

Wind Turbine Layout Optimization With Sequential DoE and Active Machine Learning

Dan Probst

Senior Principal Engineer, *Convergent Science, Inc.*

Shengbai Xie

Principal Engineer, *Convergent Science, Inc.*

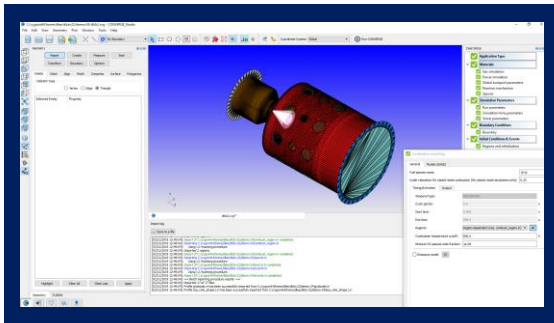
Jasim Sadique

Senior Principal Engineer, *Convergent Science, Inc.*

What is CONVERGE?

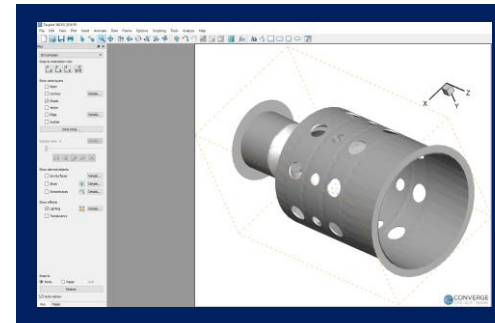
CONVERGE is an all-inclusive package for the CFD workflow

- CONVERGE Studio: Graphical user interface equipped with powerful geometry cleanup tools
- CONVERGE solver: Autonomous meshing and advanced physical models lead to highly accurate solutions
- Post-processing software: Integrated ParaView module and Tecplot for CONVERGE licenses included at no extra cost
- CONVERGE Horizon: Cloud computing platform that offers easy and affordable access to state-of-the-art hardware



CONVERGE Studio

CFD SOFTWARE

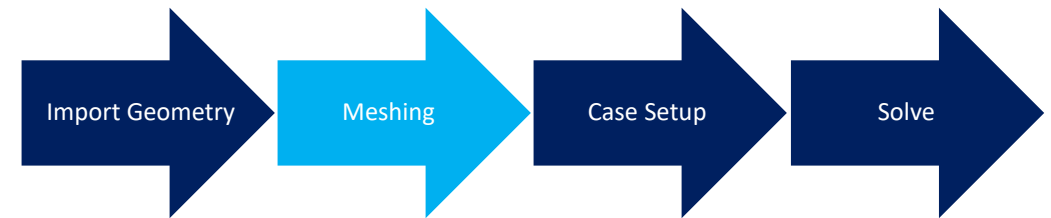


Post-Processor

H O R I Z O N

Autonomous Meshing in CONVERGE

- Traditional CFD codes require the mesh to be created manually before simulation
 - Long meshing times
 - Meshing by guessing (areas needing refinement often change in time)
 - Low-quality mesh
 - Hard to determine grid convergence (if you change your mesh, does your answer change?)

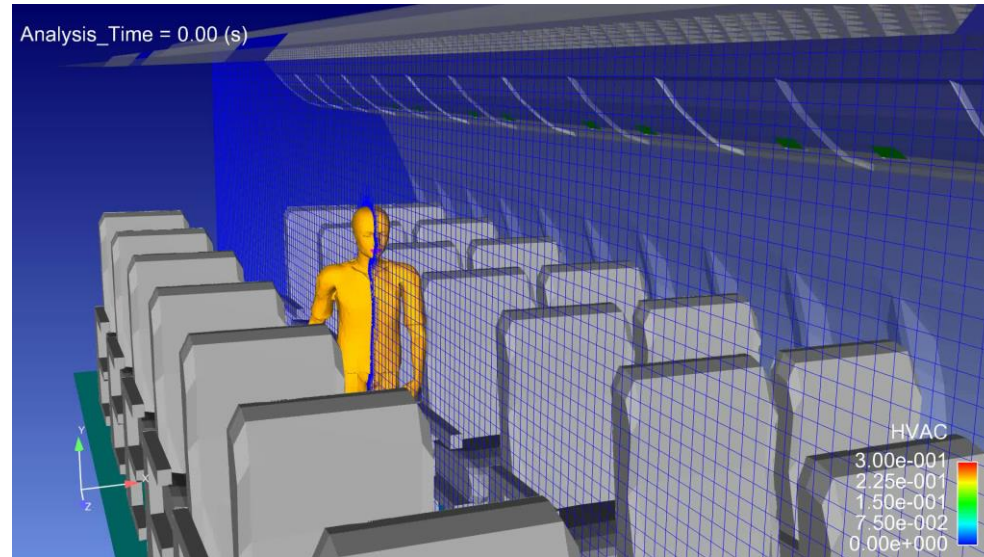


- CONVERGE automatically generates the mesh at runtime
 - No user meshing time
 - Adaptive Mesh Refinement (AMR) = no more guessing
 - Orthogonal cells
 - Grid-convergent modeling



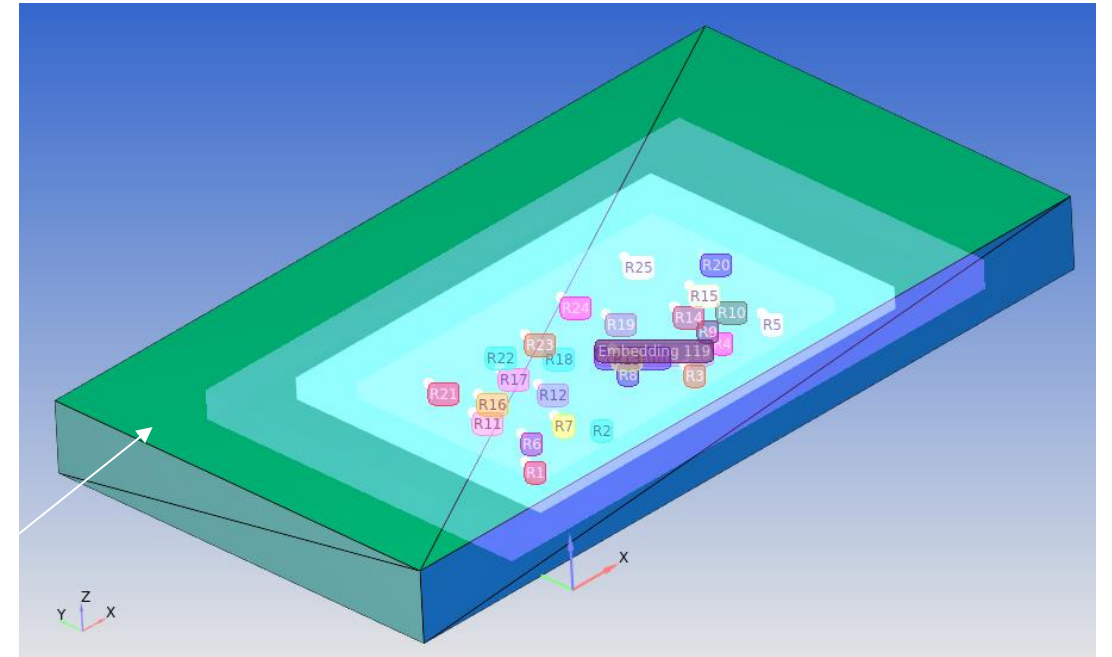
Advanced Physical Modeling in CONVERGE

- Steady-state and transient solvers
- Fluid-structure interaction modeling
- Conjugate heat transfer modeling
- Multi-phase flow modeling
- Detailed chemistry solver
- Efficient combustion models
- State-of-the-art turbulence models
- Rich suite of chemistry tools
- Machine learning optimization



Wind Farm Design

- Wind farm configurations
- 25 NREL 5MW wind turbines
- Land area: $4.8 \text{ km} * 2.6 \text{ km}$
- Neutral atmospheric condition with constant wind speed and direction
- Optimize layout for maximum power production

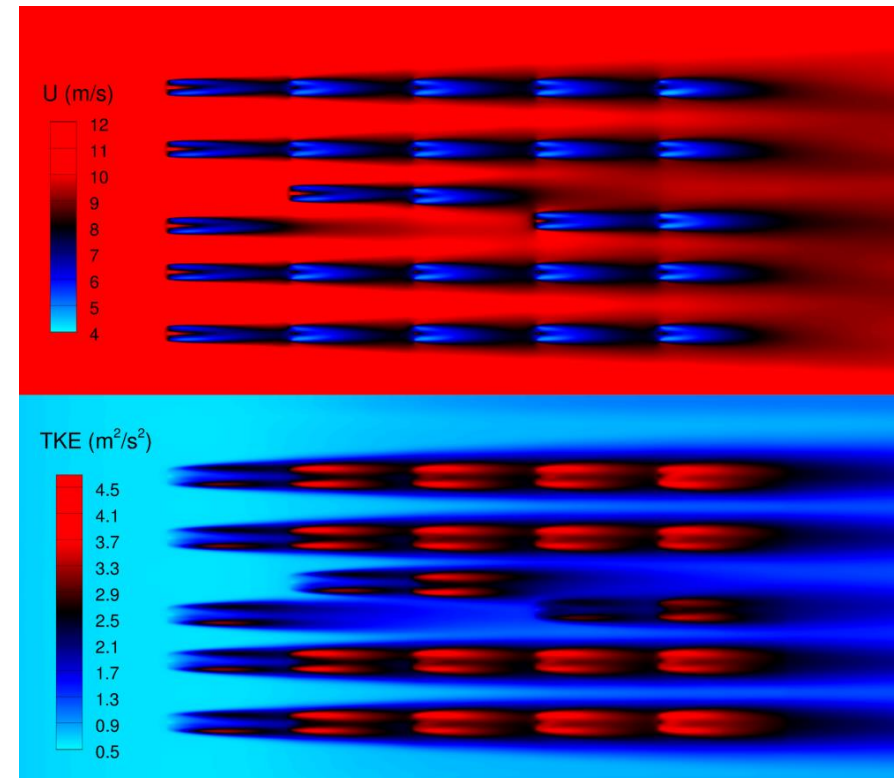


Computational domain and wind turbine locations

Wind Farm CFD

- Wind farm model configuration:
 - Mean wind speed: 12 m/s
 - Turbulence intensity: 0.1
 - Domain size: 11 km * 6 km * 1 km in x, y, z
 - Grid size:
 - 256 m base grid
 - 4 m at rotor
 - 8 m in the wakes
 - Turbulence model: Reynolds Stress RANS model
 - Rotor model: RADM
 - Physical time: 1 hour
- For each wind farm CFD run:
 - Total cell count: 8 million
 - Wall time: 2.5 hour on 1 Horizon node (192 cores)

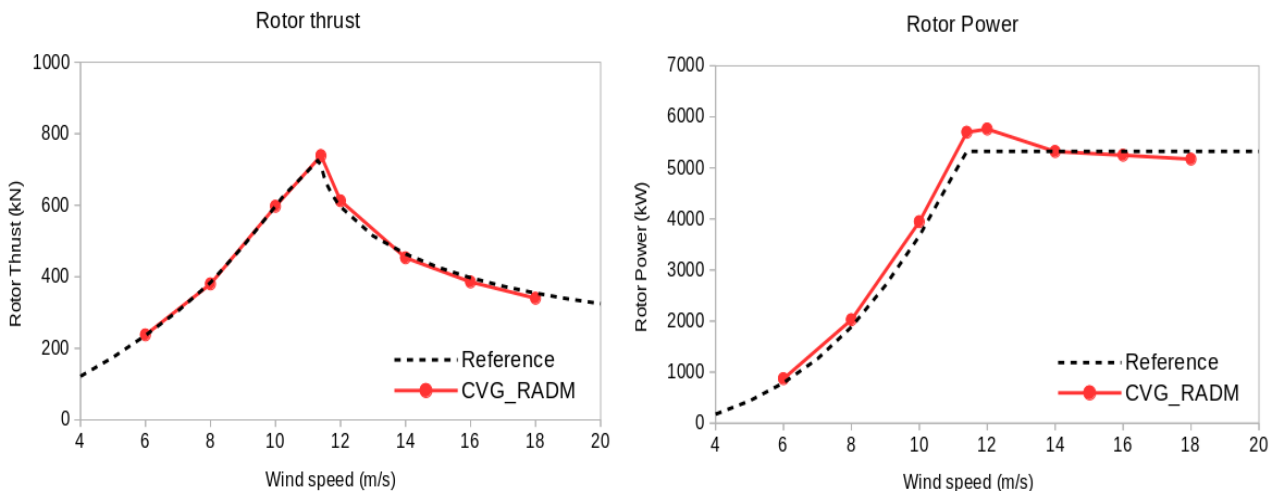
>50% loss due to wake effect



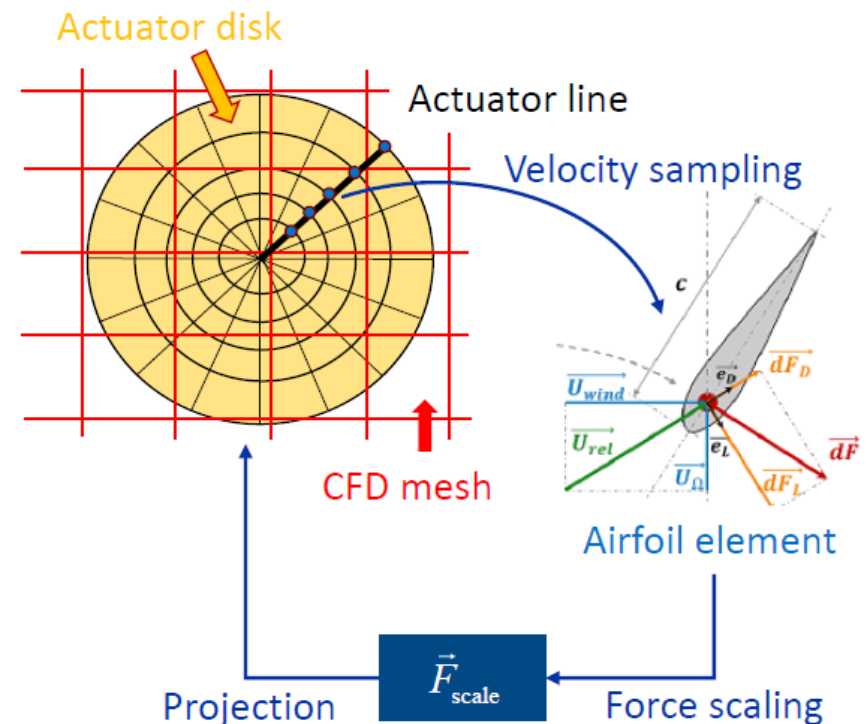
Mean velocity and turbulence kinetic energy (TKE) fields in a wind farm CFD simulation

Rotational Actuator-Disk Model (RADM)

- Capture key aerodynamics of wind turbines without resolving turbine blades
- Much lower computational cost
- Very good scalability for HPC
- Very efficient simulation of large wind farms



Validations of RADM simulating a standalone NREL 5MW wind turbine at various wind speeds
(The reference is from Jonkman et al, NREL/TP-500-38060, 2009)



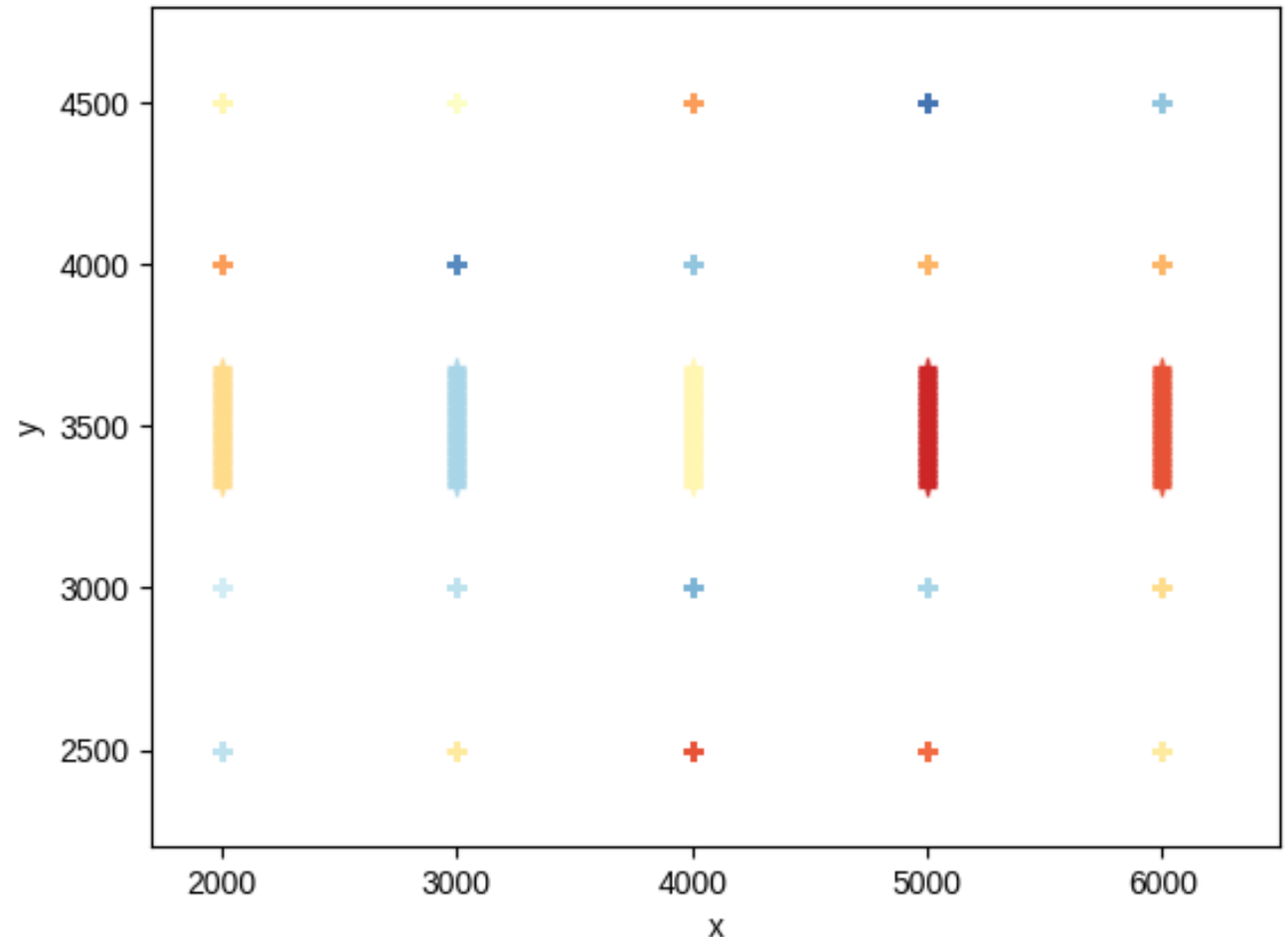
Schematic representation of the RADM

Rapid Optimization With Machine Learning

- Obtain training data with design of experiments (DoE)
 - Sequential batches
- Train & test machine learning emulator
 - Augment DoE if accuracy is unacceptable
- Run optimizer on emulator to obtain proposed optimum
- Obtain CFD result for proposed optimum

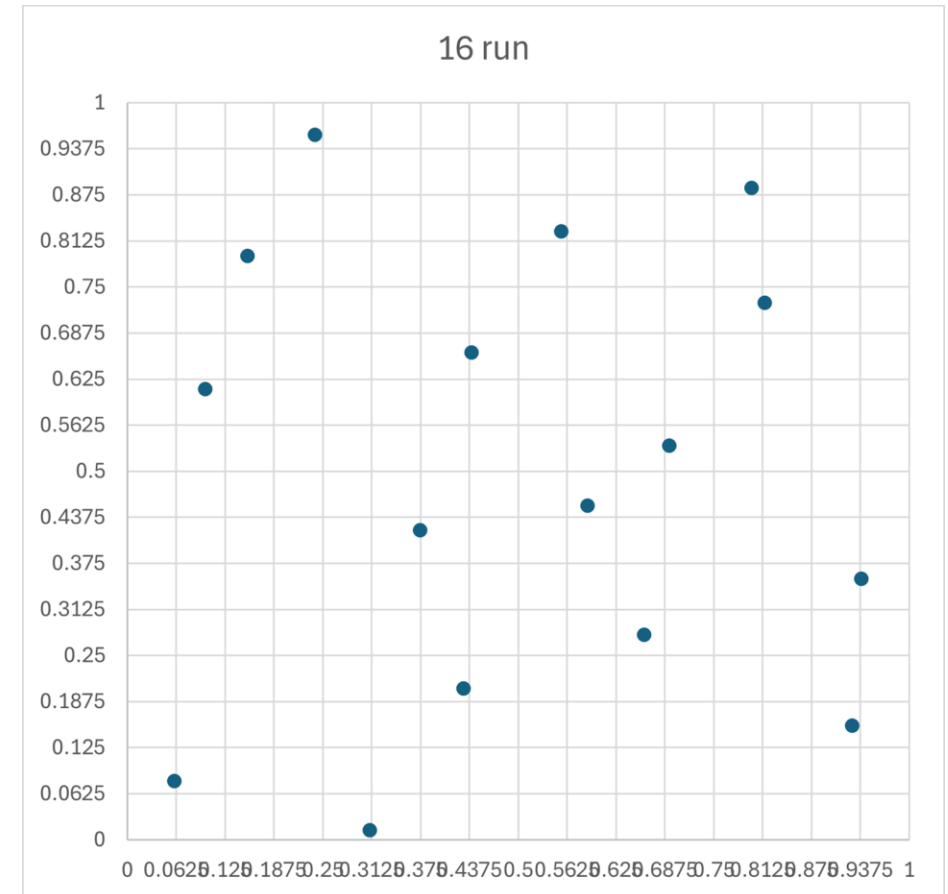
Five Parameter Optimization for Max Power

- The y position of the center five wind turbines are allowed to vary ± 187 m
- Total power of the wind farm (25 turbines)



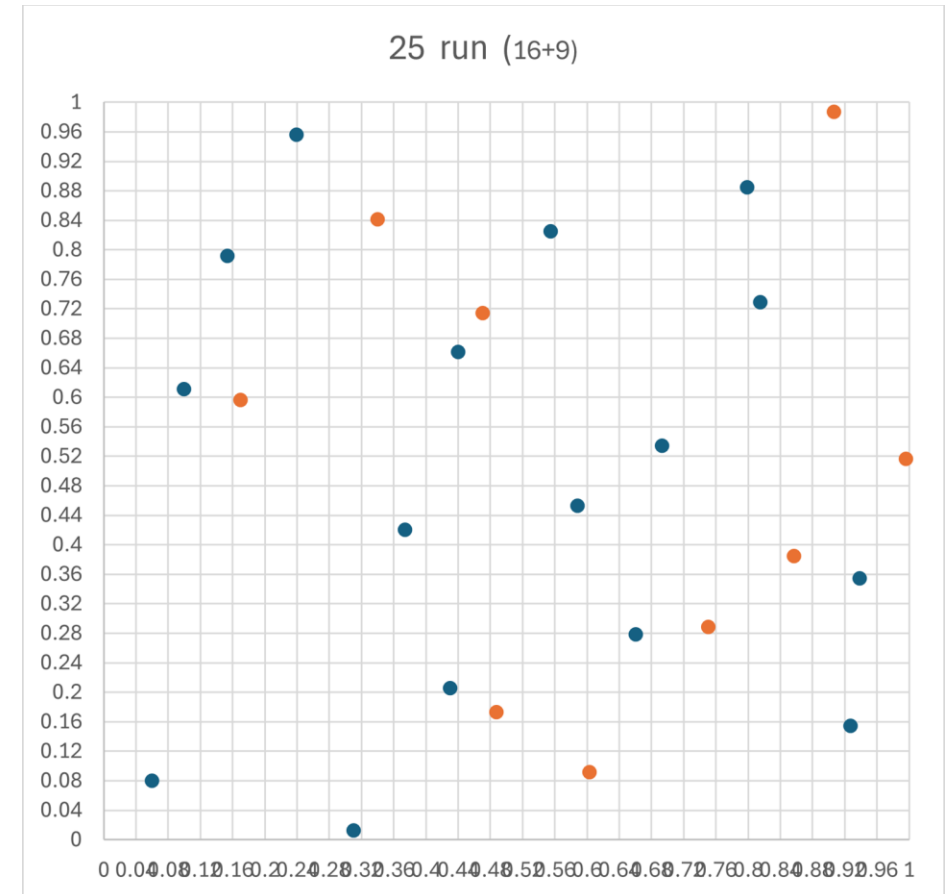
DoE Definition

- Latin Hypercube Sampling (LHS)
 - User-defined number of runs
 - Random sampling within 'cube'
 - Iterate to maximize spacing between design points
 - Maximize the minimum Euclidean distance between design points



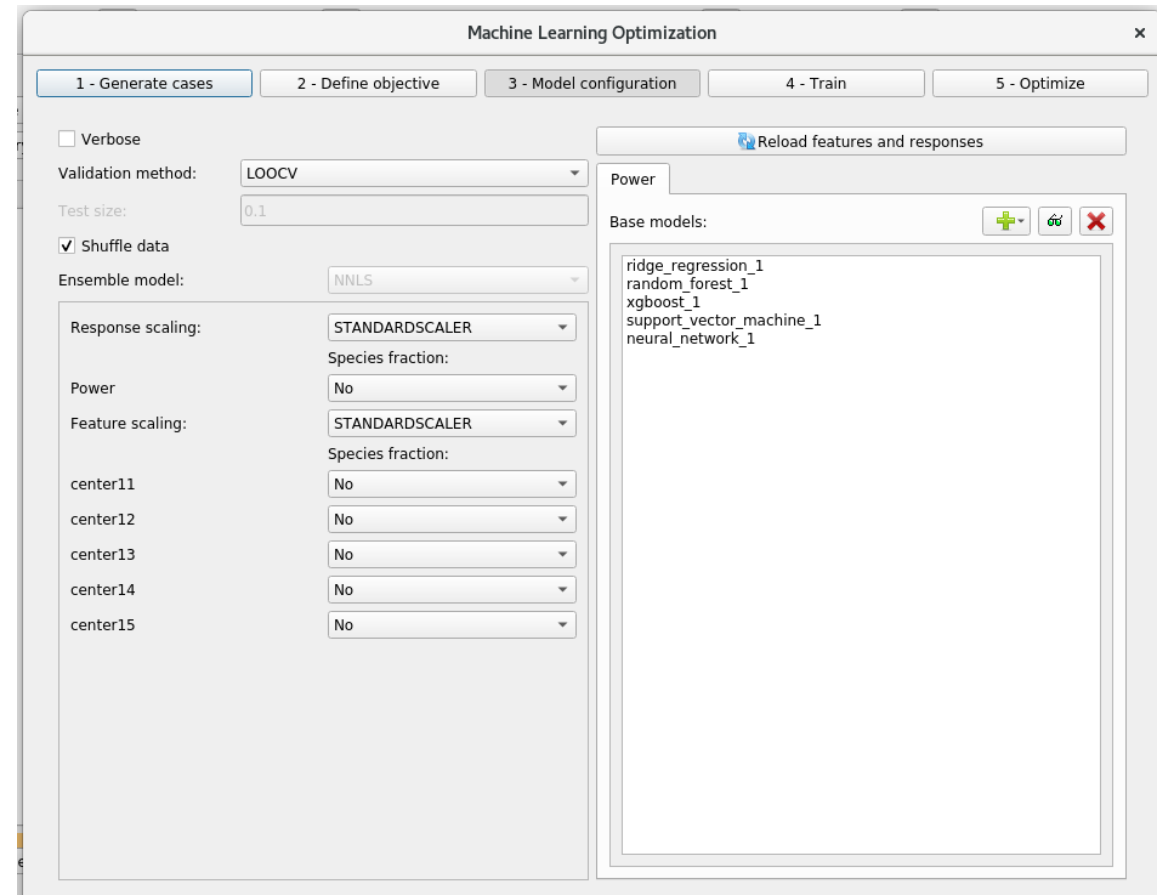
DoE Definition

- Augment design
 - Increase the number of 'cubes'
 - Find which cube each original DoE point belongs to
 - Place new designs in unoccupied cubes to create a valid DoE of total runs, iterate to maximize spacing
 - (Or as close to valid LHS as possible)



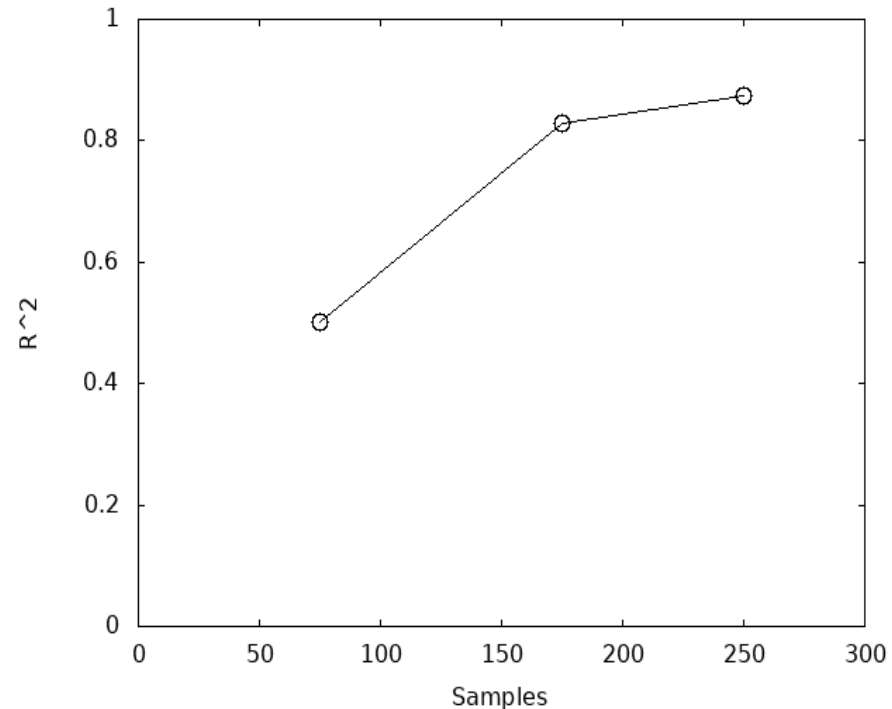
Meta Learner ML Model

- ‘Best’ machine learning algorithm is unknown a priori
- Meta learner combines multiple ML strategies
 - Ridge Regression
 - $\alpha=0.0001$
 - Random Forest
 - Depth 5, Trees 10
 - Gradient Boosting
 - Depth 5, Estimators 3000, learning rate 0.01
 - Support Vector Machine
 - $\text{Nu} = 0.5, C = 16$
 - Neural Network
 - 50 Neurons, 1 layer, Tanh activation, LBFGS optimizer
- Train/test method: “leave one out cross validation” (LOOCV)



Train/Test Results

- DOE 75: $R^2 = 0.50$
- DOE 175: $R^2 = 0.83$
- DOE 275: $R^2 = 0.87$



Machine Learning Optimization

1 - Generate cases | 2 - Define objective | 3 - Model configuration | 4 - Train | 5 - Optimize

Variable selection | Design of experiments

Method: Space Filling | Number of runs: 75 | Generate cases

Max iterations: 1000 | Load cases

	center	center	center	center	center
1	3335.88353671...	3408.86963264...	3521.40117626...	3653.41729102...	3650.3874278346702
2	3372.62679341...	3326.46159202...	3668.66031085...	3379.53719454...	3669.9556397811925
3	3519.40277247...	3387.27941588...	3632.38553860...	3579.70856205...	3584.261989716221
4	3356.10537784...	3625.10228044...	3653.01902746...	3417.99526067...	3547.7675472406645
5	3501.76838885...	3592.76897289...	3422.40336389...	3624.72709266...	3399.912331752146
6	3471.79911482...	3514.45646454...	3348.94068968...	3433.55963153...	3518.50299321524
7	3529.01912200...	3548.01006734...	3380.39122199...	3449.89284806...	3426.5284165772337
8	3590.11187669...	3562.91445083...	3536.81561348...	3607.26562403...	3515.724105392088
9	3671.07088887...	3467.66929788...	3452.64274236...	3387.93582961...	3384.8938649333145
10	3637.45967650...	3612.48845811...	3475.17502632...	3387.41818389...	3446.882960176252

Export cases path: | Export Cases

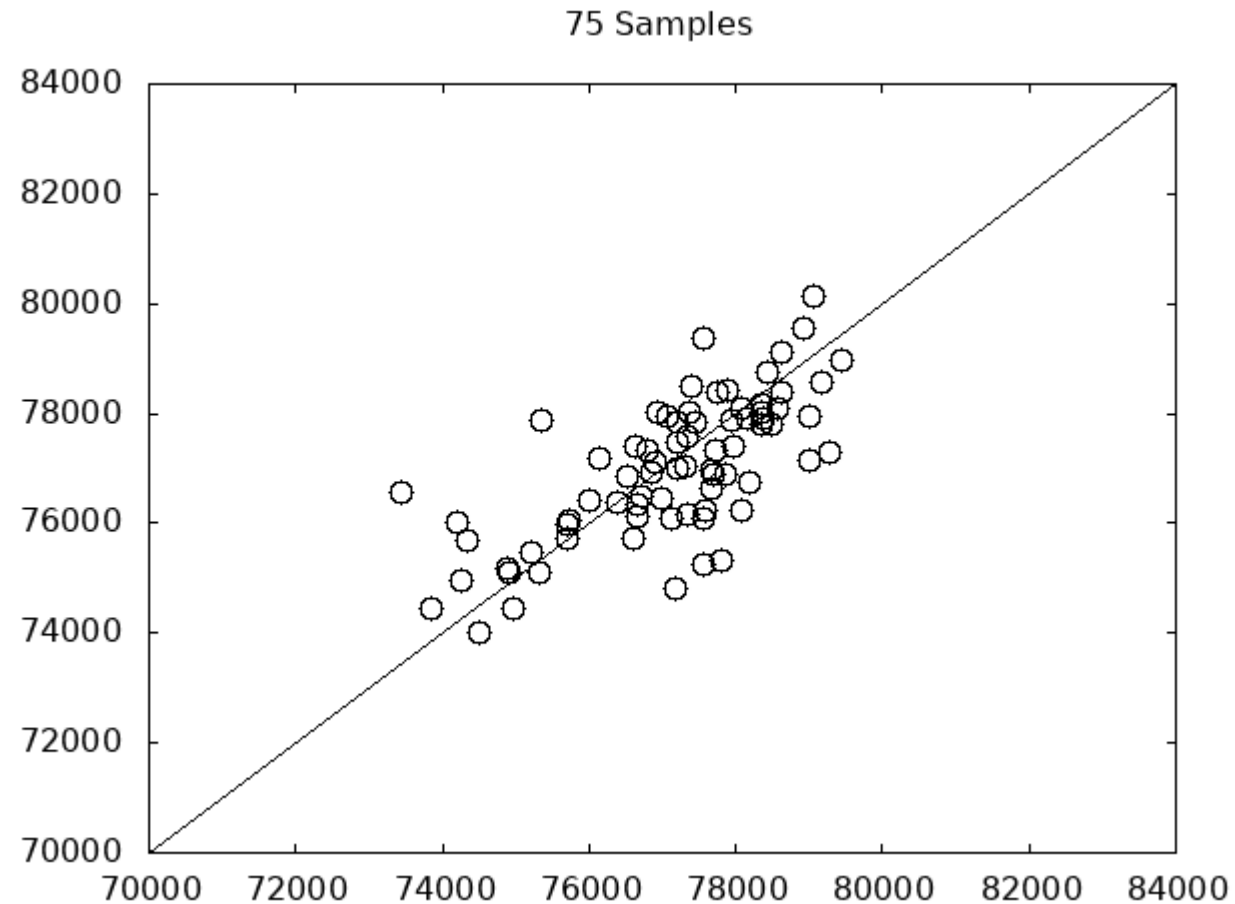
Clean folder before exporting

75 Cases successfully generated

Import | Export

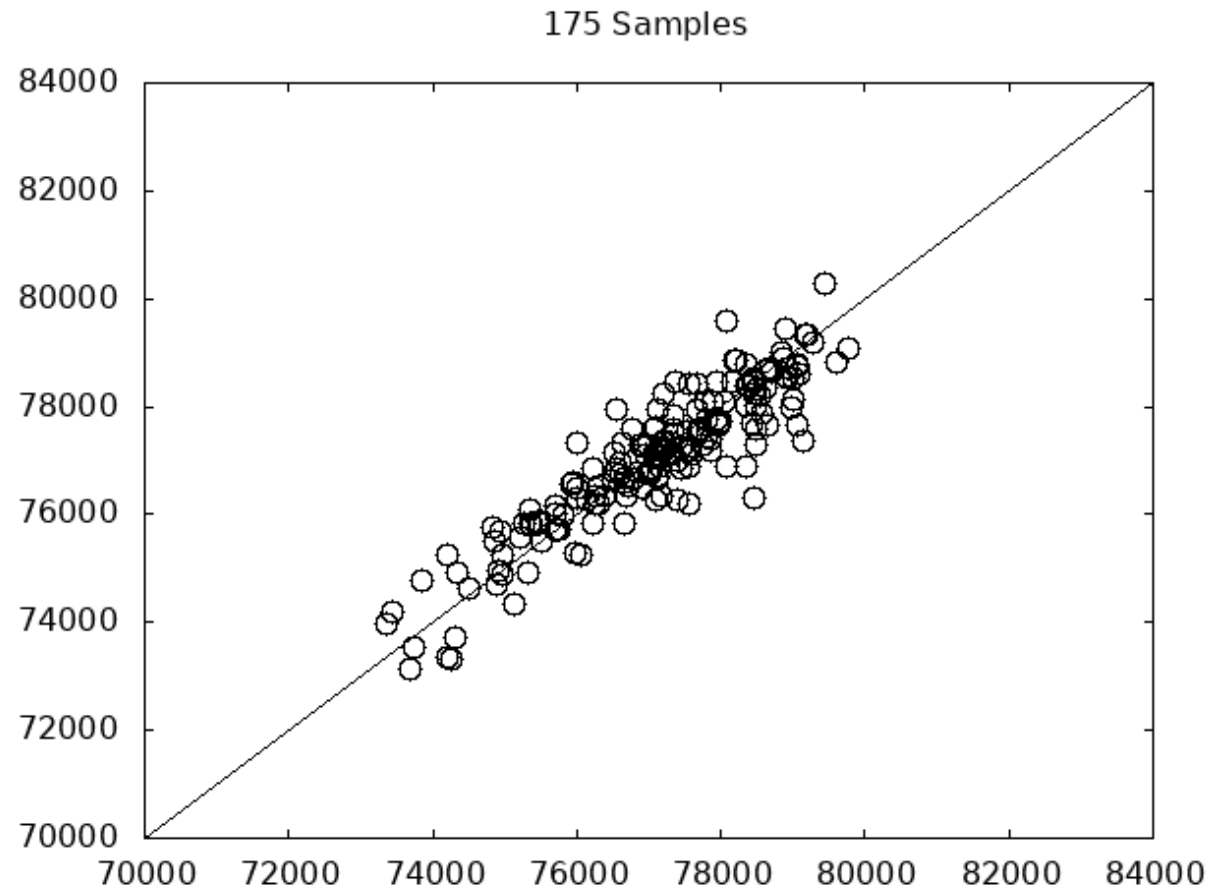
Train/Test Results, 75 Samples

- LOOCV test result
 - $R^2 = 0.50$
 - RMSE = 0.74



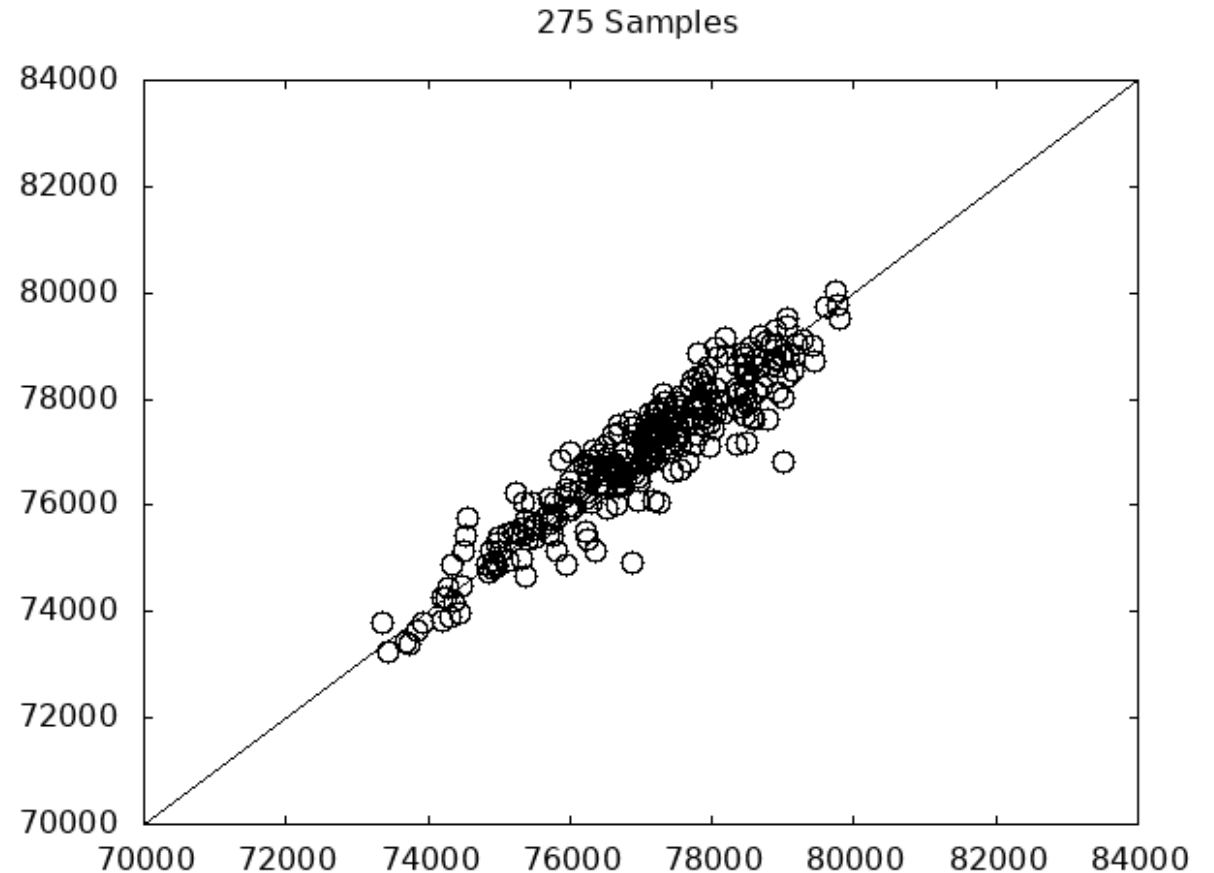
Train/Test Results, 175 Samples

- LOOCV test result
 - $R^2 = 0.83$
 - $RMSE = 0.42$



Train/Test Results, 275 Samples

- LOOCV test result
 - $R^2 = 0.87$
 - $RMSE = 0.36$
- If results have noise or variability, the upper limit on accuracy will be less than 1



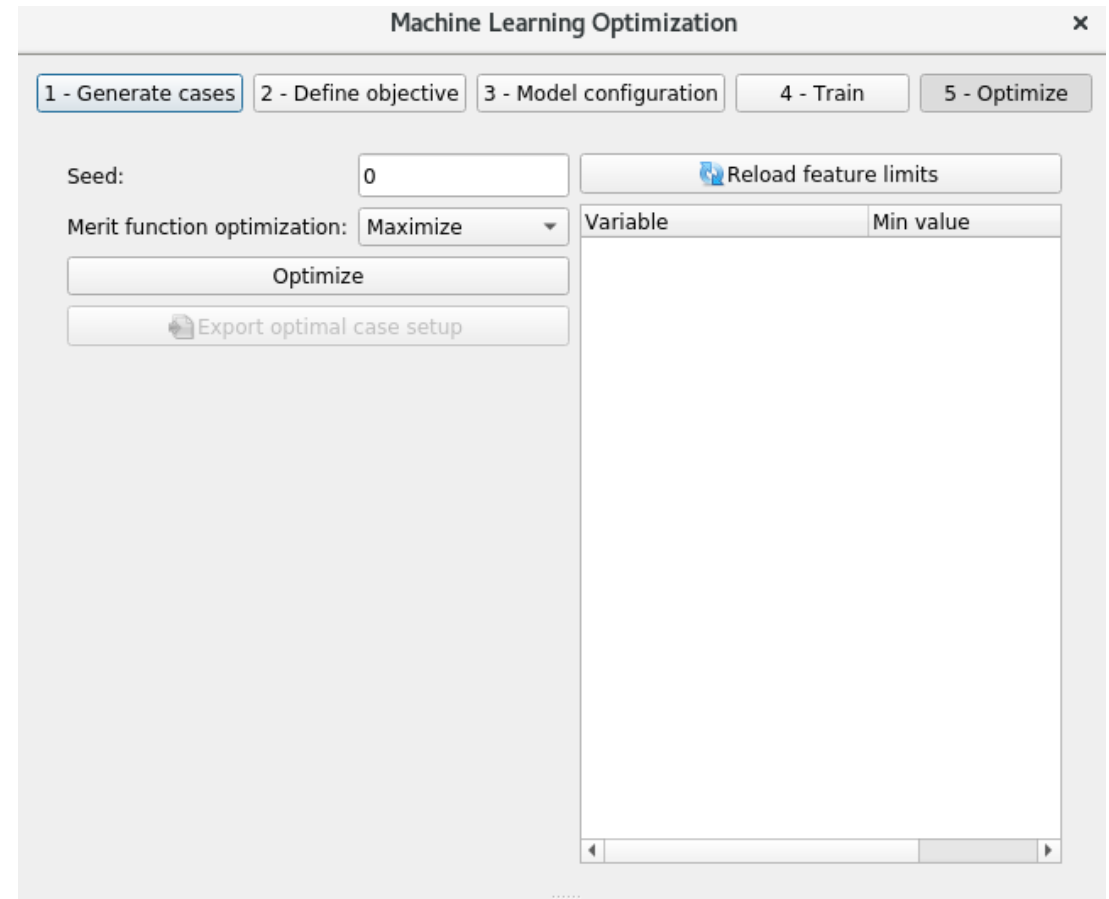
ML Model, 275 Runs

- 1 minute to train
- Each execution of trained model takes 0.0005 secs

Base_Model	CV_RMSE	Meta_Coeff
RidgeRegression_1	1.023179	0.000000
RandomForest1	0.880304	0.000000
XGBoost1	0.548271	0.070177
NuSVR1	0.359740	0.112523
NeuralNet1	0.176372	0.837697
MetaRMSE	1.651313e-01	1.000000

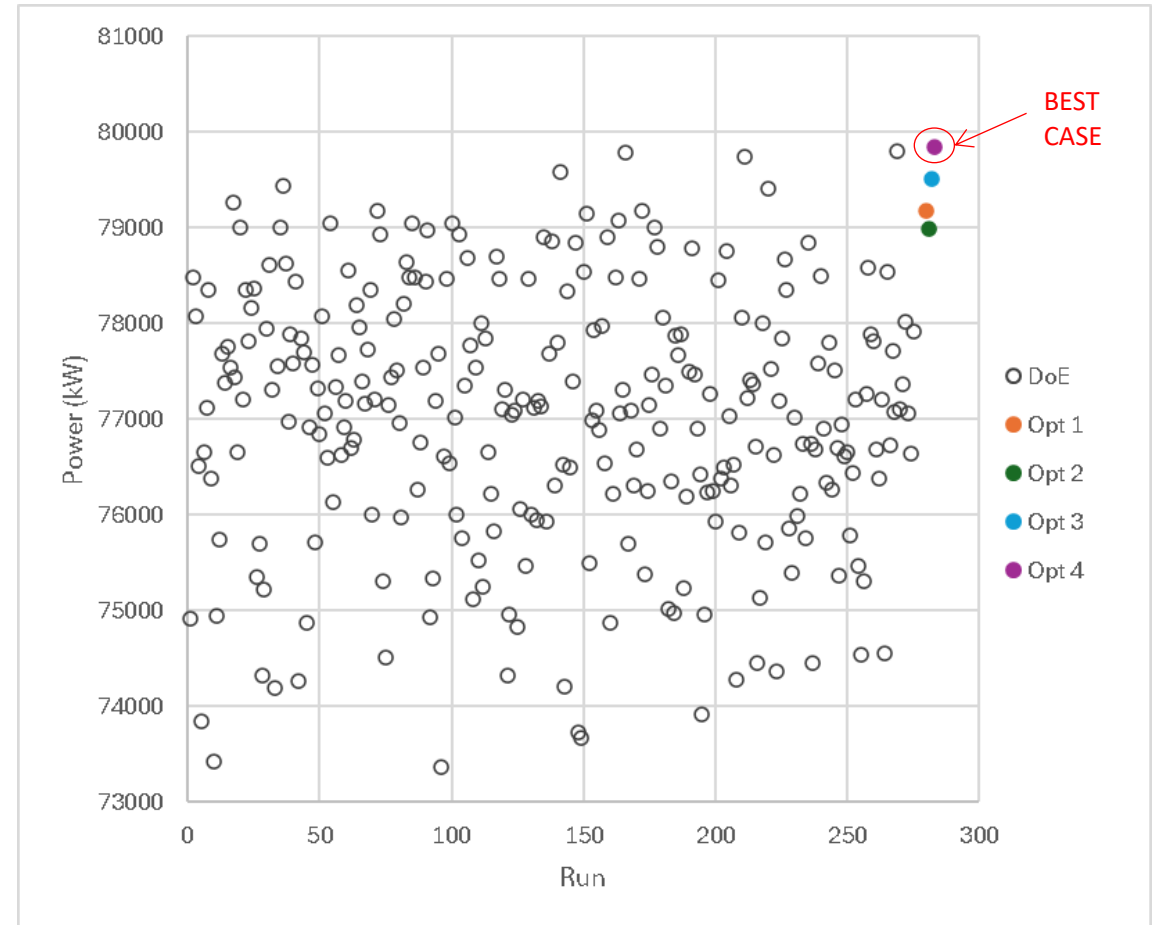
Optimization

- The ML emulator was optimized by the DIRECT algorithm
 - NLOPT library, global optimizer
 - Optimization 2.5 secs, 5000 evaluations
- The ML optimization ‘proposed’ optimum to be confirmed with CFD-predicted power



Active Learning Optimization

- The ML emulator was optimized to obtain a 'proposed' optimum that was run in CFD to obtain the power
- Four successive optimums were obtained until 'best' power case achieved
- Added to the training dataset to update the ML emulator



Optimum

Best case:

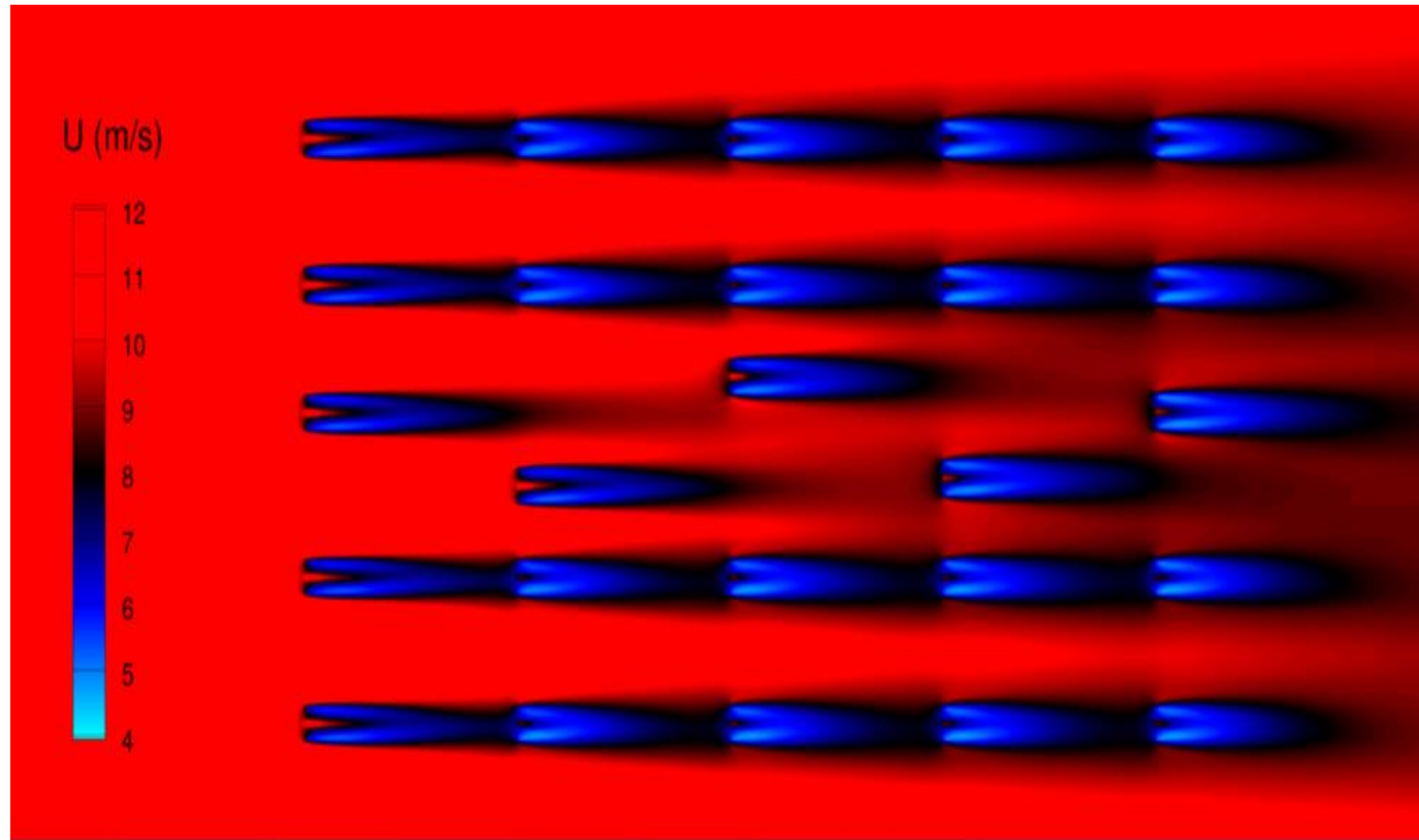
R11: 5354.52 kW

R12: 5144.49 kW

R13: 4121.79 kW

R14: 3209.89 kW

R15: 3183.21 kW



Conclusions

- DoE ML optimization method
 - Obtain DoE data in sequential batches until ML accuracy is achieved
 - Cost-effective method
 - DoE size unknown a priori (function of parameters and complexity of design space)
 - Optimize multiple times to enhance local accuracy near optimum: active learning
- Found an optimum wind farm layout for power production



THANK YOU!
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