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Wind Farm Layout Optimization Using Machine Learning-Enhanced Wake Modeling and SLSQP Optimization Techniques

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Introduction

The study introduces a supervised machine learning-based computational framework for wind farm layout optimization, addressing wake effects and wind condition uncertainties. The approach leverages the predictive power of Random Forest (RF) regression to model wake effects and integrates it with the Sequential Least Squares Quadratic Programming (SLSQP) algorithm for efficient wind farm layout optimization. Application to Horns Rev 1 wind farm demonstrates improvement in annual energy production (AEP) gains through iterative optimization, offering agile approach to windfarm layout optimization.

Methodology

The following methodology is followed in this work:

Initial Turbine Layout

Initial wake losses and power output calculated using the Jensen model.

$$s = \begin{bmatrix} x_1 & y_1 \\ x_2 & y_2 \\ \vdots & \vdots \\ x_N & y_N \end{bmatrix}$$

Data Generation for ML

Generate N layouts by perturbing initial turbine positions

$$s_{\text{perturbed}} = s + \epsilon, \quad \epsilon \sim \mathcal{U}(-50, 50)$$

Compute power outputs for each perturbed layout.

Machine Learning

Train a Random Forest Regressor using:

Input: Flattened turbine positions, $[x_1, y_1, \ldots, x_N, y_N]$.

Output: Total power output, $P_{\text{total}} = \sum_{i=1}^{N} P_i$

SLSQP Optimization

Solve: $\min_s f(s) = -\text{RF.predict}(s)$

Subject to: $s_{\min} \leq s \leq s_{\max}$

Obtain optimized turbine positions.

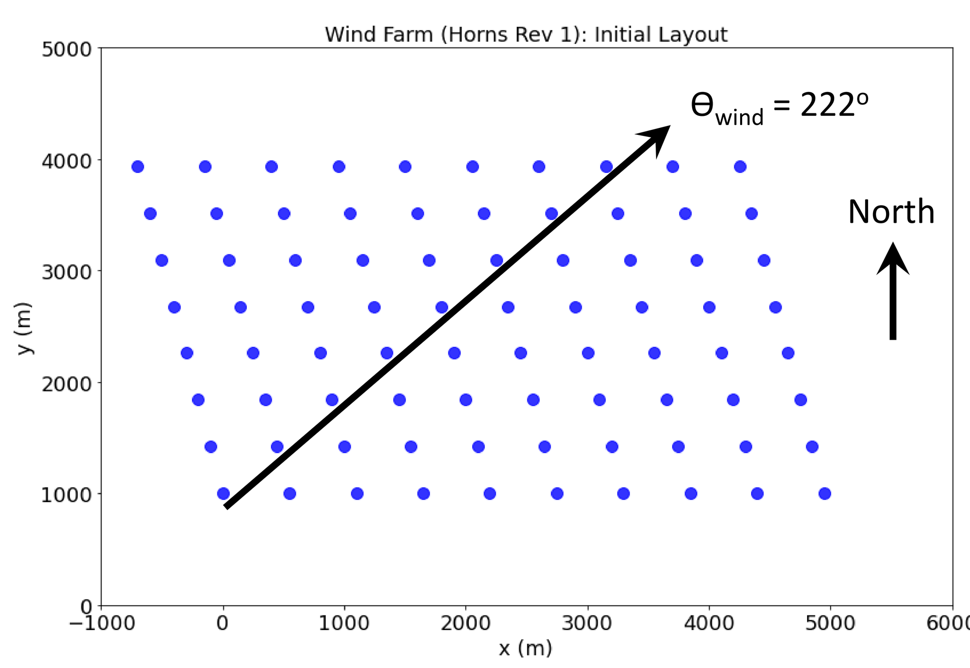
Validation

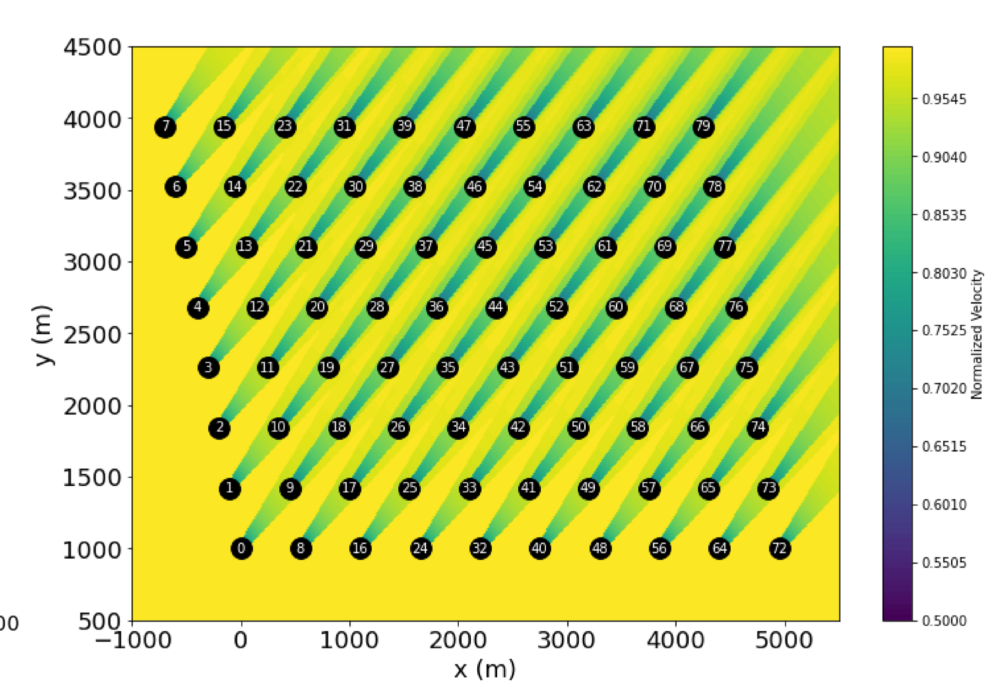
Use Jensen model for power output for optimized layout

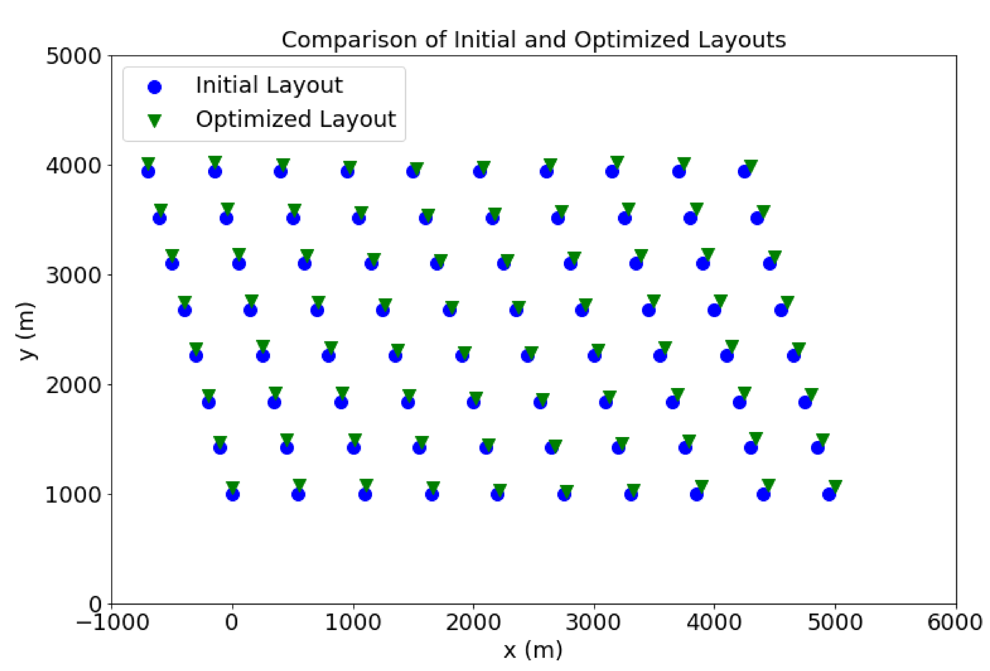
Compare with initial layout: $\Delta P = P_{\text{optimized}} - P_{\text{initial}}$

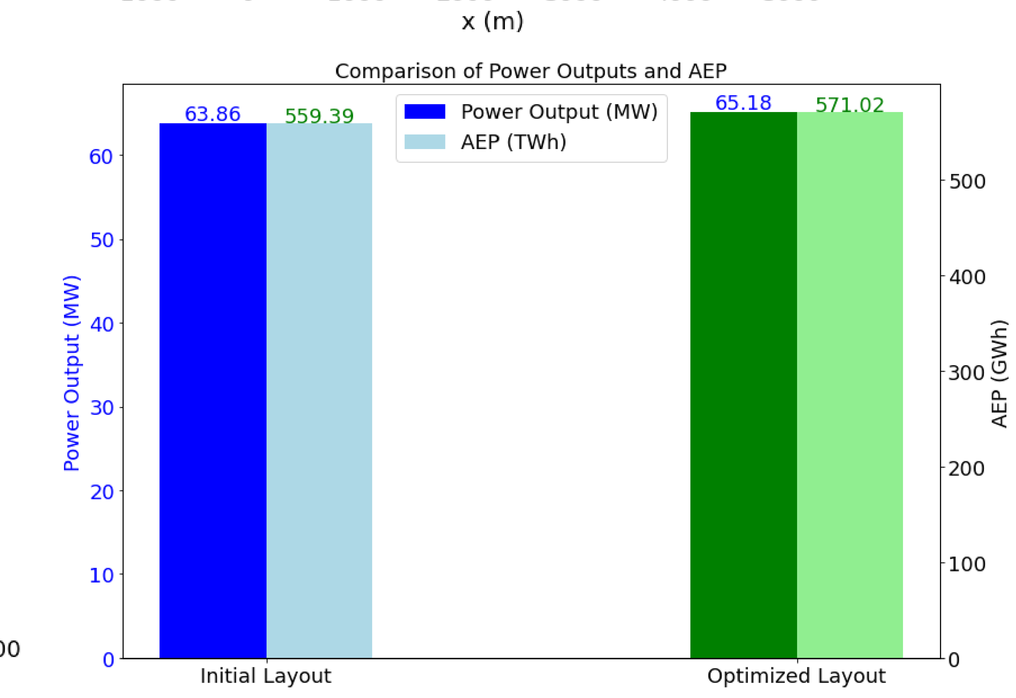
Results

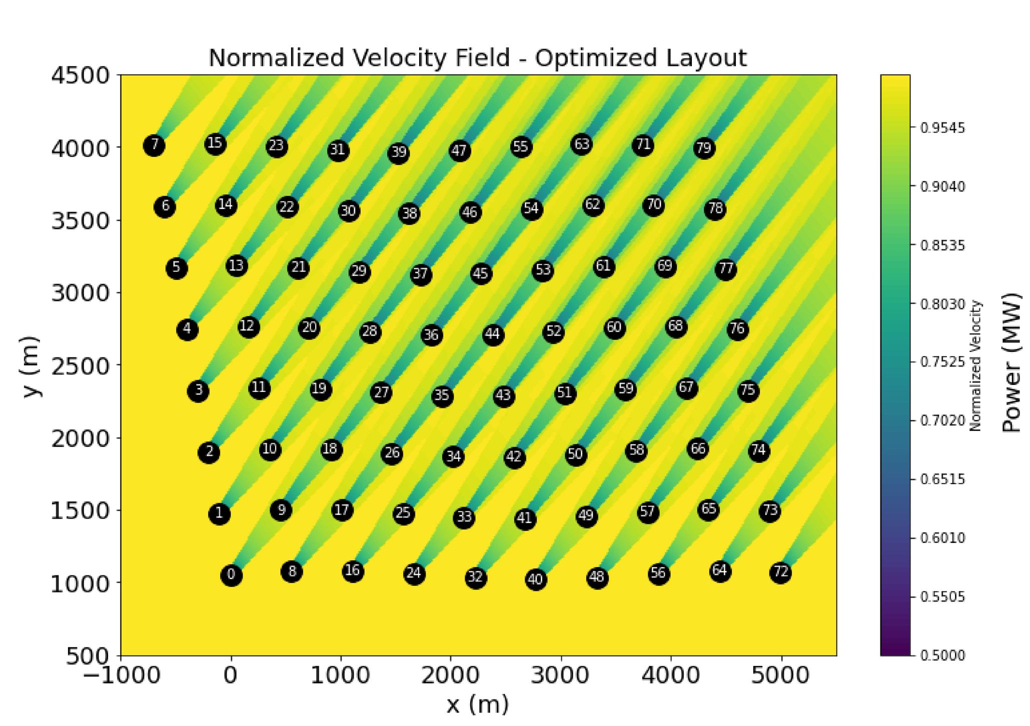
For this work, the **Horns Rev 1** wind farm was used to evaluate the effectiveness of the proposed framework. The turbines are laid out in an oblique 8 by 10 grid over an area of 5km × 3.8km, with 560 m between turbines in both directions.

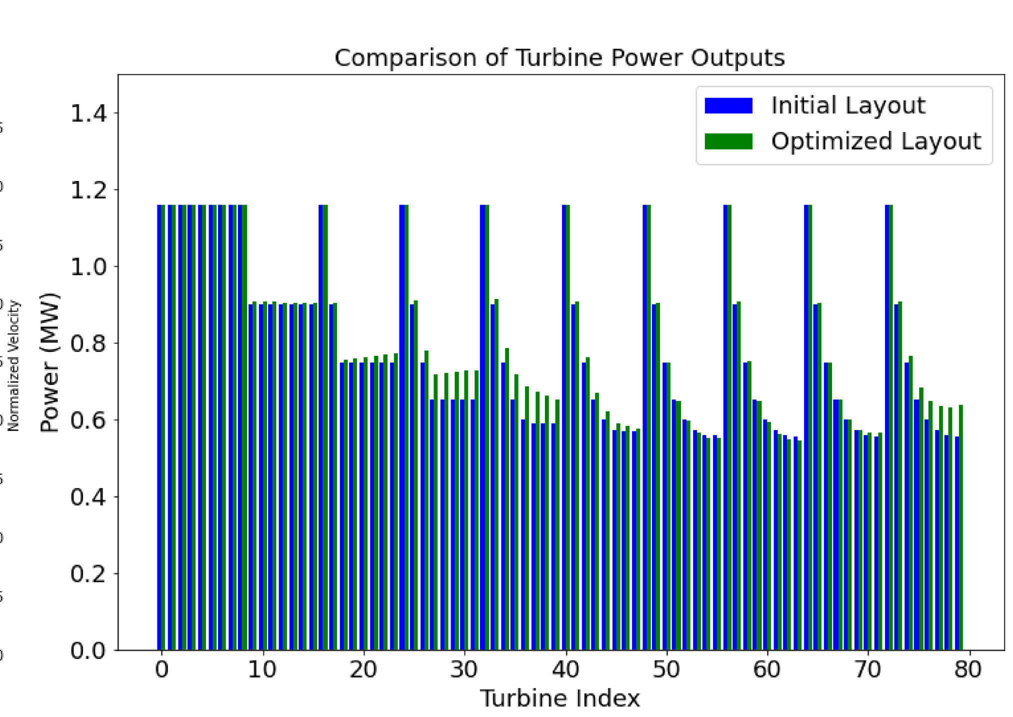












Conclusion & Future work

- Machine Learning-based wake modeling provides robust surrogate predictions for optimization.
- SLSQP effectively fine-tunes turbine positions, improving performance metrics.
- The optimized layout increases the Annual Energy Production (AEP) by approximately 2.08%, from 559.39 GWh to 571.02 GWh.
- This framework is scalable to larger wind farms and adaptable to site-specific conditions.
- Future work involves testing the performance of different ML algorithms and optimization techniques.
- Also extend it to Integrate time-series data for adaptive layout optimization under varying conditions.

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References

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Collaborators

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