PO.051

# DEEP LEARNING-BASED MODELING OF WAKE INDUCED EFFECTS IN WIND FARMS

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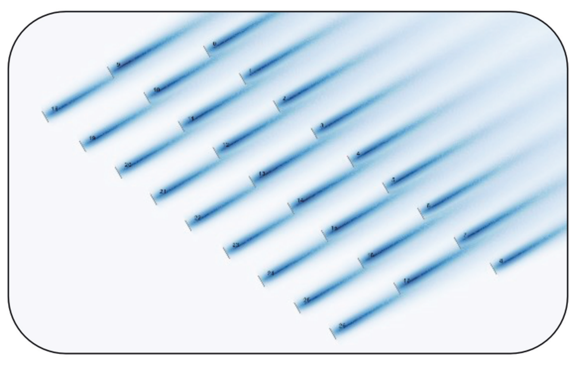
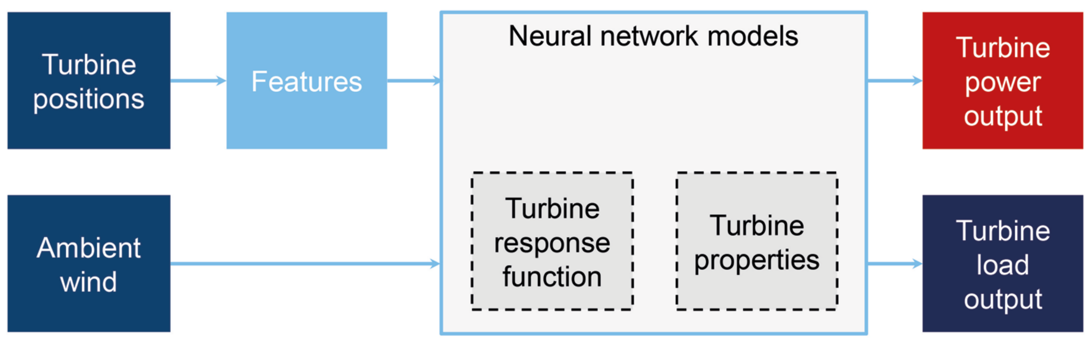
## Introduction: surrogate models for wake effects






❖Geometric features are needed to parameterize wake effects in wind farm. Existing studies are based on manually extracted features [1-3].

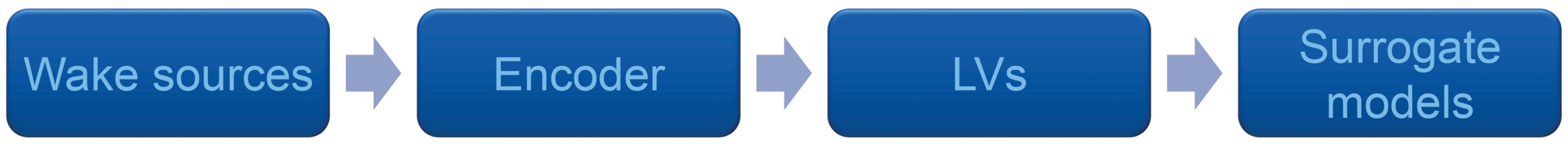
❖Dimitrov(2019): 3-parameter approach ($R_D, \theta, N_{rows}$)

❖Yan et al.(2019): 2-parameter approach (BR & BD)

❖Dimitrov et al.(2021): turbine-wise features ($R_{D,i}, \theta_i$)

## Objectives: use Latent Variables (LVs) to represent wake sources

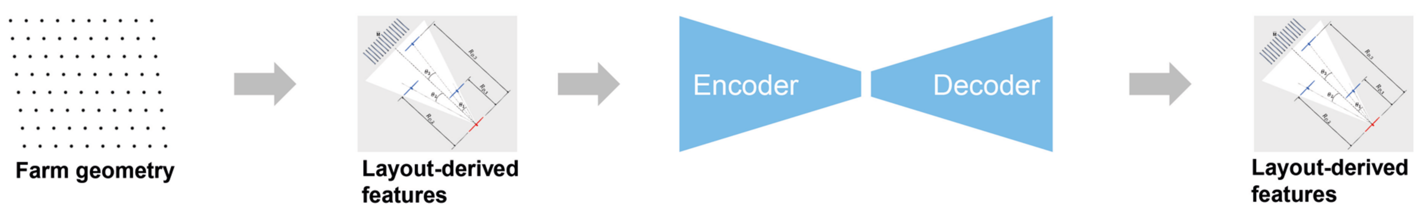
This study aims to automatically encode turbine positions in wake sources into a few latent variables that can be used for building surrogate models of wake effects.



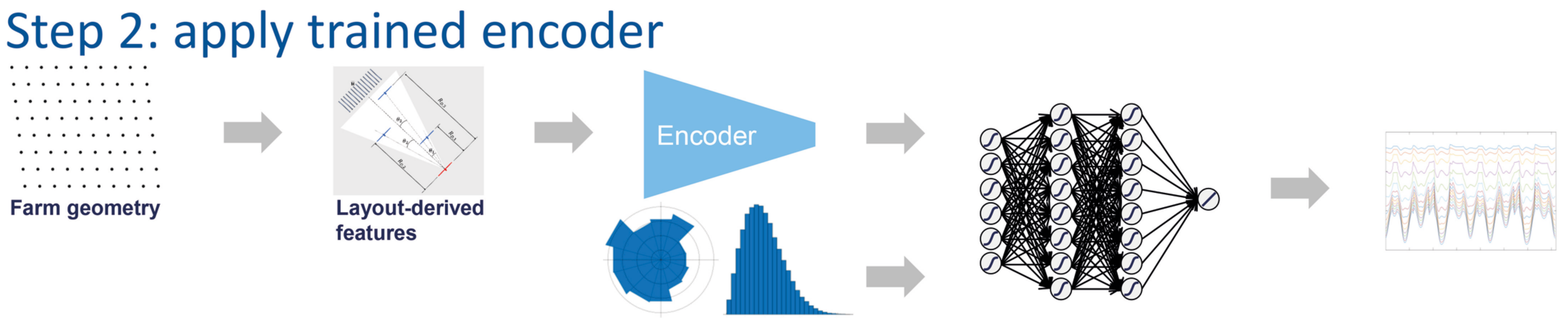

## Methods: AutoEncoder Neural Network (AENN) and Deep Learning Neural Network (DLNN)

Two AENN approaches are studied by Dou and Dimitrov (2022) [4]. One of the AENN approaches is shown below. Both input & output are geometric features. The LVs learn the best information to reconstruct geometric features. But they are not directly related to wake effects.

Step 1: train AENN

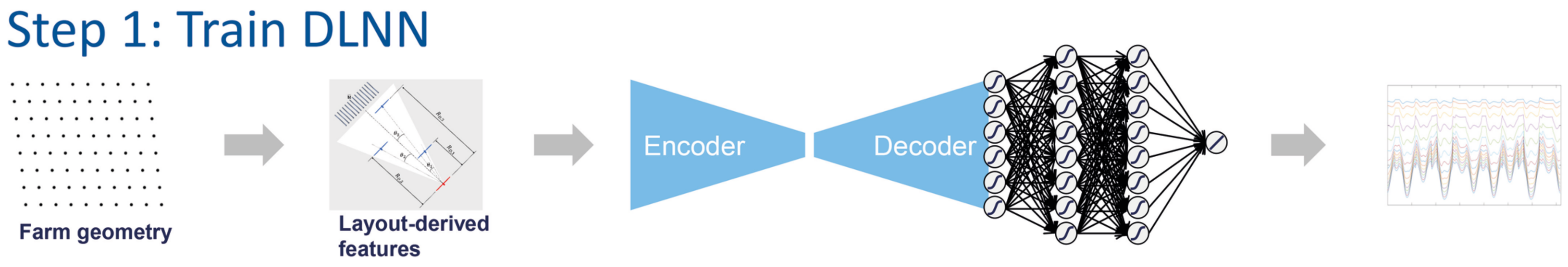



Step 2: apply trained encoder

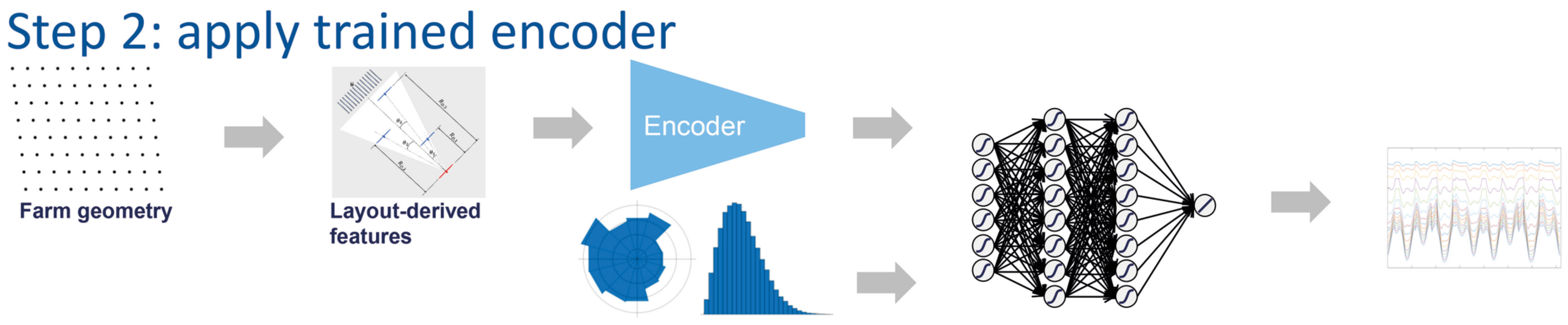



In contrast to AENN, the proposed DLNN approach maps geometric features to wake effects on a mock turbine. The LVs learn geometric features based on their resulting wake effects. Different geometric features with similar wake effects are likely to have similar LVs.

Step 1: Train DLNN

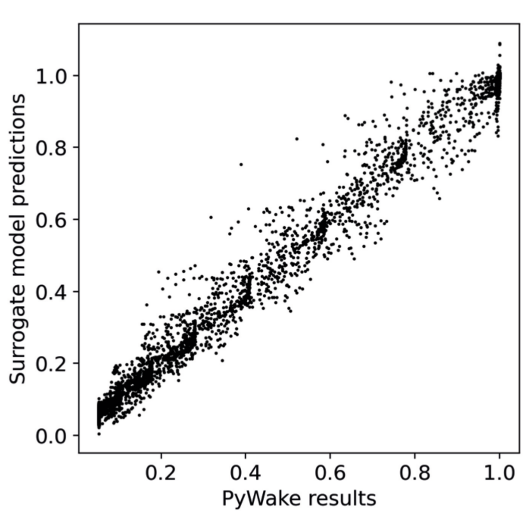


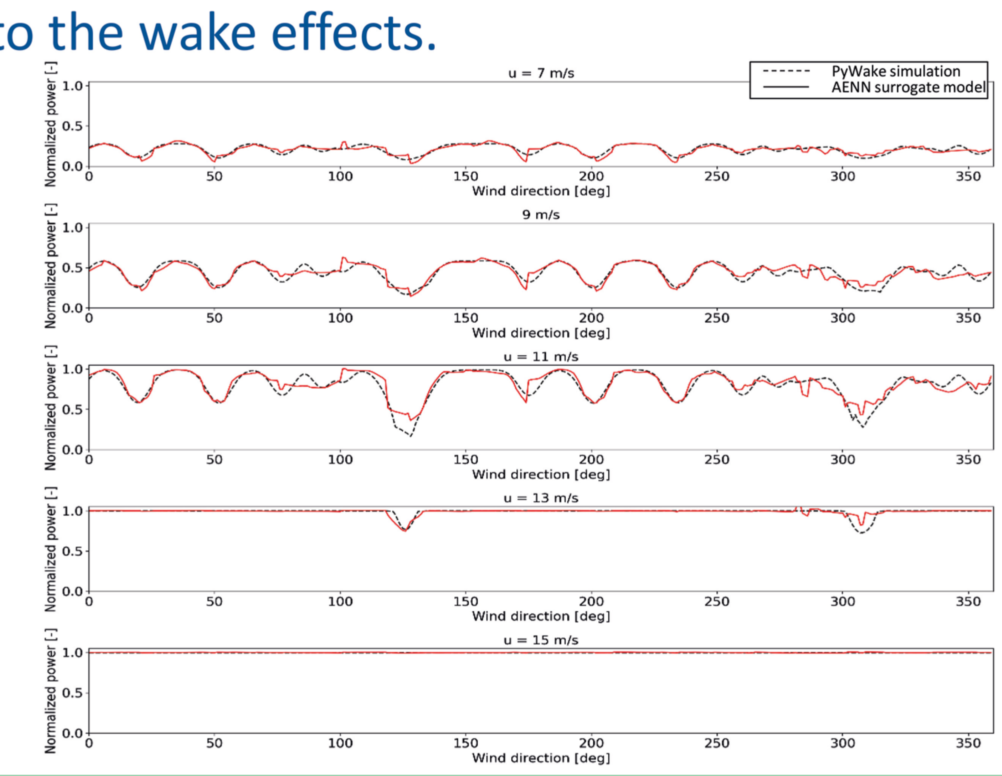

Step 2: apply trained encoder



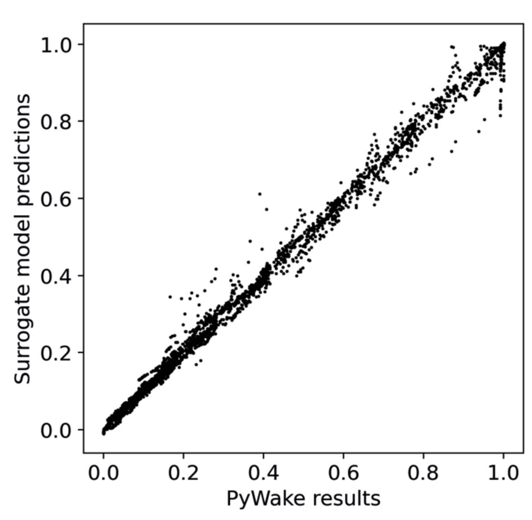

## Results

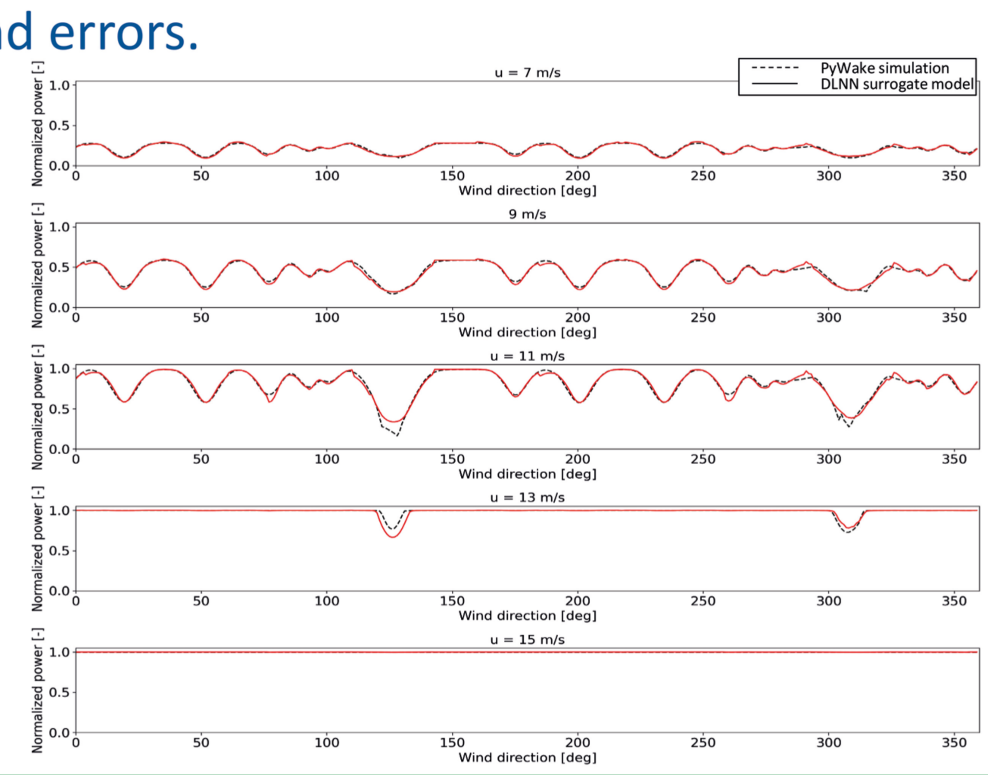
The AENN is trained on 100 wind farm layouts including 50 regular wind farm layouts and 50 random wind farm layouts. The resulting LVs represent geometric features learned from these 100 wind farm layouts. However, the resulting surrogate model does not provide desirable performance. This may be due to the fact that the features learned by the LVs are not well correlated to the wake effects.




The DLNN is trained on 20 wind farm layouts include 10 regular wind farm layouts and 10 random wind farm layouts. The resulting LVs represent geometric features learned from these 20 wind farm layouts and their resulting wake effects on a mock turbine. The surrogate model based on the trained encoder of DLNN achieves satisfactory performance in terms of both correlation and errors.




## Conclusions

- ❑ A DLNN approach is presented to include wake effects in features learned by the LVs
- ❑ LVs learned with DLNN approach outperforms LVs learned with AENN in surrogate models for estimate wake effects
- ❑ An alternative wake parameterization approach is presented by our partner IFP Energies Nouvelles (IFPEN) on poster PO103

## References

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