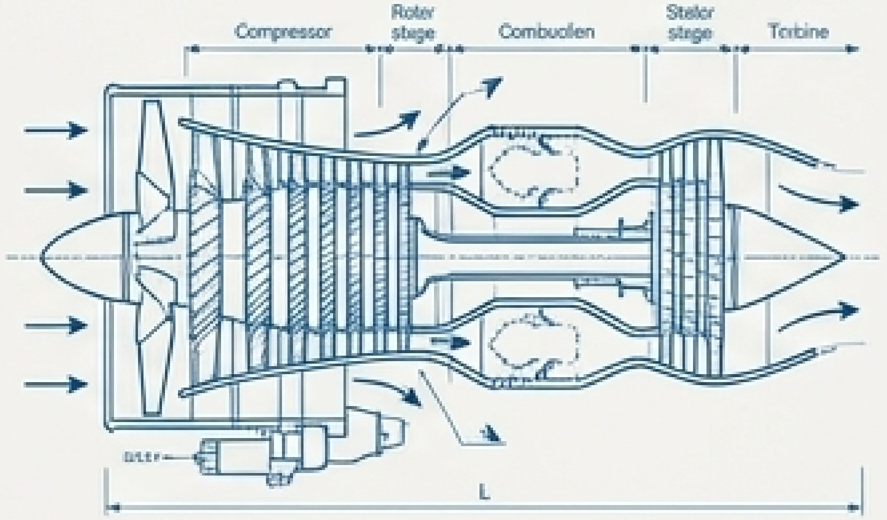
The Strategic Imperative for Next-Generation Compressors

Multi-stage turbo compressors are a cornerstone technology for critical global transitions. Their performance directly dictates the viability of future systems in three key sectors:

The Hydrogen Economy

Efficient compression is fundamental for the storage and transportation of hydrogen, making it the linchpin for a scalable clean energy infrastructure.



Advanced Aviation

Next-generation propulsion systems for commercial and military applications demand higher pressure ratios and efficiencies in increasingly compact designs.

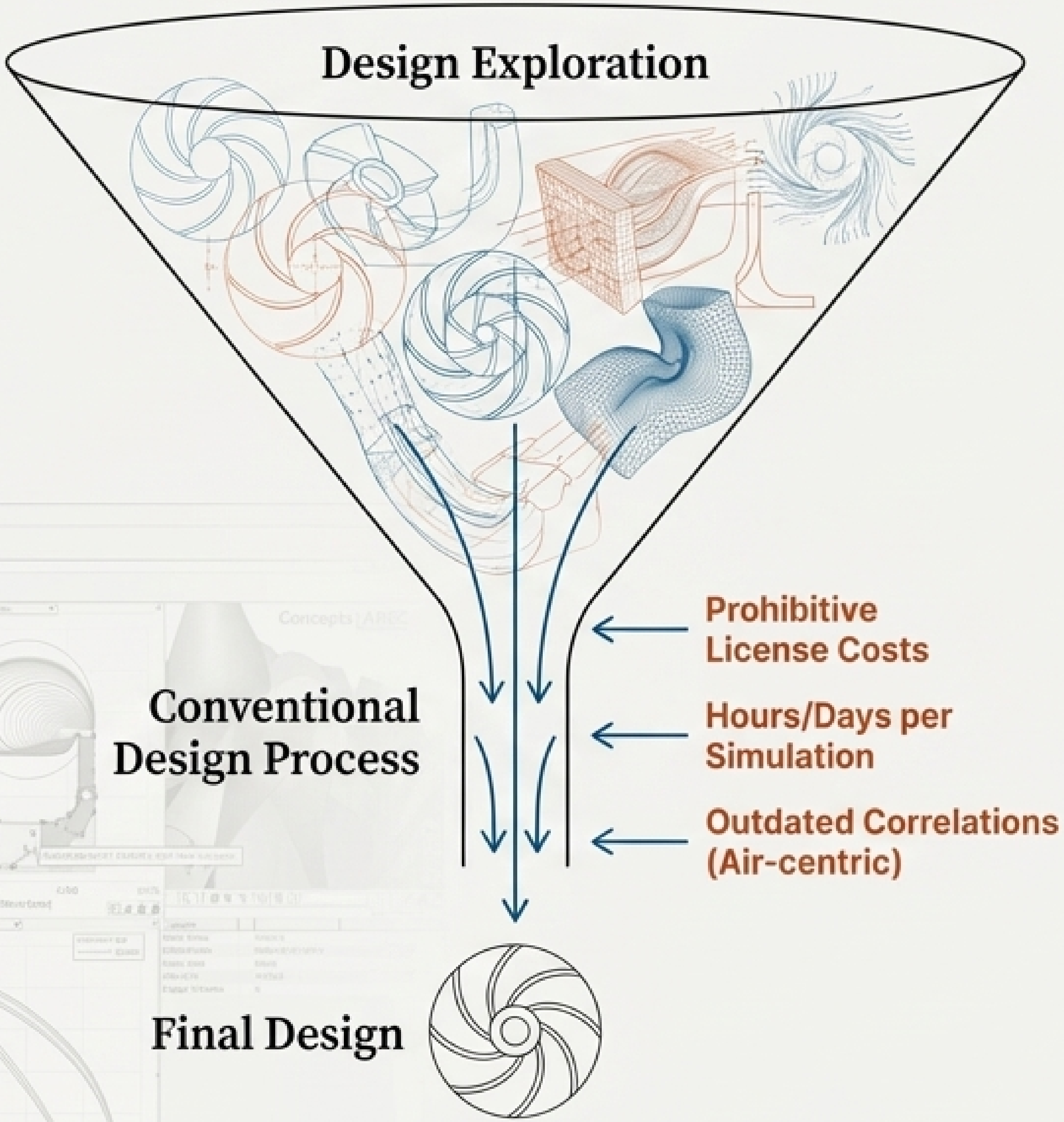
Defense Systems

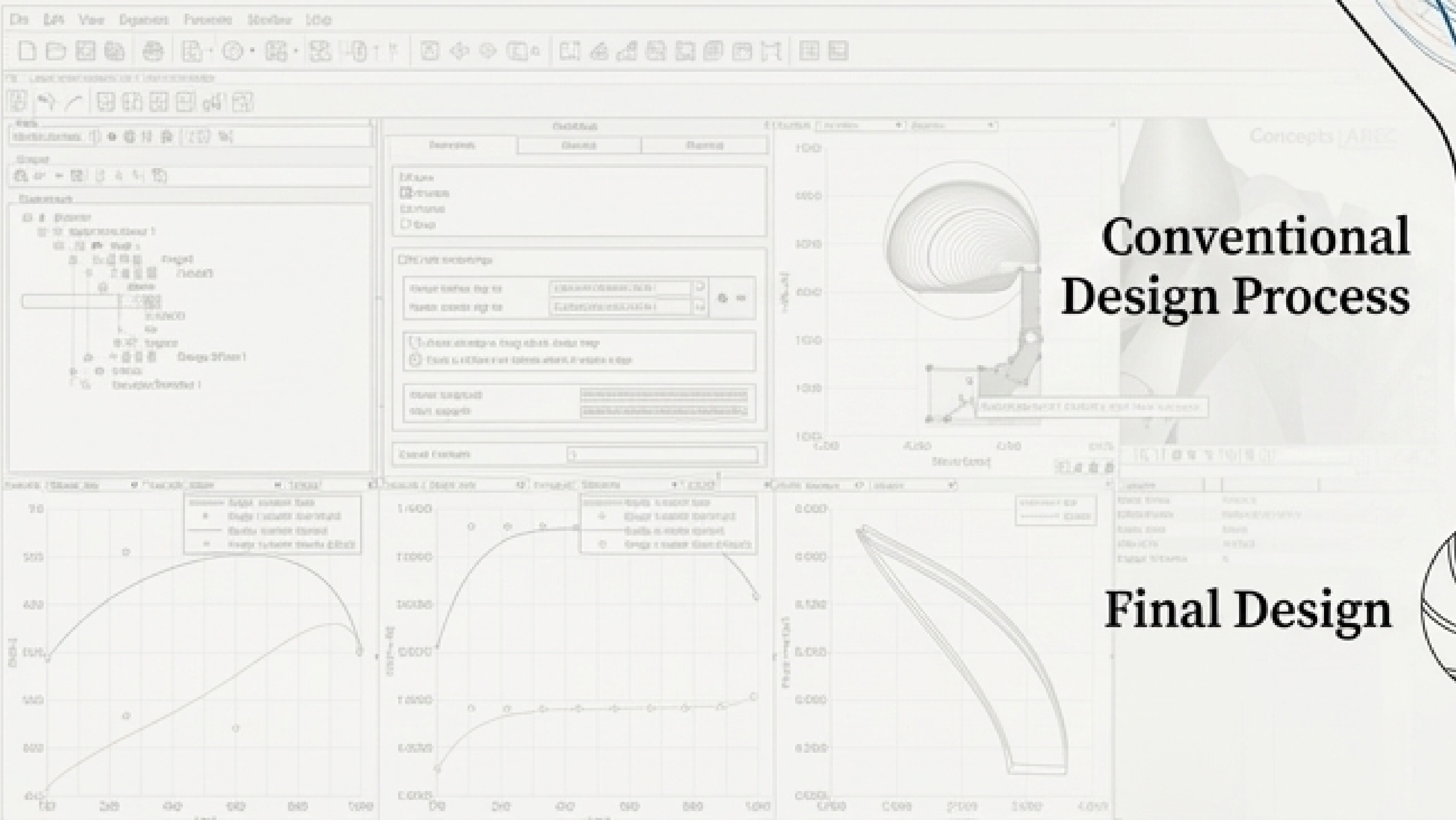
Strategic applications, from unmanned aerial vehicles to naval systems, rely on bespoke, high-performance turbomachinery that operates reliably under extreme conditions.

Achieving a step-change in compressor efficiency is not an incremental improvement; it is a strategic necessity.

The Design Bottleneck: Why Conventional Methods Are Failing

The tools used to design next-generation compressors are stuck in the past, creating a fundamental barrier to innovation.



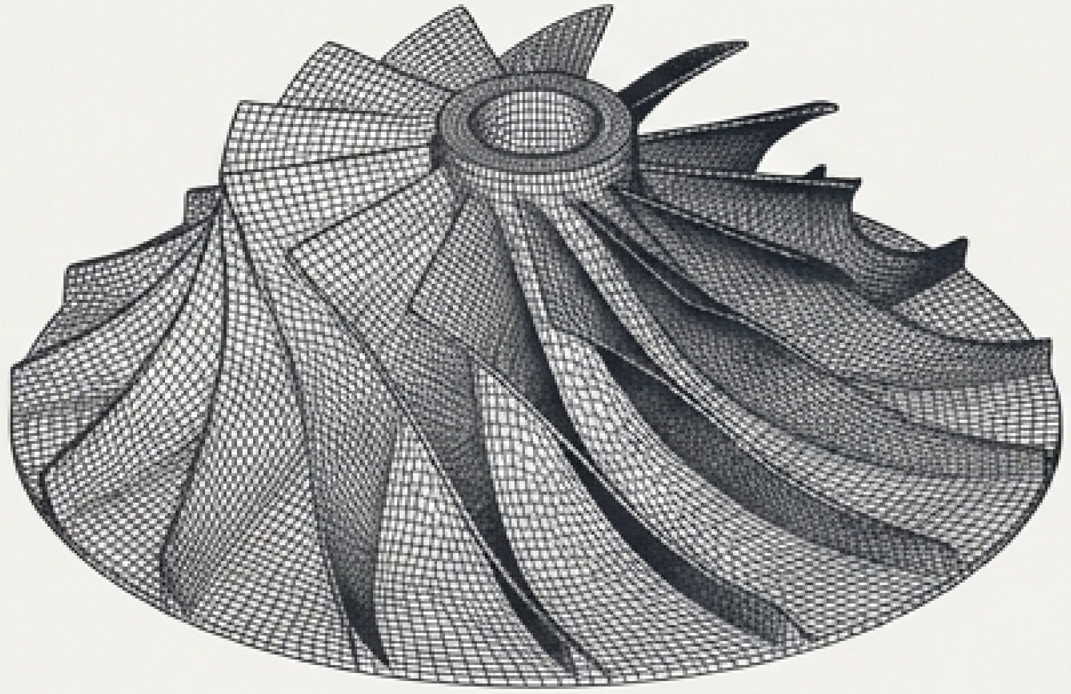


Reliance on Outdated Correlations:
Existing design software is built on narrowly scoped empirical correlations derived from limited experimental data (primarily for air). These models fail to generalize to new fluids with unique properties, such as hydrogen.

Prohibitive Costs and Cycle Times:
Commercial turbomachinery design suites carry massive license fees. Worse, their reliance on iterative, full 3D CFD analysis for optimization leads to design cycles measured in hours or days for a single design point.

Lack of Modern AI Integration:
Legacy platforms are not built to leverage modern AI. They lack the architecture to integrate deep learning surrogates, generative design, or physics-informed models, forcing engineers into a slow, manual, and intuition-driven process.

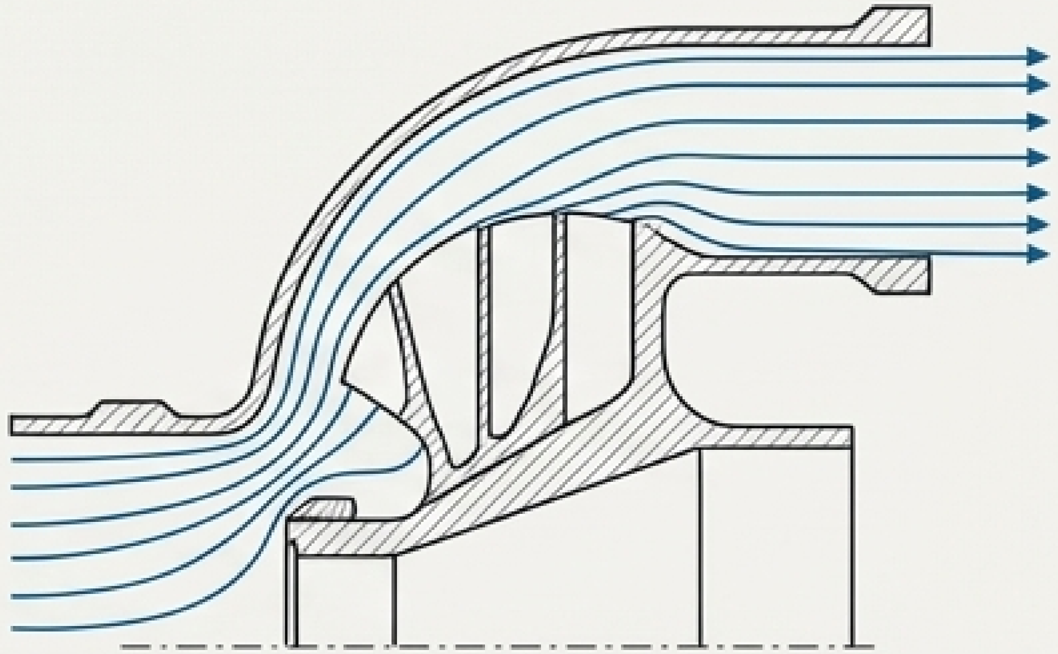
The Core Solution: An Intelligent Axisymmetric Throughflow Solver



Conventional 3D CFD

From Hours/Days

To Milliseconds



Intelligent 2D Throughflow

Our platform is built on a robust and exceptionally fast physics-based solver. We have adapted and commercialized a proprietary axisymmetric (throughflow) solver based on the Streamline Curvature Method (SLC).

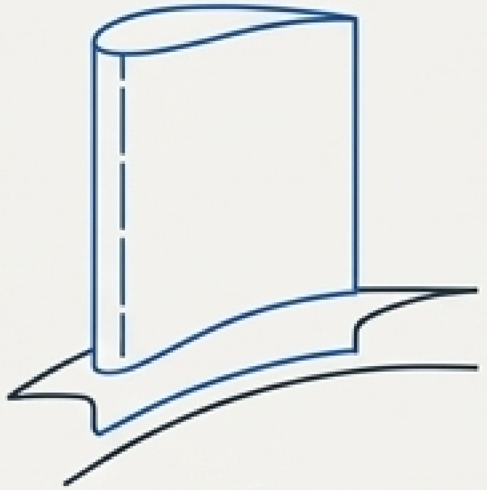
Core Function: The solver provides a rapid, high-fidelity 2D analysis of the aerodynamic and thermodynamic performance of multi-stage centrifugal compressors, with or without intercooling.

The Speed Revolution: By intelligently simplifying the 3D problem into a 2D axisymmetric model, the solver reduces the computational time for a full performance analysis from hours or days to **milliseconds.**

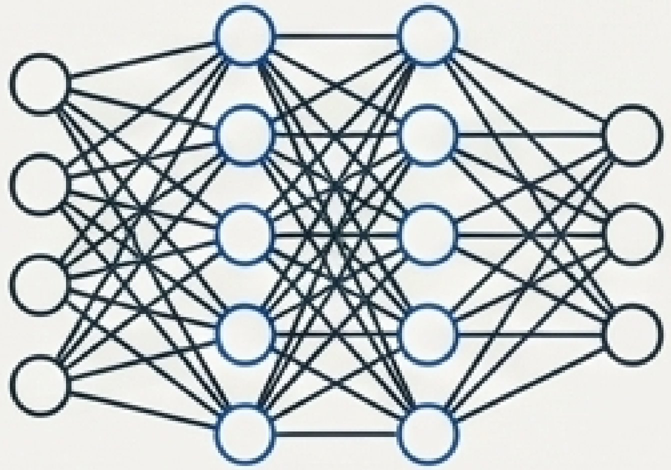
This isn't just an accelerator; it's the engine that enables real-time optimization and the effective application of AI.

AI Layer 1: Surrogate Modeling for Instant Performance Prediction

From Geometry to Performance in Milliseconds



Input Geometric Parameters
IBM Plex Mono



Trained Surrogate Model
(ANN/CNN)

Isentropic Efficiency (η): 0.915

Total Pressure Ratio (TPR): 4.52

Entropy Generation (Δs): 0.082 kJ/kg·K

Instant Performance Metrics

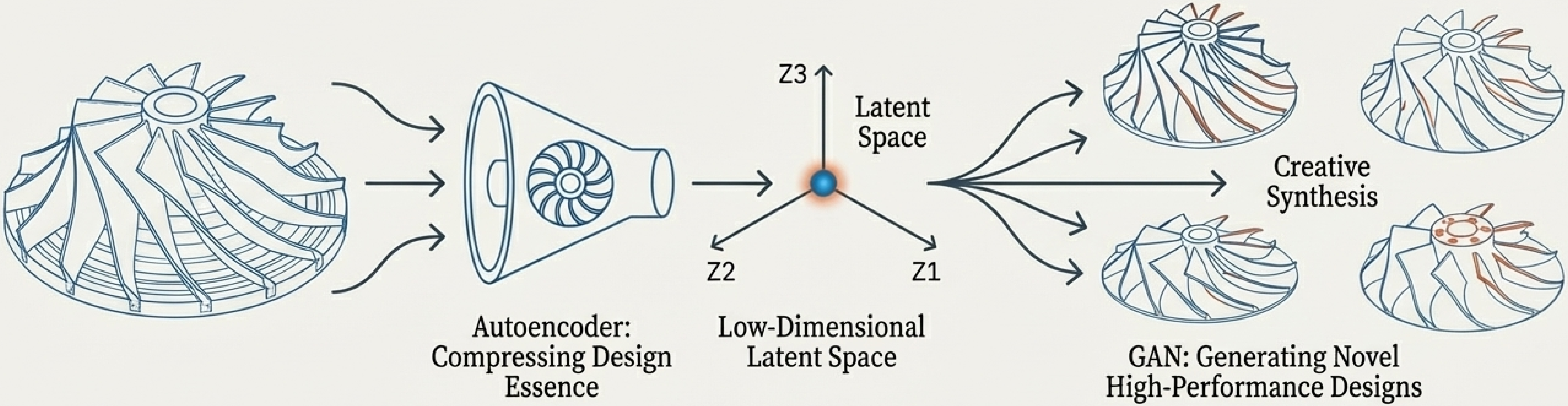
We leverage deep learning to create surrogate models that act as 'CFD shortcuts,' bypassing the need for time-consuming simulations during the optimization loop.

Methodology: We use Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) trained on vast datasets generated from thousands of CFD simulations and our throughflow solver.

Function: Once trained, these neural networks can instantly predict critical aerodynamic performance metrics—such as efficiency (η), pressure ratios (TPR), and entropy generation—directly from input geometric parameters.

This allows our optimization algorithms to evaluate thousands of design candidates per second, a task that is computationally impossible with traditional methods.

AI Layer 2: Generative Design for Creative Synthesis

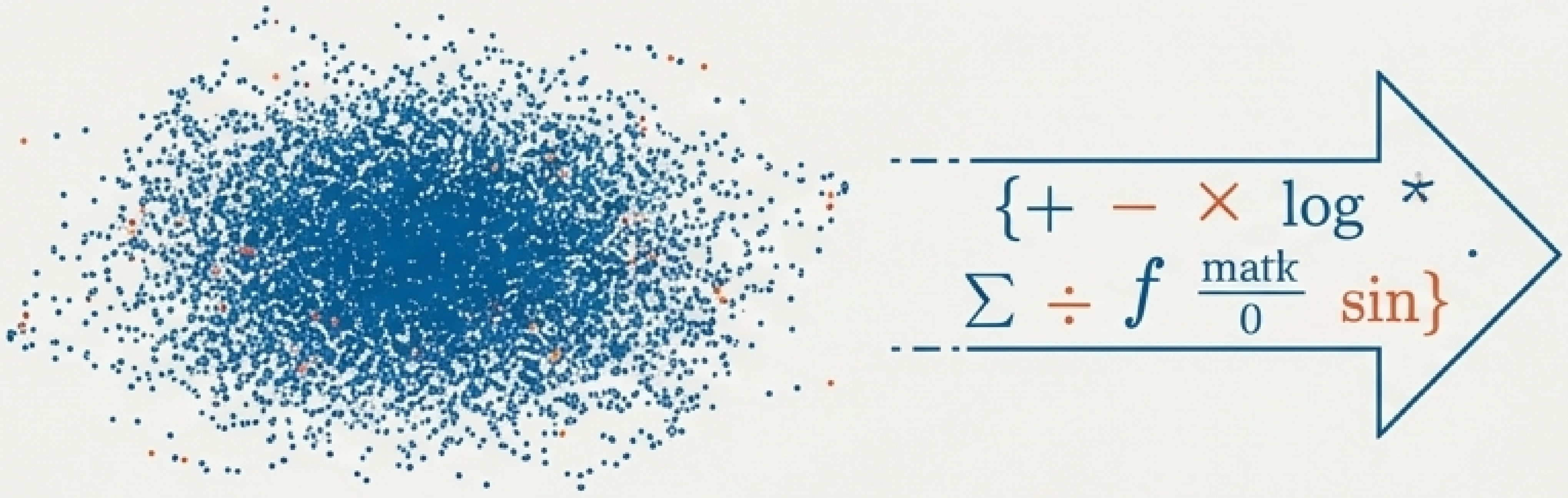


Our platform goes beyond prediction and uses generative AI to creatively synthesize new, high-performance compressor geometries.

- **Dimension Reduction with Autoencoders (AE/VAE):** We first use autoencoders to map complex, high-dimensional blade geometries into a simple, low-dimensional 'latent space.' This compresses the essence of a design into a small set of vectors, making the design space vastly more efficient to search.
- **Creative Synthesis with GANs:** Generative Adversarial Networks (GANs) are then trained on this latent space. They learn the underlying principles of high-performance designs and can generate unique new blade forms that transcend traditional design templates, suggesting novel solutions that are both high-performing and manufacturable.

AI Layer 3: Symbolic Regression for Interpretable Physics

From Chaos to Clarity



$$\Delta s = C_1 \cdot f(M, \mathrm{Re}) \cdot (1 - \sigma)$$

Raw CFD Data | **Symbolic Regression** | **Interpretable Physical Law**

Unlike opaque 'black-box' models, our system extracts new, interpretable physical laws directly from CFD data using Symbolic Regression (SR).

Discovering New Correlations: SR analyzes vast datasets to discover the underlying mathematical equations governing performance. It has successfully derived novel, closed-form empirical correlations for complex phenomena like entropy generation and slip factors.

An 'Intelligent Guide': These discovered formulas are not just for analysis; they are embedded directly back into our throughflow solver. This creates a powerful feedback loop, where the solver is guided by AI-discovered physics, improving its accuracy and generalization, especially for new fluids like hydrogen.

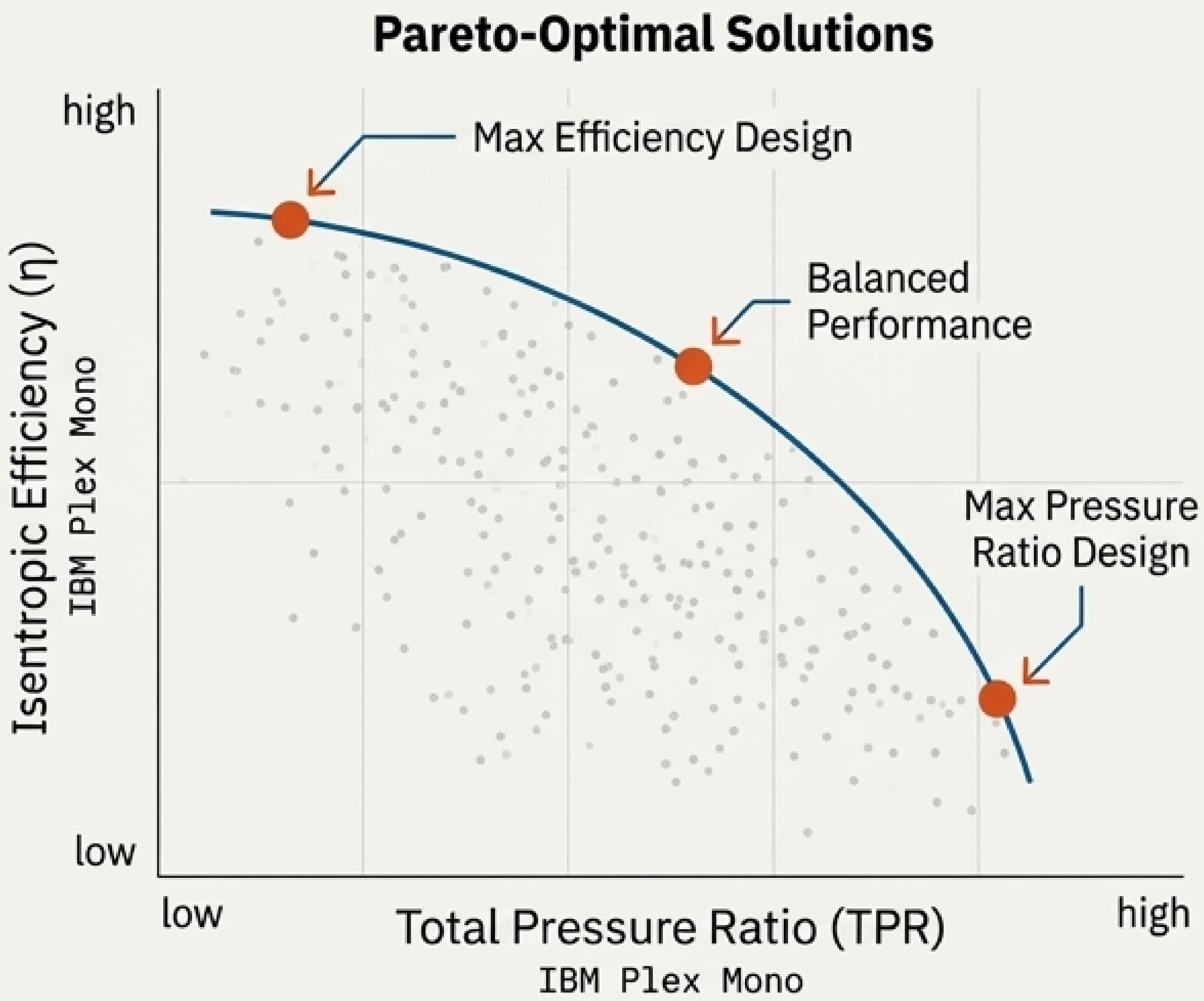
The Optimization Engine: Navigating Performance Trade-offs

At the heart of the platform are powerful multi-objective optimization engines that intelligently search the design space for superior solutions.

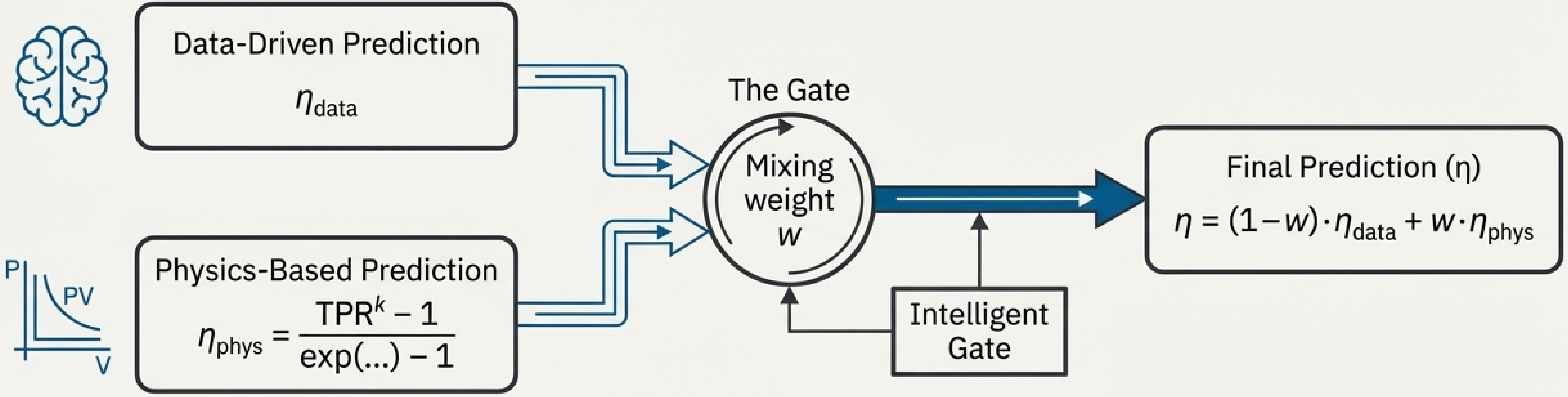
Core Algorithms: We utilize a hybrid approach combining:

- **Genetic Algorithms (NSGA-II):** For robustly exploring the global design space and identifying a diverse set of high-performing candidates.
- **Reinforcement Learning (PPO/DQN):** For fine-tuning designs in a continuous parameter space, allowing an ‘agent’ to learn the optimal policy for step-by-step design improvement.

Pareto-Optimal Solutions: The system automatically identifies the Pareto front, presenting the user with a set of optimal solutions that balance competing objectives. This allows engineers to make informed decisions based on the explicit trade-offs between, for example, maximizing aerodynamic efficiency versus achieving a target pressure ratio or maximizing operating range.



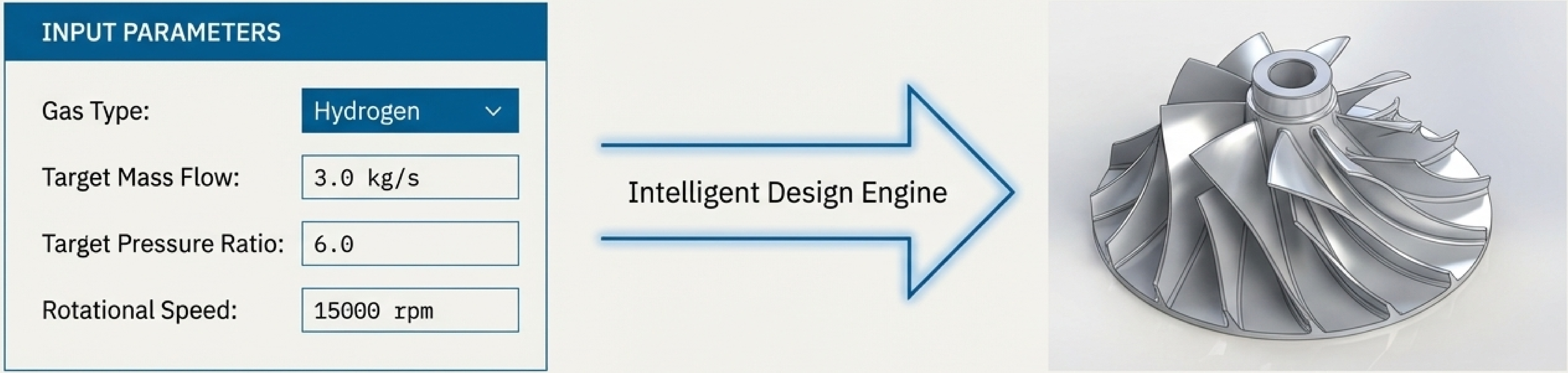
The Guardian: Physics-Guided Hybrid Modeling (v35)



To ensure all AI-generated outputs are physically realistic and thermodynamically consistent, we employ a physics-guided hybrid modeling framework. This is the key to our model's ability to generalize reliably to unseen data.

- **Physics Core** (`dsfactor`)**:** The model is anchored by a core thermodynamic variable, the `dsfactor`, which is derived from first principles. This variable relates efficiency (η), pressure ratio (TPR), and entropy.
- **Controlled Blending:** We use two parallel predictions for efficiency: $\eta_{\mathtt{data}}$ from our surrogate models and $\eta_{\mathtt{phys}}$ derived by inverting the `dsfactor` equation.
- An intelligent **"Gate" mechanism** then creates a controlled mixture of these two predictions. This prevents non-physical outputs and dramatically improves prediction accuracy on external validation data by grounding the AI in thermodynamic laws.

Seamless User Experience: From Input Parameters to 3D CAD



- The entire intelligent design platform is accessed through a clean, interactive interface that empowers engineers without requiring deep expertise in AI or CFD.

- **Simple Inputs, Powerful Outputs:** The user enters a few high-level system parameters, and the software's AI and optimization engines work in the background to generate a Pareto-optimal set of designs.
- **Automated Design & Generation:** With a single click, the integrated 3D CAD module instantly generates a manufacturing-ready geometry (e.g., hub, shroud, and blade profiles) for the selected design.

- This transforms the design workflow, enabling rapid exploration and instant manufacturability.

Unmistakable Proof: Industrial-Grade Accuracy and Validation

The performance of our v35 physics-guided model has been rigorously validated against external, unseen data sets. The results demonstrate the platform's industrial reliability.

Key Accuracy Metrics (External Validation):

- Efficiency (ETA) Prediction: $R^2 \approx$ **0.916**
- Total Pressure Ratio (TPR) Prediction: $R^2 \approx$ **0.997**
- Entropy (ENT) Prediction: $R^2 \approx$ **0.966**

These metrics, particularly the high R-squared value for the complex ETA prediction, confirm that our physics-guided approach successfully generalizes beyond its training data and produces results with the accuracy required for real-world engineering applications.