

CASE STUDY

Orbital Process Simulation Identifies **\$119K** Savings in Annual Hydrotreater Operations

Industry - Oil and Gas



Goals

Hydrotreating is a widely used chemical process for removing sulfur from natural gas and refined petroleum products. This study, using a simulation of the Reliance Jamnagar Refinery, aims to:

- Optimise the process using the Orbital foundation model within the DWSIM simulator, comparing its performance against best-in-class alternatives, including Linear Programming and Ensemble methods.
- Leverage Orbital's recommendation engine to optimise for reduced total input energy while maintaining consistent product quality specifications.

Challenges

- **Complexity:** Modeling the intricacies of the refinery process presents significant challenges due to its inherent complexity.
- **Physical Constraints and Interpretability:** Refinery processes are governed by physical and chemical laws. Deep neural networks are often black-box models, making it difficult to incorporate domain knowledge or ensure they obey these constraints.
- **Generalization:** Refinery processes may face unseen conditions (e.g., changes in feedstock or equipment). Neural networks can struggle to generalize to unseen or rare scenarios.

Results

Energy Consumption

16.56% reduction in energy intensity was achieved, representing a significant efficiency improvement.

Annual Cost Savings

Energy optimisation is projected to yield annual cost savings of **\$118,634.70**.

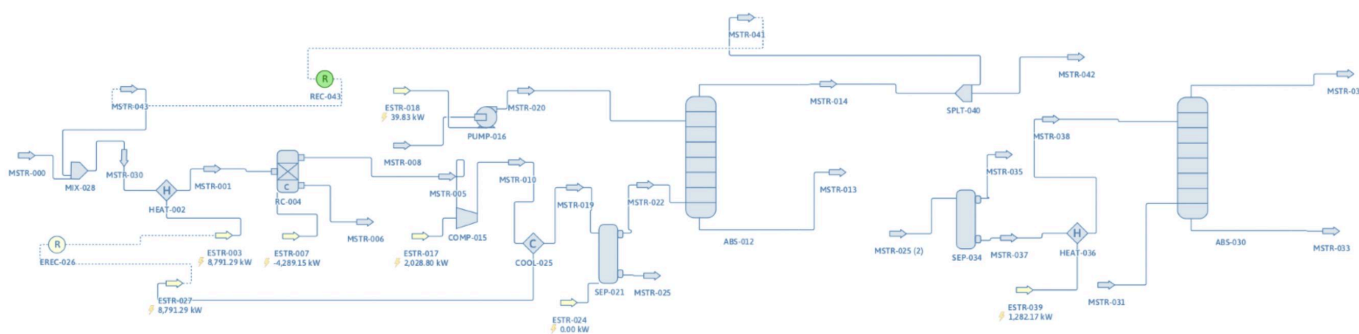
Carbon Emissions

Based on the energy optimisation, an estimated reduction of **967.95** metric tonnes of CO₂ emissions annually.



Process Background

The high sulphur content in crude oil presents major challenges in refining, particularly in processes like fluidised catalytic cracking and platforming, where it can poison catalysts and hinder efficiency. Furthermore, stringent regulations on SO_x emissions require the effective removal of sulphur from fuels to meet environmental standards and improve product quality.



Technical Architecture

Orbital is an on-prem foundation model that can operate on small edge devices. It is designed to learn generalisable representations from all refinery data, which are then repurposed for recommendations and process optimisation. Orbital was deployed within the DWSIM Chemical Process Simulator, enabling the modelling and optimisation of the process to reduce energy intensity while ensuring that all purity standards were met.

Steps necessary to run the experiment were as follows

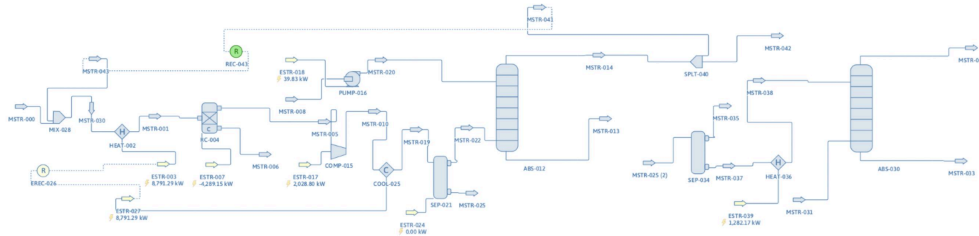
1 Data Collection

Process data was generated by running the simulator with varying input feeds at set intervals, capturing data for both training and testing phases.

2 Model Training

Orbital's patented learning algorithms were used to train the foundation model, along with the prediction and recommendation submodels. The goal was to predict product purity and recommend unit variables to reduce energy consumption. The condition was set to achieve a product purity deviation of less than 0.005 MSE from the actual value, while lowering energy usage for each simulation run.

Process flow simulation (Data Generation)



Feed Composition (Mole Fractions)

Hydrogen Sulfide	0.0754572
Methylethanolamine	0
Methyl DiEthanolAmine	0.923249
Water	0

Unit process parameters

	Temperature (C)	Pressure (bar)
MSTR-000	25	1.01325
MSTR-043	14.623	90
	Heat Added (kW)	Efficiency (%)
HEAT-002	2569.1	100
	Rotation Speed (RPM)	Outlet Pressure (bar)
COMP-015	1500	90
	Outlet Pressure (bar)	Efficiency (%)
PUMP-016	80	100
	Outlet Temperature (C)	Efficiency (%)
COOL-025	25	100

Input Energy (KW) per Unit

ORBITAL
FOUNDATION MODEL



Product
(Mass Fractions)



Feedback

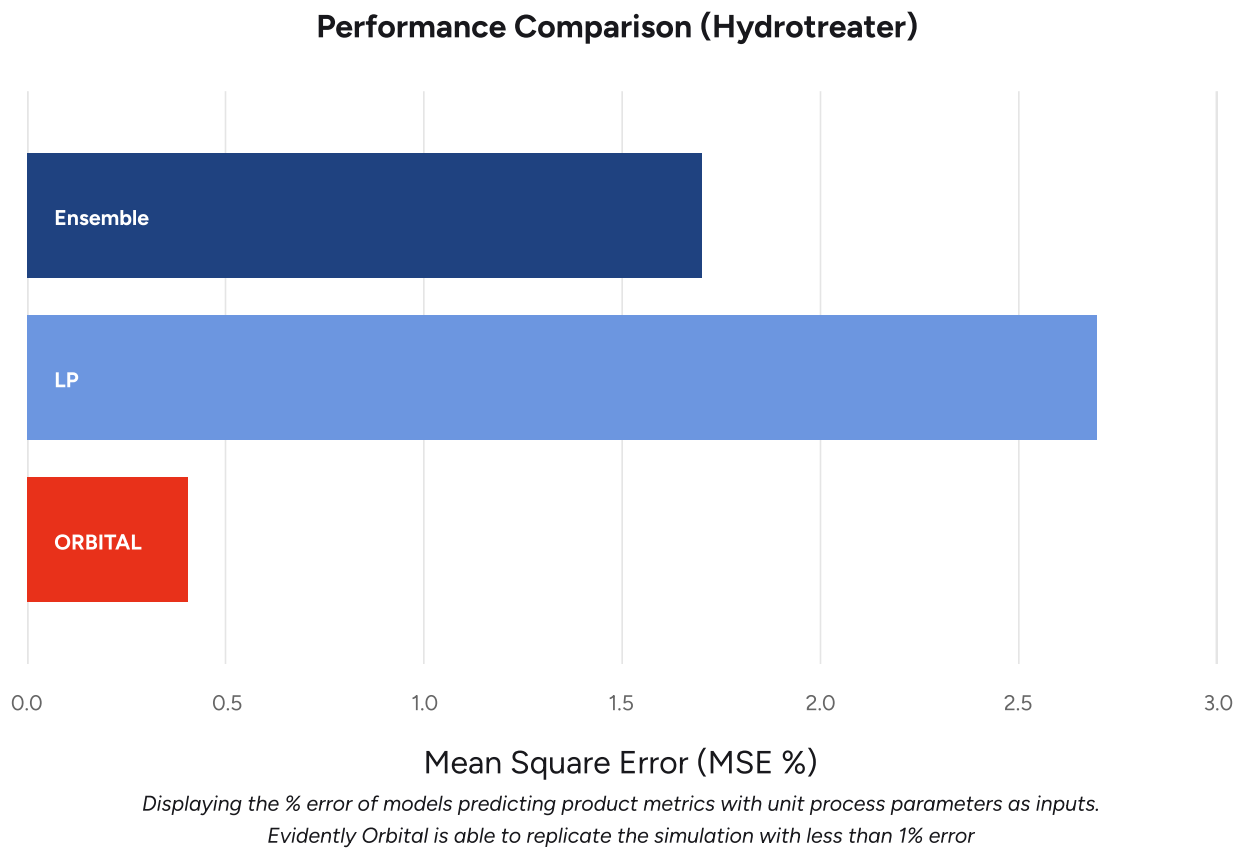
**New Unit Process
Parameters**

Conclusions

This simulation-based study demonstrated the significant potential of decentralised deep learning in reducing energy intensity in refinery operations. Orbital’s predictive models outperformed traditional methods, providing a more efficient approach to optimising energy use.

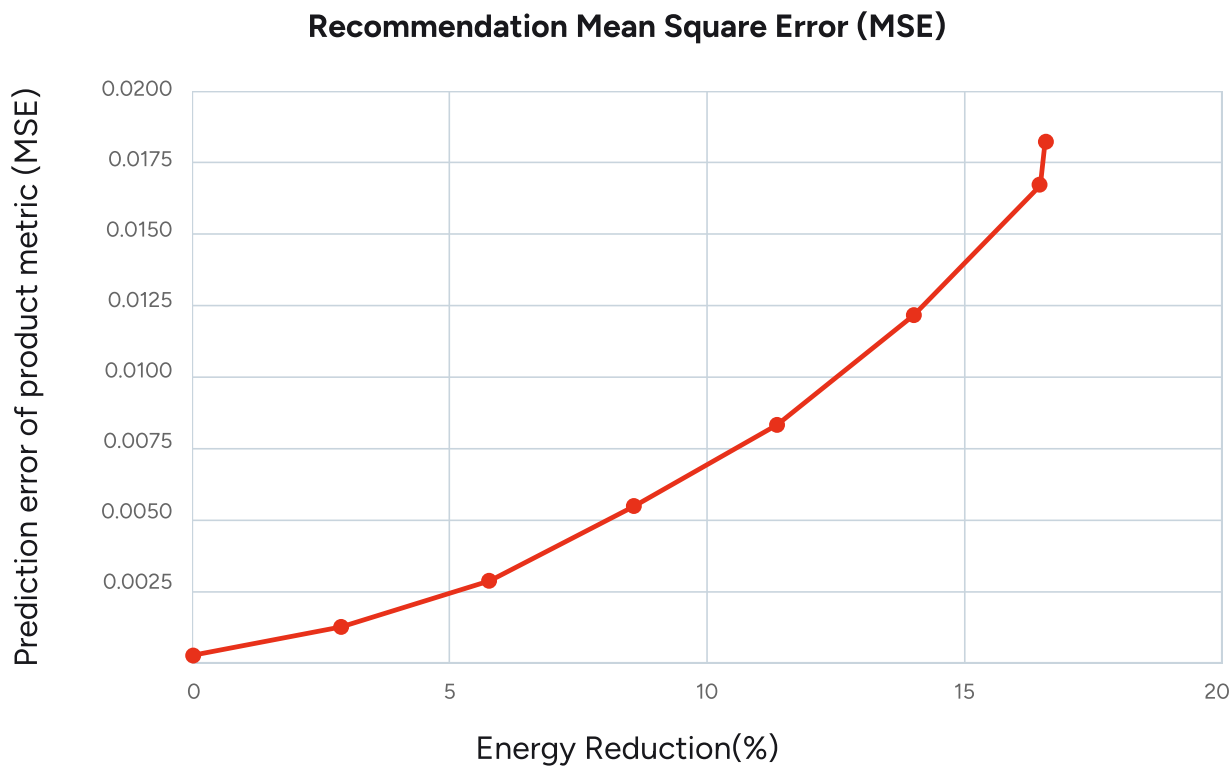
Model Performance

- **85%** improvement over linear programming (LP) methods in predicting product metrics.
- **76%** improvement over ensemble methods in predicting product metrics.



Energy Consumption Performance

Orbital's deep learning models optimised the process, leading to a projected reduction of **16.56%** in energy intensity. This reduction was achieved while maintaining all purity requirements, demonstrating the effectiveness of AI-driven solutions in energy optimisation.



Showing predicted vs. actual product metric deviation using Orbital's recommended process parameters, with energy controlled in 5% steps. Orbital reduces energy by 18% with only a 0.0030 deviation in mass fraction.

Projected Cost Savings

The projected energy savings equates to an annual cost savings of **\$118,634**, alongside a significant reduction in carbon emissions. Orbital's recommendation system was able to suggest operational inputs that aligned with energy-saving objectives while ensuring optimal product performance.

Emissions Reduction

Showcasing the effectiveness of AI-driven optimisation in reducing the carbon footprint of refinery operations, Orbital's deep learning models optimised the process. The reduced energy usage leads to an estimated annual reduction of **967.95** metric tons of CO₂, based on natural gas as a fuel source.



Applied AI for Energy Operations

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