

# Design Optimization of Floating Offshore Wind Turbine Substructures using Frequency Domain Dynamic Model and Genetic Algorithm

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*This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement N° 860879.*



# Floating Offshore Wind



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- High potential Worldwide, particularly in Europe



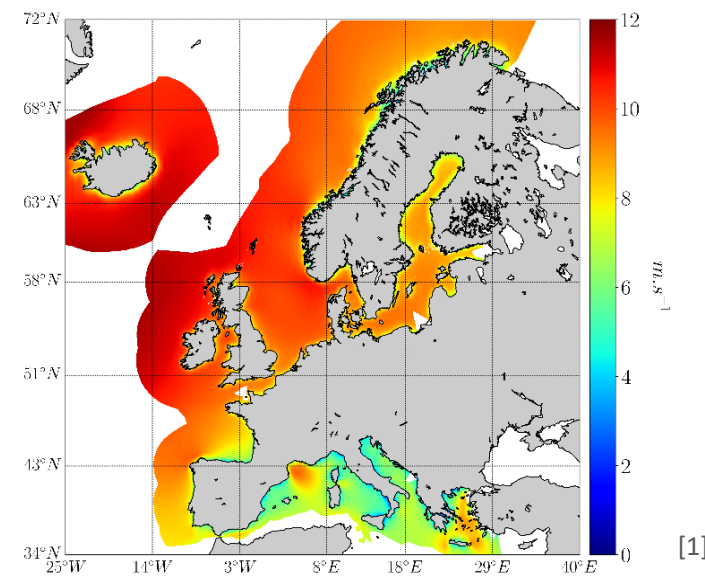
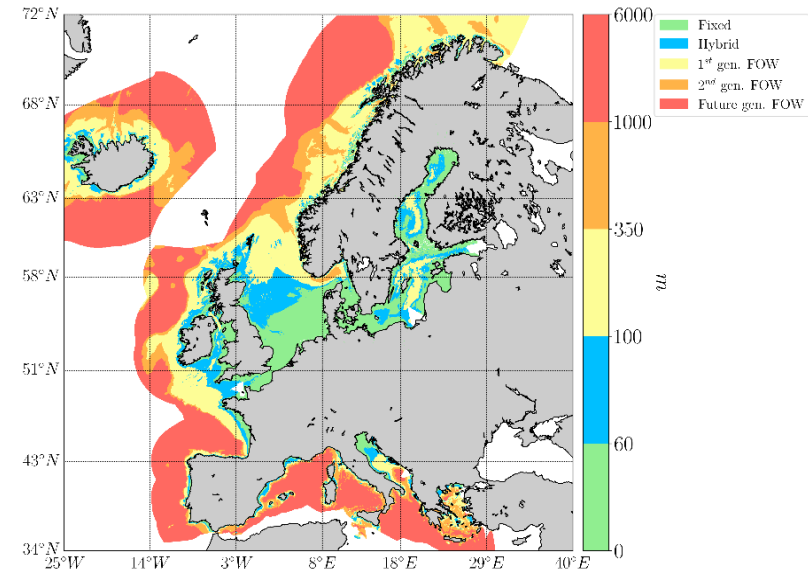
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- High potential Worldwide, particularly in Europe
- Higher wind loads and extreme sea state



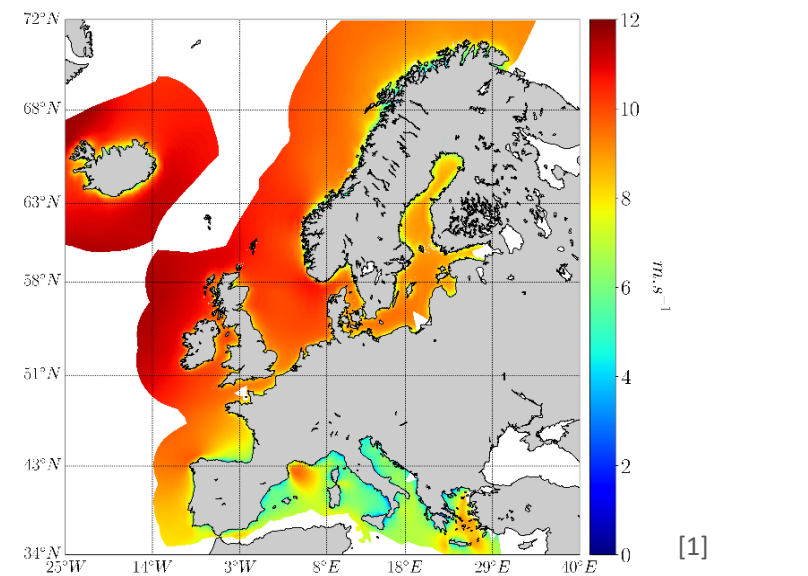
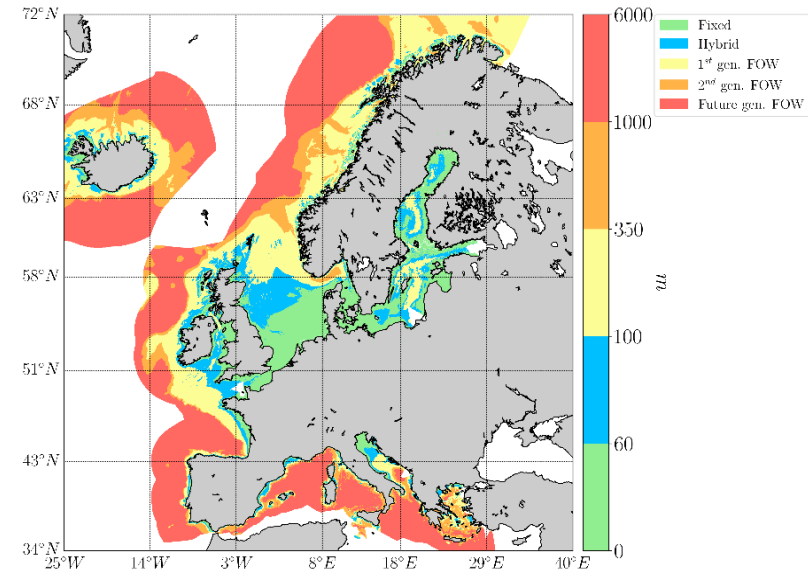
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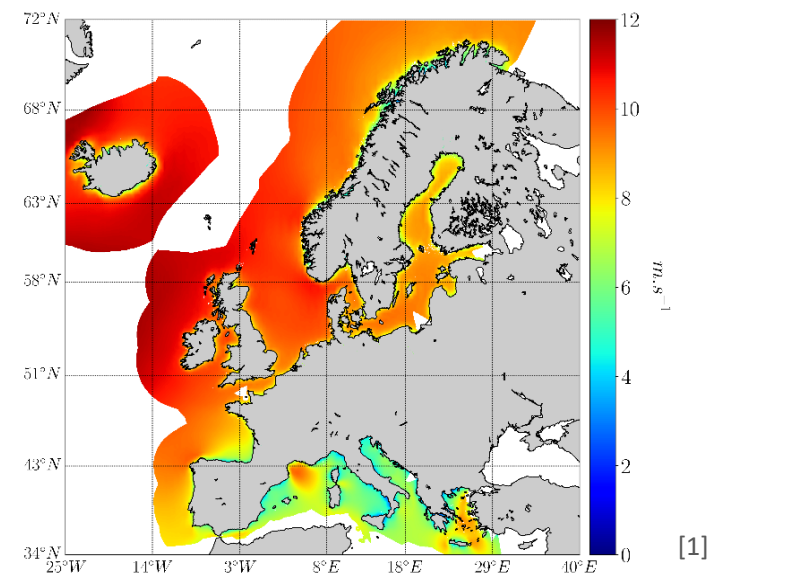
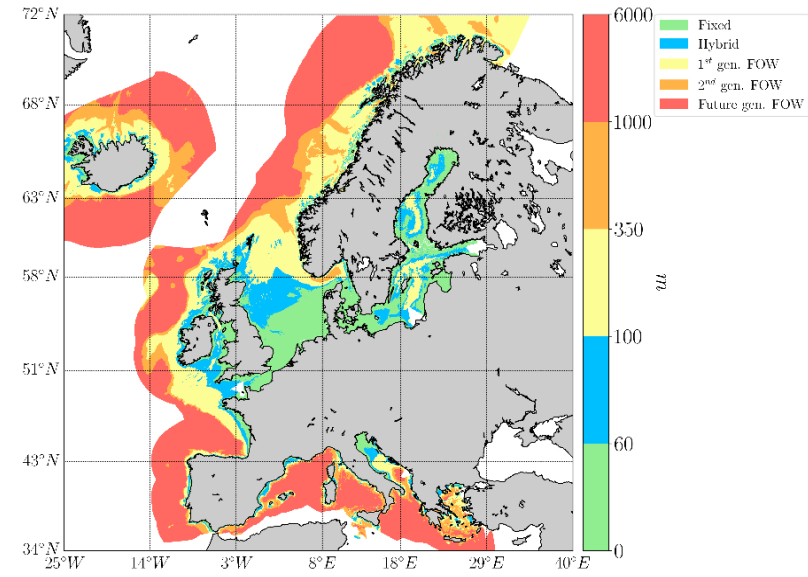


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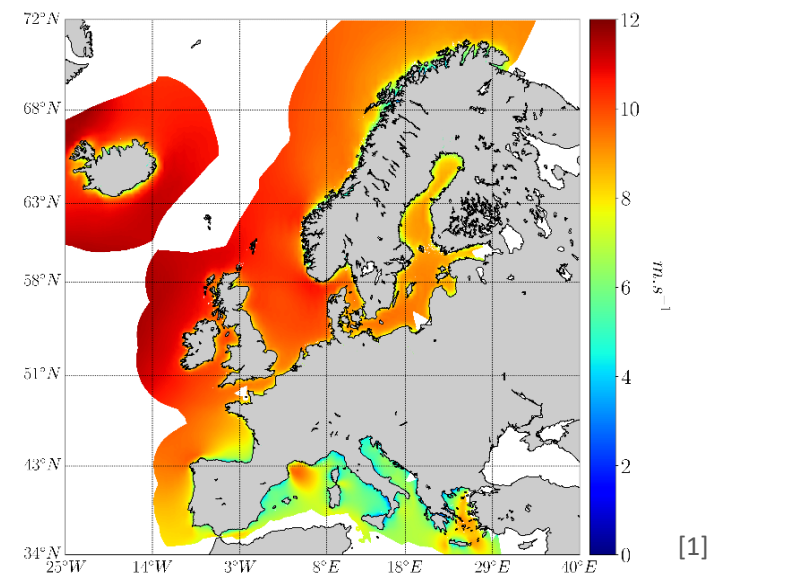
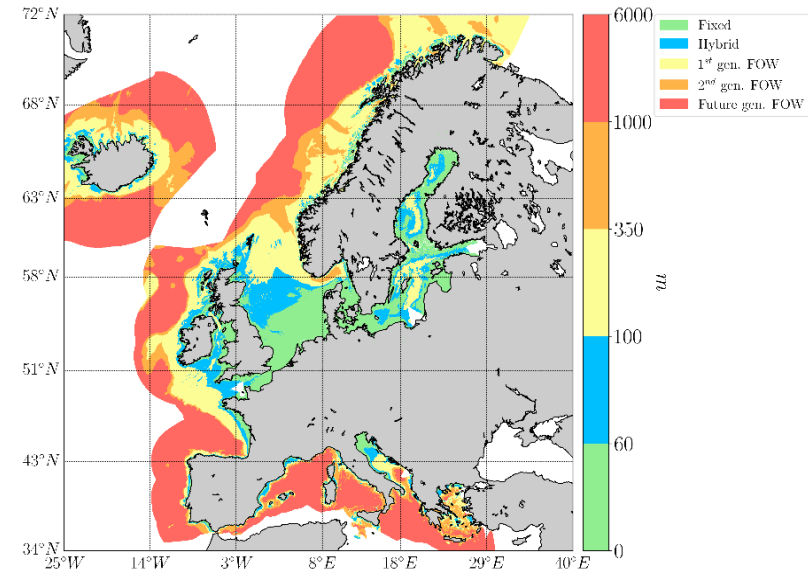
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- ❑ Different type of substructures
- ❑ Complex manufacturing and low production rate
- ❑ High Levelized Cost of Energy



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# The GICON-TLP







# The GICON-TLP

□ Steel and concrete Tension Leg Platform



[2]



# The GICON-TLP

- ❑ Steel and concrete Tension Leg Platform
- ❑ Simple manufacturing and installation process
  - 4 buoyancy bodies
  - diagonal, vertical and horizontal pipes



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- ❑ Steel and concrete Tension Leg Platform
- ❑ Simple manufacturing and installation process
  - 4 buoyancy bodies
  - diagonal, vertical and horizontal pipes
- ❑ Numerical and experimental analysis
- ❑ Optimization framework for the design of the Universal Buoyancy Body (UBB) <sup>[3]</sup>



[2]



# Design Optimization Framework



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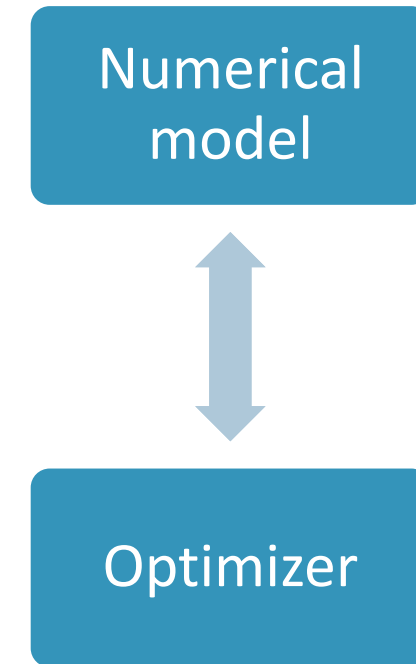
# Design Optimization Framework

- Numerical model: frequency domain dynamic model

Numerical  
model

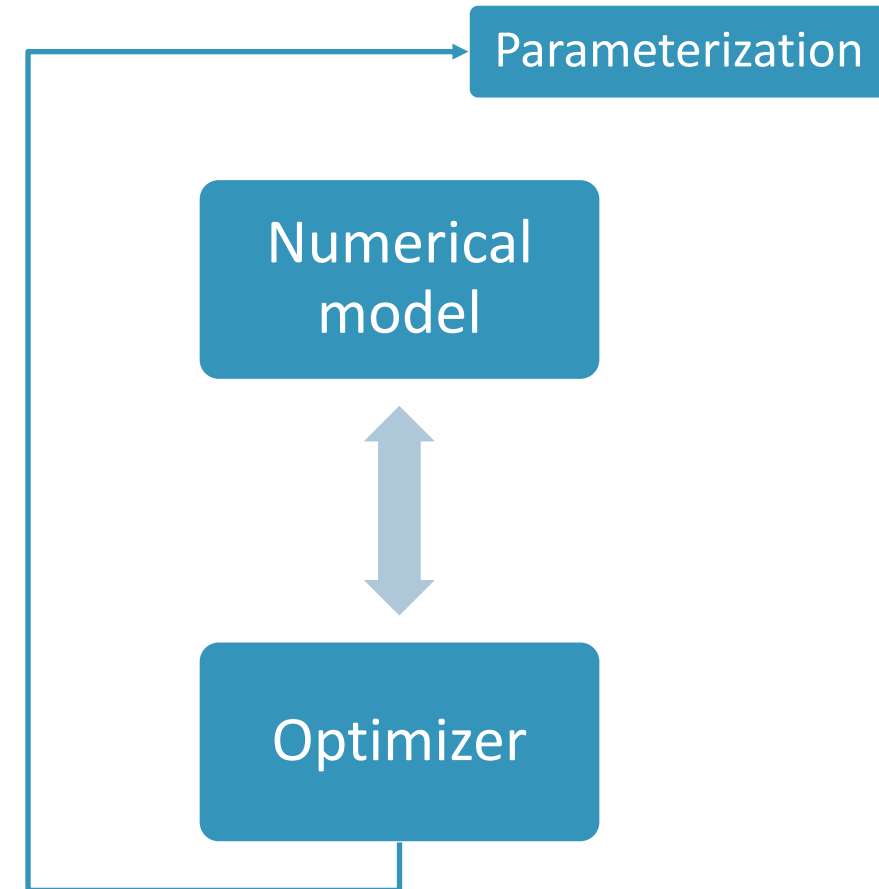
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- ❑ Numerical model: frequency domain dynamic model
- ❑ Optimizer: genetic algorithm
- ❑ Design parameterization: geometrical

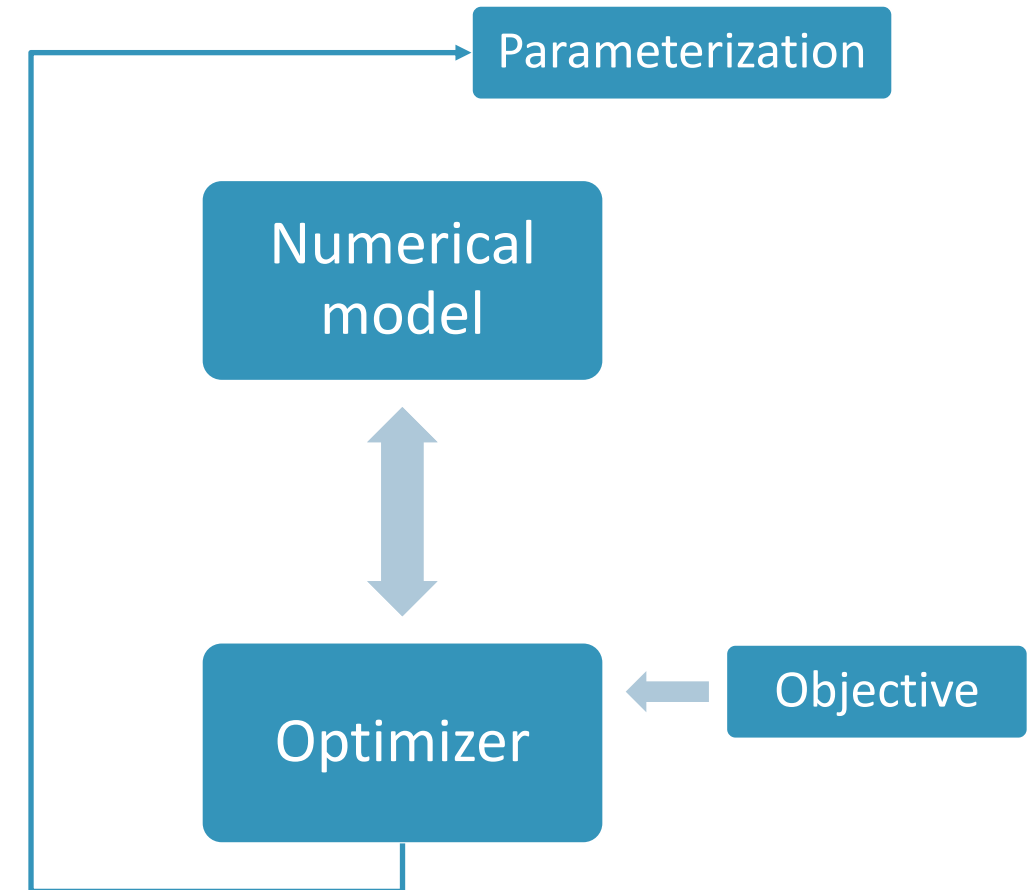






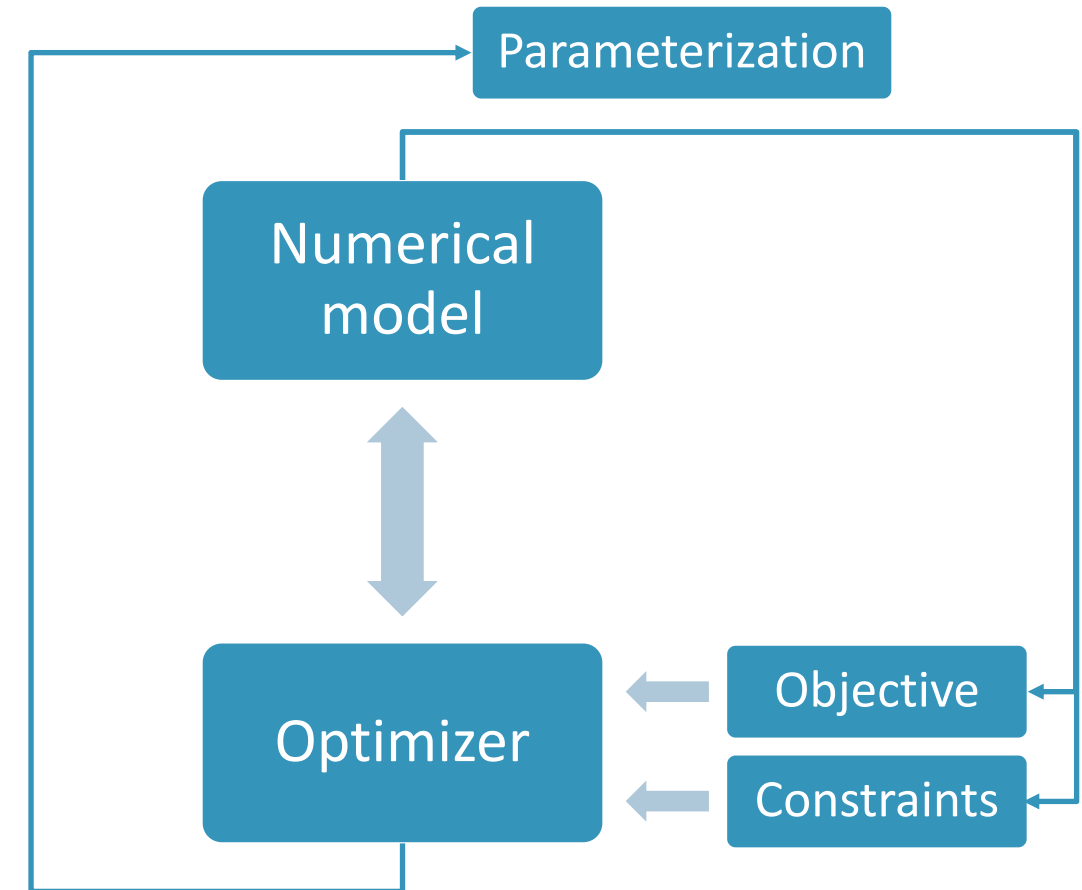
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- ❑ Design parameterization: geometrical
- ❑ Objective: minimize the substructure's mass/cost
- ❑ Constraints: system's dynamic response





# Numerical model



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# Numerical model

Response Amplitude for Floating Turbine (RAFT) <sup>[4]</sup>



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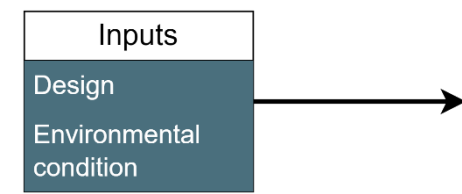
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  - Moorings: quasi-static model



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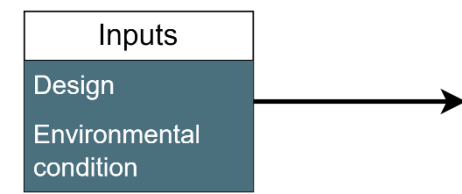
□ GICON-TLP with IEA 15-MW wind turbine





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- GICON-TLP with IEA 15-MW wind turbine
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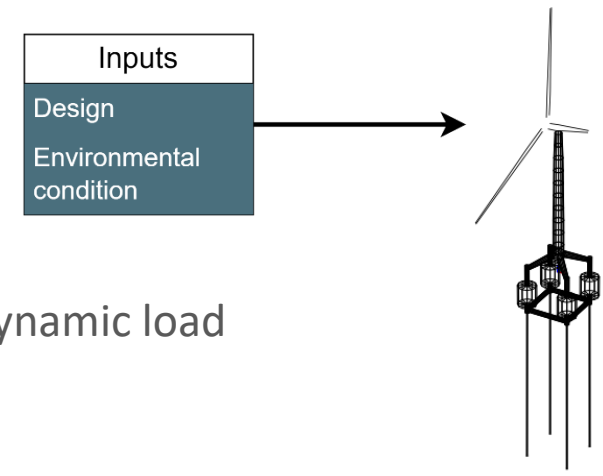




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## □ GICON-TLP with IEA 15-MW wind turbine

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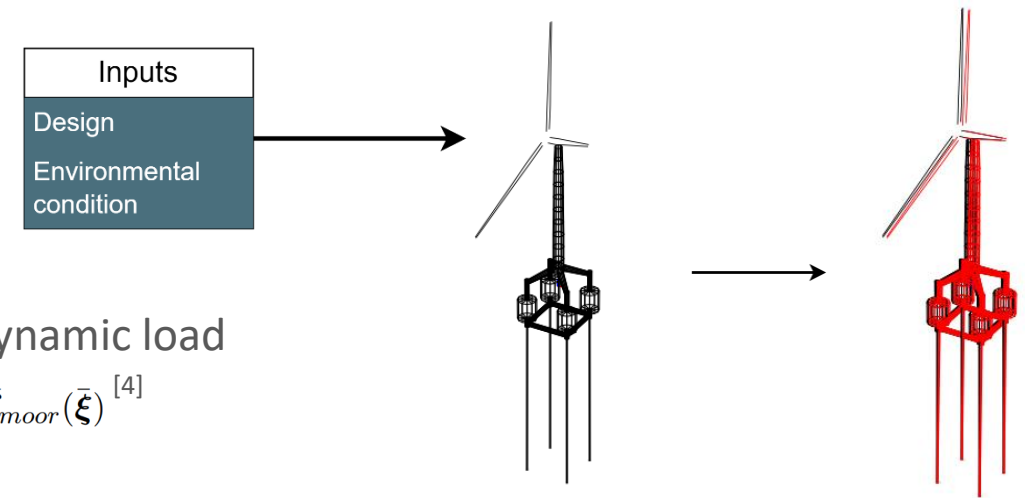


# Numerical model

## □ GICON-TLP with IEA 15-MW wind turbine

- mass and hydrostatic properties
- linear hydrodynamic coefficients and mean aerodynamic load
- solve mean offset position

$$C_{struc} \bar{\xi} = \bar{f}_{aero} + \bar{f}_{hydro} + \bar{f}_{moor}(\bar{\xi})^{[4]}$$

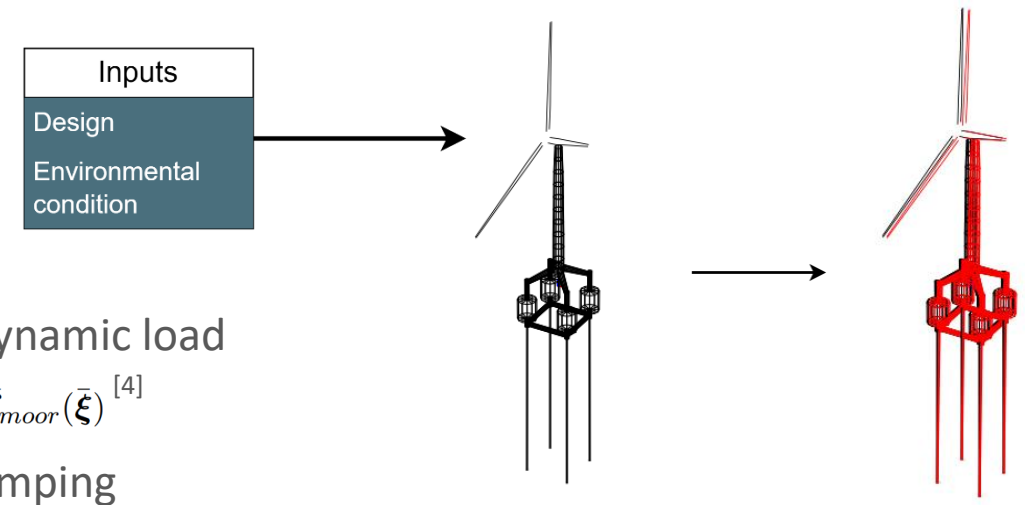




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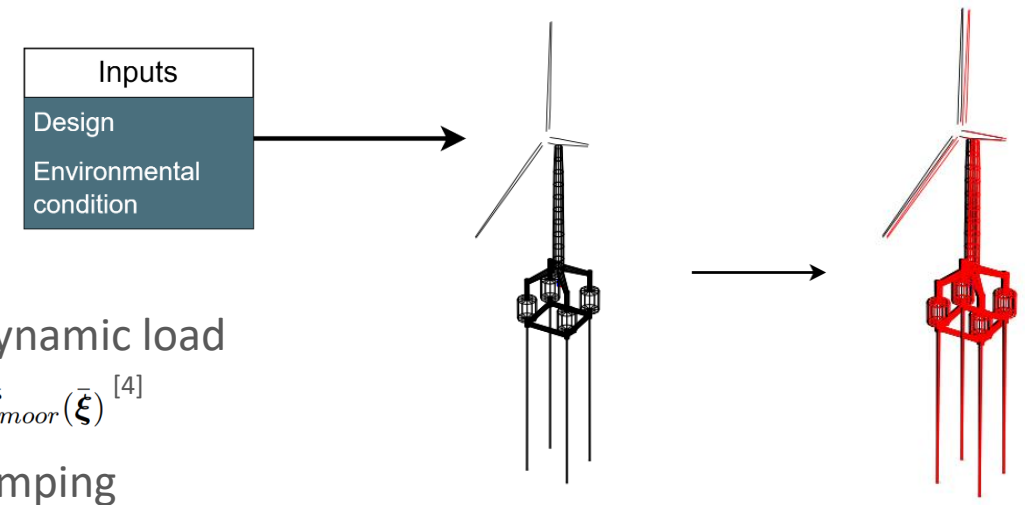


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$$(-\omega^2 [\mathbf{M}_{struc} + \mathbf{A}_{sub}(\omega) + \mathbf{A}_{aero}(\omega)] + i\omega [\mathbf{B}_{sub}(\omega) + \mathbf{B}_{aero}(\omega)] + \mathbf{C}_{struc} + \mathbf{C}_{moor}) \hat{\xi}(\omega) = \hat{\mathbf{f}}(\omega)$$
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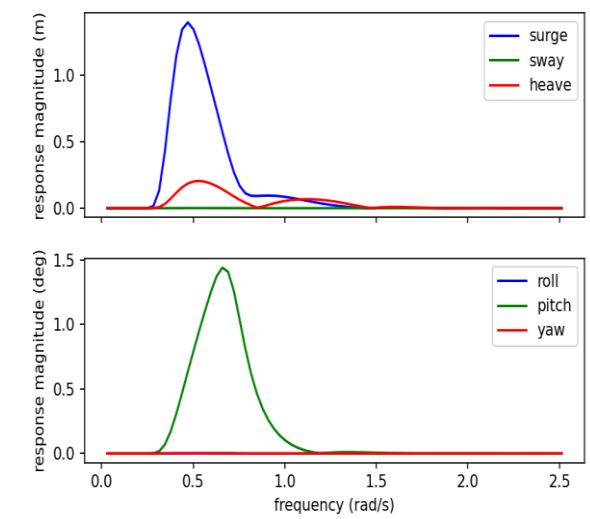
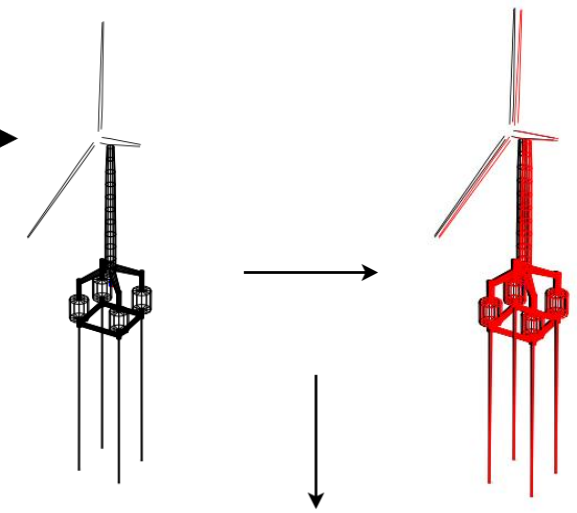
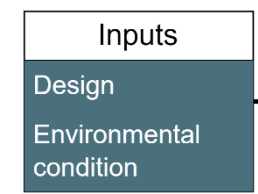
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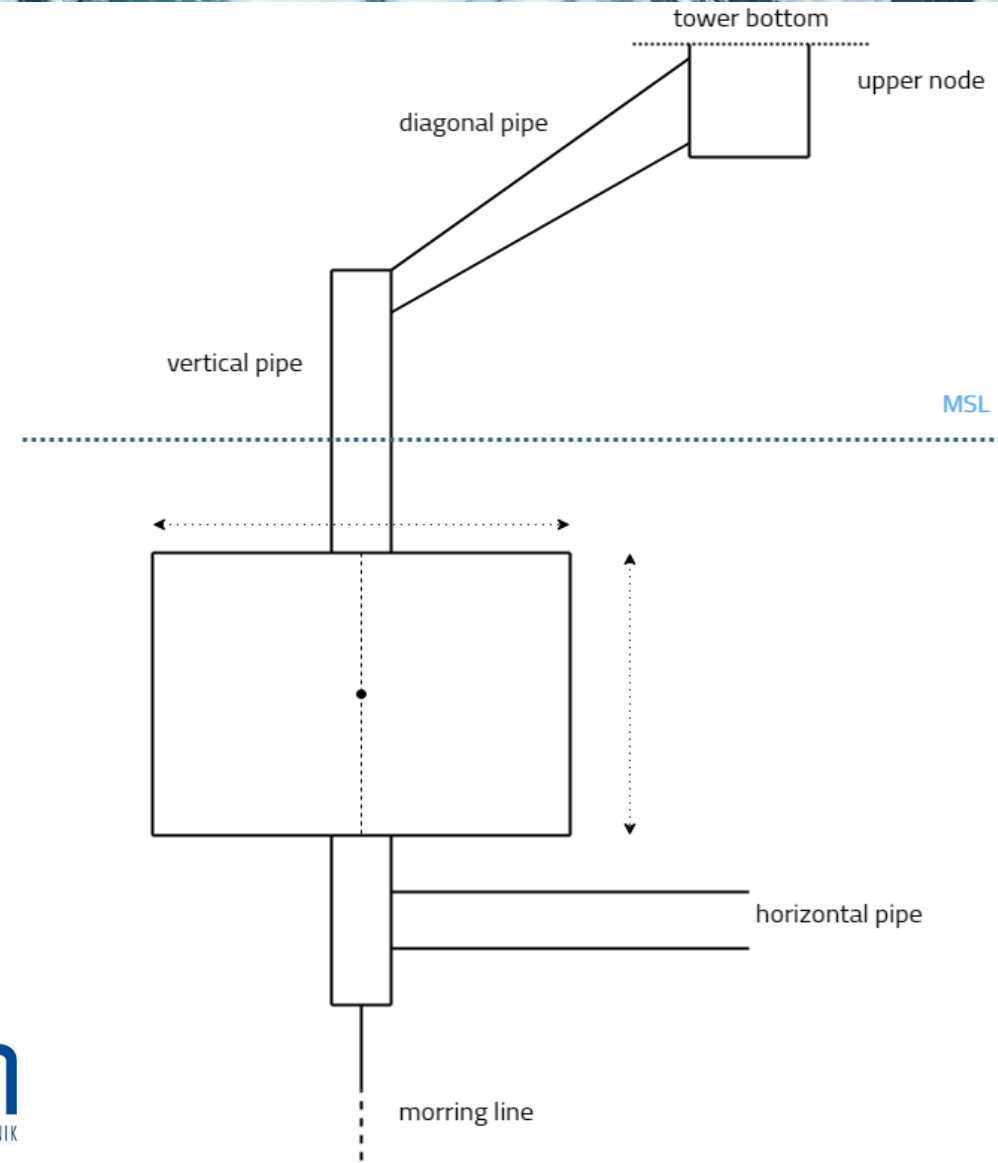
- get system's mean offset and extreme values from standard deviations (RMS) of the response spectra.







# Design parameterization



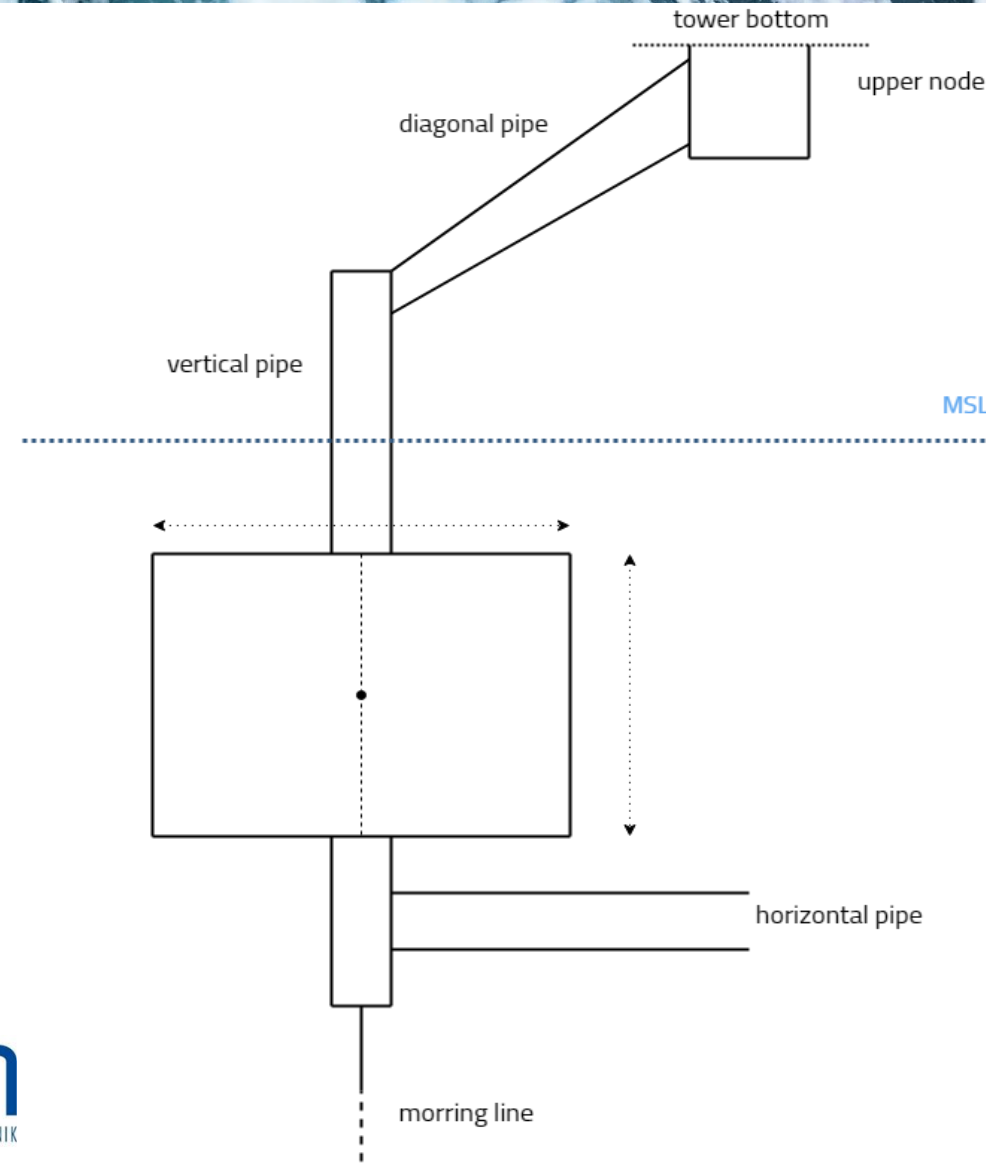


# Design parameterization

[5]

## □ IEA 15MW wind turbine:

- $D_{rot} \sim 240 \text{ m}$ ,  $RNA_{mass} \sim 1000 \text{ t}$
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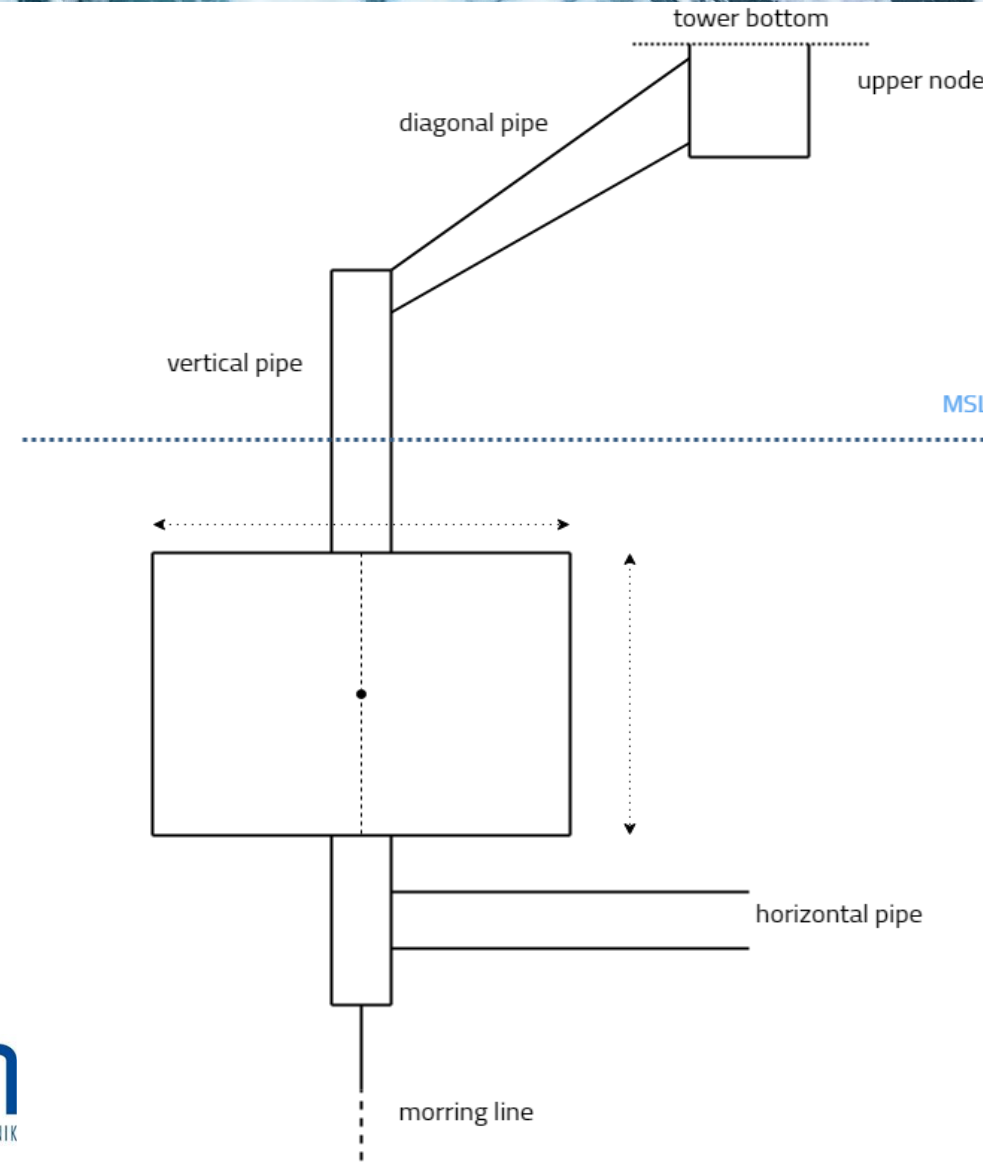
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## □ Mooring lines:

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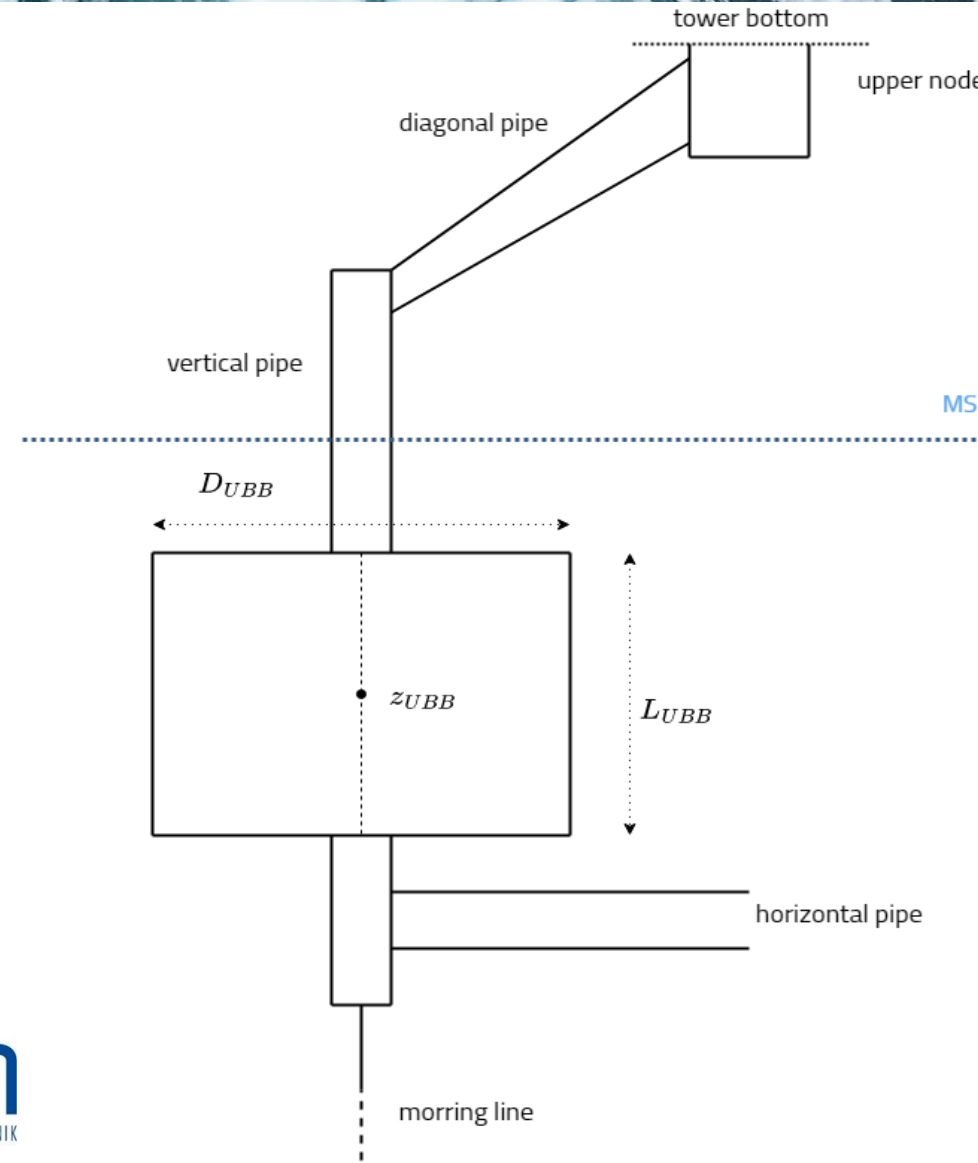
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## Design variables:

- length  $L_{UBB}$  and diameter  $D_{UBB}$
- center  $z_{UBB}$





# Optimizer: Genetic Algorithm



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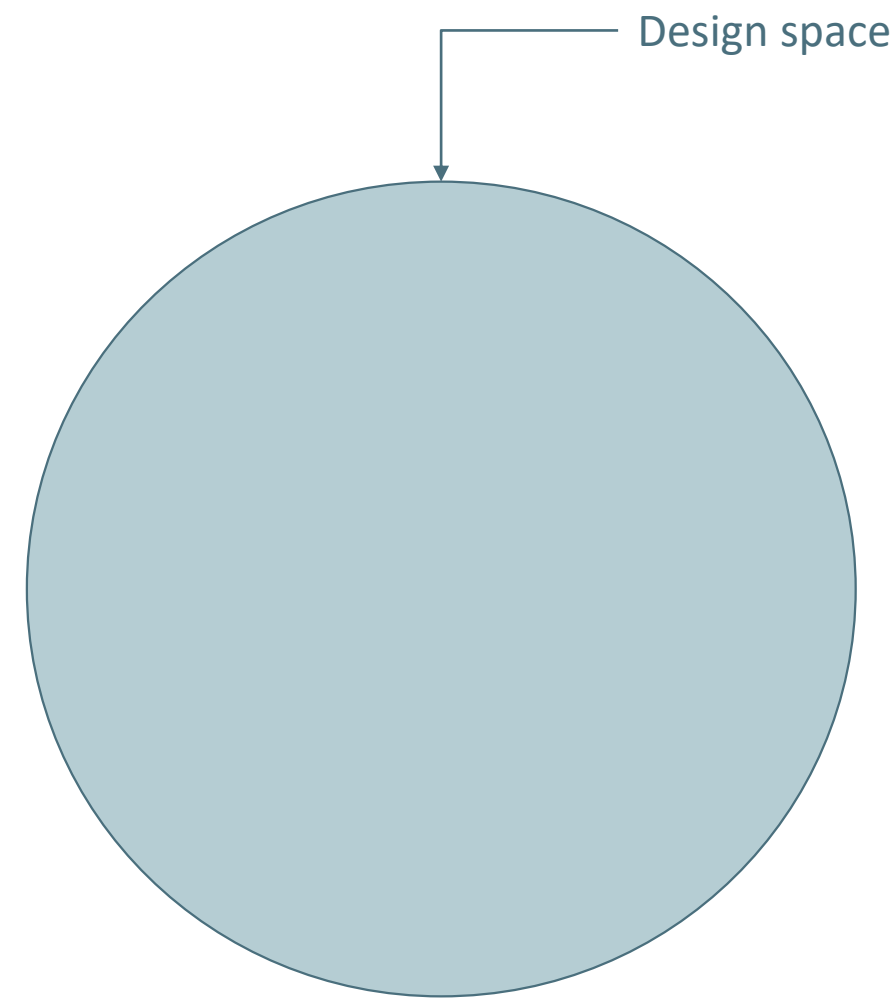
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- ❑ Fitness:  $-1 * M_{\text{substructure}}$
- ❑ Constraint handling technic: efficient penalty function
- ❑ Fitness scaling and addition operation: <sup>[6]</sup>
  - global and Local optima
  - fewer fitness function evaluation



# Optimizer: Genetic Algorithm

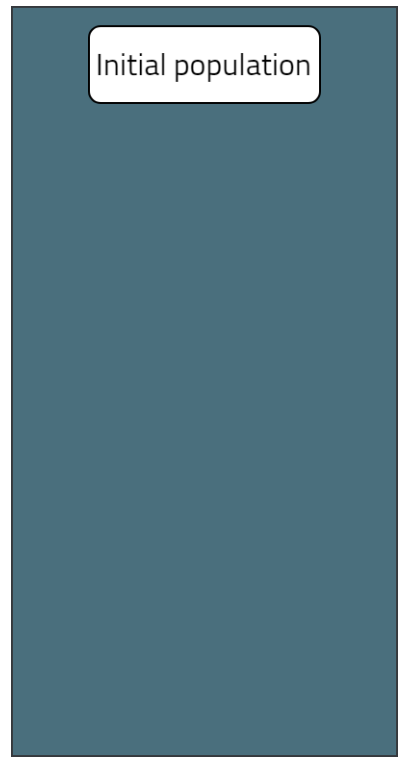




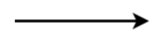
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Indiviudal ●

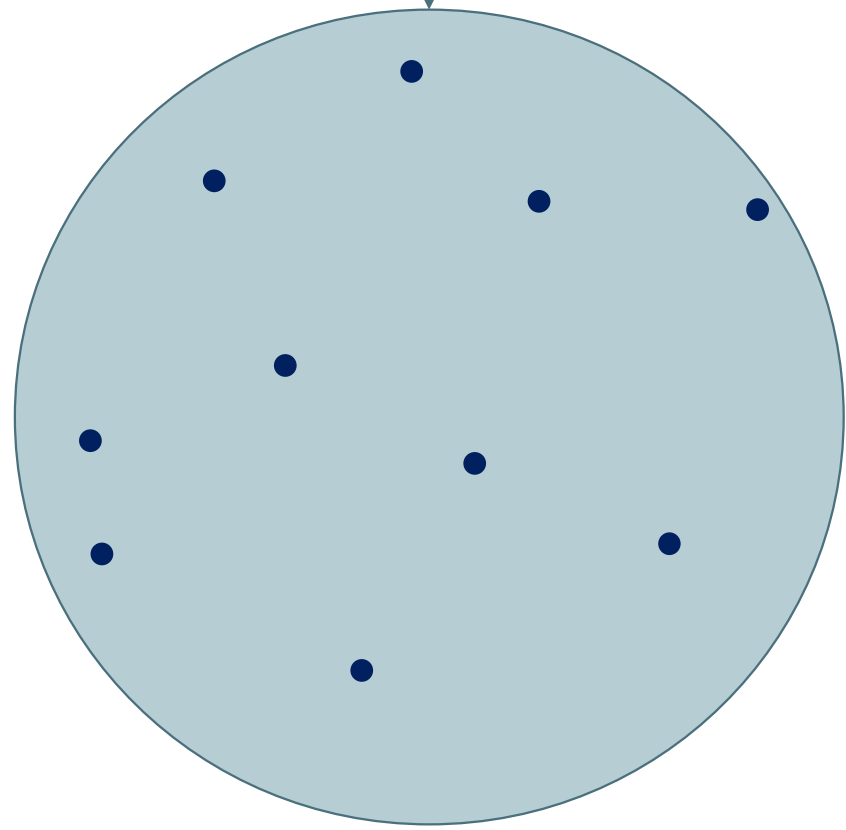
Design space



Initial population



Latin Hypercube Sampling



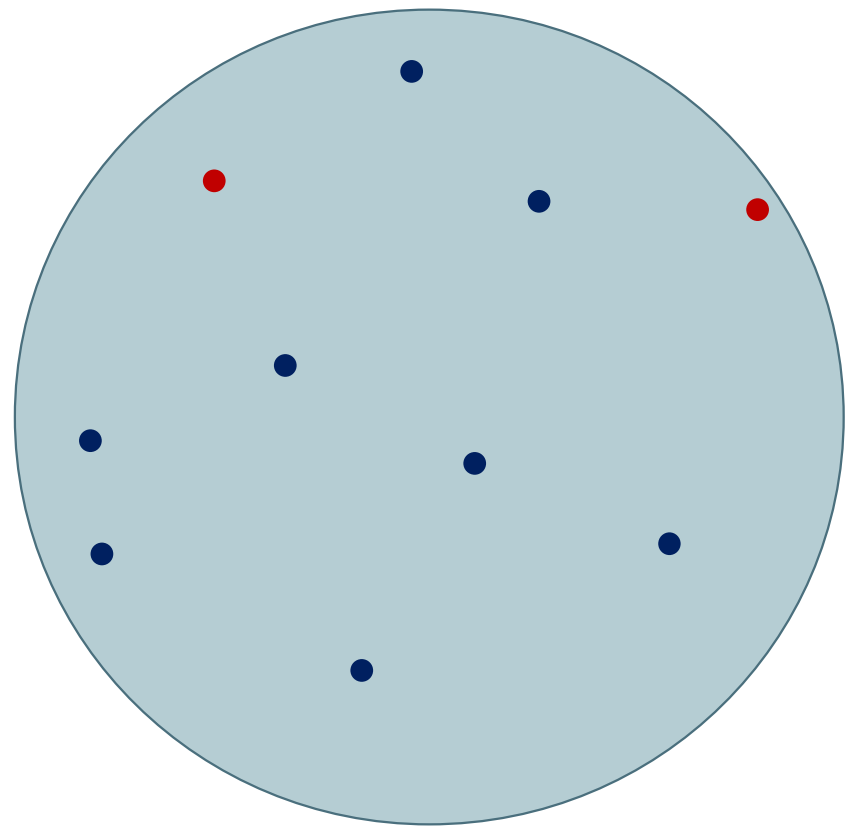


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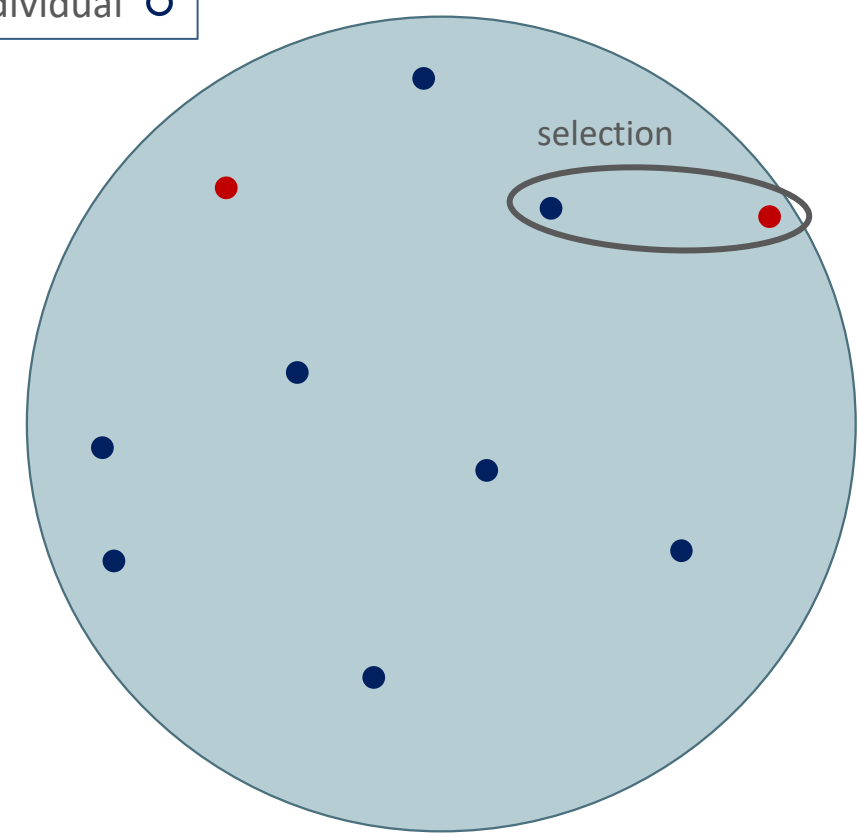
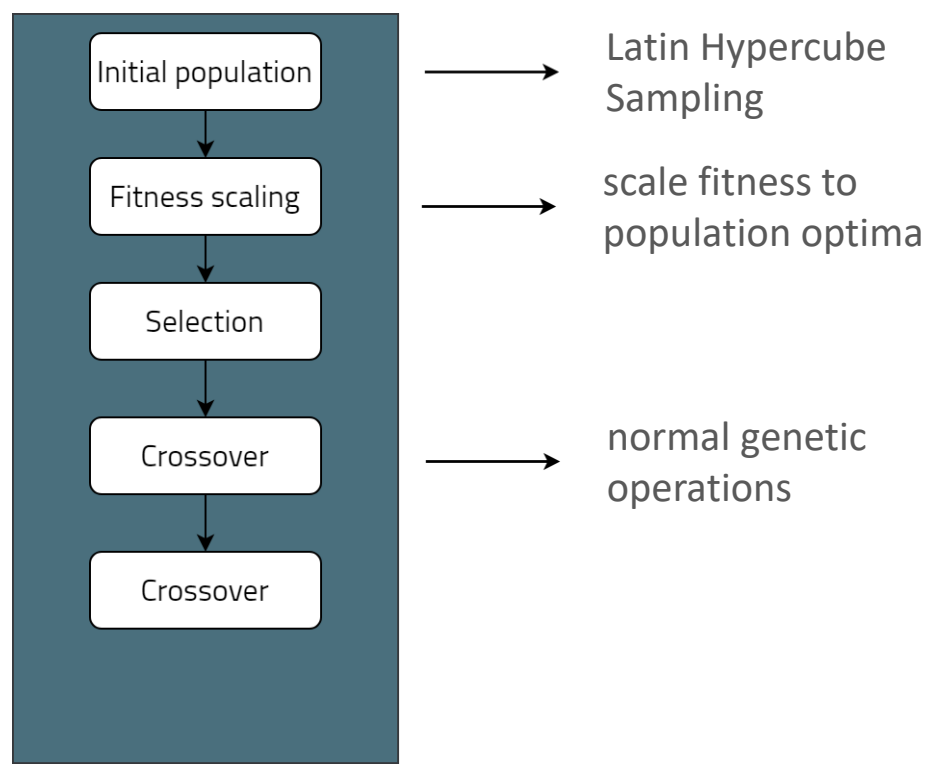
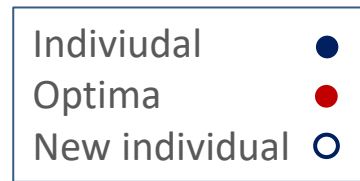


Latin Hypercube Sampling  
scale fitness to population optima





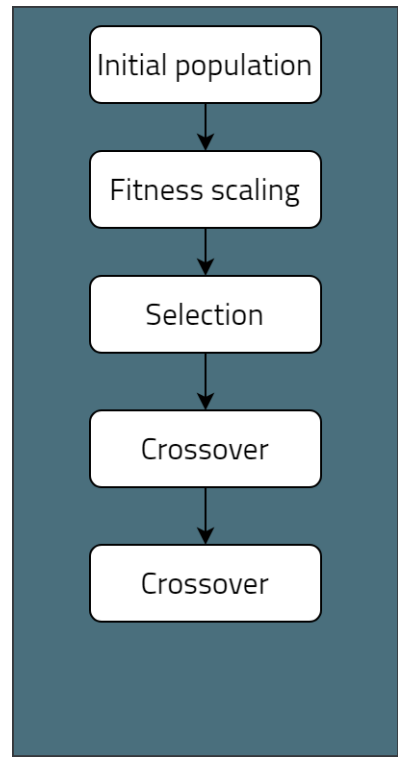
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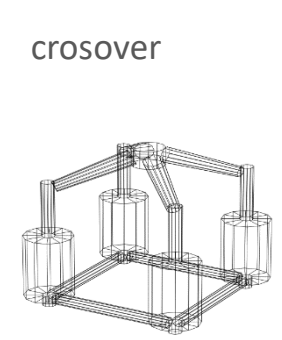
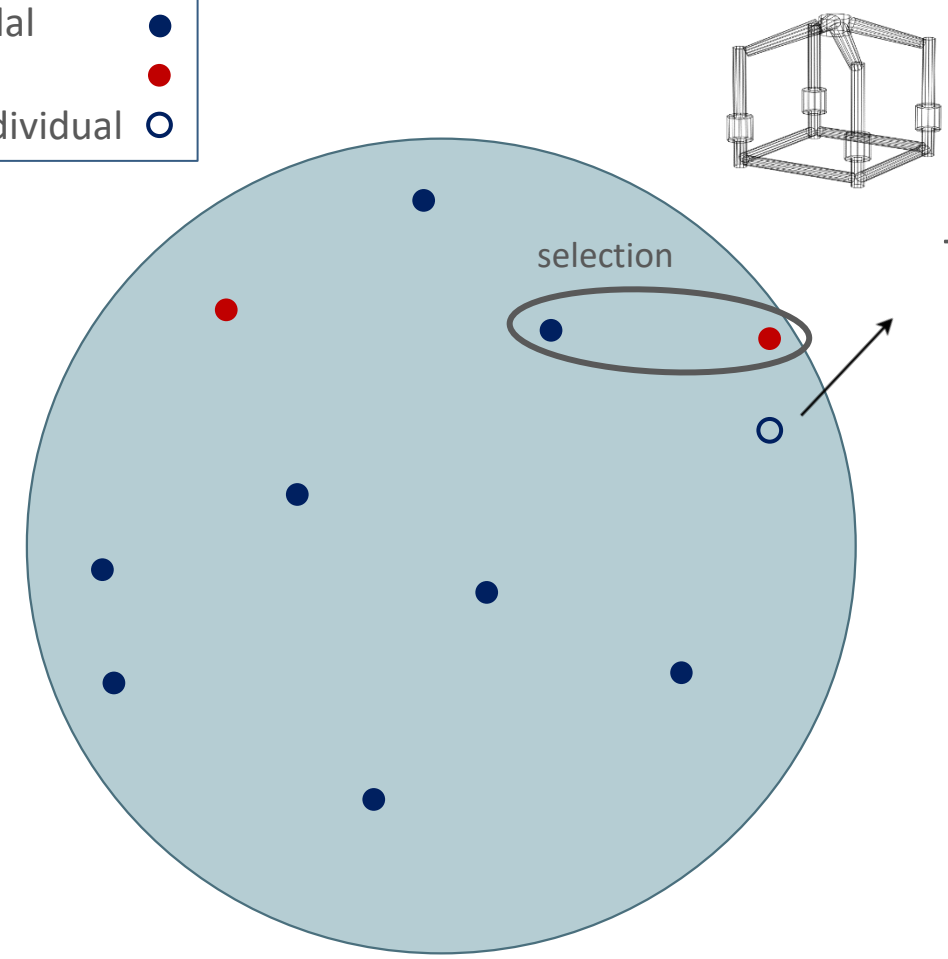
- Indiviudal ●
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- New individual ○



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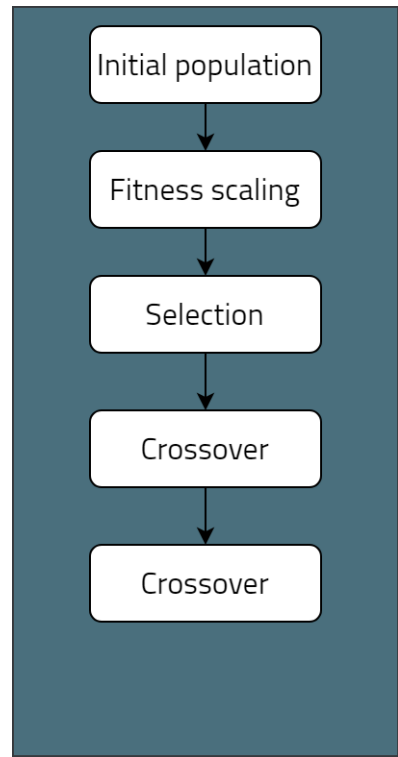
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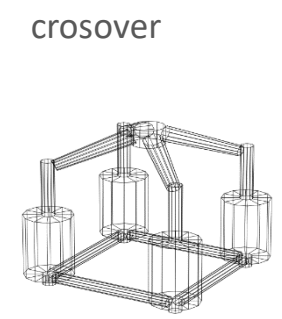
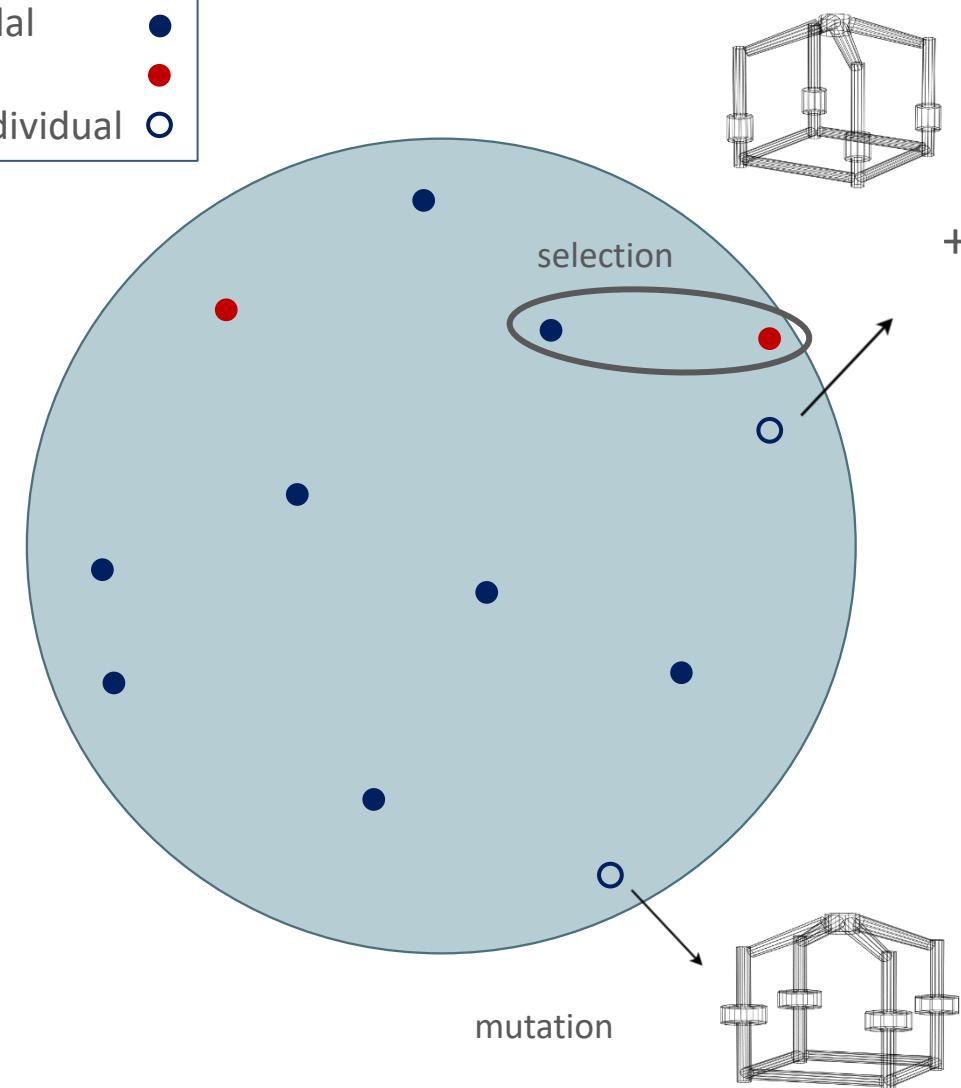
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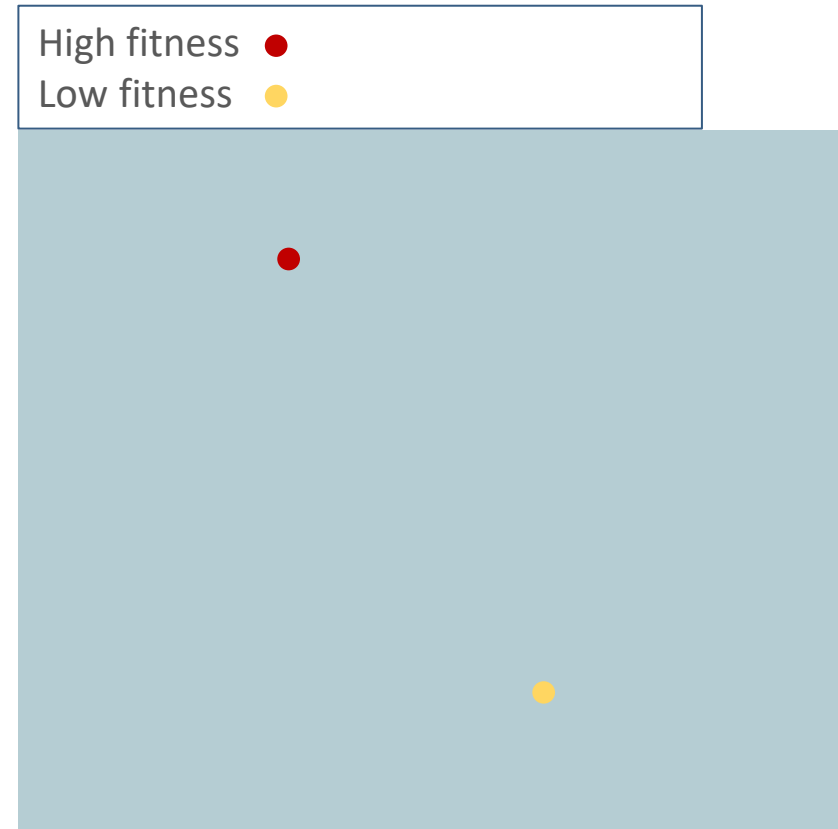
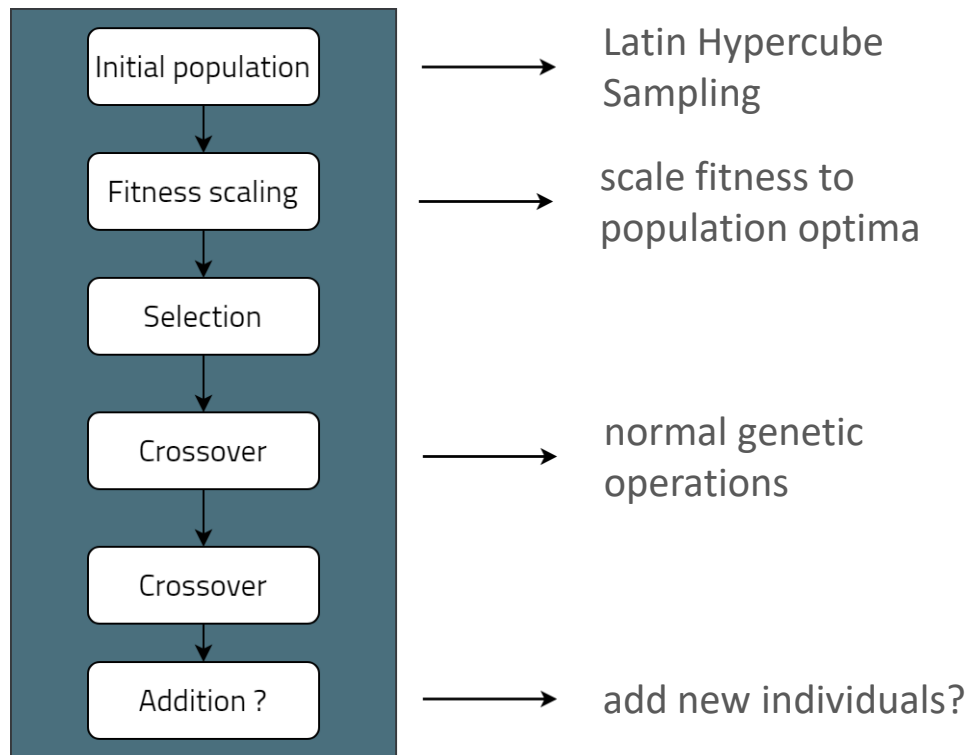
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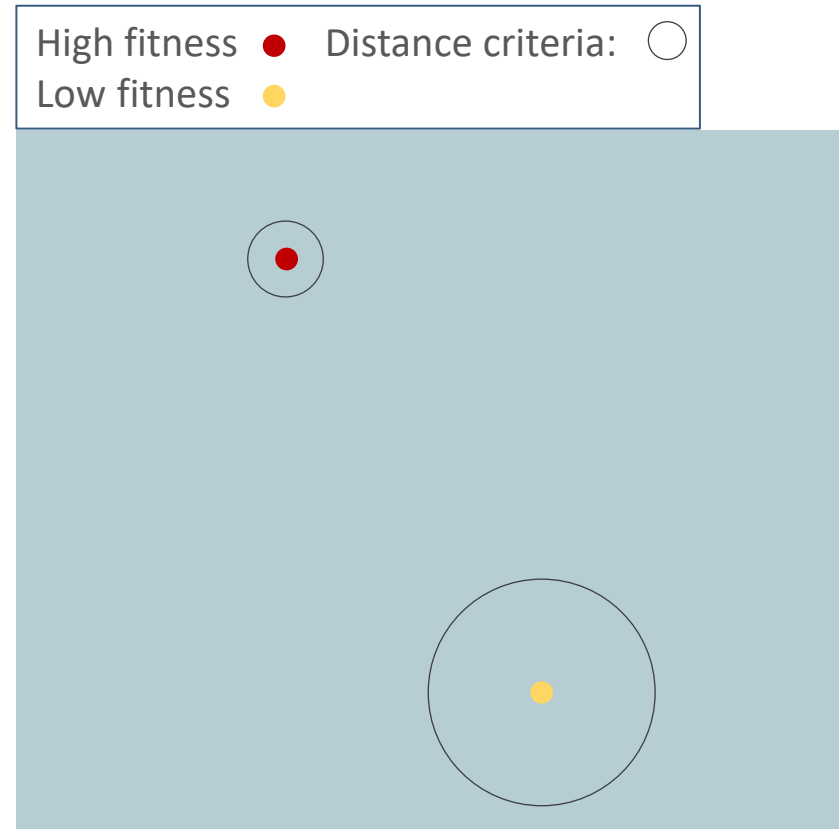
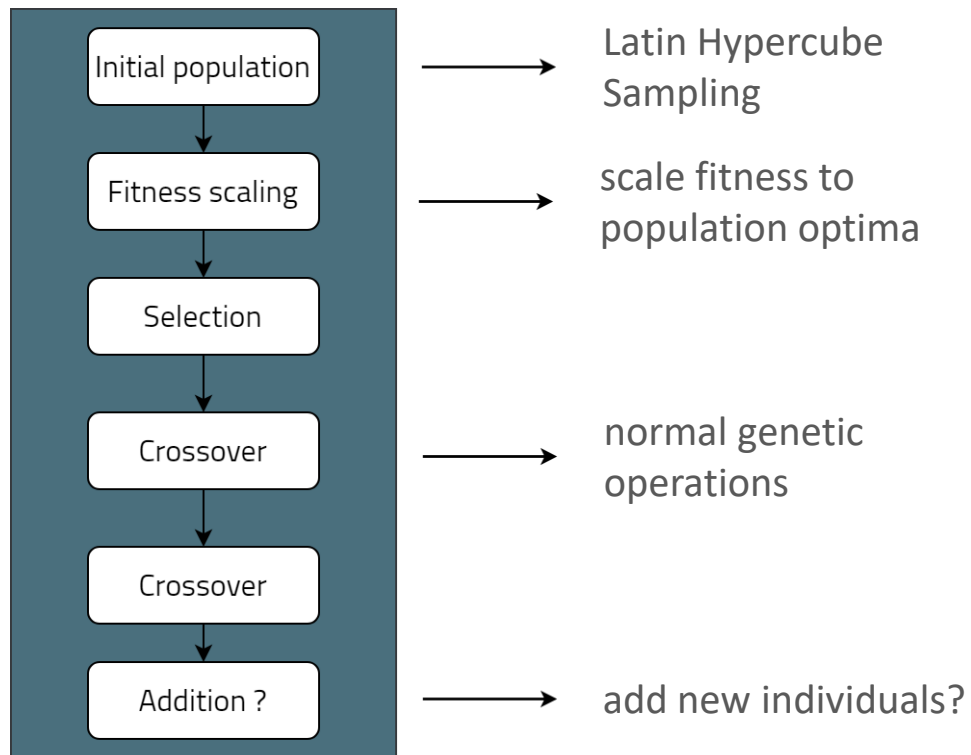


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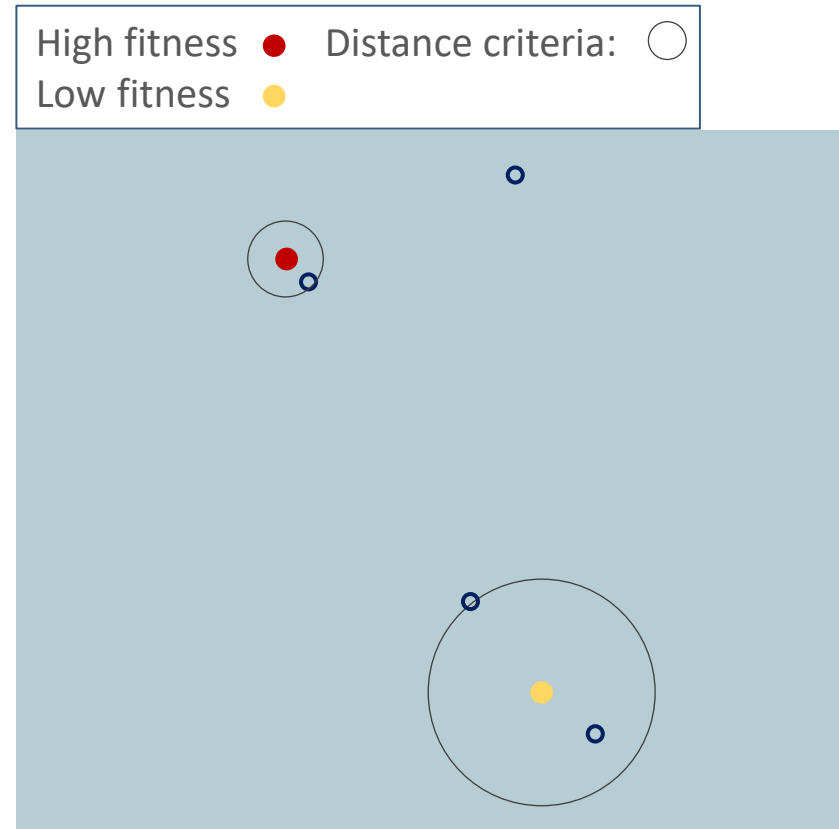
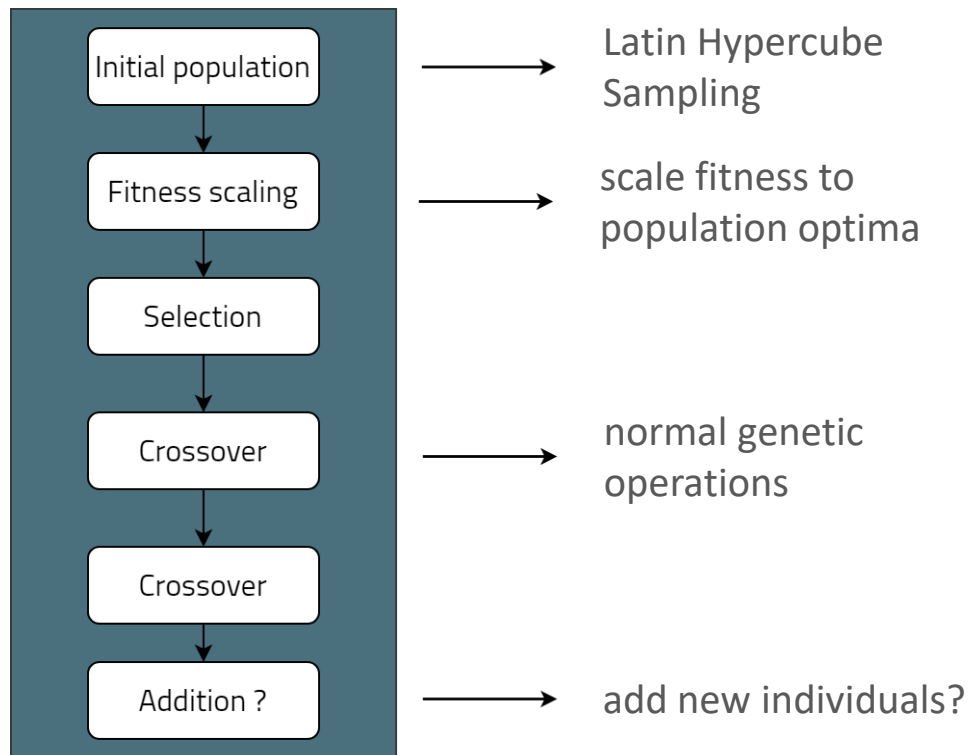


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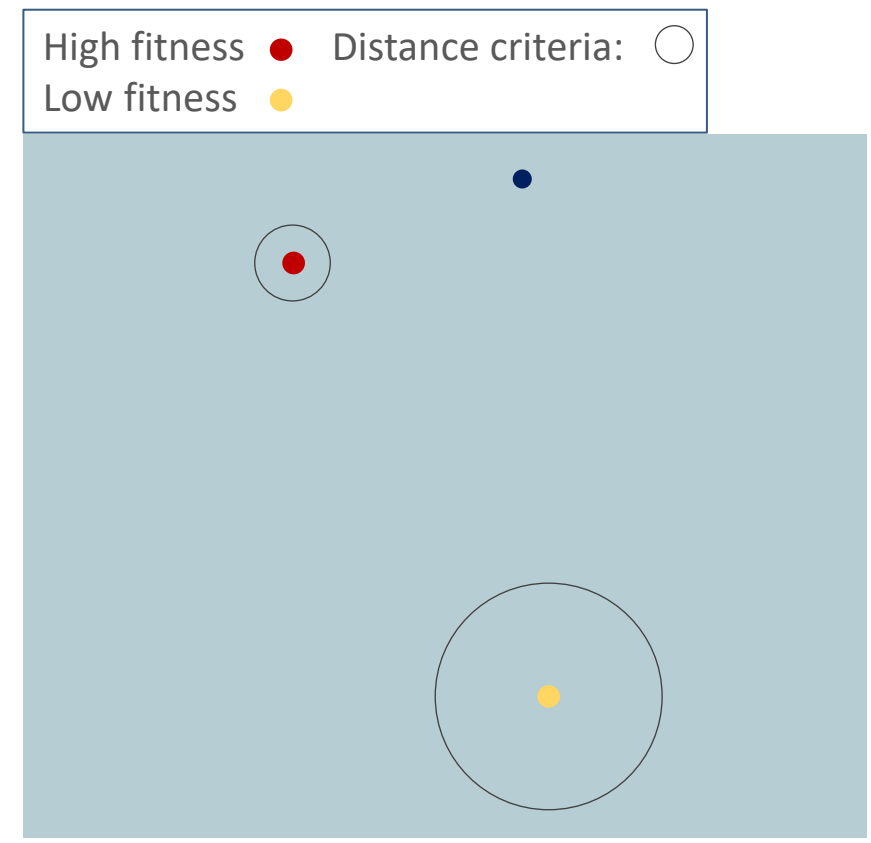
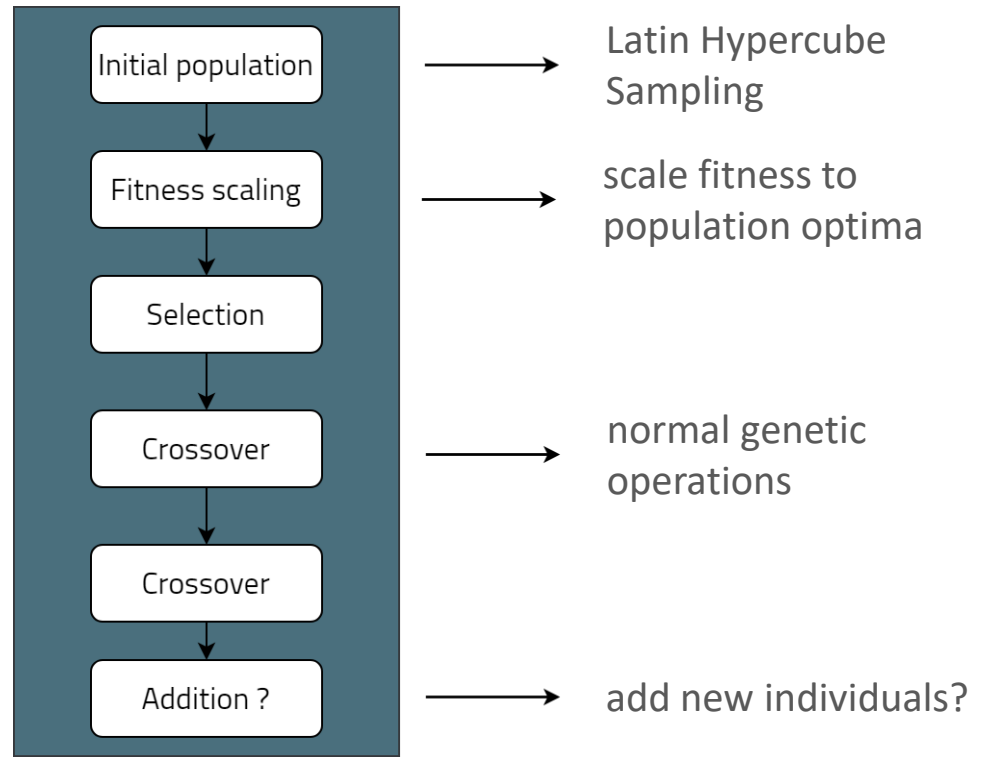


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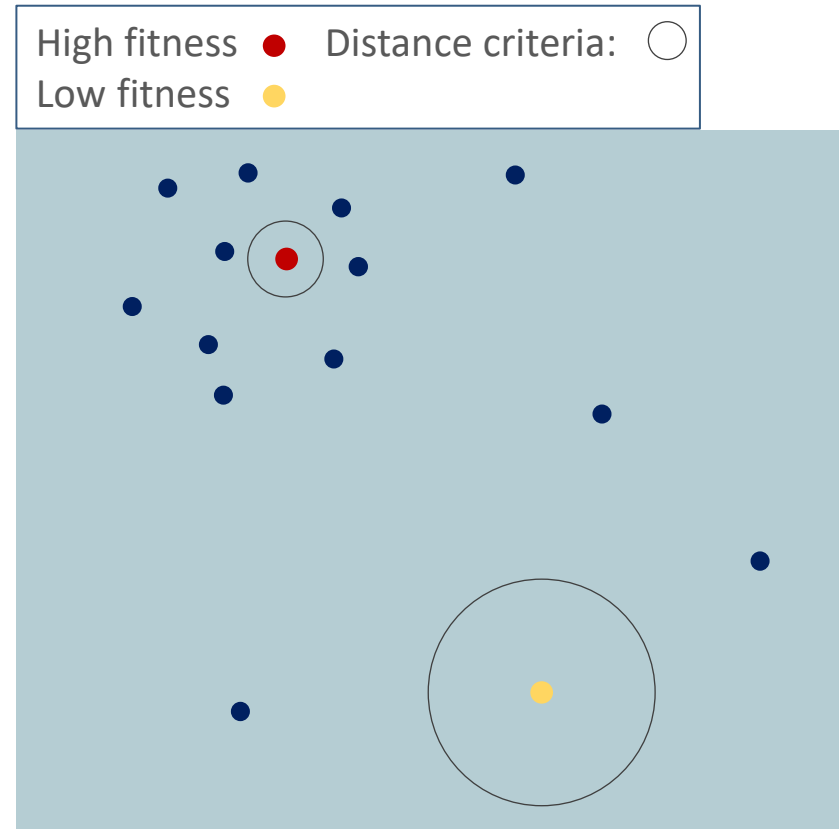
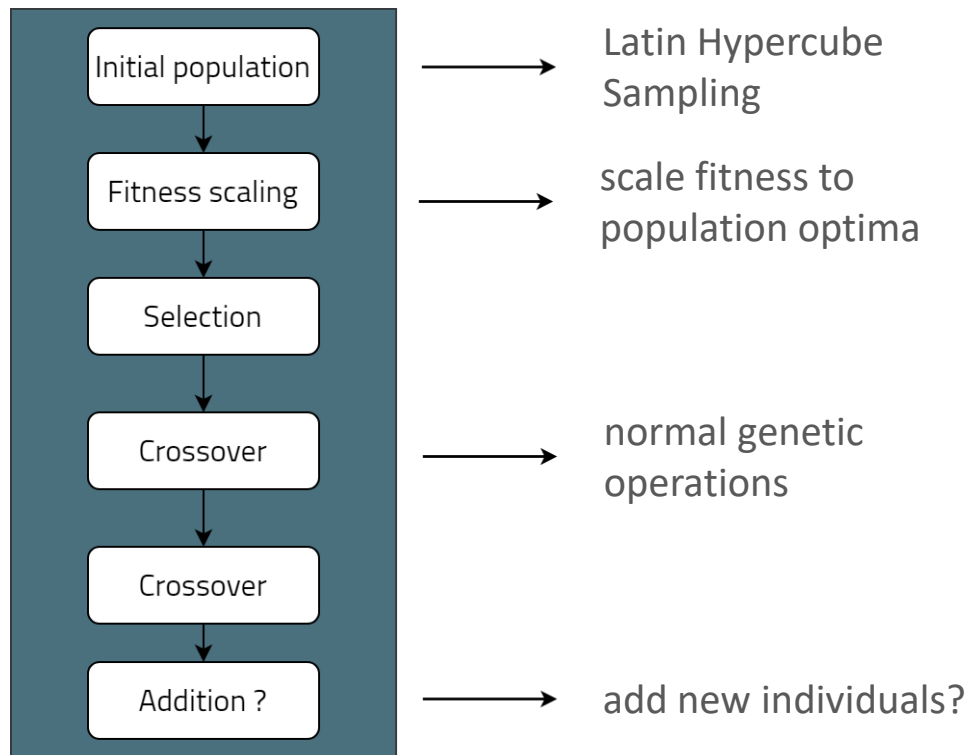


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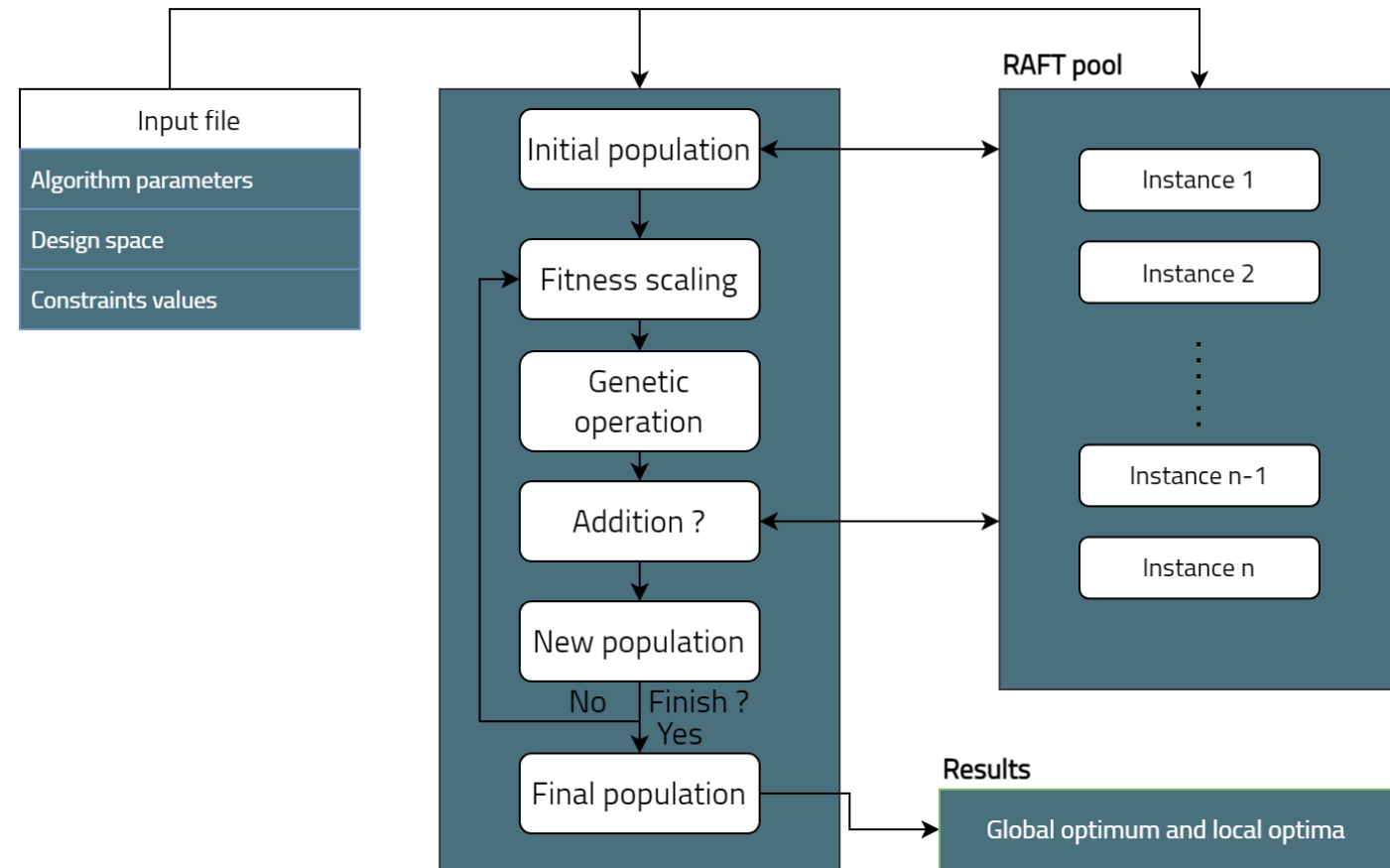




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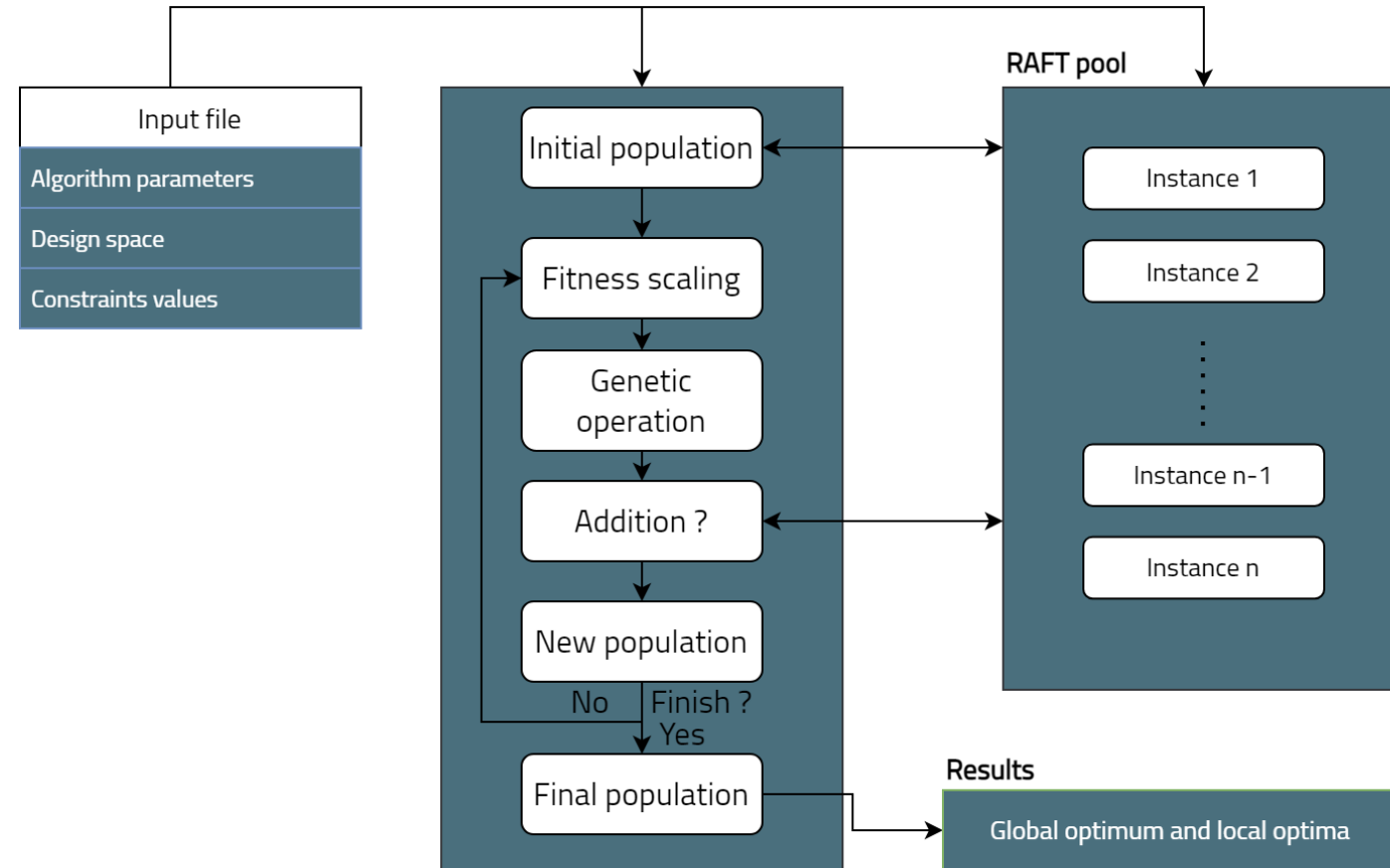
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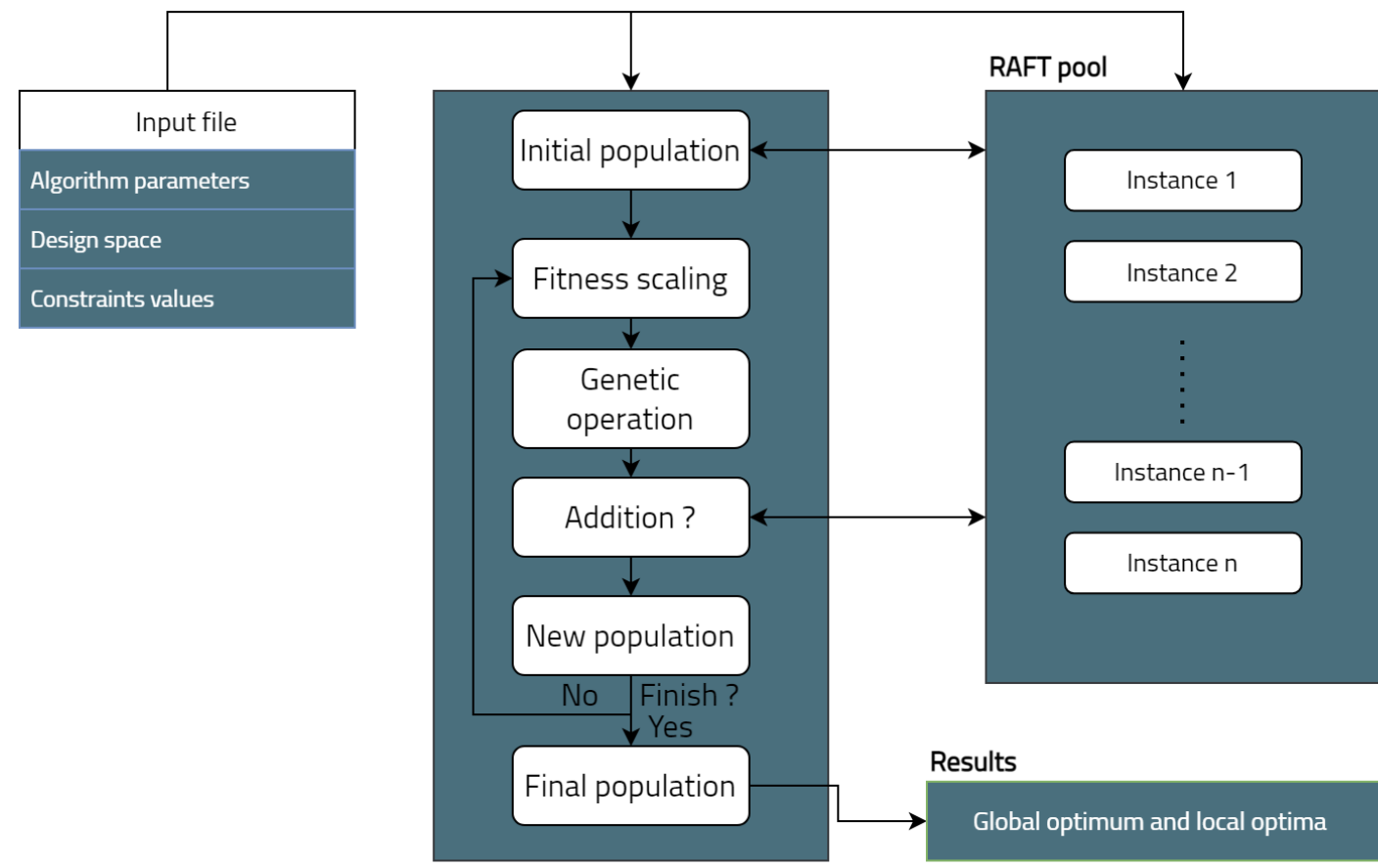
Object Oriented (python)





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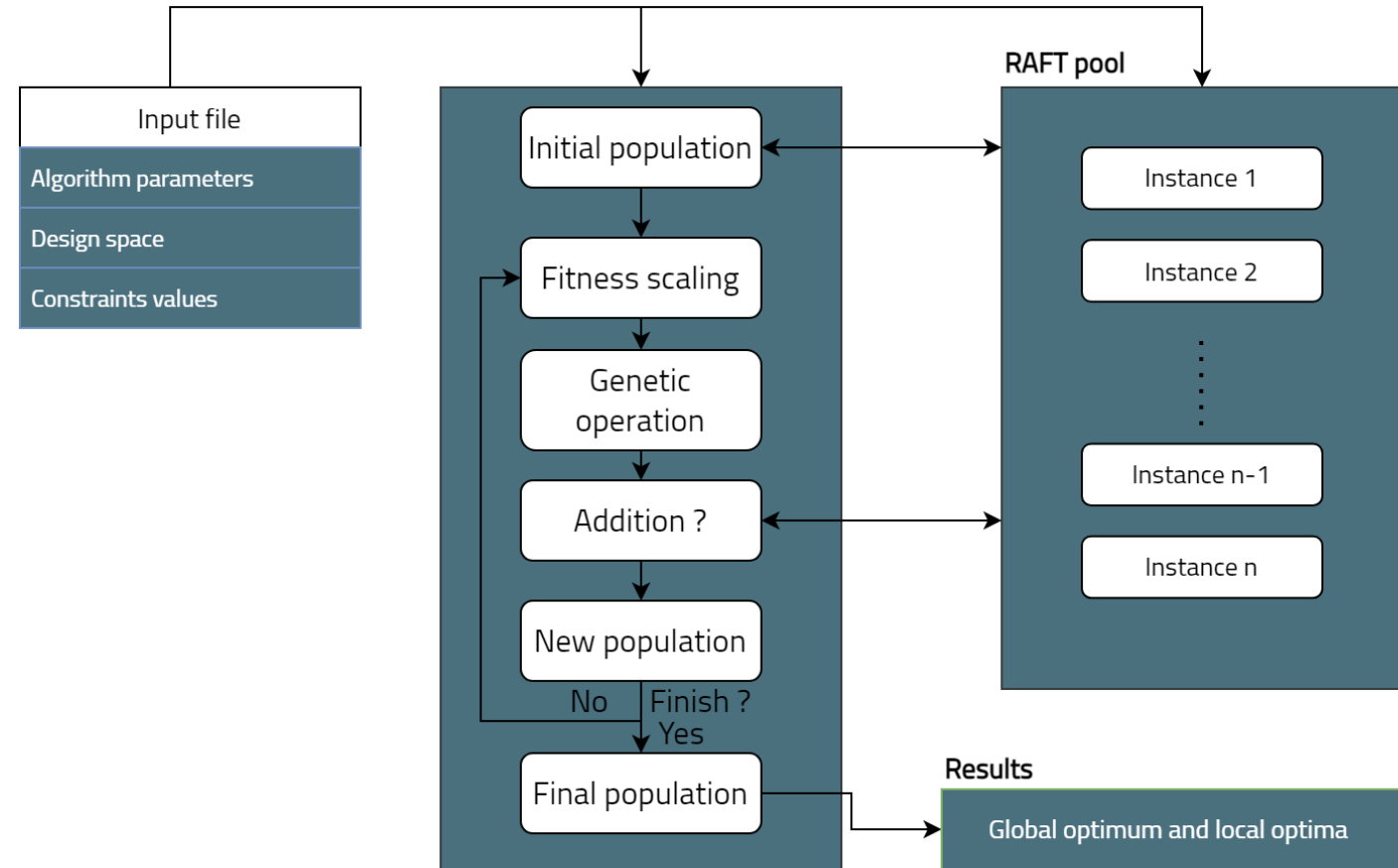
- ❑ Object Oriented (python)
- ❑ Modular approach





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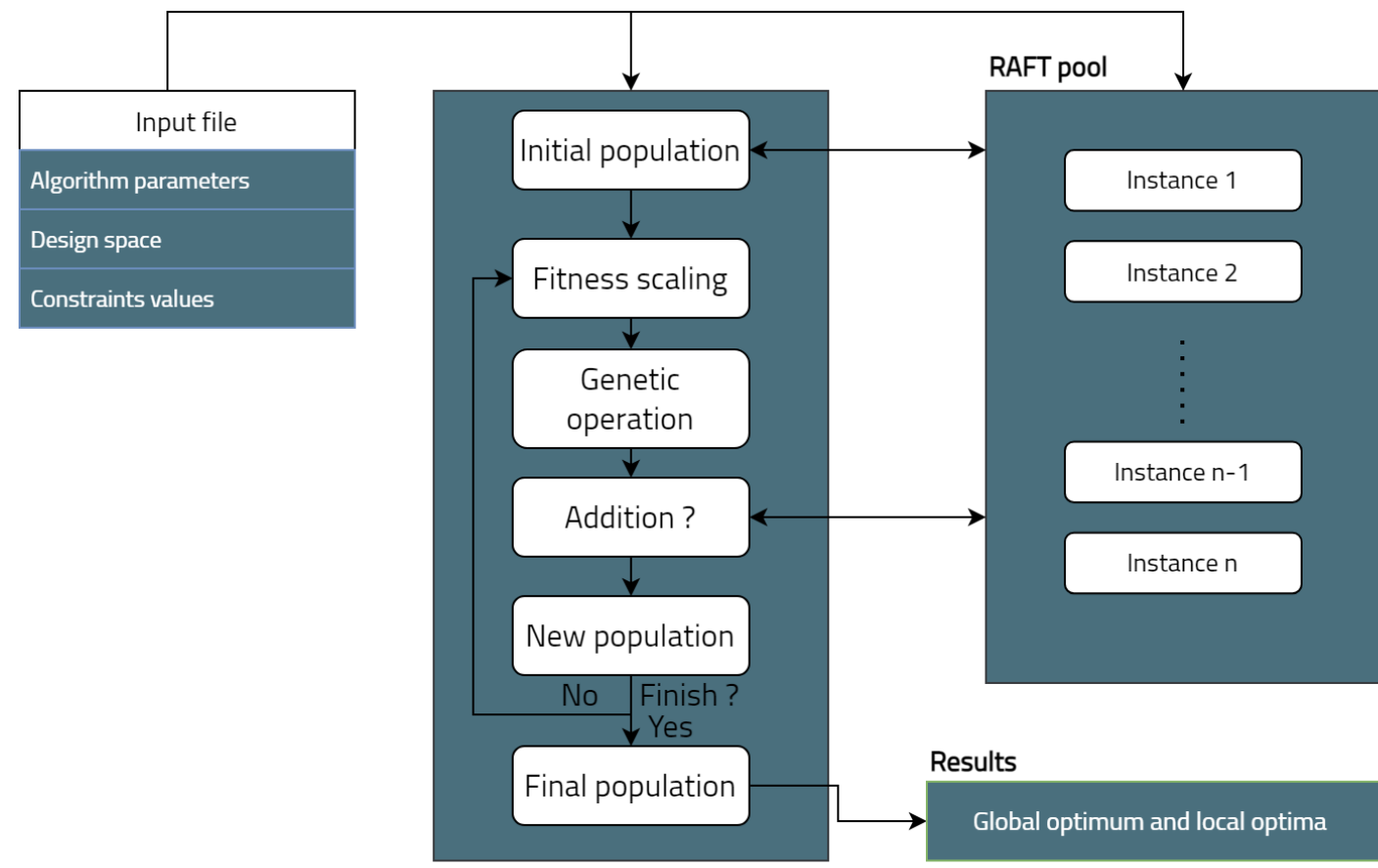
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- ❑ Multiprocessing





# Optimization Framework

- ❑ Object Oriented (python)
- ❑ Modular approach
- ❑ Multiprocessing
- ❑ Easy to use (GUI)





# Results



*This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement N° 860879.*





# Results

➤ Study case:

- ❑ GICON-TLP with IEA15 MW



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## ➤ Study case:

- ❑ GICON-TLP with IEA15 MW

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  - $U_w = 12 \text{ m.s}^{-1}$  ,  $H_s = 4 \text{ m}$  ,  $T_p = 12 \text{ s}$

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❑ Design variables:

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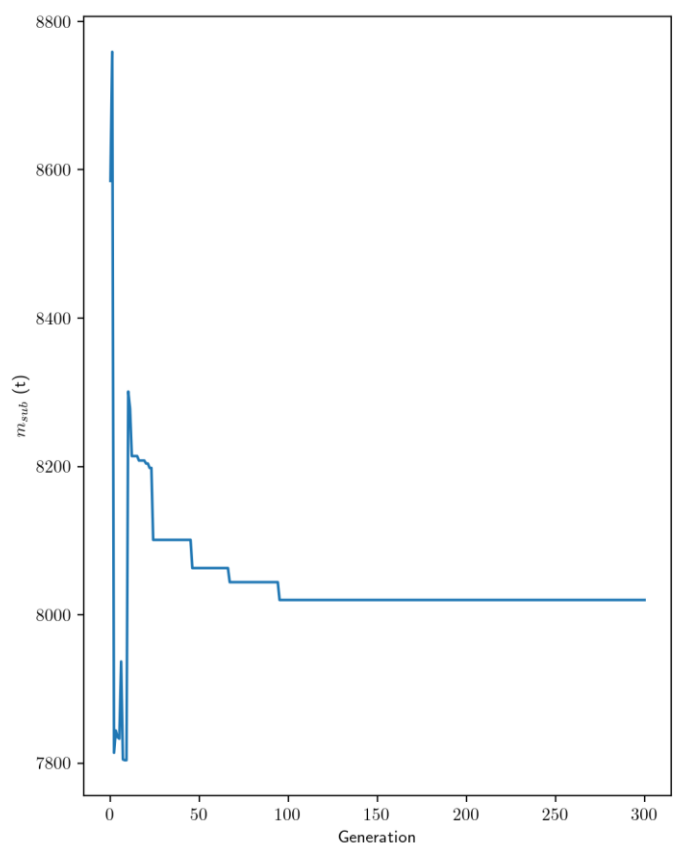
❑ GA Parameters:

- Initial population size: 10
- Max population size: 1000
- max generation number: 300





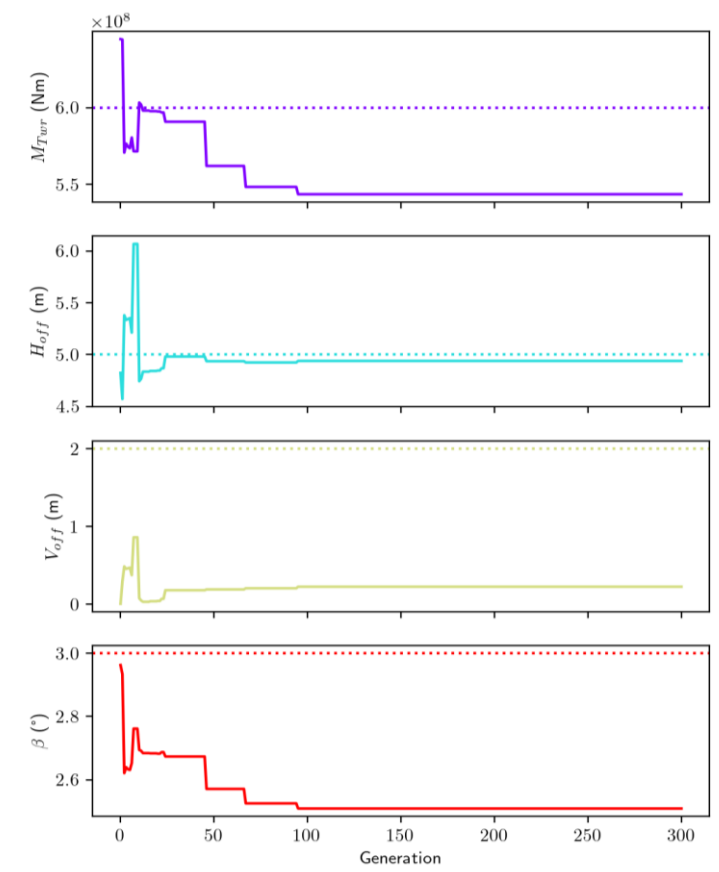
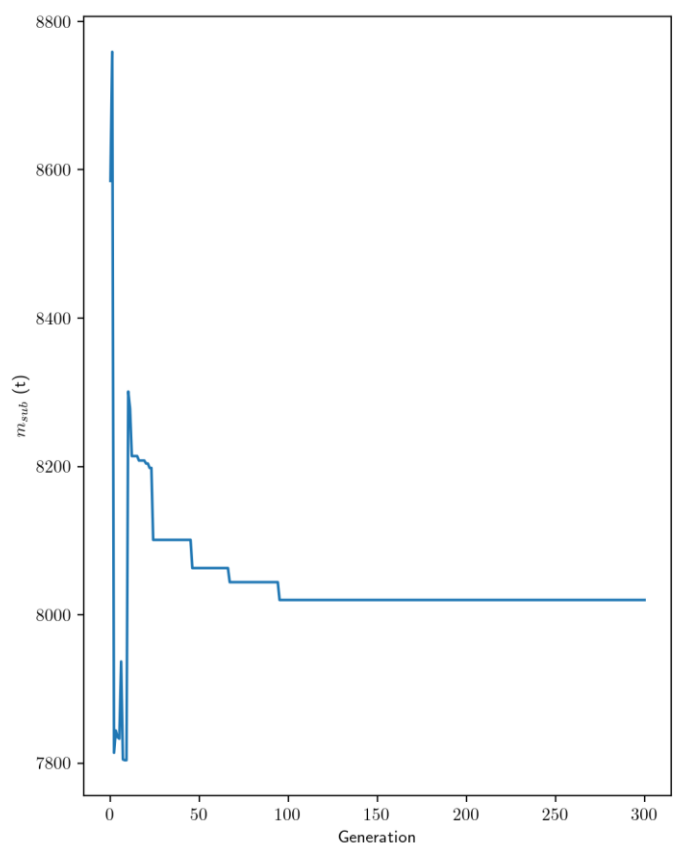
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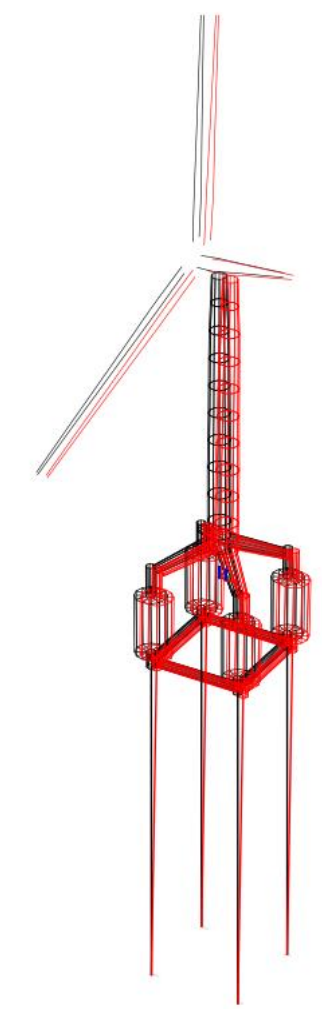
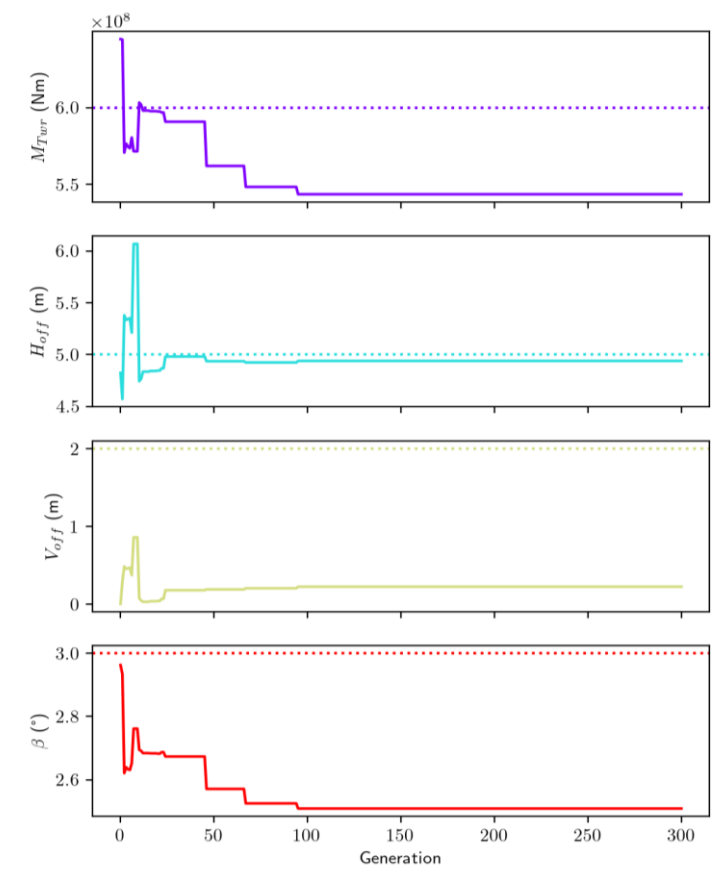
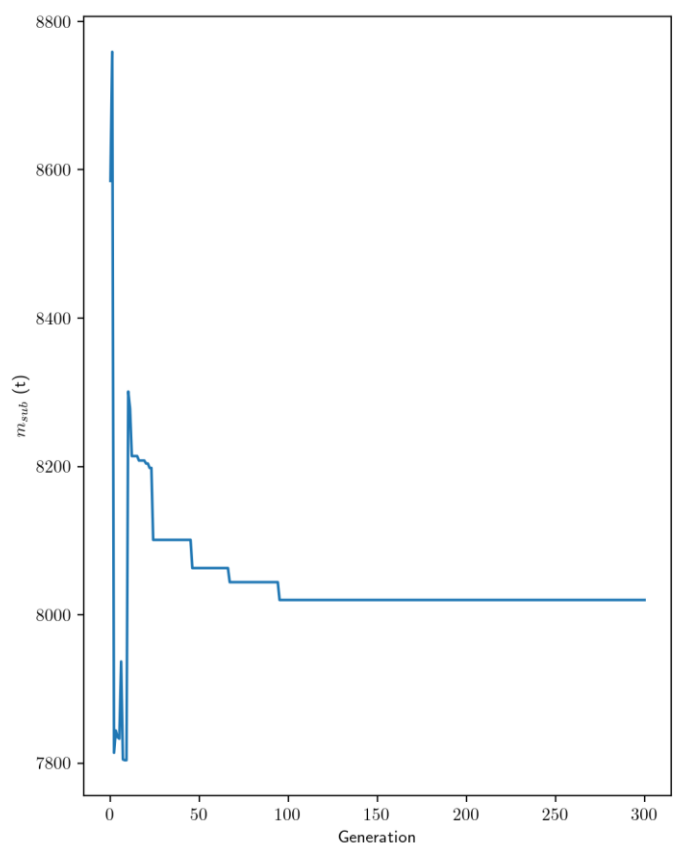


# Results





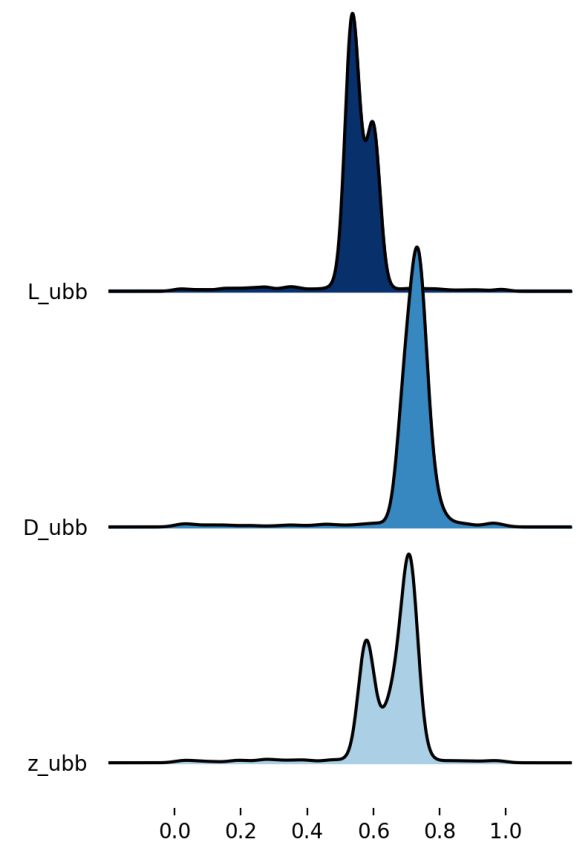
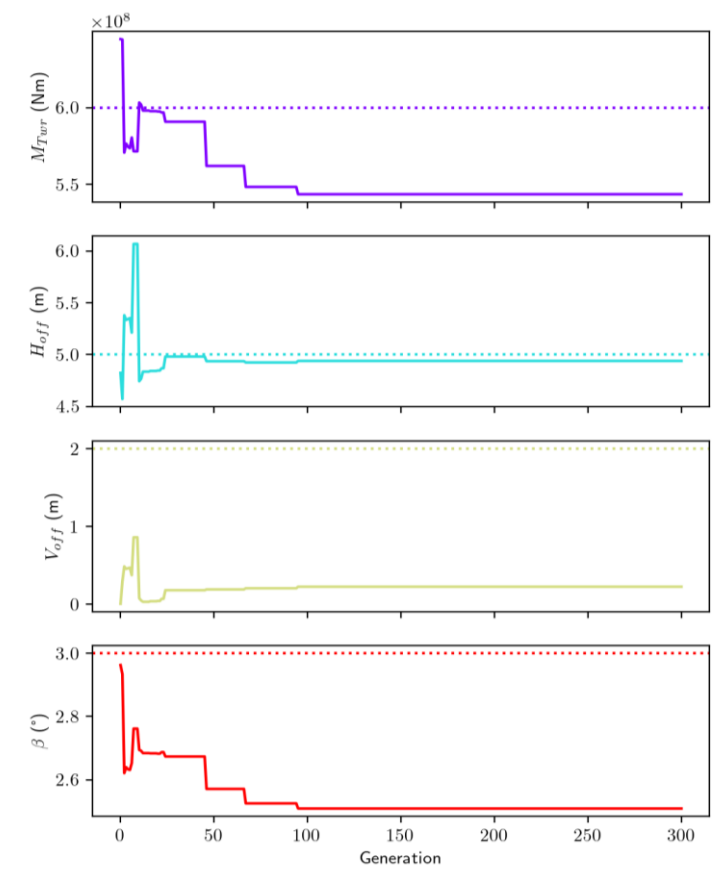
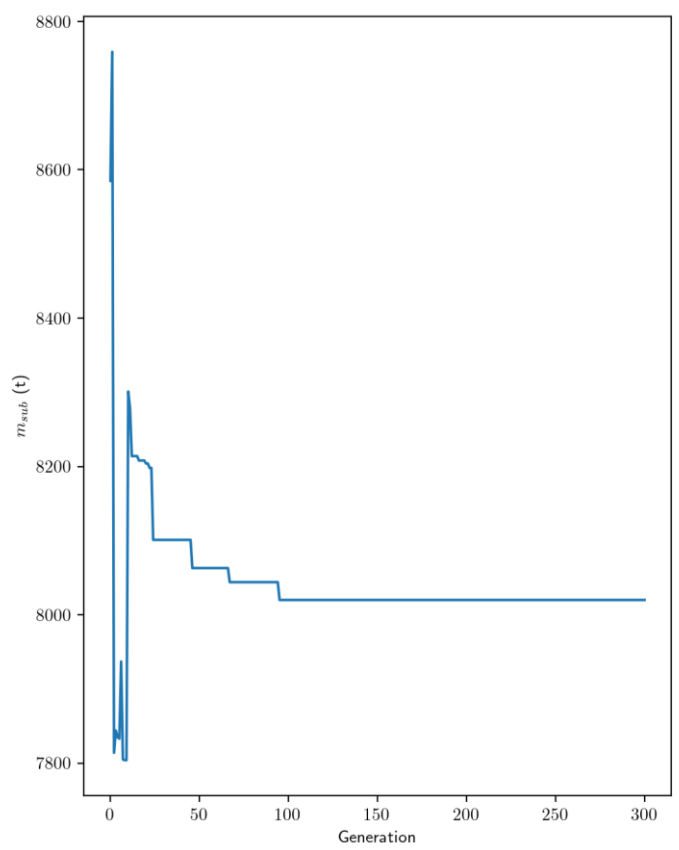
# Results



- $L_{UBB} = 24$  m
- $D_{UBB} = 15$  m
- $Z_{UBB} = -24$  m



# Results



## Conclusion & Outlook

- ✓ Model of the GICON-TLP with IEA 15 MW
- ✓ Asses its dynamic in the frequency domain using RAFT
- ✓ Design optimization framework coupling a genetic algorithm with RAFT
- ✓ Preliminary results with minimized material cost and verified constraints
- Enhance hydrodynamic model
- Compare numerical model with time domain model and experimental data
- Consider other design variables and constraints



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# References

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