HMEL QUEST 2025

Problem Statement:
AI-based wind pattern analysis to site mini turbines around refinery land

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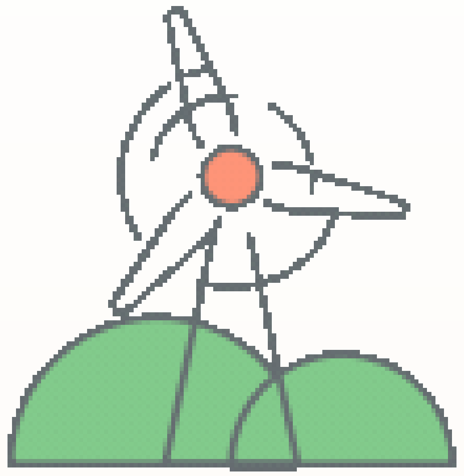
Need of this Problem Statement

- **Inadequate Traditional Siting Methods →** Dense infrastructure and limited land make turbine siting difficult. Traditional methods cannot capture complex wind patterns, risking low efficiency and safety concerns.
- **Irregular Airflow and Reduced Turbine Performance →** Refinery structures like columns and cooling towers cause chaotic airflow, leading to turbulence and wind shadows. This puts stress on mini wind turbines, reducing their efficiency and lifespan.



Existing Solutions in Industry

Problem 01

Meteorological Mast Studies

- **Use:** Long-term wind measurement at different heights for resource assessment.
- **Limitations:** Limited spatial coverage; cannot capture turbulence from refinery structures.

Problem 02

Power Curve Extrapolation

- **Use:** Power curves with measured wind data guide turbine location and height selection.
- **Limitations:** Assumes uniform wind flow, making it unreliable in congested, turbulence heavy refinery sites.

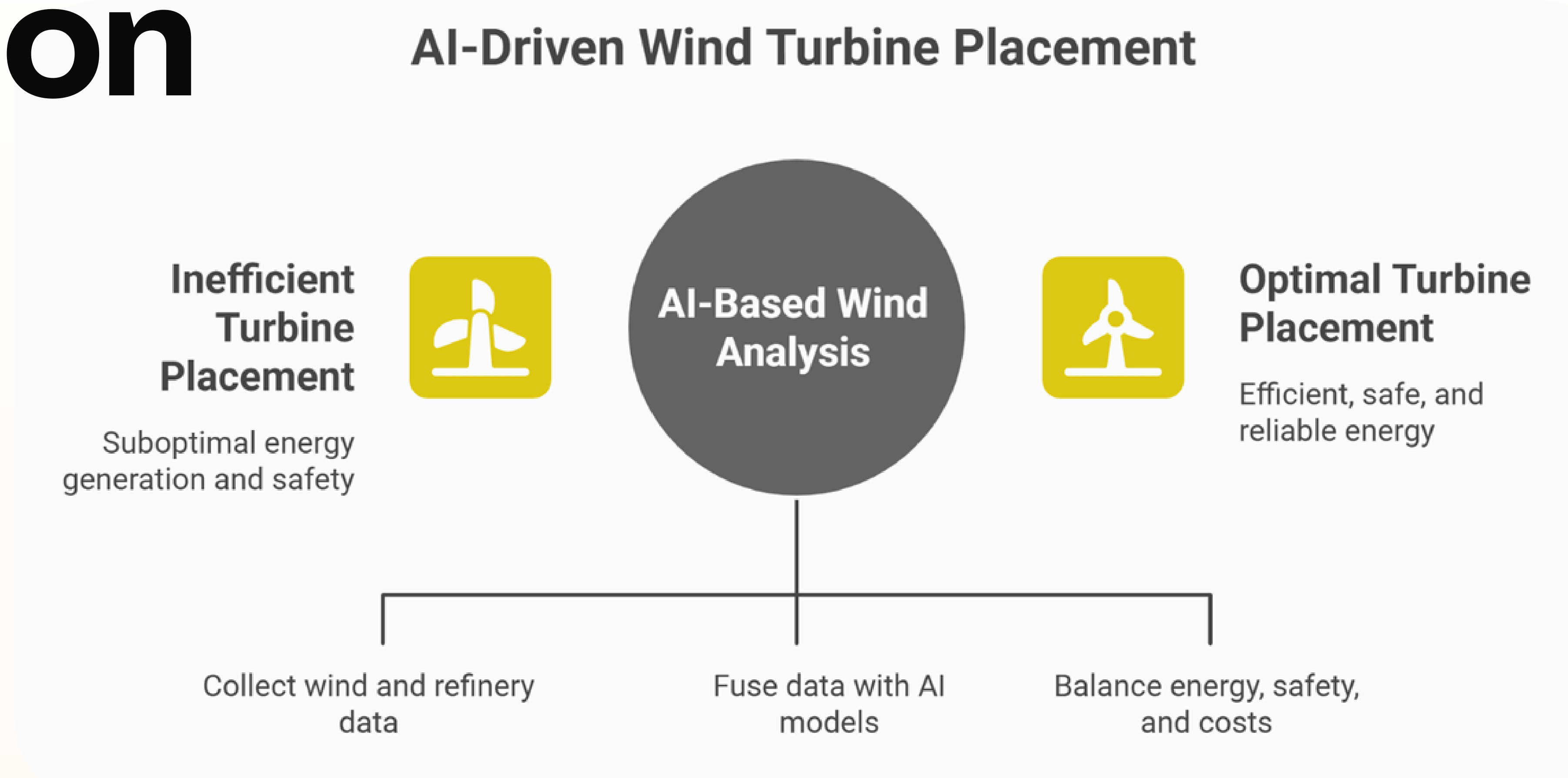
Problem 03

Expert Judgment & Rule-of-Thumb Guidelines

- **Use:** Industry experts rely on site visits, experience, and safety rules to suggest turbine positions.
- **Limitations:** Subjective, lacks precision; cannot handle complex turbulence in dense refinery layouts.

Our Solution

- AI-based wind analysis framework, used to identify optimal sites for mini turbines within refinery premises.
- Airflow, turbulence & wind availability are predicted to optimize turbine placement for maximum energy output, reduced maintenance, and operational safety.
- Enables seamless integration of renewable energy while lowering dependence on the grid.



Key Technologies

Photogrammetry, LiDAR–SoDAR :

Uses laser light & sound waves respectively to measure distances, map surfaces, & study atmosphere

PINNs (Physics-Informed Neural Networks)

Embeds physical laws into its learning process to solve scientific & engineering problems more accurately.

CFD (Computational Fluid Dynamics)

Numerical approach in fluid dynamics for simulating & analyzing fluid flow

BiLSTM (Bidirectional LSTM)

Processes data in both forward and backward directions to capture past and future context.

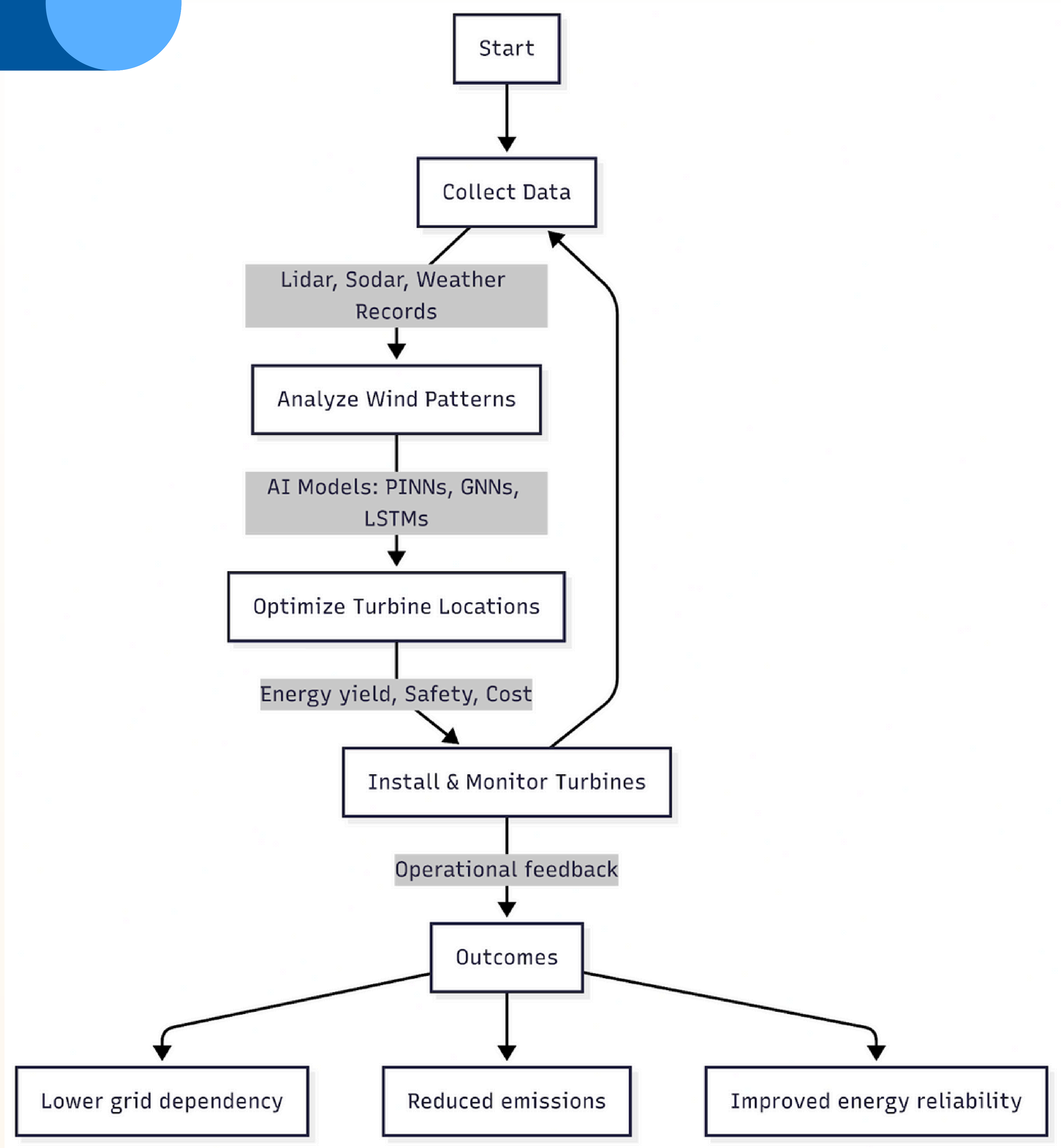
GNNs (Graph Neural Networks)

Capture relationships & patterns in graph-structured data through node & edge representations.

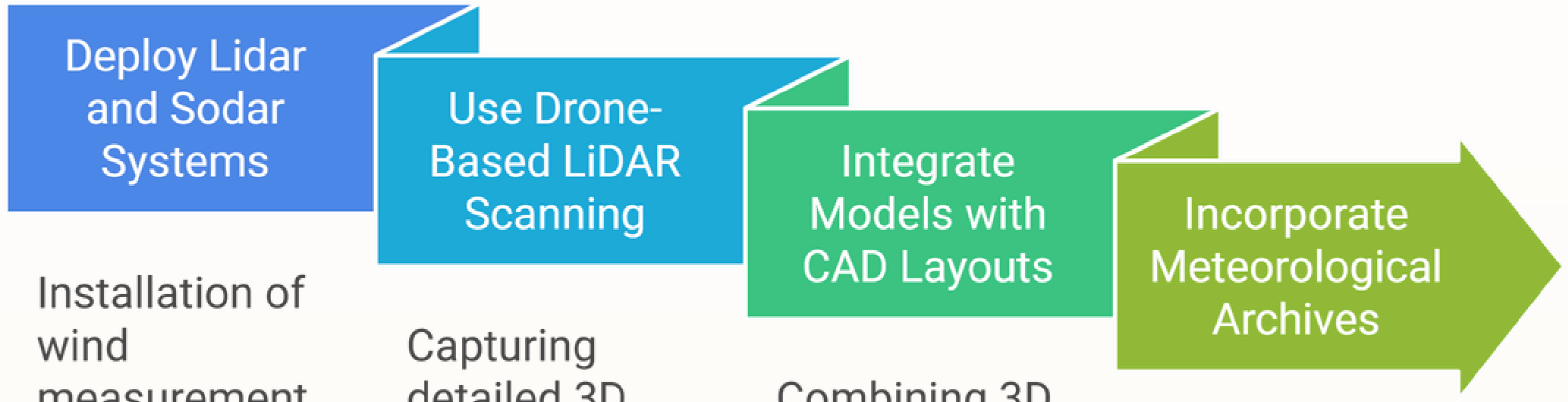
LSTM (Long Short-Term Memory)

Capture long term dependencies in sequential data using memory cells.

Flowprocess and Working



Data Acquisition and Modeling



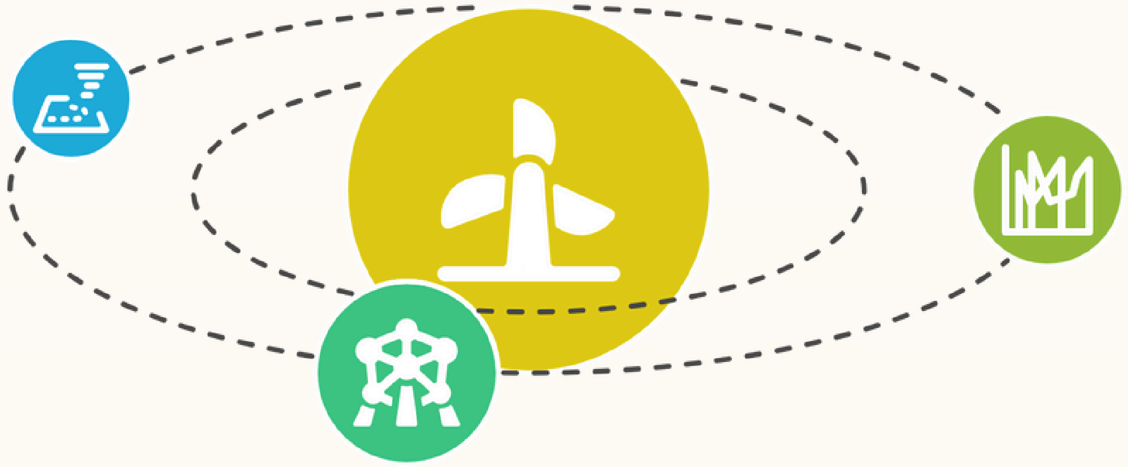
Installation of wind measurement devices at strategic locations

Capturing detailed 3D models of refinery structures

Combining 3D models with existing spatial data

Analyzing long-term weather data for wind trends

Data Interaction with Neural Networks



Physics-Informed Neural Networks

Combines CFD simulations with on-site data for high-resolution predictions

Graph Neural Networks

Analyzes spatial relationships to identify turbulence zones

LSTM Networks

Forecasts temporal variations for seasonal and diurnal predictions

Advantages of our Solution

Precision Siting

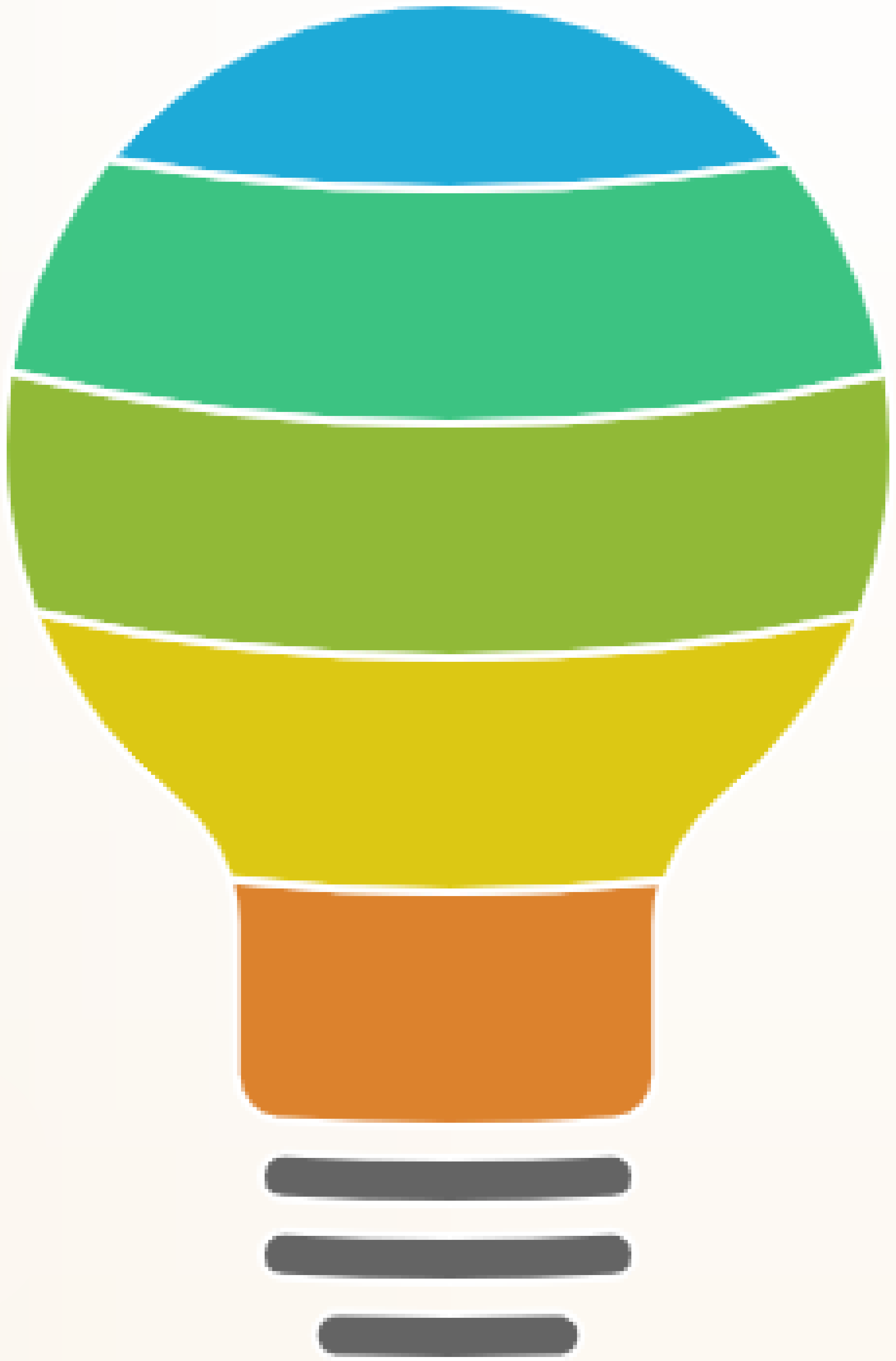
Identifies optimal turbine positions to minimize turbulence

Cost & Safety Optimization

Reduces costs and maintains safety near critical assets

Reliability & Scalability

Adapts with new data for long-term reliability and deployment



Higher Energy Yield

Ensures accurate AEP estimation for maximum power generation

Sustainability

Lowers emissions and supports clean energy integration

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