CASE STUDY

Orbital Unlocks 25% Efficiency Improvements in Simulated Distillation Process

Industry - Oil and Gas

Goals

The alkylation of 1-butene to produce octane and dodecane is a common refining process in the petrochemical industry. This study 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.

Results

Energy Consumption

25.05% reduction in energy intensity was achieved, representing a significant efficiency improvement.

Annual Cost Savings

Energy optimisation is projected to yield annual cost savings of **$116,645.02.**

Carbon Emissions

Based on the energy optimisation, an estimated reduction of **952.12** metric tonnes of CO2 emissions annually.

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.
- **Generalisation:** Refinery processes may face unseen conditions (e.g., changes in feedstock or equipment). Neural networks can struggle to generalize to unseen or rare scenarios.

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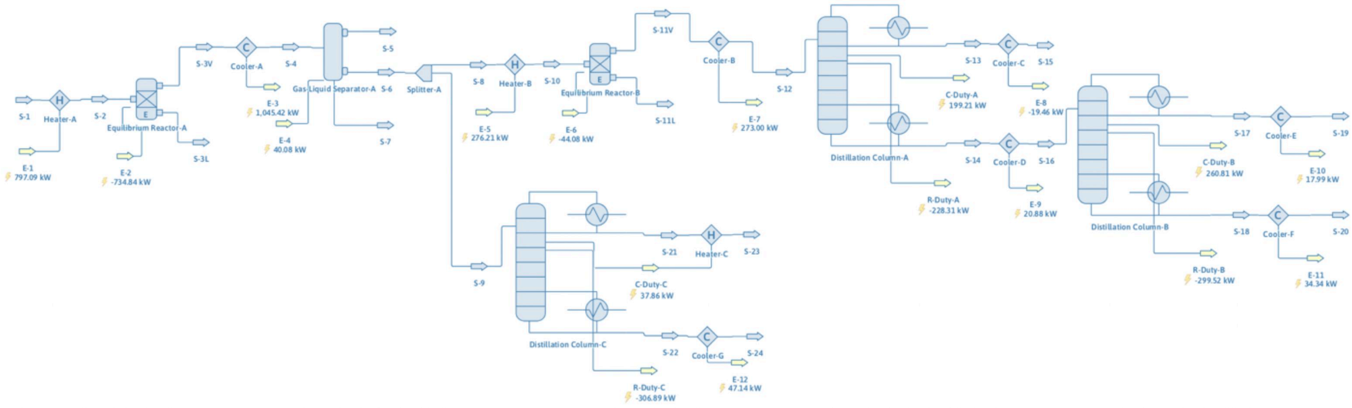
Process Background

N-Octane (C_8H_{18}) and N-Dodecane ($C_{12}H_{26}$) are critical hydrocarbons in the petrochemical industry, used extensively in petrol production and as solvents. The alkylation of 1-butene is a key step in producing these compounds, which typically requires significant energy input to sustain the necessary reaction conditions. Optimising this process for energy efficiency is vital to enhancing overall operational sustainability.



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

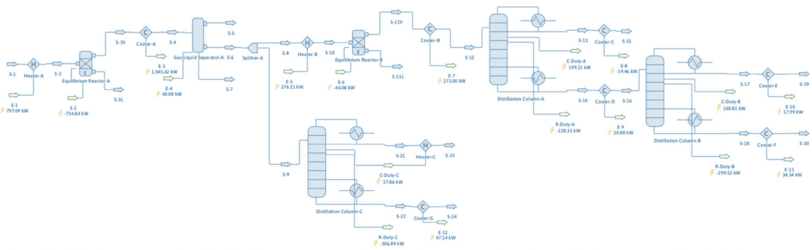
1 Data Collection

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)

1-butene	0.67
Hydrogen	0.33
N-octane	0
N-dodecane	0

Unit process parameters

	Outlet Temp (C)	Heat Added (KW)
Heater-A	475	797.09106
Heater-B	300	276.21157
Heater-C	35	37.86427

	Outlet Temp (C)	Heat Removed (KW)
Cooler-A	10	1045.4222
Cooler-B	30	272.99927
Cooler-C	25	-19.458895

	Reflux/Boil-Up Ratio	Molar Flow Rate
Distillation Col-A	10	6.7177154
Distillation Col-B	3	1.9519258
Distillation Col-C	5	6

	Temperature (C)	Molar Flow Rate
S-1	25	3

Input Energy (KW) per Unit

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FOUNDATION MODEL

Recommender

Product (Mass Fractions)

Predictor

Feedback

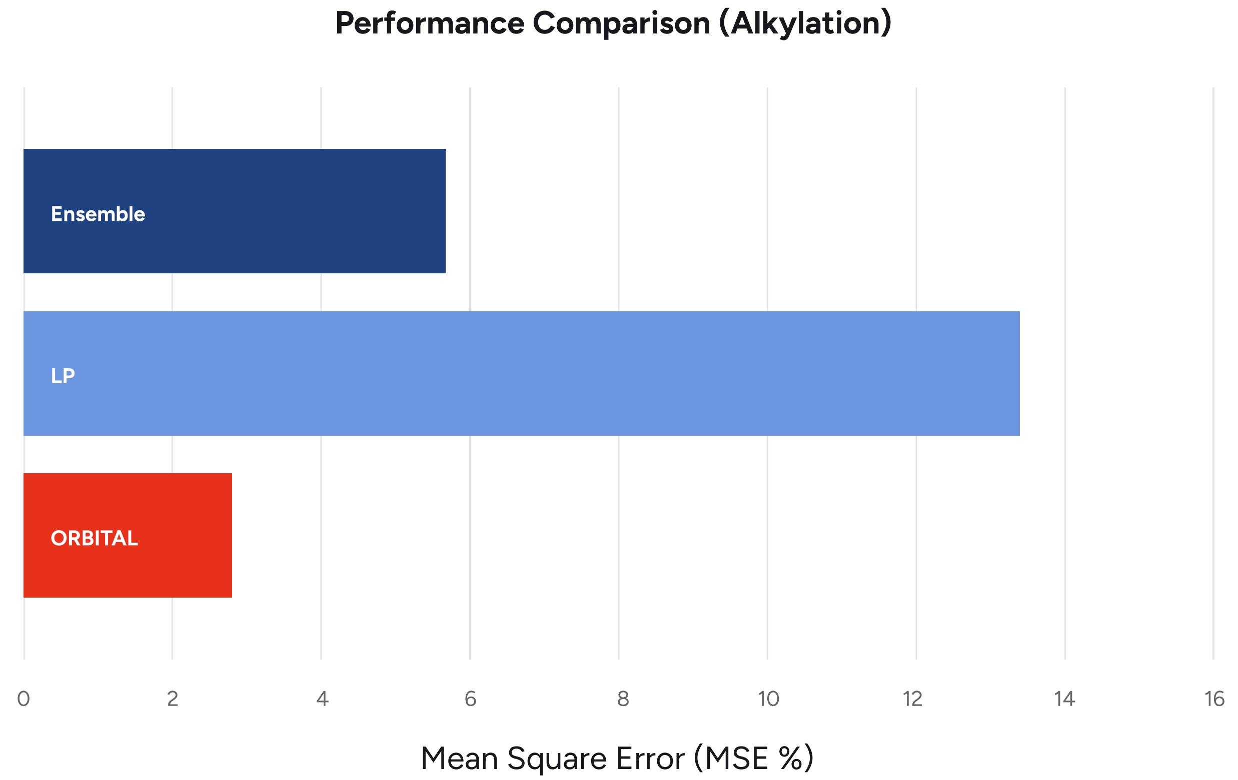
New Unit Process Parameters

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

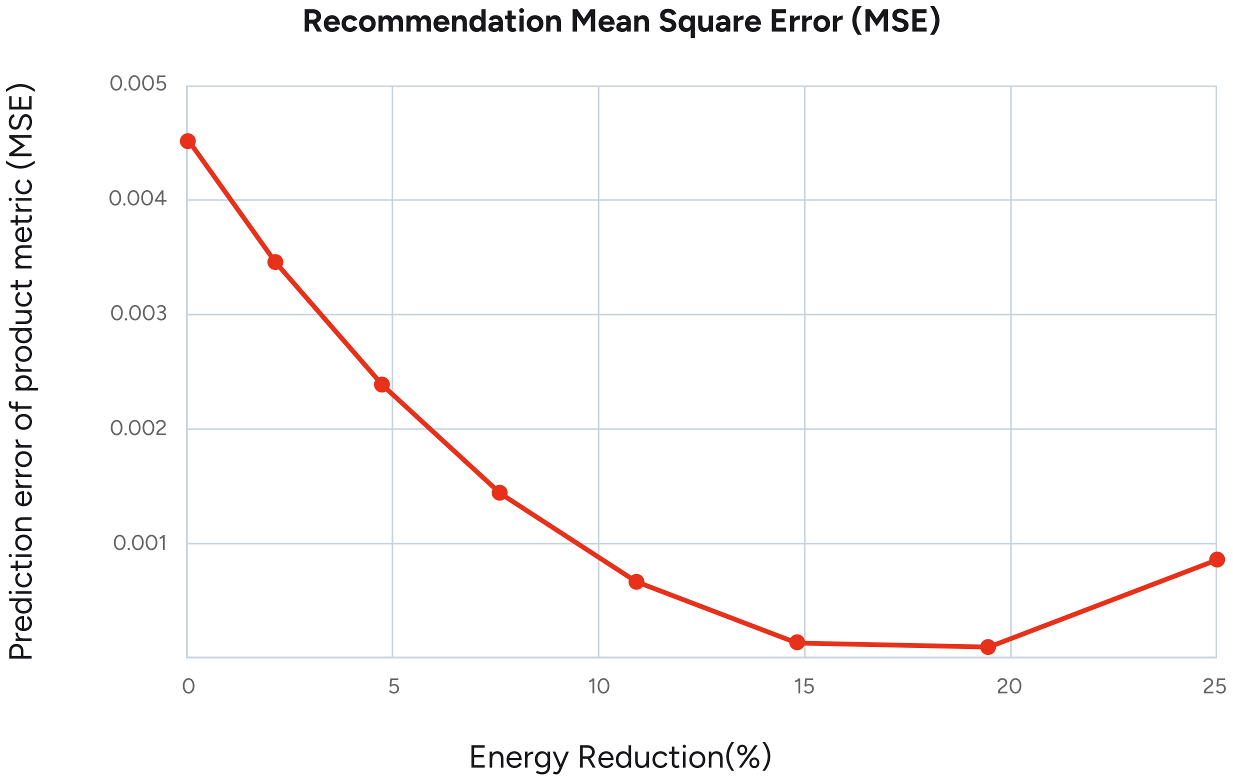
- Orbital predicts yield with **99.3%** accuracy (for any given product parameters).
- **79%** improvement over linear programming (LP) methods in predicting product metrics.
- **51%** improvement over ensemble methods in predicting product metrics.



Displaying the % error of models predicting product metrics with unit process parameters as inputs. Evidently Orbital is able to replicate the simulation with less than 3% error

Energy Consumption Performance

Orbital's deep learning models optimised the alkylation process, leading to a projected reduction of **25.05%** 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.

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 **952.12** metric tons of CO_2, based on natural gas as a fuel source.

Projected Cost Savings

The projected energy savings equates to an annual cost savings of **$116,645.02**, 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.

APPLIED COMPUTING

Refineries Powered by Superintelligence

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