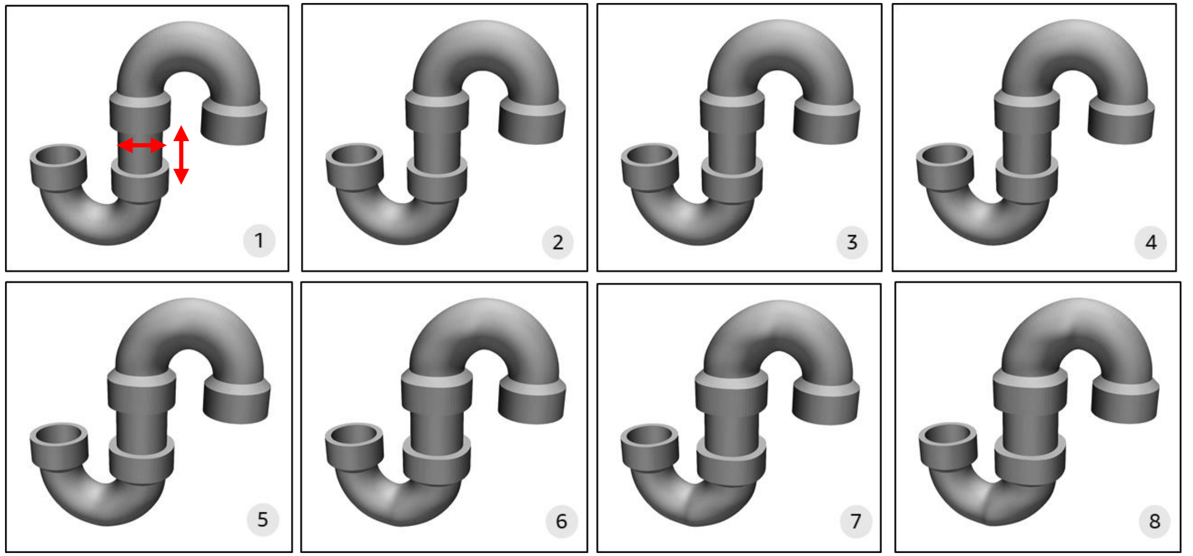


- Asset model
  - Images* / Scans
  - CAD / DWG
- Requirements
  - KPI (Mfg, Cost, CTQs..)
  - 2D/3D Sim. Fidelity
- Existing results
  - Simulation
  - Testing
  - Field operations

**Image to 3D model through Stable Diffusion pipeline*







Accelerated Non-Linear Design Convergence

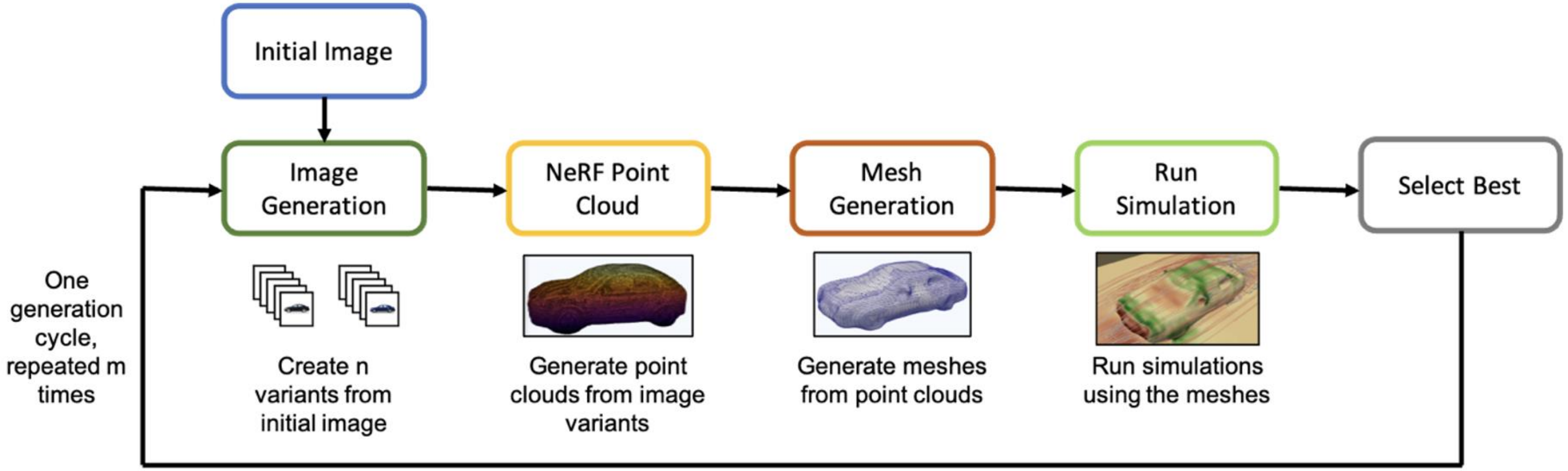
Geometry modification based on inputs

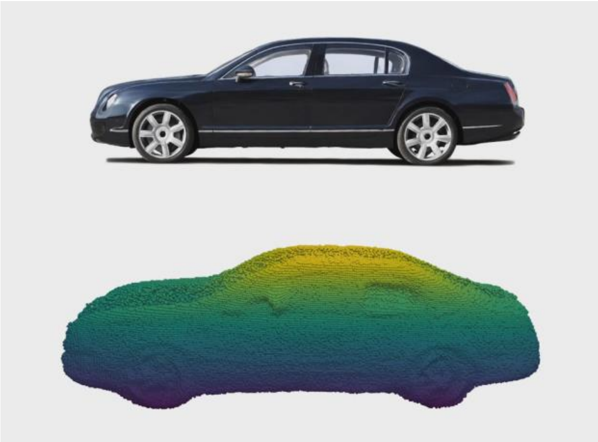
Seamless extract design options based on KPI (Performance (ΔP, Mixing ratio), Cost, Material..)

Ref: https://aws.amazon.com/blogs/hpc/conceptual-design-using-generative-ai-and-cfd-simulations-on-aws/

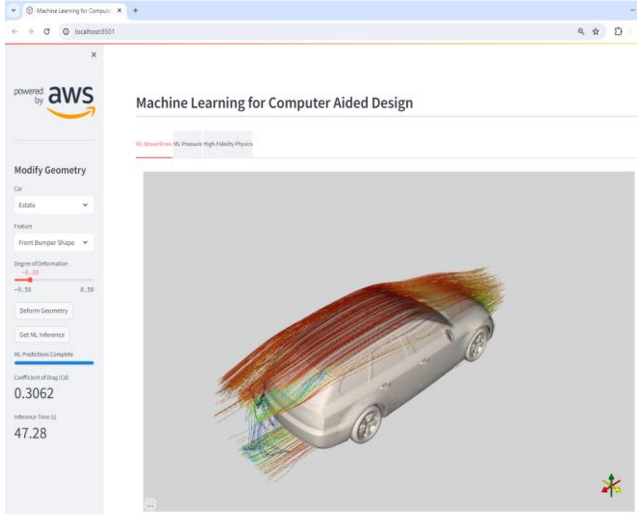
Generative AI for Design Iterations

WORKFLOWS AND SIMULATION PREPARATION

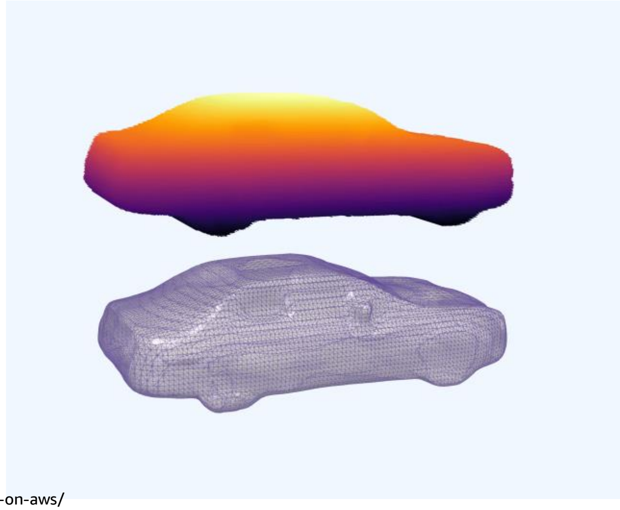




Neural Radiance Fields (NeRF)



User Centric Workflows



Neural Kernel Surface Reconstruction (NKSR)

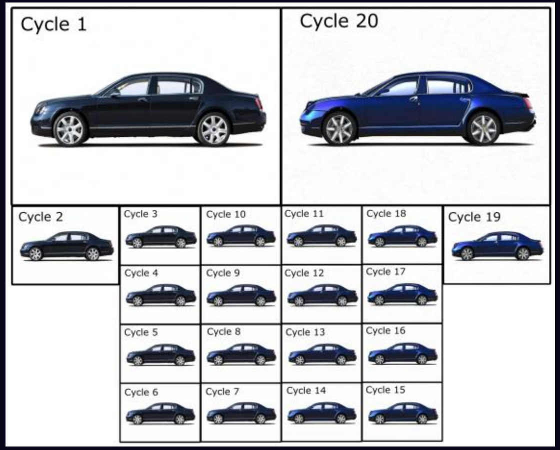
Ref: https://aws.amazon.com/blogs/hpc/conceptual-design-using-generative-ai-and-cfd-simulations-on-aws/

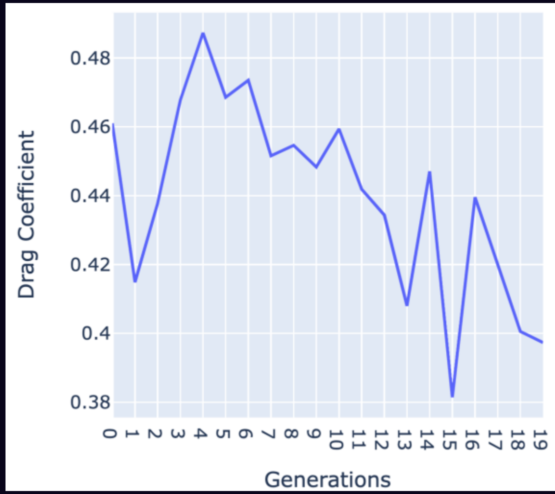
Physics Enabled GenAI Design Acceleration

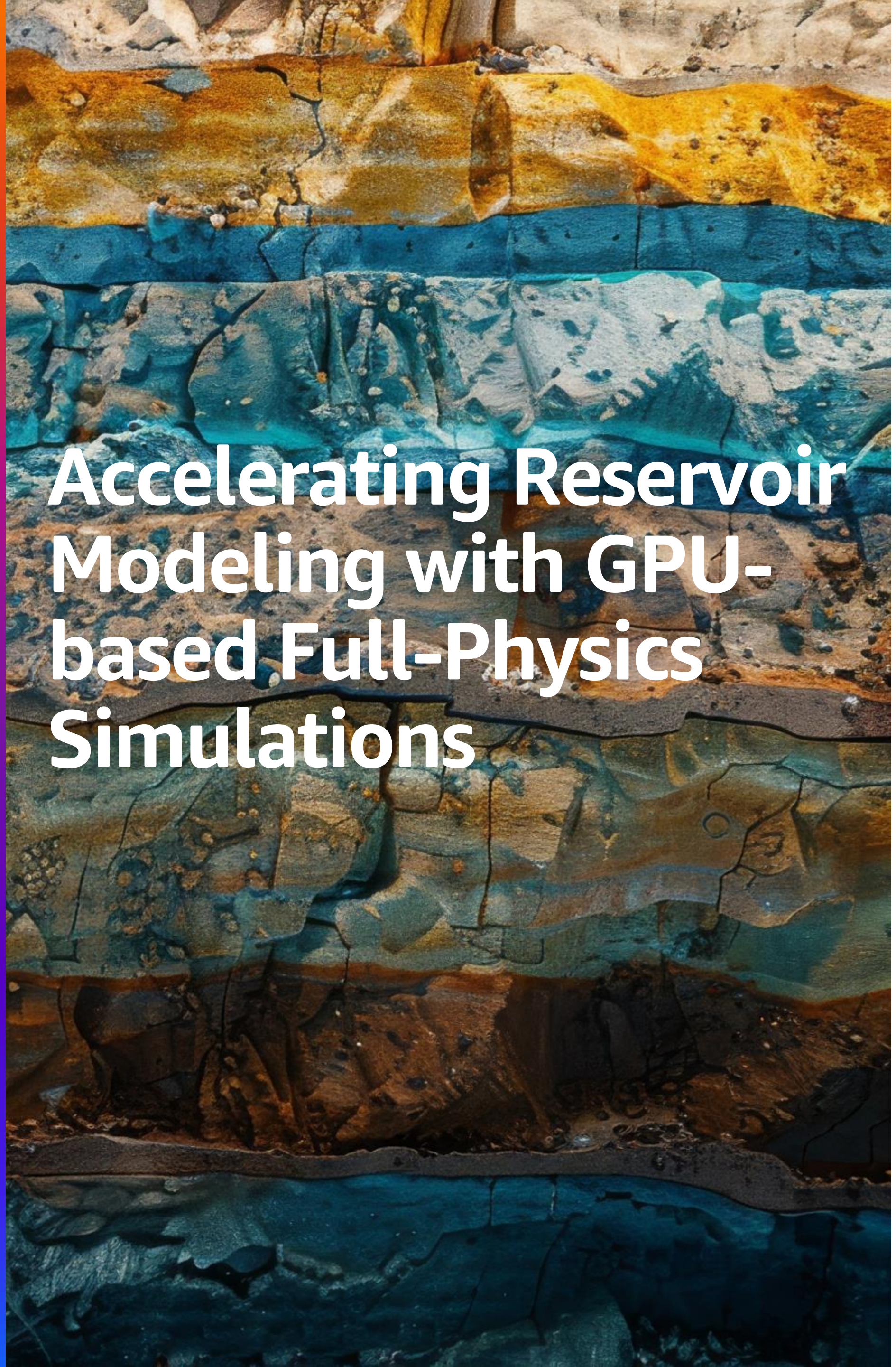
"make the car sporty and aerodynamic"

400 OpenFoam Simulation
(375 training, 25 validation)

Training: p5.48xlarge instance with 8 H100 GPUs (28 hours)



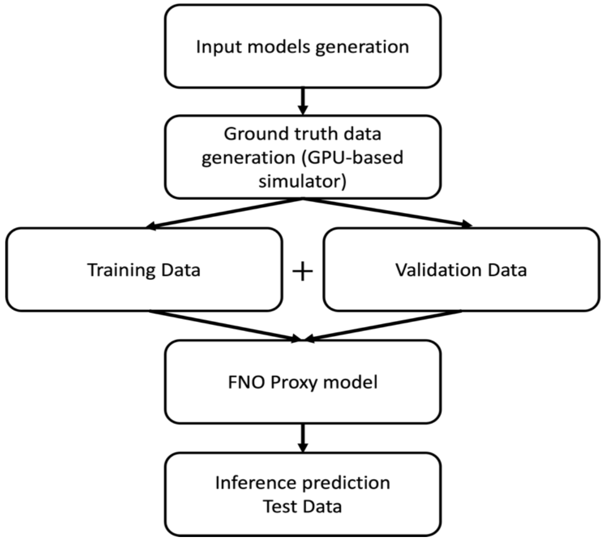




Accelerating Reservoir Modeling with GPU-based Full-Physics Simulations

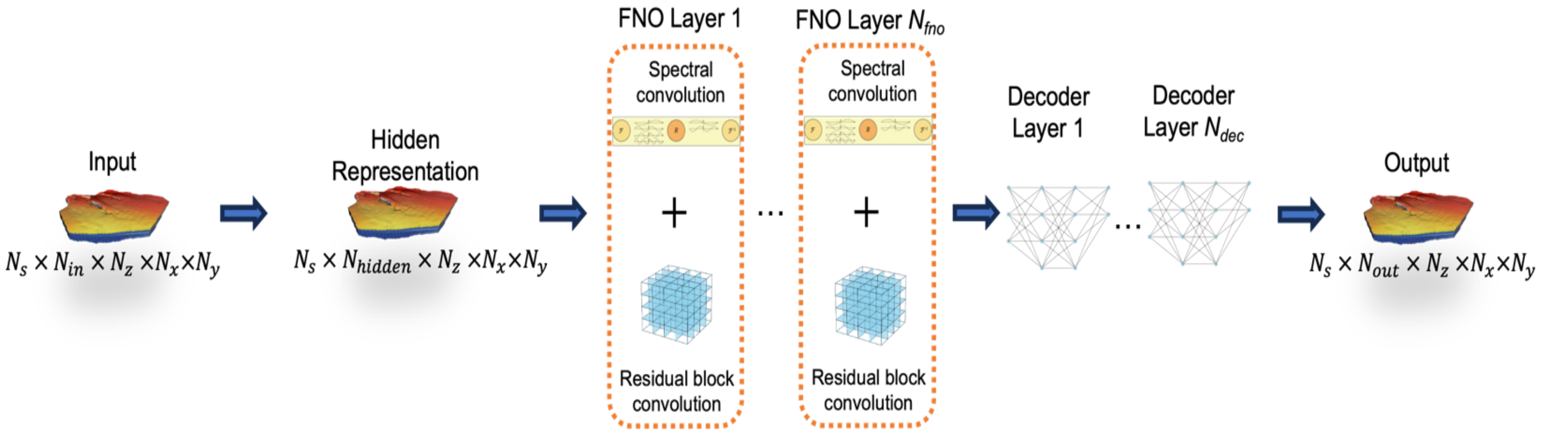
Generating full-field proxy models for predicting the time-evolving state variables for reservoir flows

Collaborators: Stone Ridge Technology & NVIDIA



Workflow

- ✓ Generate ensembles through statistical variation of well locations
- ✓ GPU based reservoir simulator for forward simulation (ground truth) data
- ✓ 80/15/5 rule for training/validation/testing



- N_s denotes the number of samples used for training/validation/testing
- N_{in} is the number of input features (permeability, porosity, initial conditions of state variables, well positions)
- N_x, N_y, N_z are the spatial dimensions of the reservoir, N_{fno} is the number of FNO layers
- N_{dec} is the number of decoder layers, and N_{out} is the number of output channels (time snapshots of the state variables, pressure and saturations)

AI/ML for Subsurface Flows

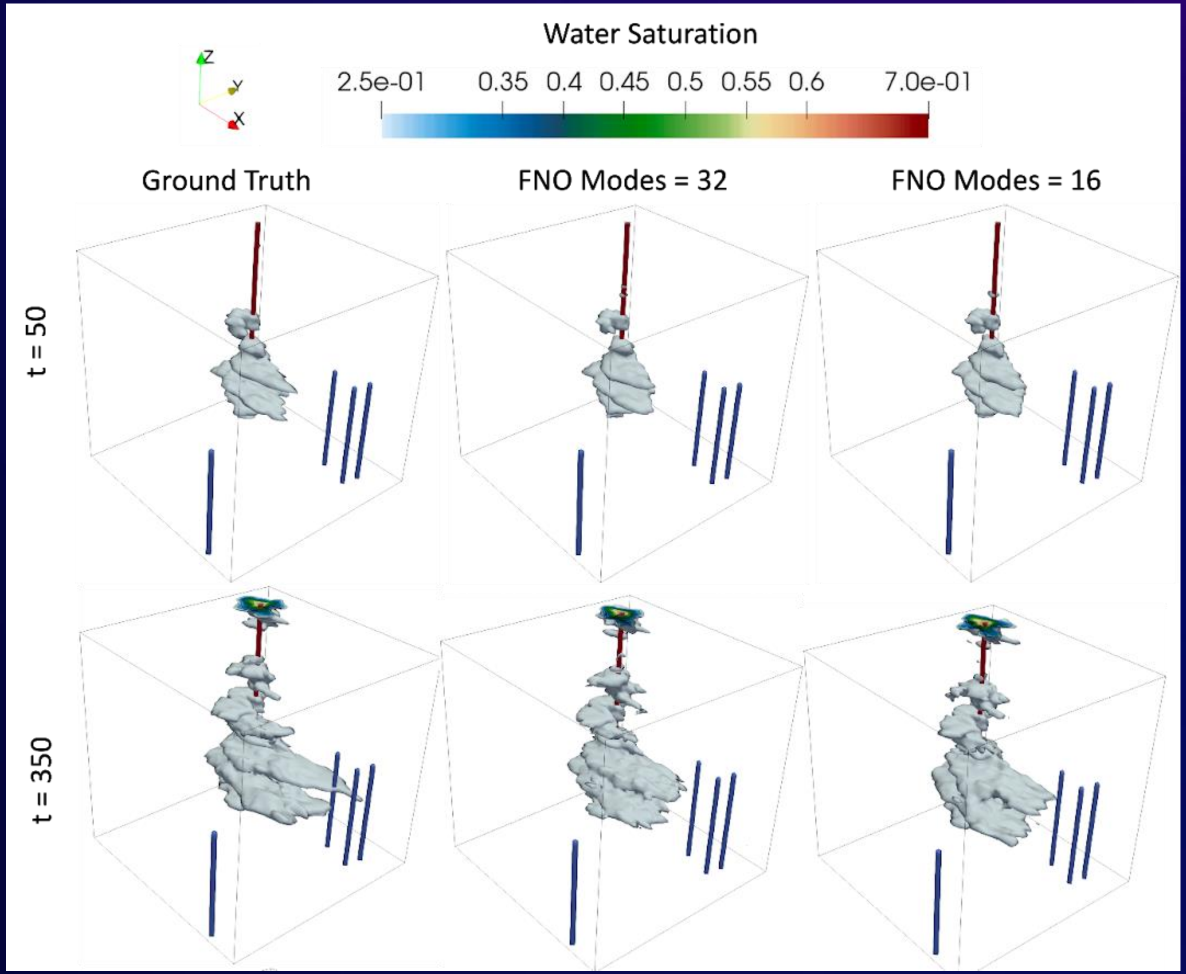
Collaborators: Stone Ridge Technology & NVIDIA

TRAINING LARGE 3D MODELS FOR HISTORY MATCHING, WELL PLACEMENT, INJECTION RATE OPTIMIZATION

Input features used for the FNO ML model
Static permeabilities in all three spatial dimensions (3 channels)
Porosity (1 channel)
Initial conditions of the state variables (pressure and water saturation) (2 channels)
Binary encoding of well positions (1 for location of producers, -1 for injectors) (1 channel)

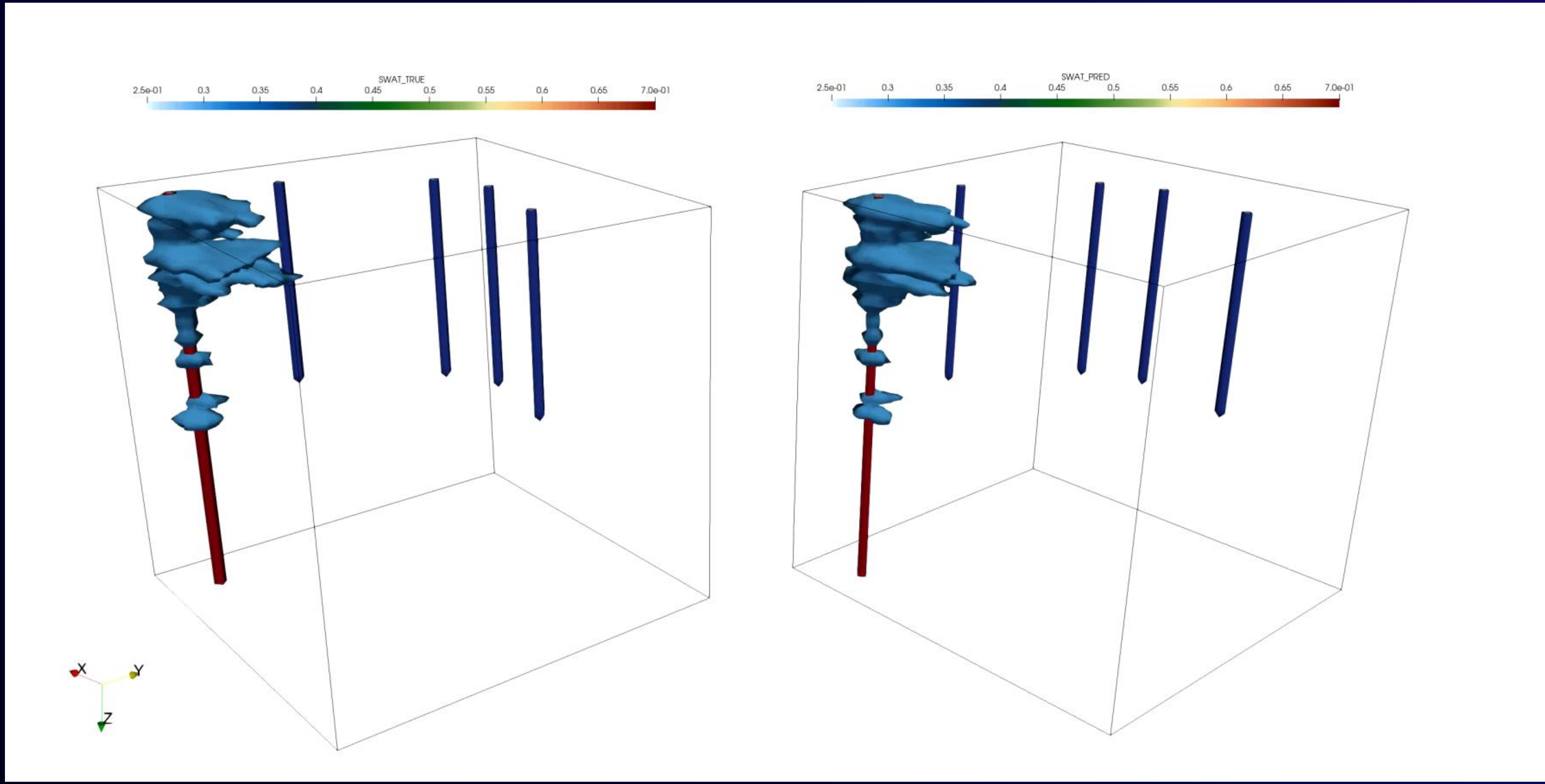
Grid	64 x 64 x 64 orthogonal grid
Grid spacing	30 ft. x 30 ft. x 30 ft.
Permeability - x-, y-directions	200 mD
Permeability - z-direction	40 mD
Porosity	0.174
Water injector rate control (1 well)	5000 stb/day
Producer bottom hole pressure (4 wells)	4000 psia

500 samples, 400 are used for training, 75 for validation, and 25 for testing



For visual purposes, wells are pointing up (Z is positive)

AI/ML for Subsurface Flows



- ➢ *Plot of water front (0 water, 1-100%, contour ~0.25). Water injected from red well into reservoir.*
- ➢ *Channelized behavior captured pretty well across long time horizon*

Left

- Full physics simulation
- Using MP Porous Media flow simulator
- 1 hr. for full physics

Right

- FNO Surrogate model
- Test on unseen data set
- ~10-15 sec (inference incl. data processing)

- ✓ 2 H100 GPUs ~10 hours for training
- ✓ Inference run on A10G

Collaborators: Stone Ridge Technology & NVIDIA

aws

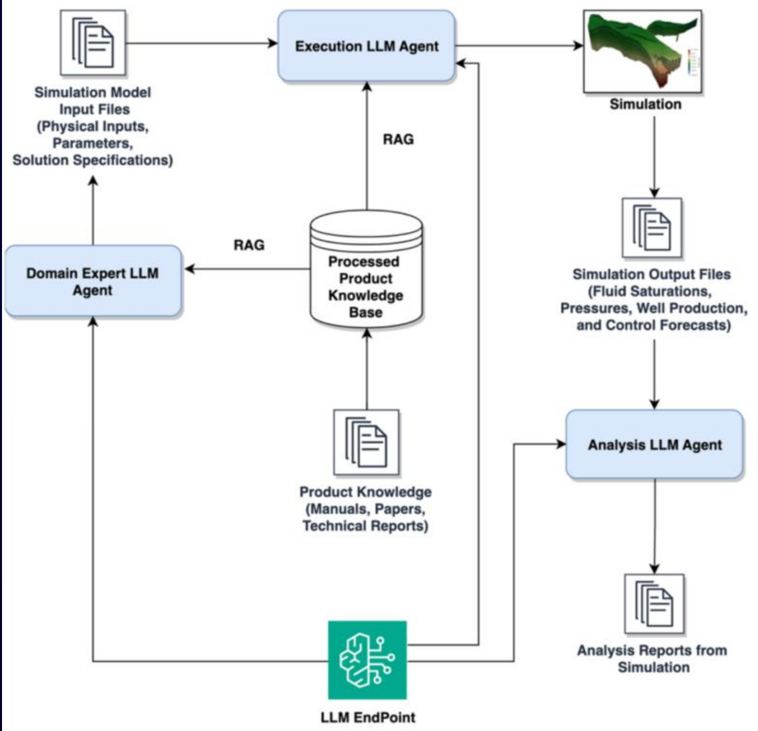
GenerativeAI driven Asset Optimization

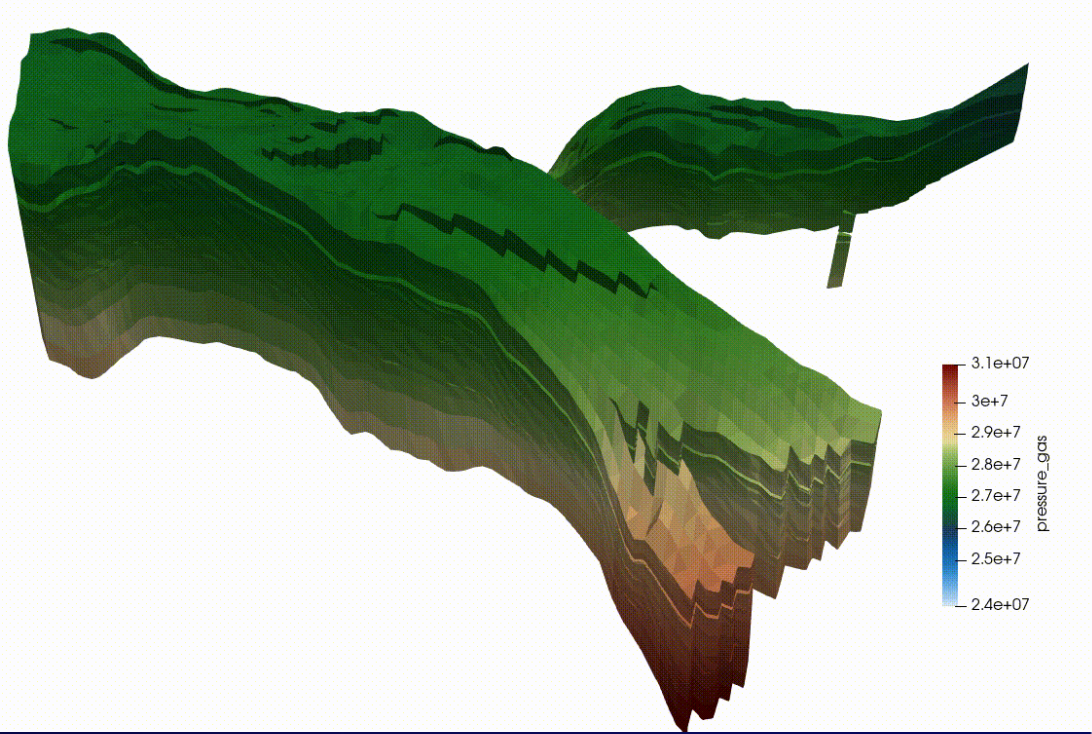
RESERVOIR SIMULATION ASSISTANT

Model Analysis & Issue Identification: Analyze simulation input data for inconsistencies and issues | Alert users for potential problems

Simulation Analysis and Optimization: Analyze the logs/results files → Identify bottlenecks and provide recommendations for simulation optimization

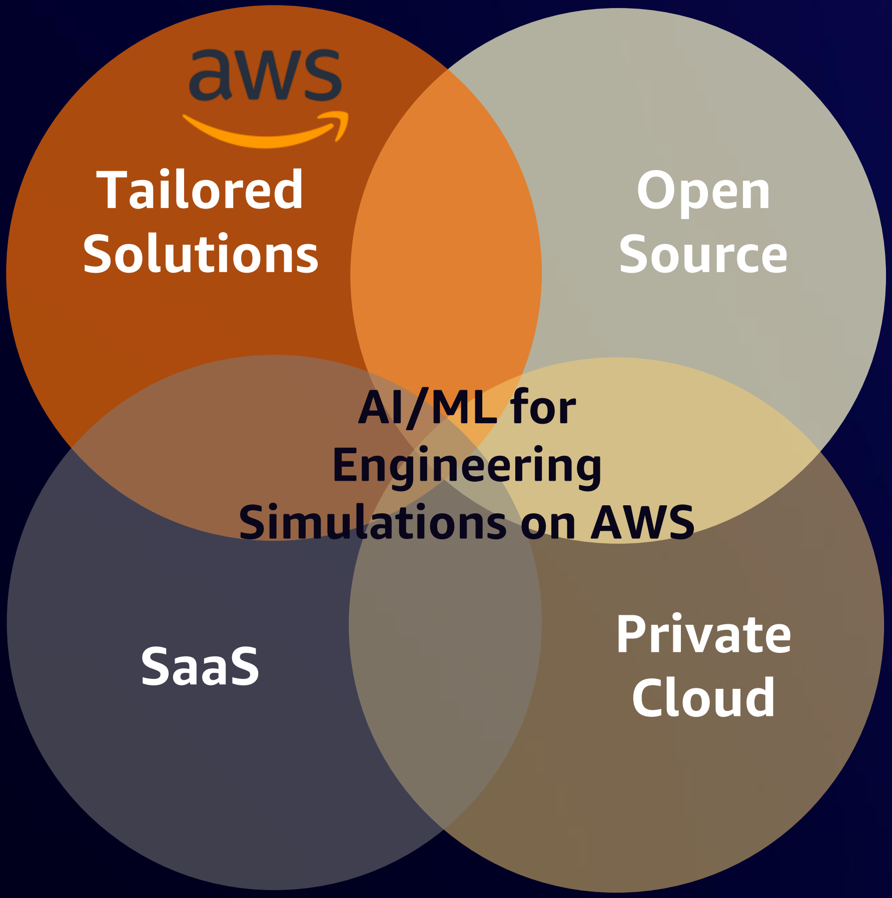
Interactive model manipulation/Re-Runs: Modify simulation models directly | Assistant can initiate and monitor new simulations from updated models





https://aws.amazon.com/blogs/industries/building-a-generative-ai-reservoir-simulation-assistant-with-stone-ridge-technology/

AWS collaborates with solution providers



AWS: Provides advanced compute services and solutions to enable user's ML for Simulation journey on the cloud. Innovates with customers to build tailored solutions.

SaaS: Provides software as a service (SaaS) applications on AWS that are user-friendly for simulation engineers and product designers without AIML expertise.

Private Cloud: Provides API based software solutions that can be deployed into user's own AWS account. It provides the flexibility and capability to preprocess data, train models and make predictions.

Open Source: Provides open-source framework for building, training, fine-tuning, and inferencing Physics-ML models on AWS. Users only pay for the underlying cloud infra/services.

Acknowledgements

- Dr. Vidyasagar Ananthan *Senior Solutions Architect, Advanced Computing & Emerging Technologies Domain*
- Mr. Kumar Lakshmipathi *Principal Solutions Architect, Generative AI, Energy & Utilities*

Accelerating Asset Design & Optimization using AI/ML

ACCESSIBLE RESOURCES FOR FURTHER DISCUSSIONS

[AWS Engineering Design Solutions Library]

[Blog: GenAI enabled Reservoir Assistant]

[AWS Solutions for Energy & Utilities]

[Blog: Machine Learning for faster design cycles]

Thank you!

For feedback/questions, contact: Dr. Vedanth Srinivasan (Vedsrin@amazon.com)