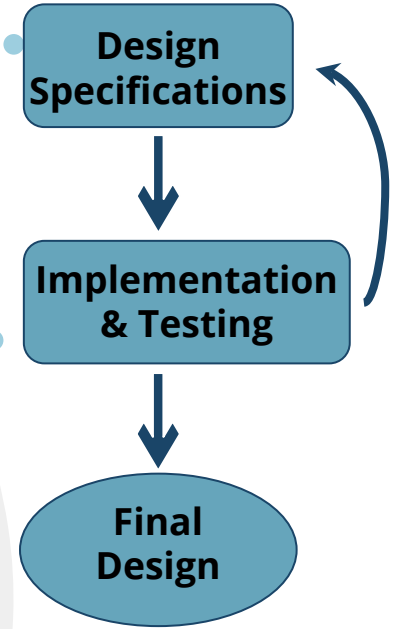
Inverse Design of Wave Energy Converter Using Artificial Intelligence

Christopher Snook

REU Mentor: Dr. Yufei Tang

Methods of Design



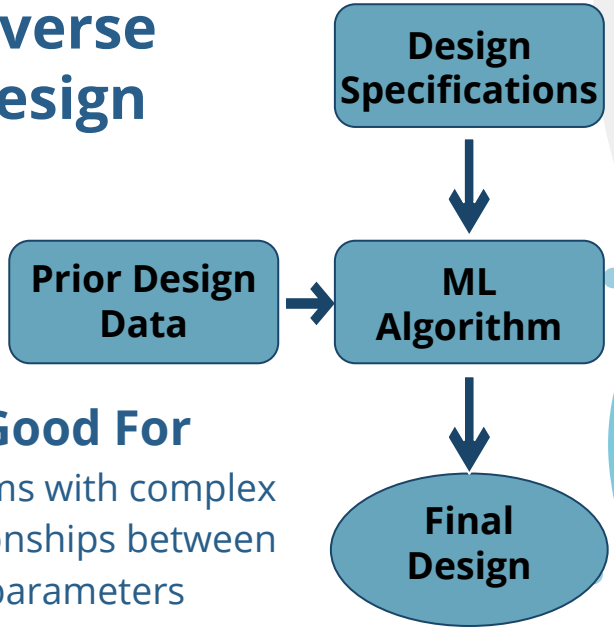
Traditional Design

Good For

Areas with few prior designs

Simple systems with describable relationships

Inverse Design

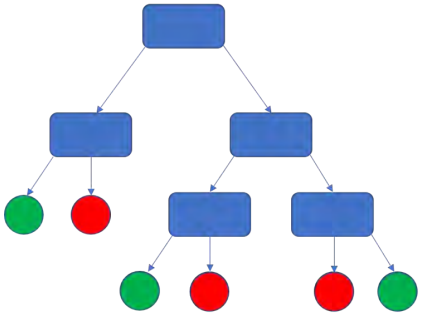


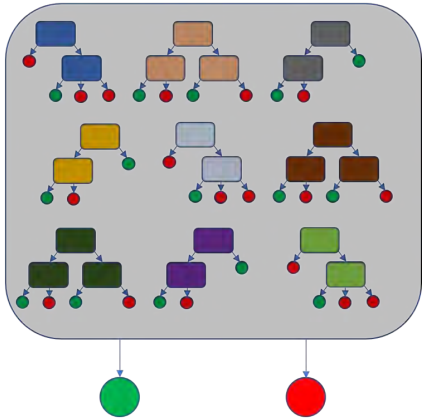
Good For

Systems with complex relationships between parameters

Efficient optimization

Machine Learning Algorithms





https://commons.wikimedia.org/wiki/File:Decision_Tree_vs._Random_Forest.png

Decision Tree

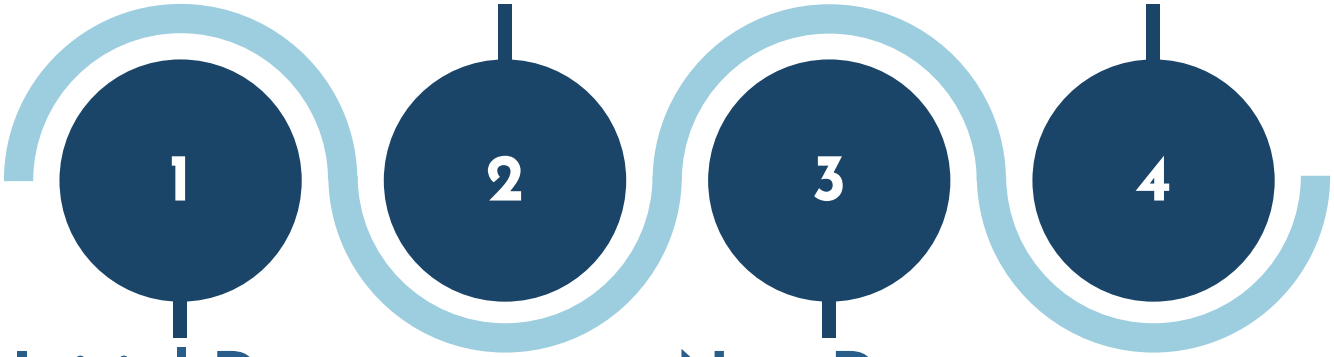
- Path of decisions from input to output
- Good for inverse design

Random Forest

- Combines multiple decision trees
- Generally more accurate than a decision tree

We need a decision tree to implement inverse design but want the accuracy of a random forest

Model Manipulation



Initial Data

Original dataset from simulation

Random Forest

High accuracy ML model

New Data

Large quantity (1000x size)

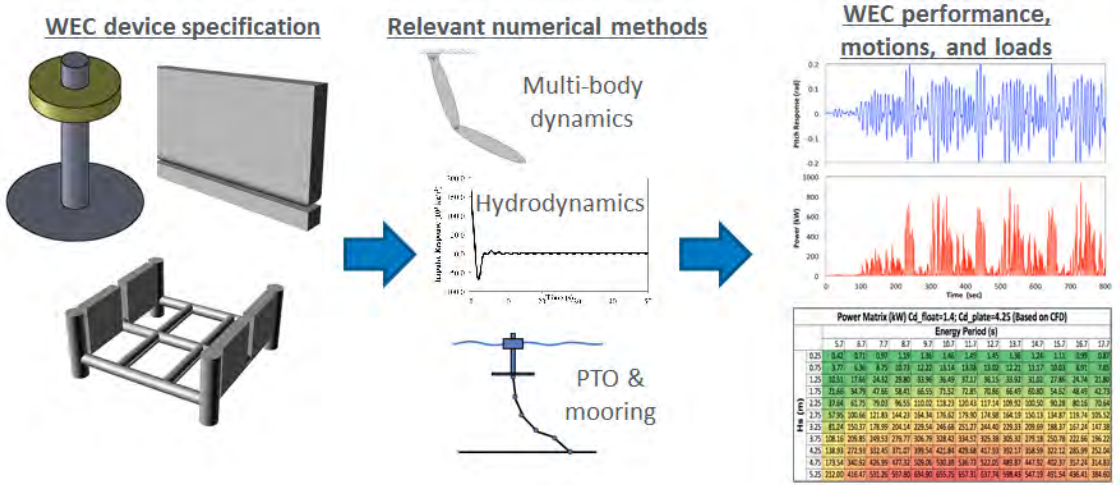
Decision Tree

Accurate and usable for inverse design

Initial Data Generation

WEC-SIM

Software developed by National Renewable Energy Lab and Sandia National Lab



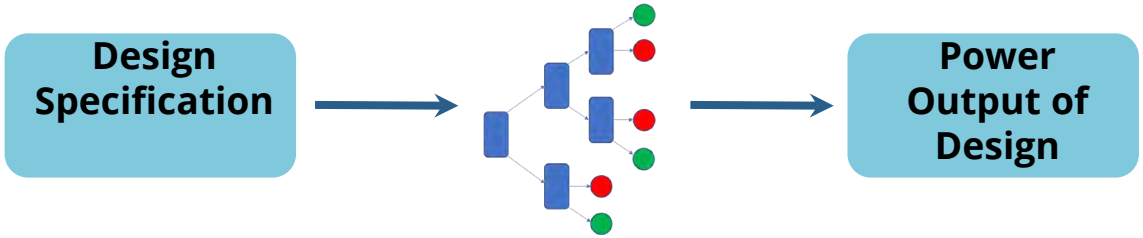
https://wec-sim.github.io/WEC-Sim/master/theory/theory.html

Data

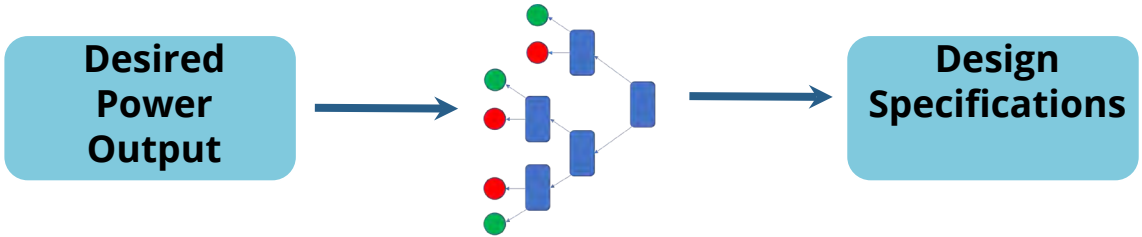
- RM3 wave energy converter
- Design variables
  - Damping coefficient
  - Mass of float
  - Mass of base
- Power as output
- 10000 data points generated

What the Model Does

Forward Design & Training



Inverse Design



Results

Accuracy

R^2 of DT trained on original data: 0.9999827285388839

R^2 of RF trained on original data: 0.9999785551484541

Efficiency

Initial data generation: ~7s/sample

Model training and analysis: 3s total

Conclusions

Was this practical?

- Inverse design worked
- Actual results were limited due to data

What next?

- More Data
- More complex systems
- Optimize ML algorithm