Physics-Informed AI for Robust Decision Making

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Geminus

Silicon Valley Deep Tech Meets AI

We are accelerating the pace of industrial innovation by empowering industries to overcome data and computational challenges, paving the way for robust, real-time decision-making and industrial autonomy at scale.

Best-in-Class Research

We were born from the minds of pioneers and visionaries in AI-augmented computational physics and computational autonomy.

Best-in-Class Product

Our leadership has led innovative product initiatives, creating and delivering high-impact solutions across diverse industries.

Bridging the Simulator-Operations Gap

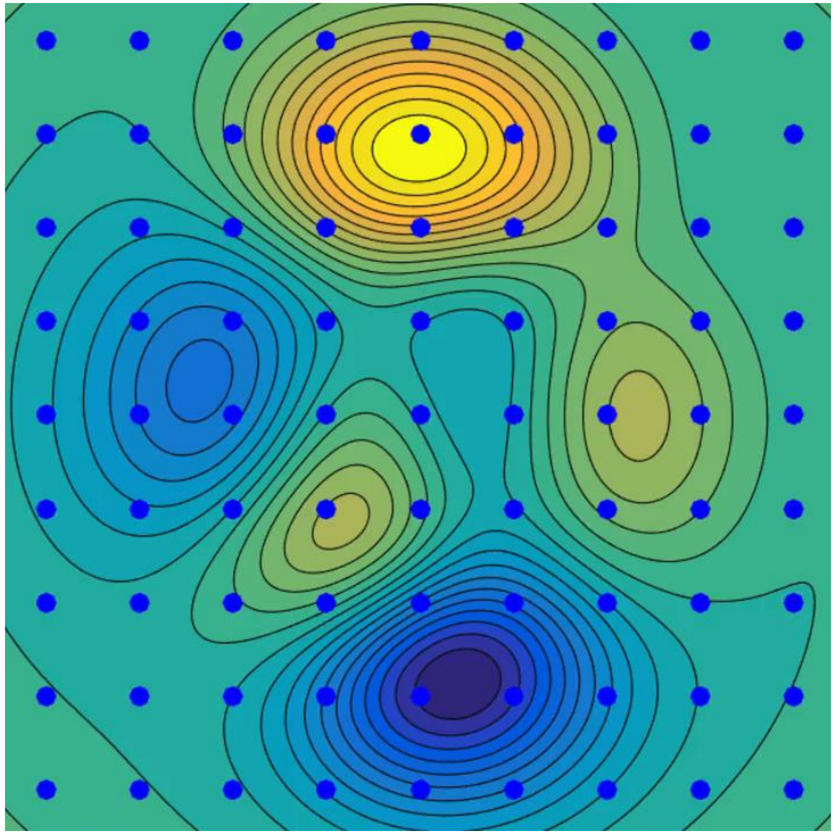
High-fidelity simulation tools are more accurate and widely used but **increasingly computationally expensive.** As sensor coverage grows, quality control improves, emissions standards tighten, and operational **optimization becomes more complex and constrained**.

Challenge:

While we have the predictive capability, we can't access necessary high-fidelity information in an **operations timescale**.

Requirements to bridge the gap:

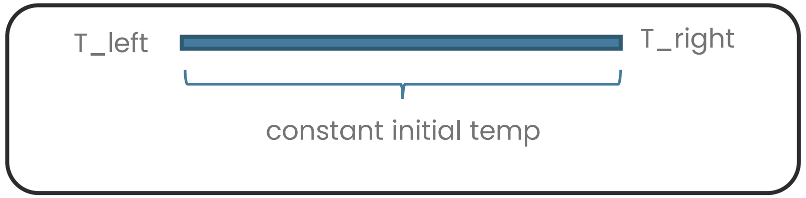
1. Hi-fidelity predictions
2. Speeds fast enough for thousands of solves in an operations time scale (seconds/minutes)
3. Robust optimisation algorithms
4. Confidently used without experience in numerical simulation



Optimisation is expensive.

Physics-Informed AI

Simulation: The TL;DR



Guiding example: 1D heat transfer in a rod

Input Parameters

Physical

- Boundary Conditions
- Initial Conditions
- Geometry
- Constants

Numerical

- Discretization
- Tolerances
- Tuning parameters

Simulator: Solve PDEs via traditional numerical methods

$$\frac{\partial u(t,x)}{\partial t} = \alpha \frac{\partial^2 u(t,x)}{\partial^2 x}$$

Output Parameters

- Spatio-temporal history of quantities of interest
- Integral / derived quantities

Validation: Ph.Ds and the like...

Experimental/ Analytical observations

Simulation tools as black box models: Input -> Output mapping based on **known** governing equations

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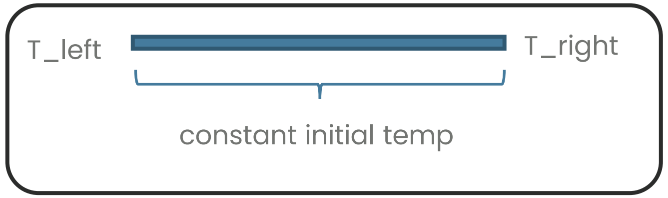
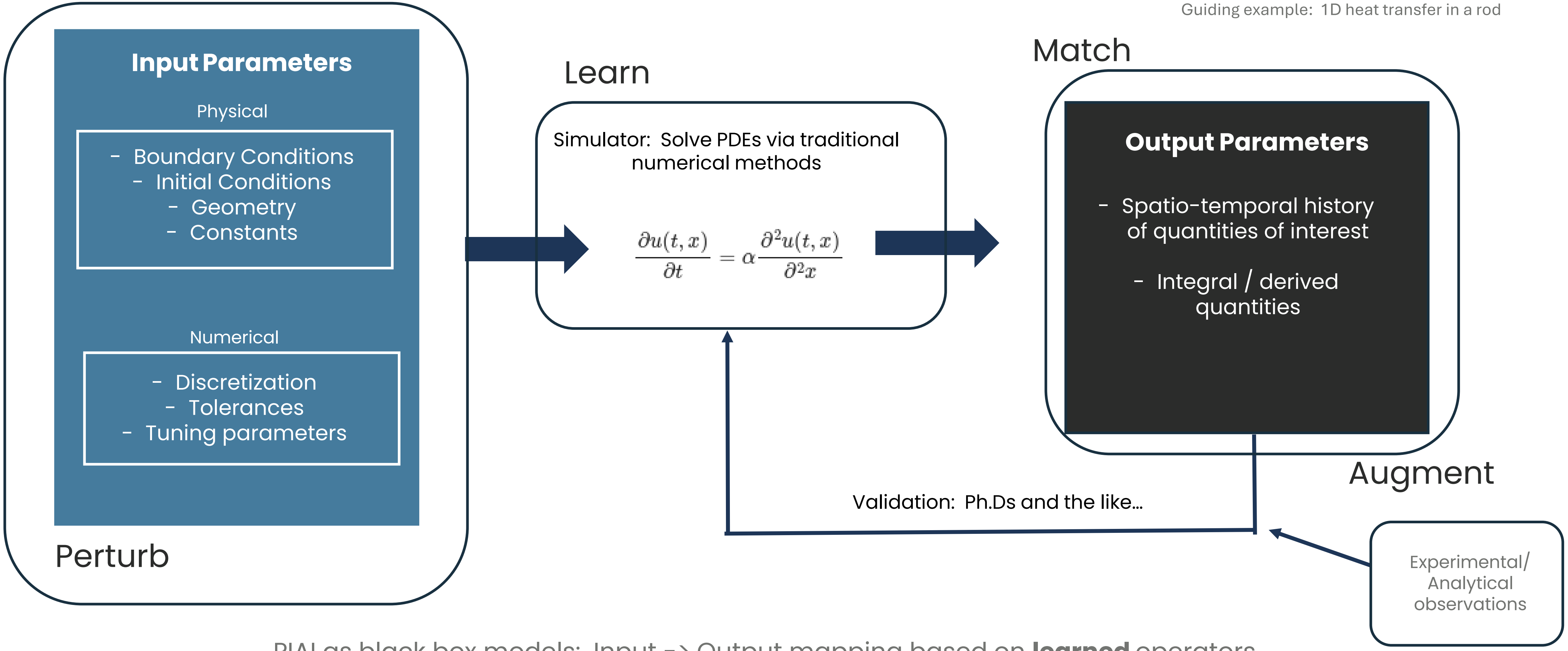
Simulation: The TL;DR



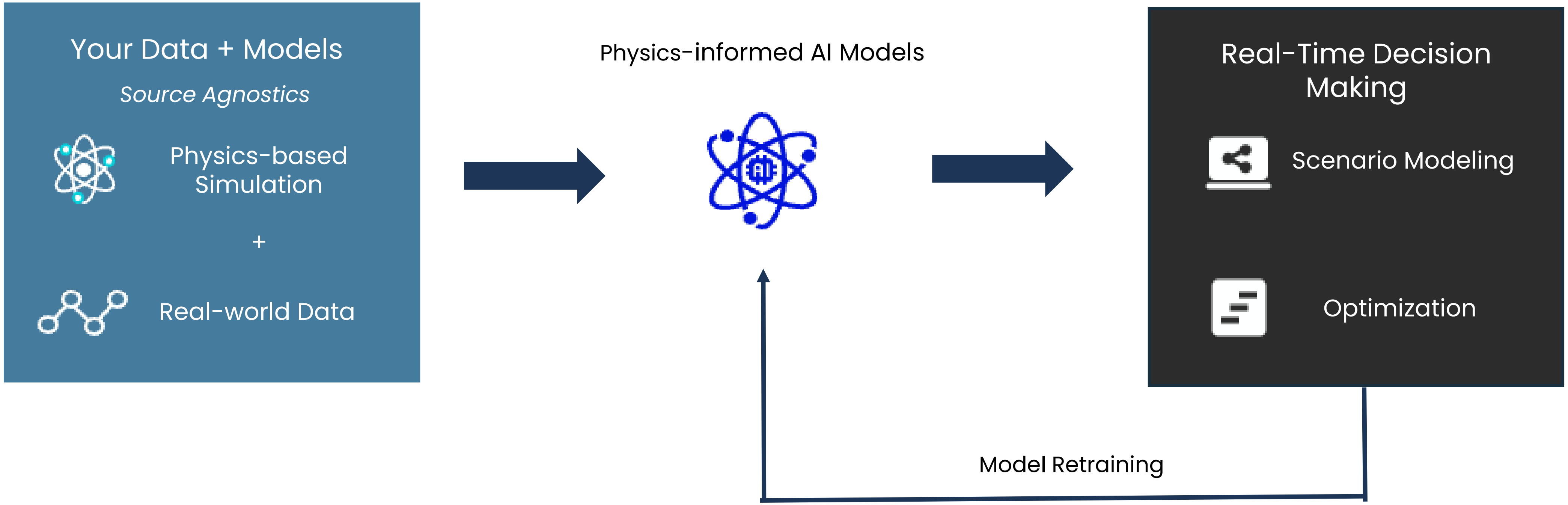
Guiding example: 1D heat transfer in a rod



PIAI as black box models: Input -> Output mapping based on **learned** operators

Phyics-Informed AI

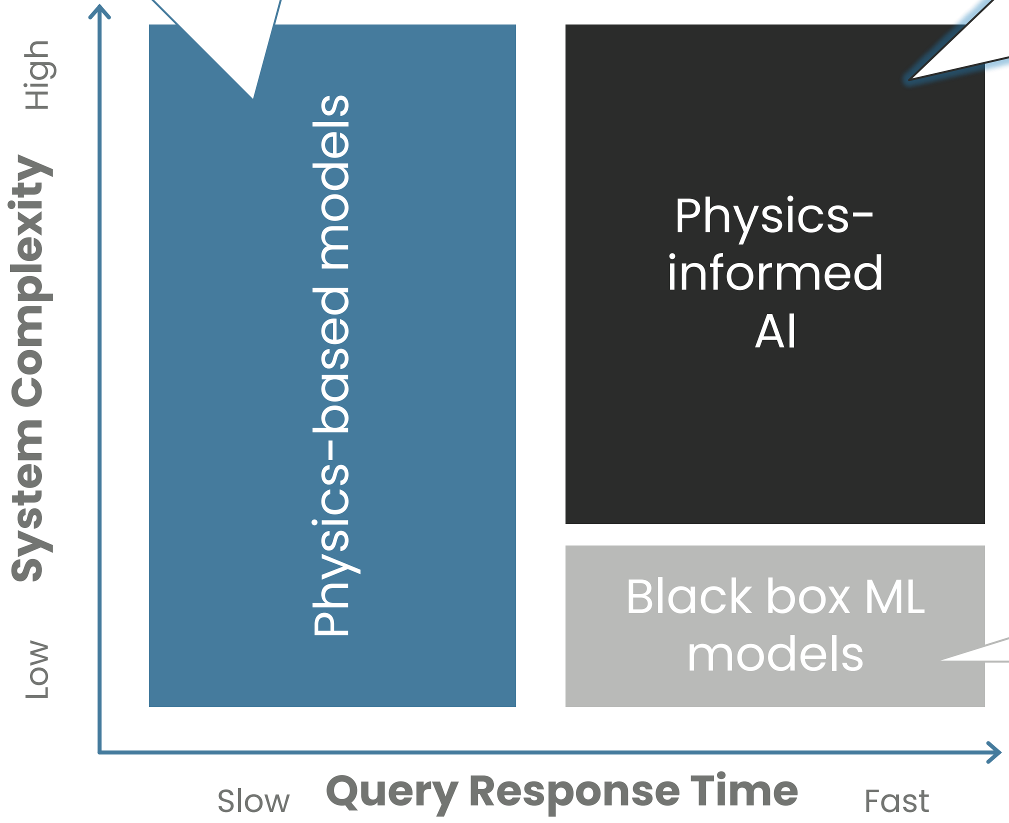
Fusing Physics-Based Simulation and Process Data



Operationalizes and scales investment in simulation | Accuracy that builds trust | High speed ROI in days, not months

Real-time Intelligence, for Complex Systems, at Scale

- → Long compute times, specialized hardware
- → Not suited for real-time decision making
- → Requires expert users



- → Run times >1,000x faster than physics-based simulations
- → High accuracy, sparse data
  - → Train with 1-10% data required by traditional data approaches
- → Scientifically rigorous
  - → Accurately capture highly non-linear and dynamic behavior
  - → Explainable models build user trust
- → Extensible to very large systems (systems of systems)
- → Fast, repeatable model creation & retraining

- → Large data requirements
- → Long, bespoke model build & retraining times
- → Difficulty capturing non-linear, dynamic behavior
- → Prone to results inconsistency
- → Lack of explainability limits user trust

Physics-Informed AI Model Generation and Deployment

Geminus Model Recipe

Simulation Data

Source agnostic

Process Data

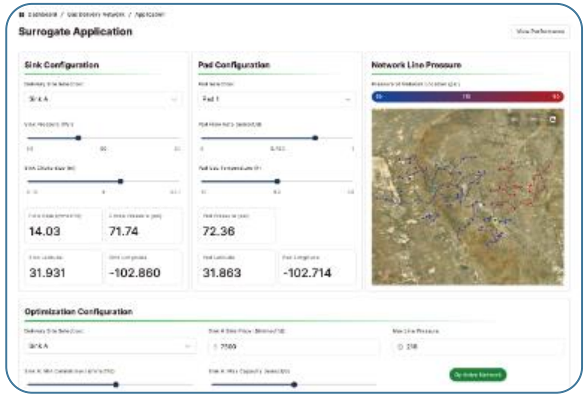
Geminus

Model training, tuning & validation

Inferencing & model-based optimisation

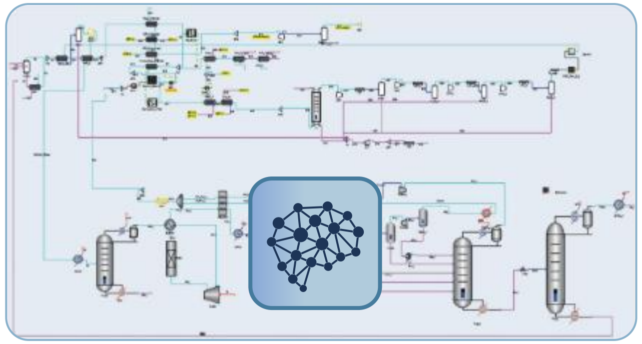
Cloud and Enterprise On-Prem Hosting Options

Real-time Advisors



Advanced Process Control

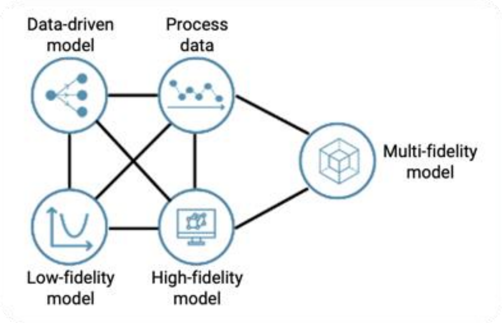
Simulation Acceleration



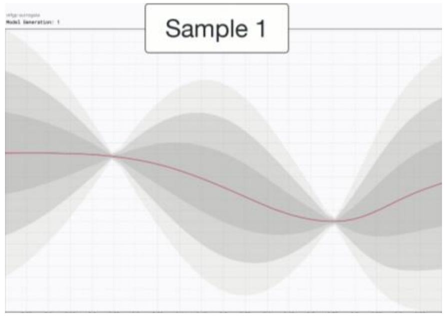
Geminus' Proprietary Technology Delivers Decision Intelligence

Efficient Training, Sparse Data, High Confidence

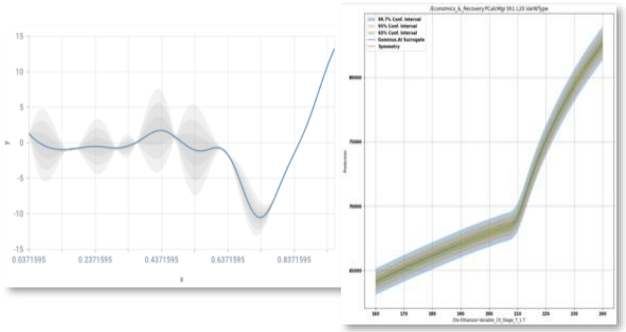
Multi-Fidelity



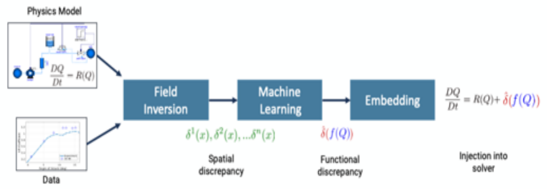
Adaptive



Probabilistic



Embedded Learning



FAST

Recommendations at the speed of real-time operations and critical decision time scales

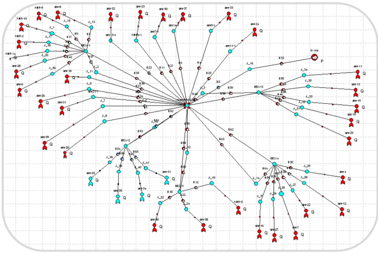
ROBUST

Credible, high-quality, defensible recommendations that account for system uncertainty

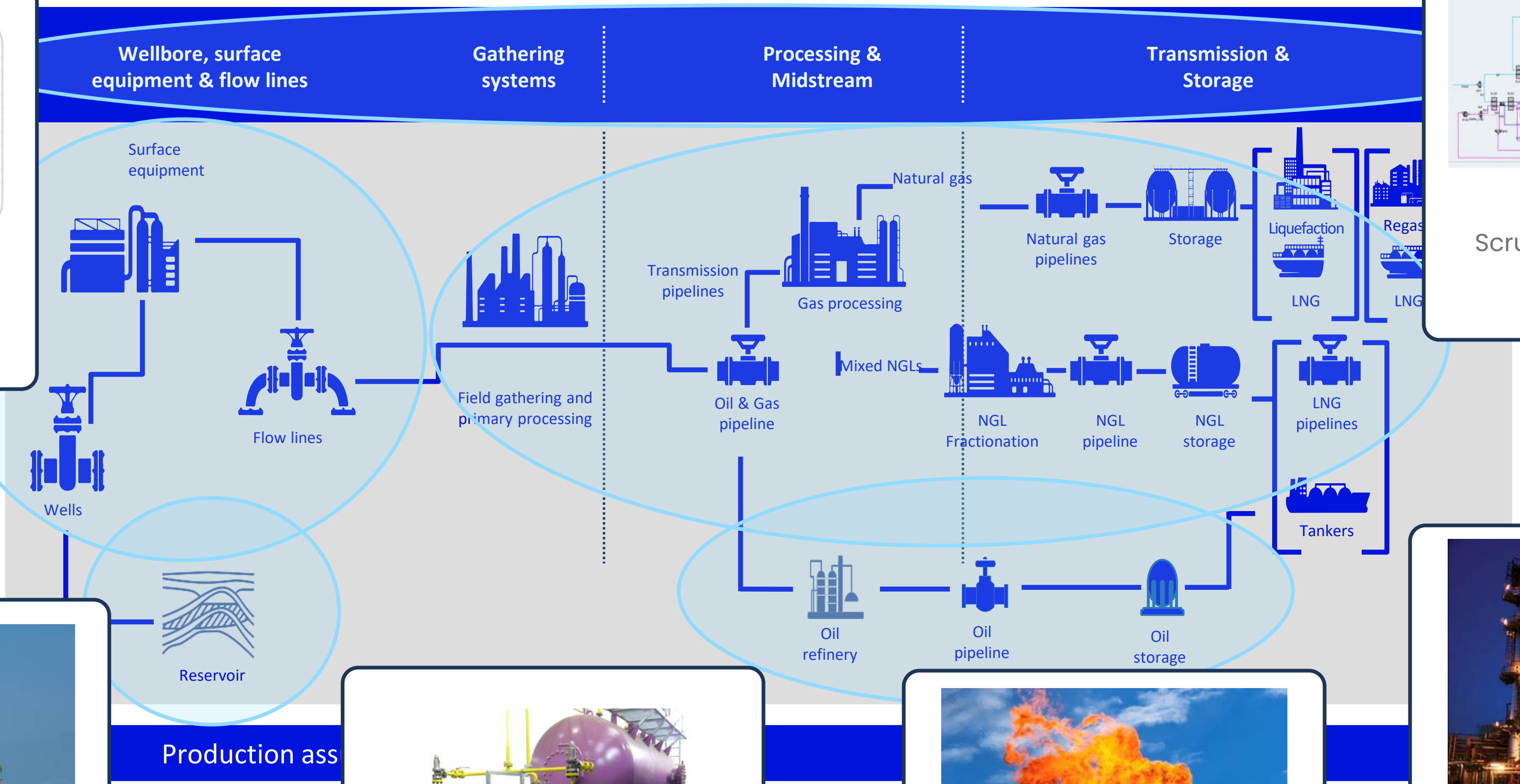
SCALABLE

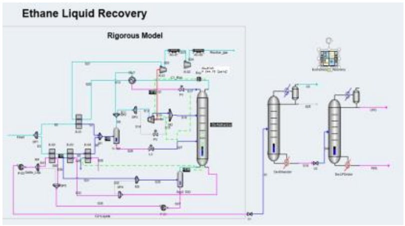
Ultra-fast model creation and deployment, capable of operating across multiple systems at enterprise level

Geminus Use Cases:
Across the O&G Value Chain



Well ESP and
Well Network Optimisation





Combined Amine
Scrubbing & NGL Recovery
Profit Optimisation

Offshore Gas Lift
Distribution and
Slugging Mitigation

Gas Hydrate Inhibitor
Injection Optimisation

Gas Gathering
and Flaring Mitigation

Real-time Optimisation
for Refinery Units

Challenges Optimising Gas-Producing Well Networks

High complexity exceeds abilities of human operators

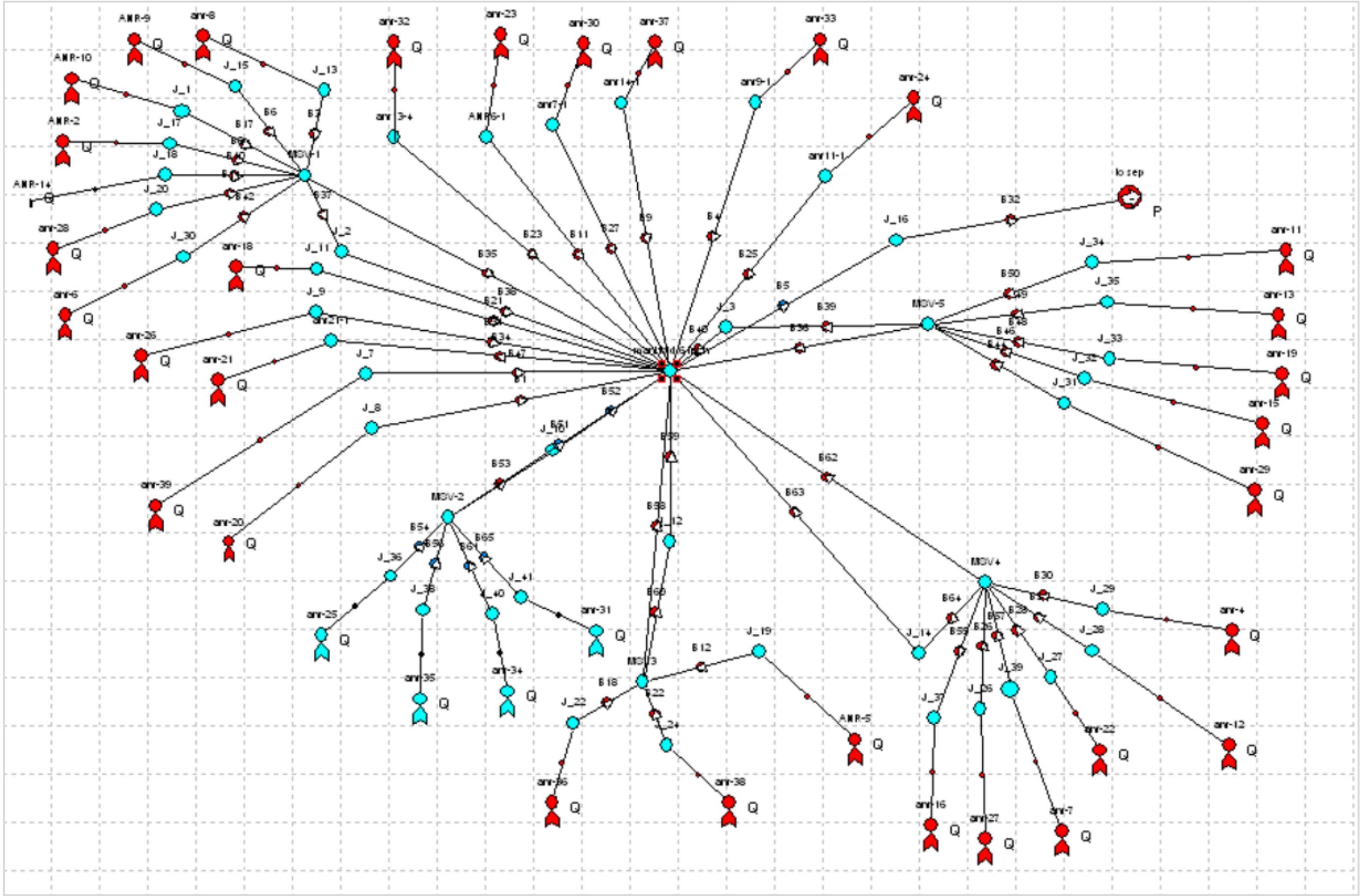
Tens to hundreds of thousands of parameter combinations must be evaluated

Simulation-based optimisation is intractable

Due to computational expense & short time horizons for decision making

Models are difficult to scale and keep evergreen

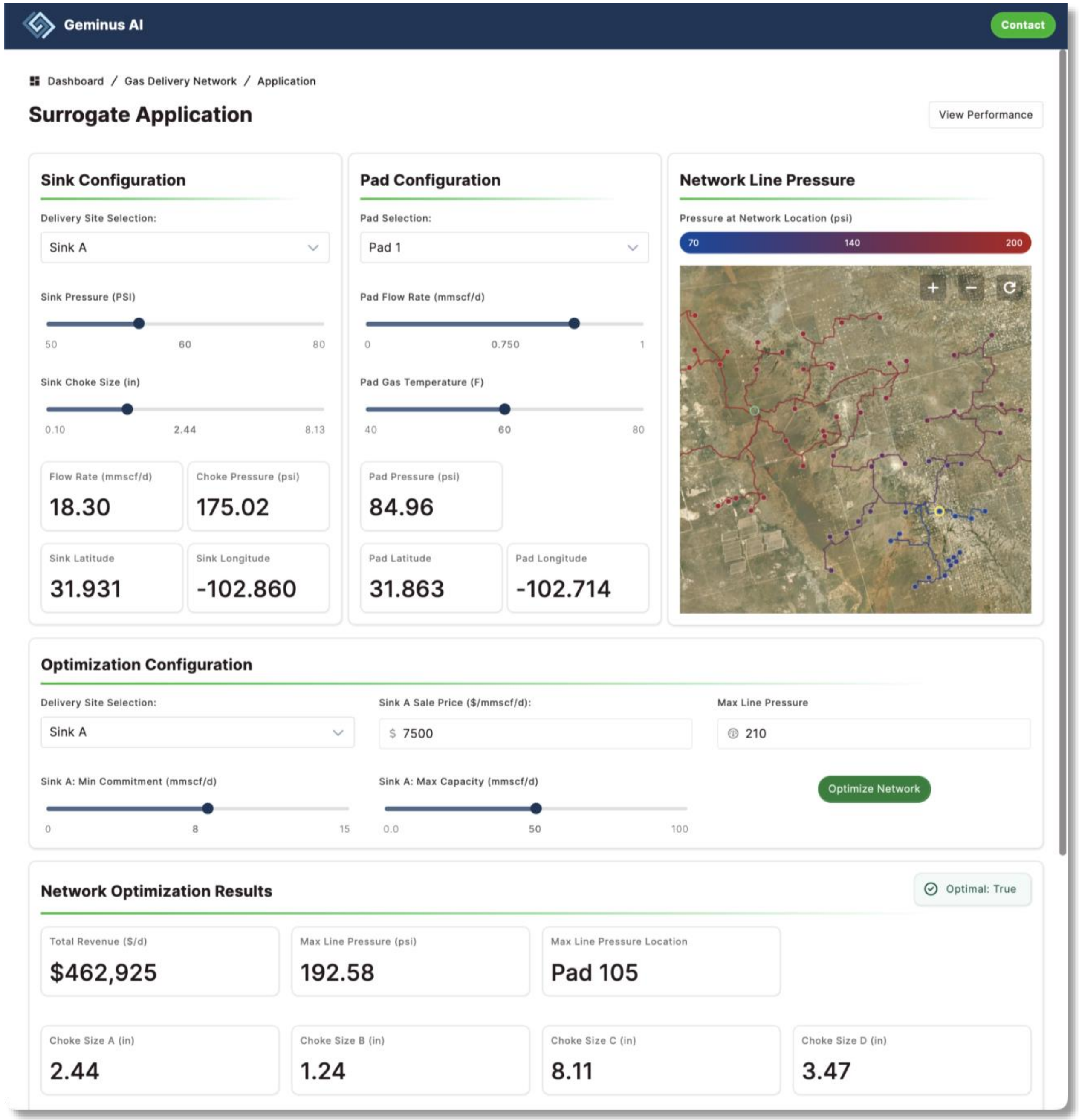
Wells and reservoirs are continually changing



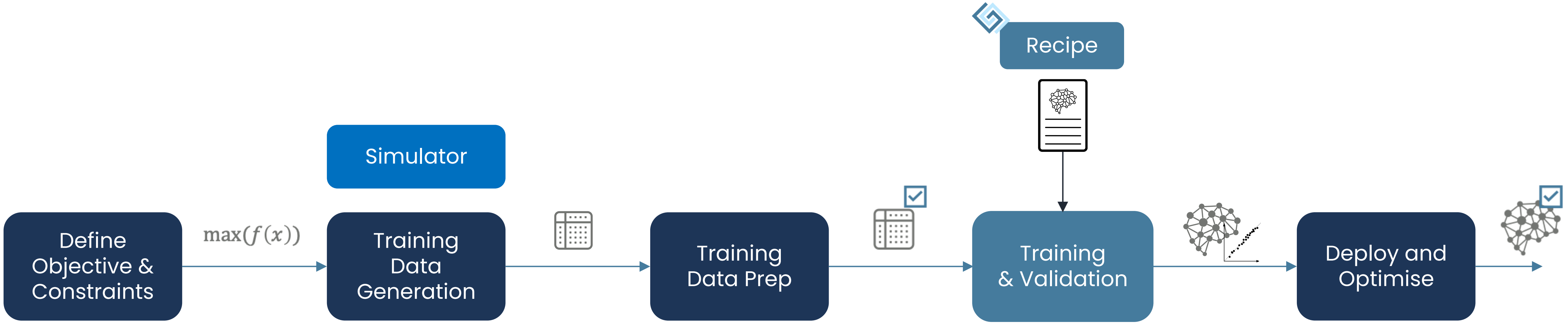
Geminus-Powered Advisor for Well Network Operations

- Intelligent advisor application allows process engineers to evaluate “what-if” scenarios and optimise network productivity in near real-time.

- Under the hood:
  A high-accuracy and fast-executing physics-informed AI surrogate model, derived from detailed Pipesim network model

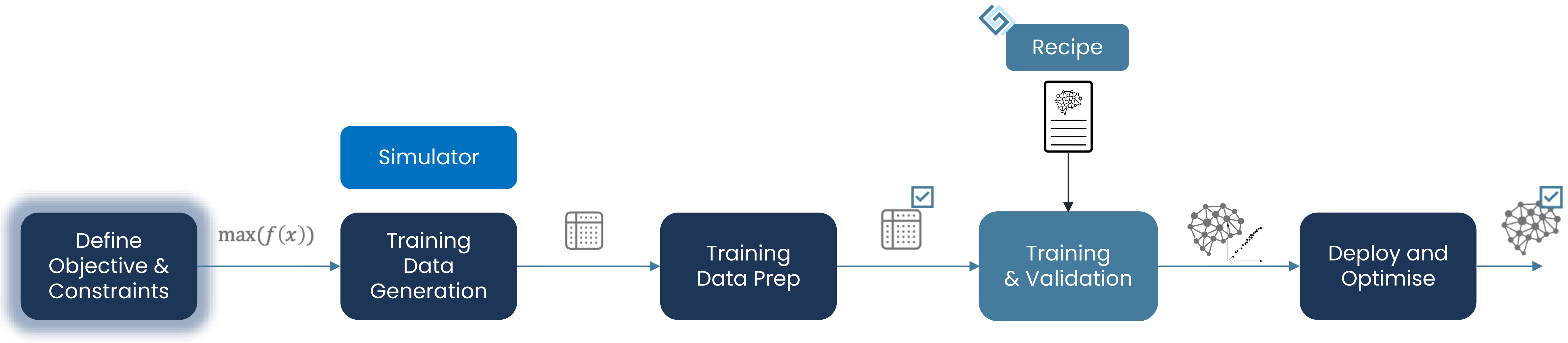


End-to-end Workflow for Well Network Optimisation



Sample › Train › Validate › Deploy › Optimise

End-to-end Workflow for Well Network Optimisation

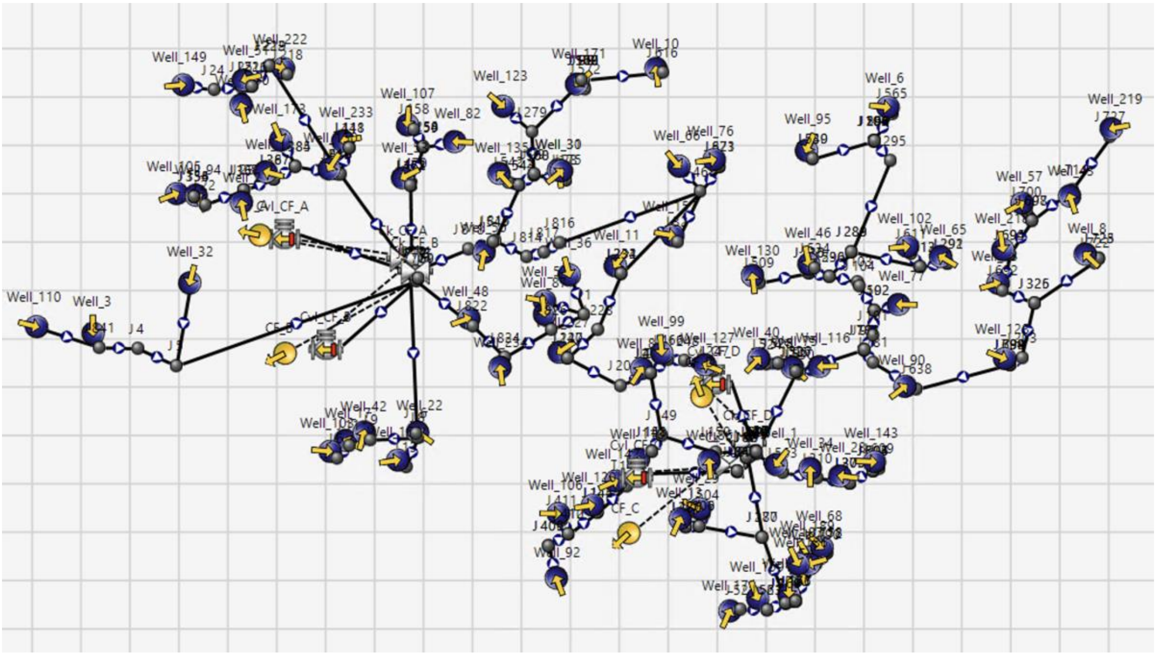


Simulator
SLB PIPESIM

Network Summary
80 natural gas pads (gas flowrate and temperature BC at each)
4 sinks/compressor stations
4 chokes (1 per sink)

Operational Constraints & Pricing
Minimum gas flowrate commitment per delivery point/sink
Maximum gas flow rate capacity per delivery point/sink
Maximum pad/flowline pressure to prevent flaring/damage
Varying purchase price per unit volume at each per delivery point

Objective
Given pad flowrates and selling price per delivery point:
maximize revenue
meet sink rate upper/lower constraints
meet pressure constraints



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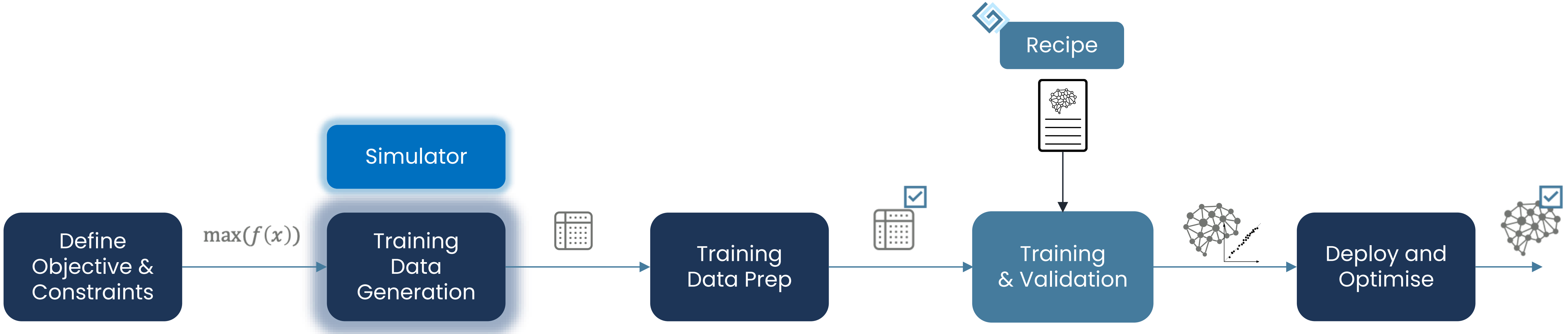
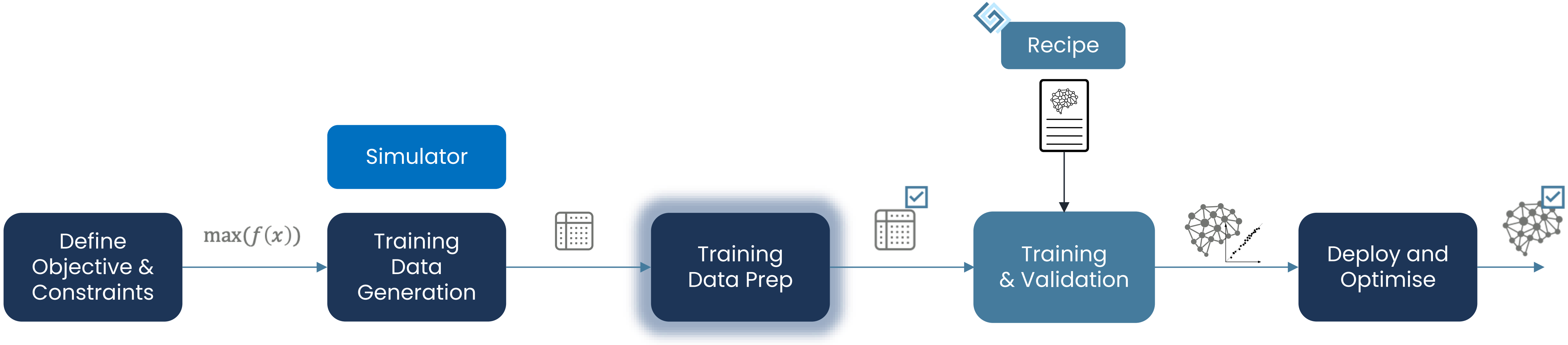


1. Construct DOE (Latin Hypercube, N=17,000)
    - 168 independent variables
        - Gas Flowrate and temperature per pad
        - Choke size and sink pressure per sink
    - 185 dependent variables
        - Pressure at each pad and max pressure of each flowline
        - Flowrate at each sink
2. Execute parallel simulations on shared memory multicore compute hardware
    - Full training dataset constructed in ~24 hours
    - 60 seconds / simulation computed in parallel across 12 cores
    - Readily supported by Pipesim Python Toolkit

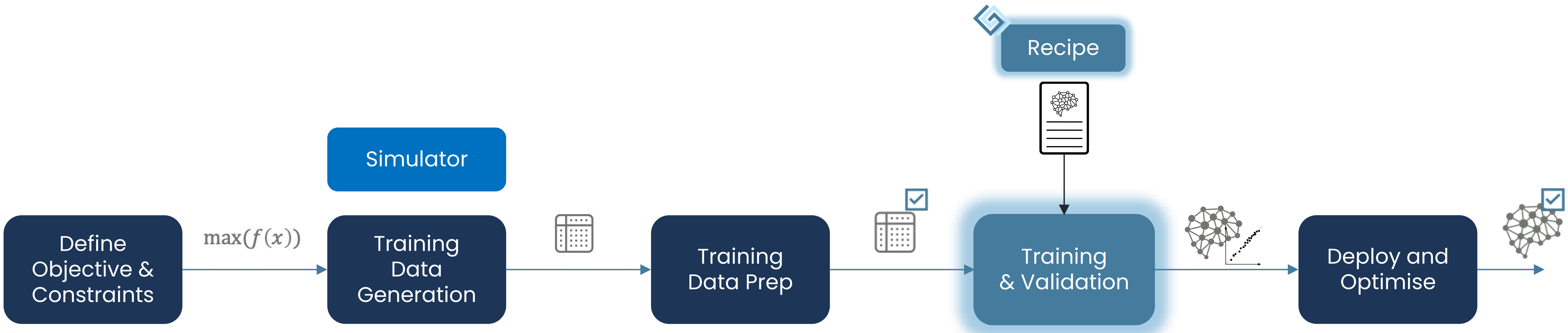
End-to-end Workflow for Well Network Optimisation



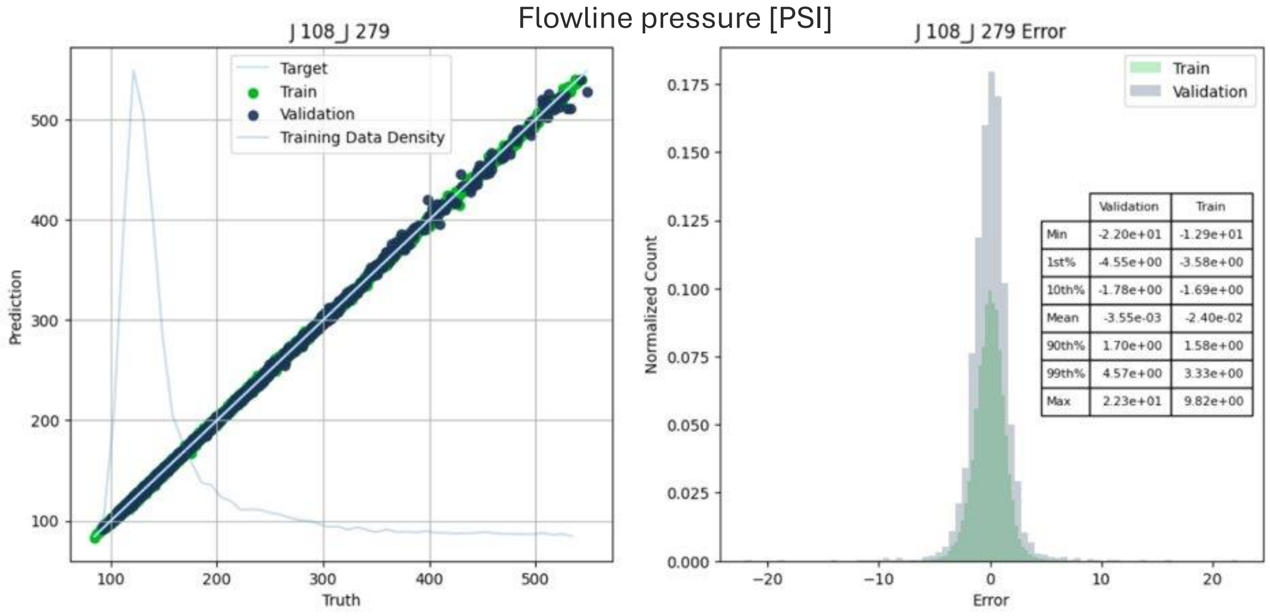
Data pipeline to filter and clean data for:
- Outliers
- Simulator errors (e.g. non-convergence)
- etc.

Additional processing to ensure consistent units, column names, etc.

End-to-end Workflow for Well Network Optimisation

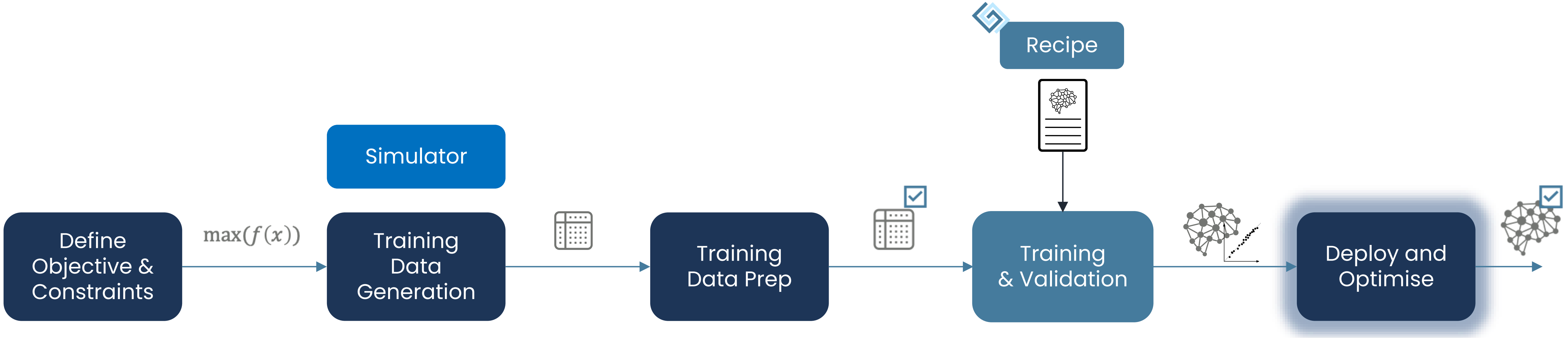


1. **Load Geminus recipe for well network model**
   - Application-specific & repeatable training and validation pipeline
   - Optimized deep learning architecture, training, and data pre-processing operations
   - Differentiable by design
2. **Execute ML training**
   - GPU accelerated (also compatible w/ CPU)
   - ~25 minutes clock time
3. **Render comprehensive validation reporting across training and withheld validation datasets**
   - Per-output R^2
   - Accuracy plots
   - Error distributions



	Validation	Train
Min	-2.20e+01	-1.29e+01
1st%	-4.55e+00	-3.58e+00
10th%	-1.78e+00	-1.69e+00
Mean	-3.55e-03	-2.40e-02
90th%	1.70e+00	1.58e+00
99th%	4.57e+00	3.33e+00
Max	2.23e+01	9.82e+00

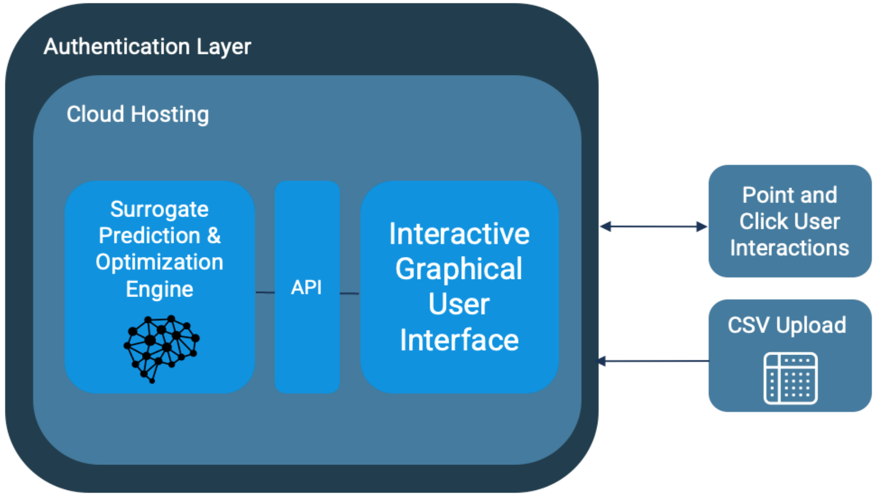
End-to-end Workflow for Well Network Optimisation

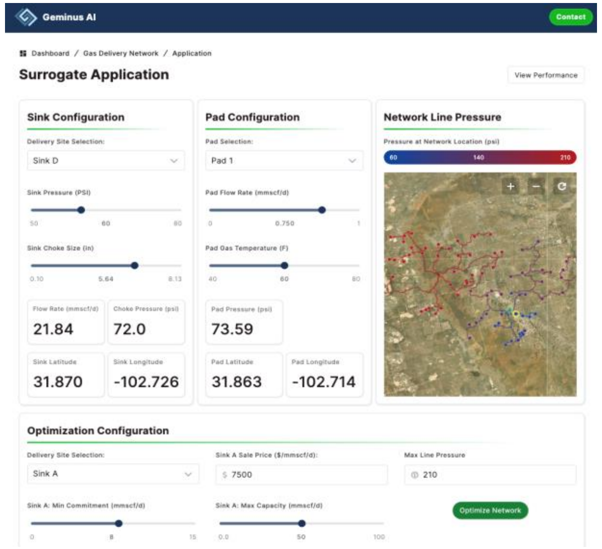


Surrogate model integrated into a robust non-linear constrained optimization framework

Model query time: < 1 ms
Optimisation time: < 3 sec
1000's of rapid forward solves

Export to portable runtime formats including proprietary Geminus Surrogate Runtime (GSR) and ONNX





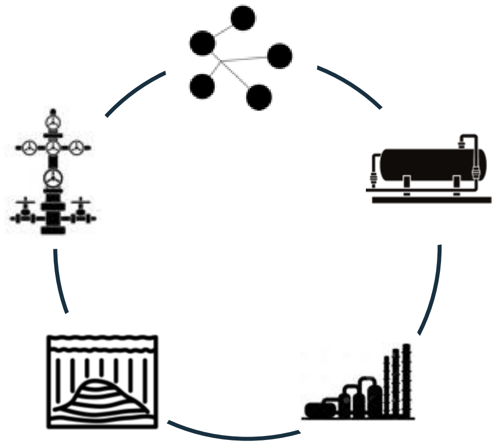
Improving Productivity of Large Well Networks

- **Optimised recommendations based on trusted physics**
  Maximized productivity unlocks millions in incremental profits. Multiplying return of customer’s investment in Pipesim

- **Decision-making to meet critical time scales**
  Instant model query times enable large-scale optimisation in seconds

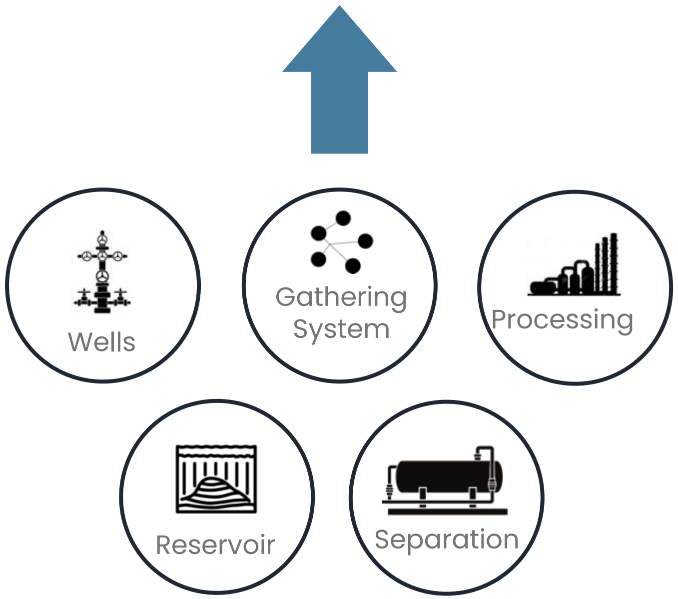
- **Scalable AI workflow**
  Data-efficient, automated training processes handle network topologies with hundreds of wells

Pathway to Systems: Combining Physics-informed AI with Model-based Systems Approaches to Tackle Complexity at Scale



Enables integrated systems-of-models

- Preserves interactions within and between different domains
- Enables real-time optimisation across multiple domains, multiple simulators, and multiple objectives
- Provides path to efficiently scaling high complexity



Physics-informed AI surrogates liberate & democratize domain simulations

Q&A

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