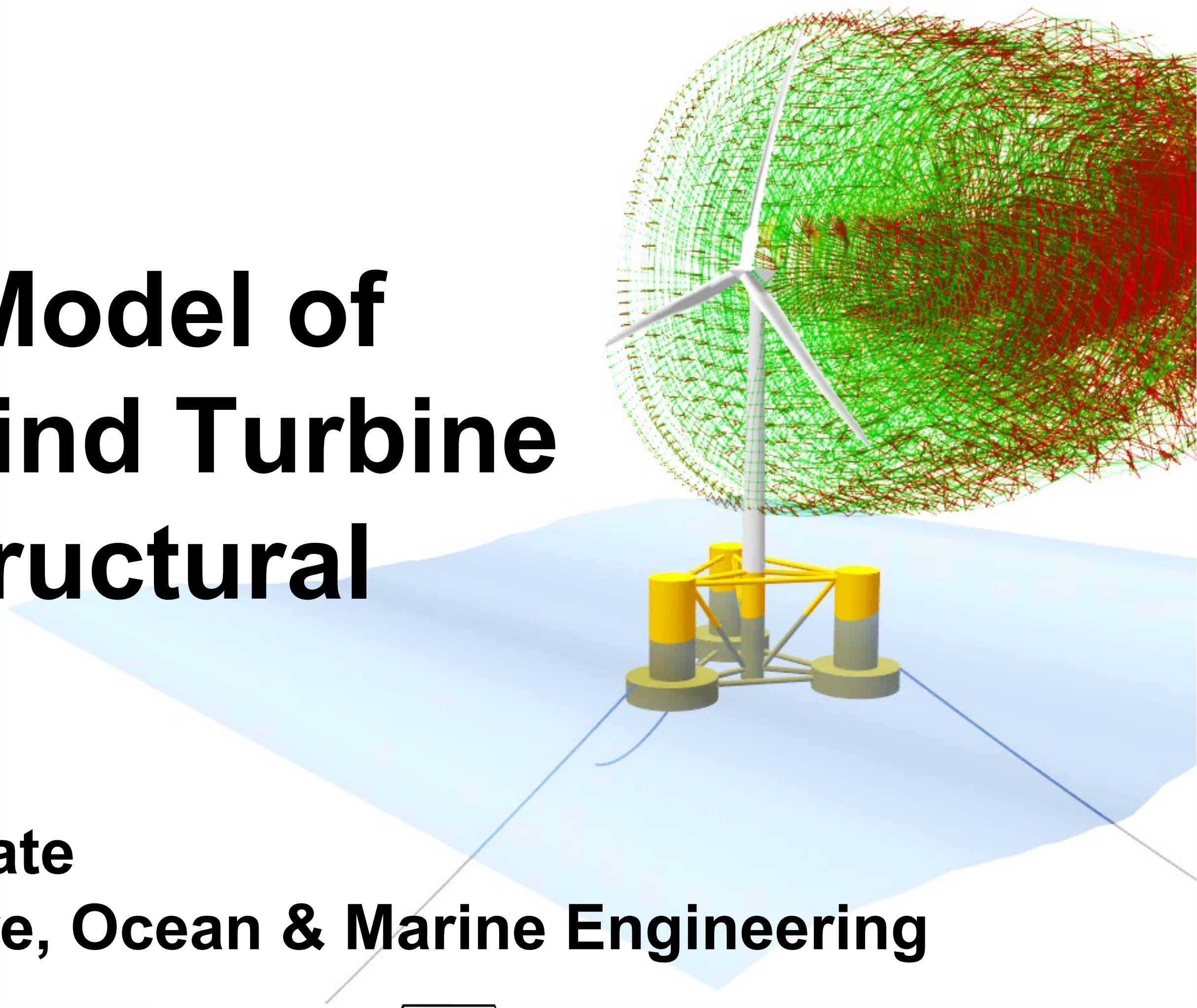
THE FACULTY OF ENGINEERING

ALL-ENERGY EXHIBITION AND CONFERENCE 2024

A New Digital Twin Model of Floating Offshore Wind Turbine for Cost-effective Structural Health Monitoring



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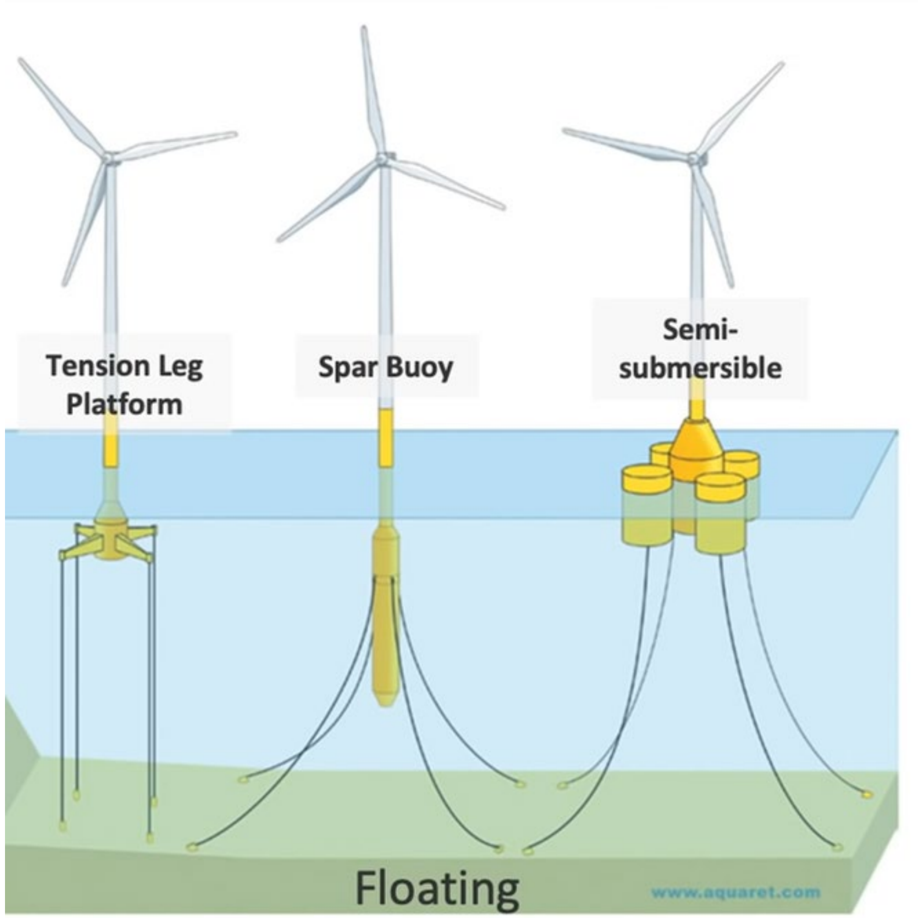
Quiz time!!

Can you guess which component that …

- *governs the survivability of FOWT*
- *its internal forces cannot be measured directly or easily*
- *difficultly repaired and maintenance*
- *extremely high OPEX with large scale*

???



Source: National Renewable Energy Laboratory (NREL)

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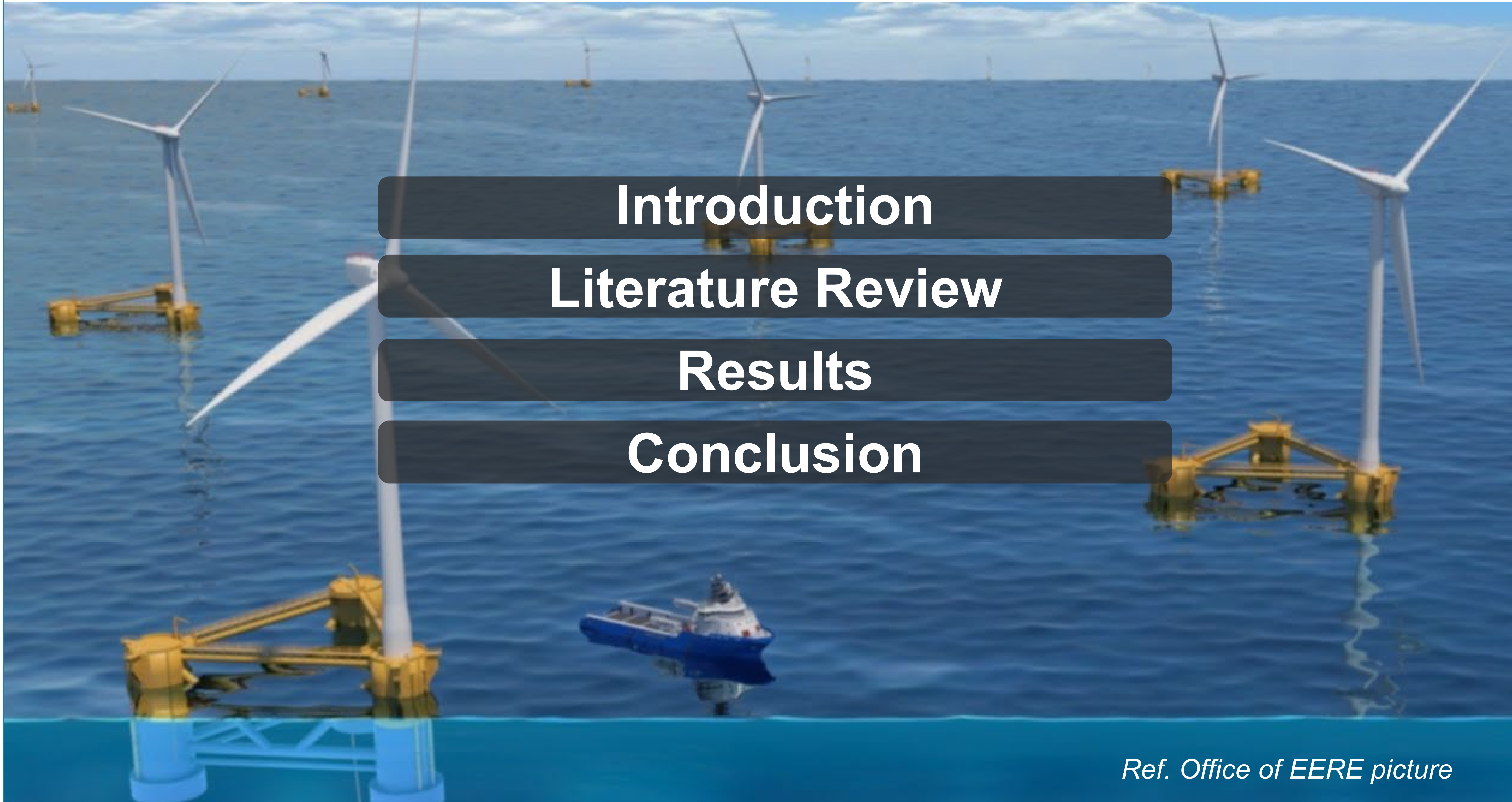


- Introduction
- Literature Review
- Results
- Conclusion

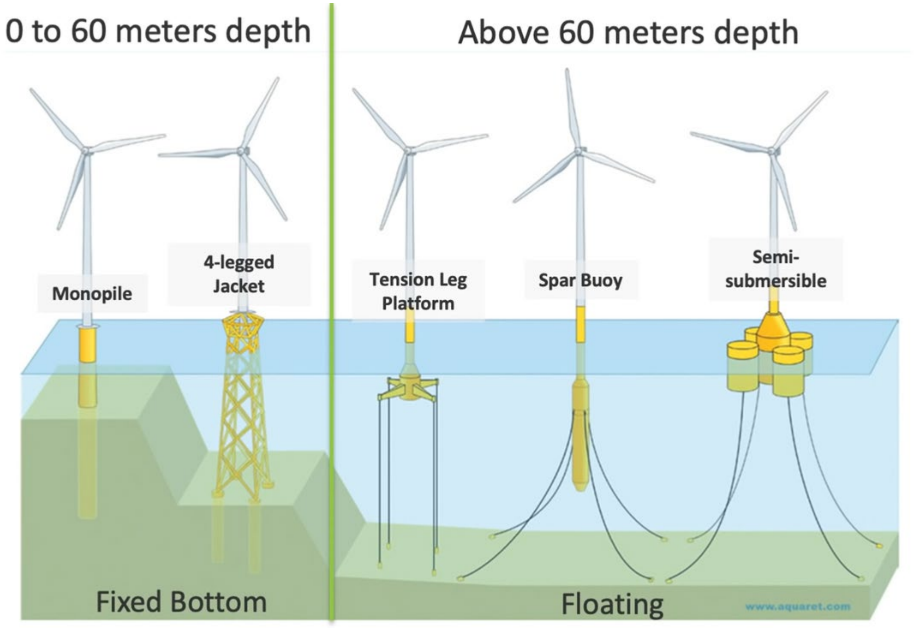
Ref. Office of EERE picture

Introduction

Introduction

Background - *Why Floating Offshore Wind?*

- *"Floating turbines could unlock enough potential to meet the world's total electricity demand 11 times over in 2040" (World Energy Outlook Special Report 2019, International Energy Agency)*
- *48.2 GW offshore wind capacity was completed by 2021 (Crown Estate's tenth annual Offshore Wind Report)*



Some Areas of the World Being Considered for Floating Wind

Source: National Renewable Energy Laboratory (NREL)

Introduction

High cost of FOWT

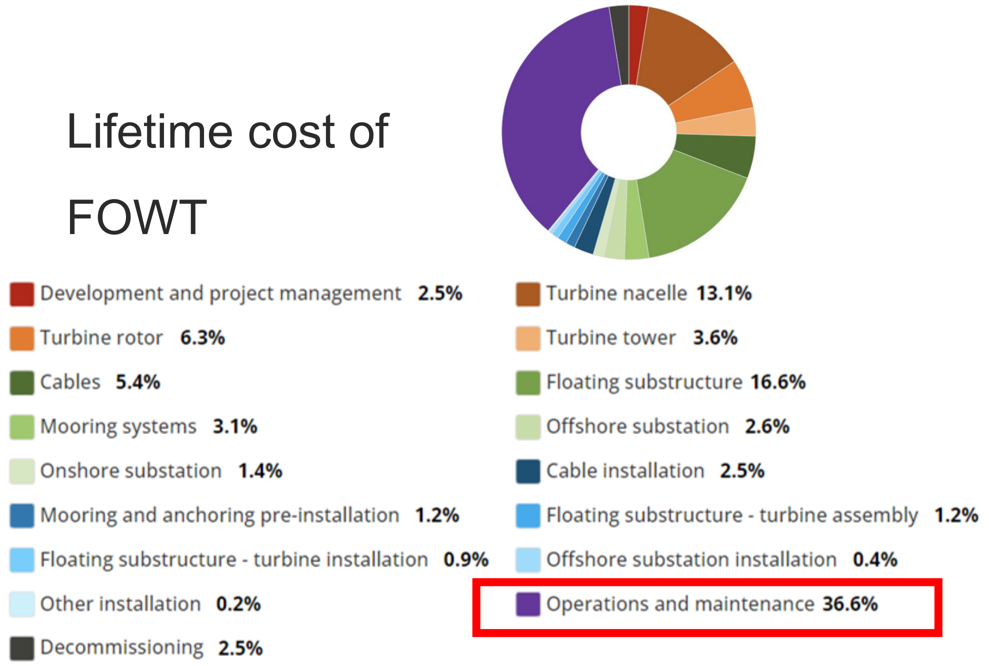
- Operations and maintenance is 36.6% (71000£/MW/year, typically 1 offshore wind turbine rates 15MW) of total life cost
- Maintenance of the plant is 62% of OPEX

Structural health monitoring problems

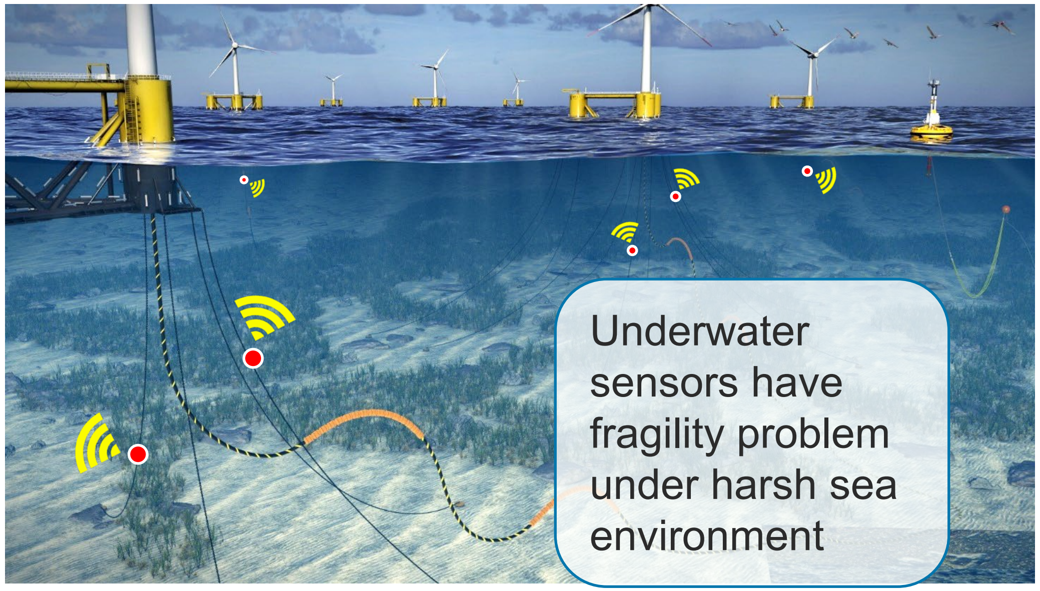
- Mooring monitoring has fewer details in codes comparing to other parts e.g. turbine, tower
- Mooring failure means “Total loss” of FOWT asset and damage electrical cable
- Current in-service mooring monitoring technologies/methods cannot support large scale of floating wind farms

Currently, there is no comprehensive Digital Twin can solve the problems!

Lifetime cost of FOWT



(BVG Associates, 2023)

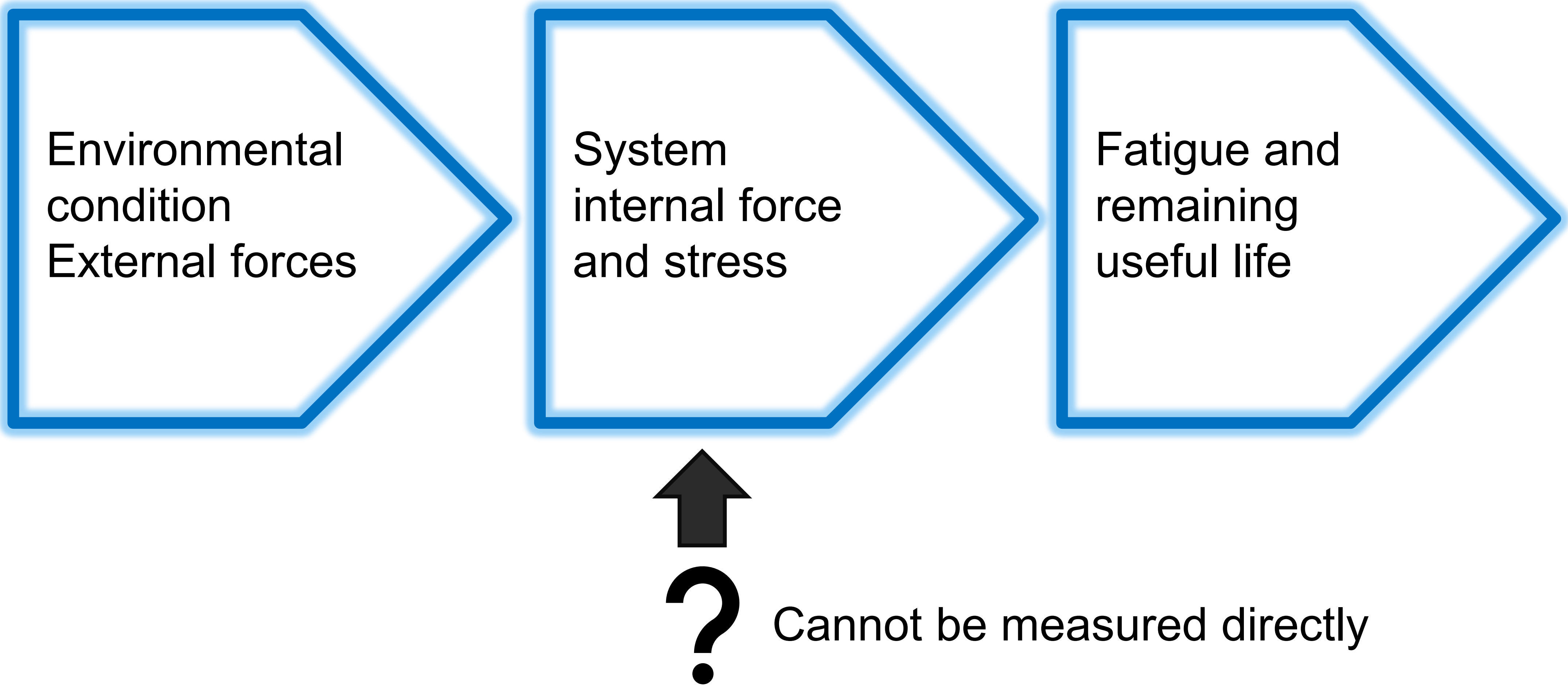


Original photo: Furgo

Literature Review

Literature Review

Structural health monitoring



Literature Review

Current practice for mooring health monitoring:

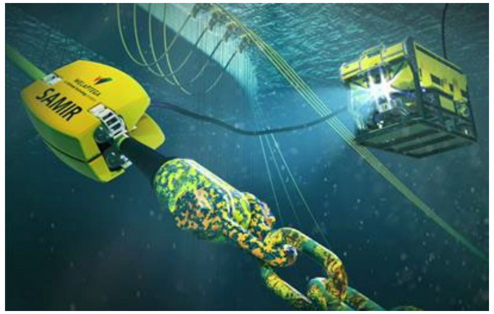
Visual inspection by diver and robot

	Average day rates [€/day]
Support Vessel	10,000 – 30,000
Inspection class ROV	3,000-5,000
ROV crew (*)	1,000
Other inspection equipment (**)	1,000-10,000

(*) cost per person. Gnerally 4-6 people required for 24hr operation

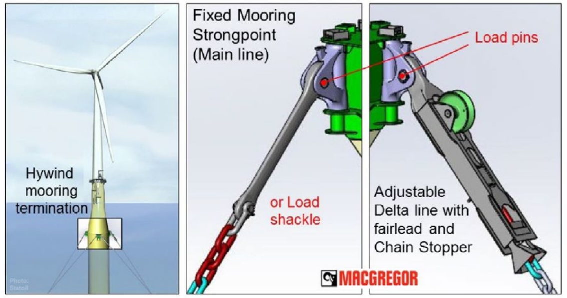
(**) depends on the type of inspection

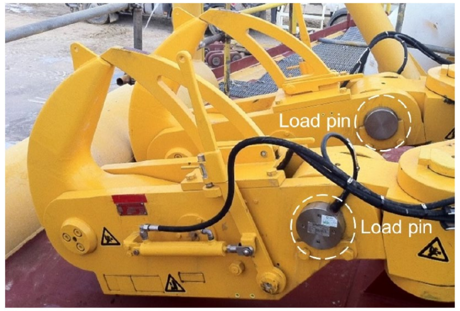
SAMIR (Ashtead Technology)



- High cost (total daily cost of 30,000EUR)
- Risk exposure of human

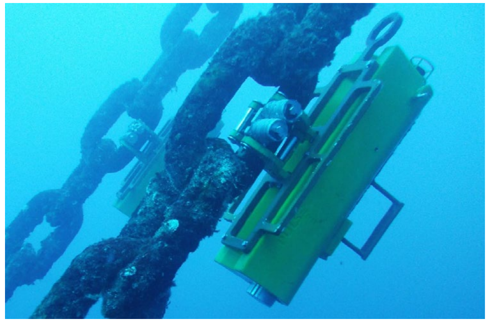
Measuring force in mooring





Load pin installed at Hywind mooring termination

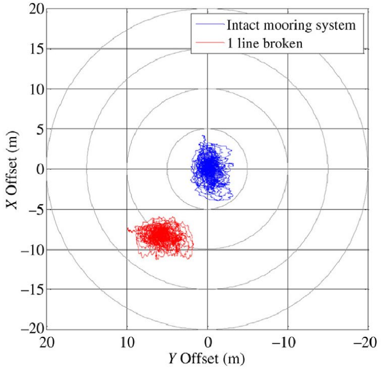
(Ma, Luo, Kwan, & Wu, 2019)



Inclinometers installed on top chain

- High cost
- Inaccurate measurements underwater
- Sensor fragility

Indirect detection



(Ma, Luo, Kwan, & Wu, 2019)

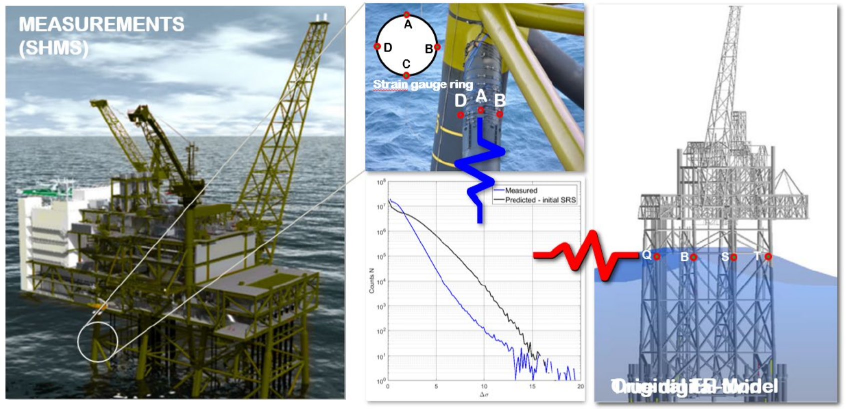
- Intention is not to estimate the mooring forces

Literature Review

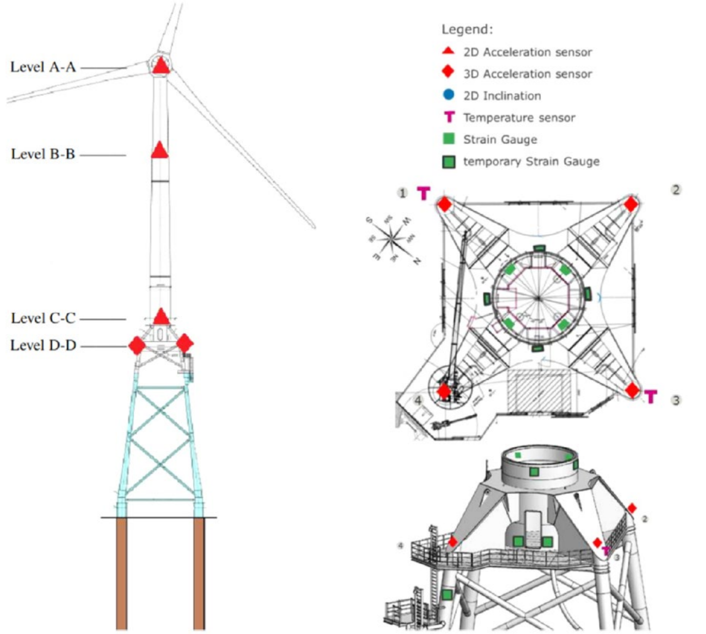
Digital Twin (DT)

It is a virtual representation of the physical asset which can real-time reflect the response and internal states. In 2012, the NASA showed the superiority of DTs and the concept became well developed with the advanced of sensor technology and internet-of-things.

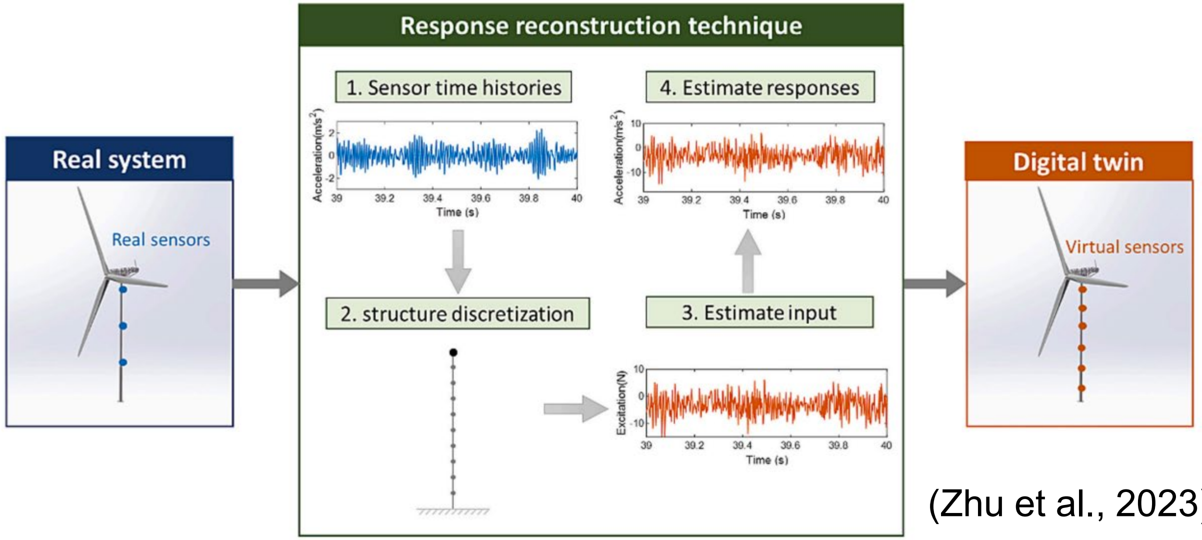
DT is widely adopted for Structural Health Monitoring and perform "virtual sensing" which is used to reconstruct the unmeasurable states based on limited sensor data in real life:



(Tygesen, et al., 2021)



(Augustyn, Smolkac, Tygesen, Ulriksen, & Sørensen, 2020)



(Zhu et al., 2023)

Literature Review

DT Modeling Approach

White Box

First Principle Models

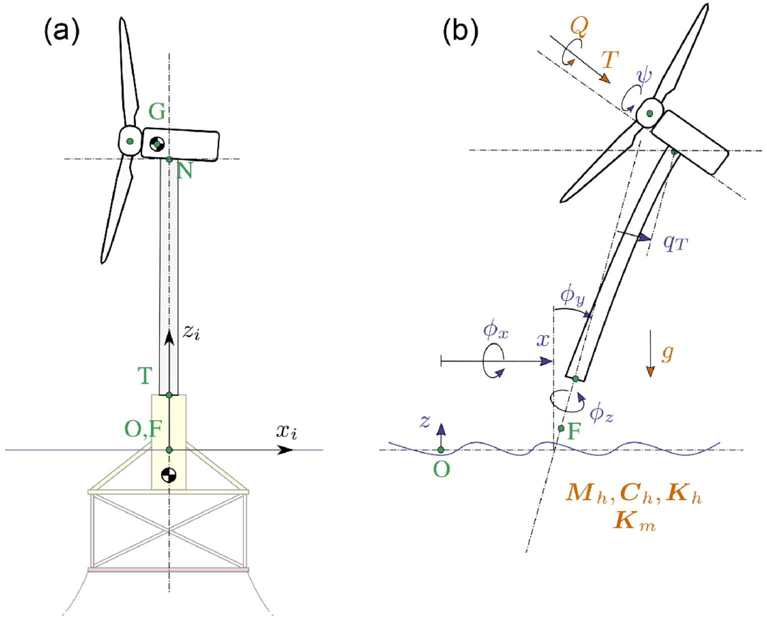
"Grey Box"

Black Box

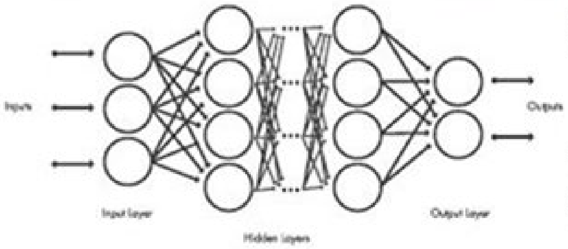
Data-Driven Models

Physics-based model with adequate performance

Accurate but lack of physical interpretation



(Branlard, Jonkman, Brown, & Zang, 2024)



$$\hat{L}_n(h) = \frac{1}{n}\sum_{i=1}^{n} \ell(h(\boldsymbol{x}_i), y_i) = \frac{1}{n}\sum_{i=1}^{n} [h(\boldsymbol{x}_i) - y_i]^2$$

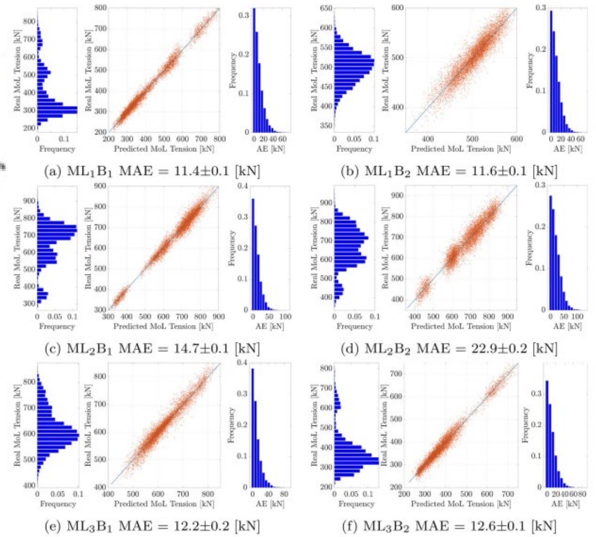


Fig. 3 First DT: scatter plot (real versus predicted) the real distribution, and the error distribution for the axial tension of the different MoLs and bridles

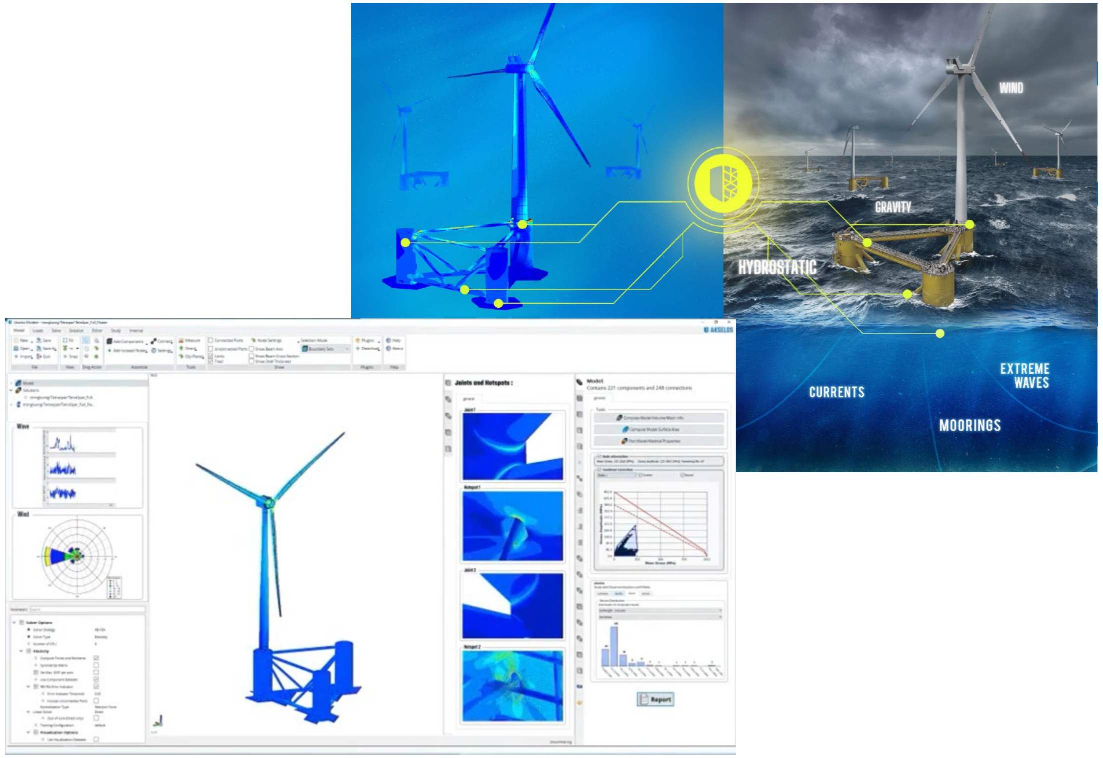
(Walker, Coraddu, Collu & Oneto, 2021)

Currently there is lack of accurate and physically interpretable DT, a new hybrid solution is required to capture the complicated dynamic coupling!

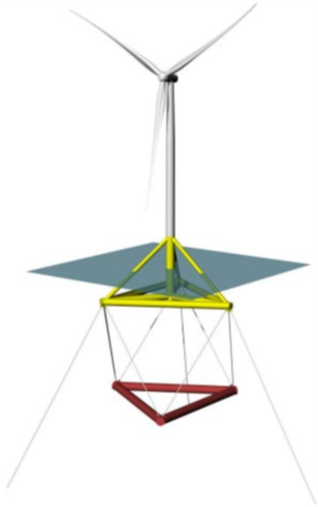
Literature Review

Existing Digital twin models (joint industry project)

DigiFloat (Principle Power and Akselos)

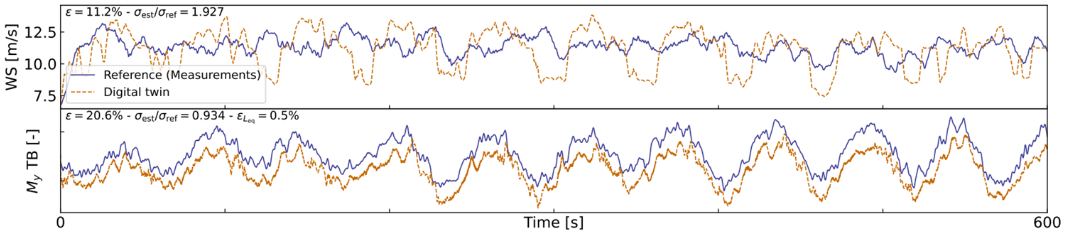


National Renewable Energy Laboratory, USA
Stiesdal Offshore A/S, Denmark



OpenFAST and WELIB

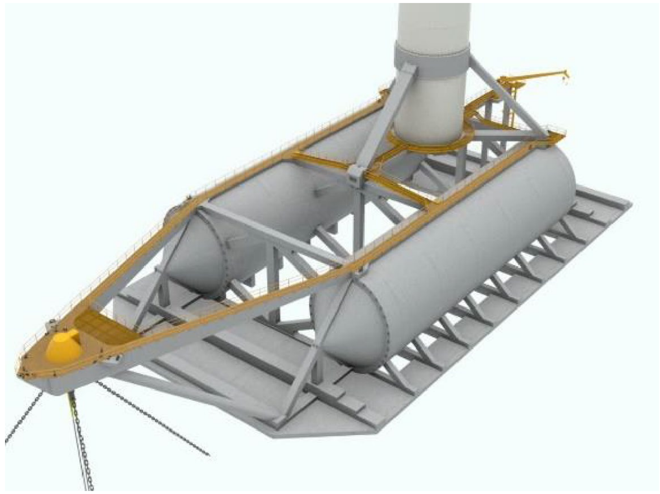
(Branlard, Jonkman, Brown, & Zang, 2024)



Literature Review

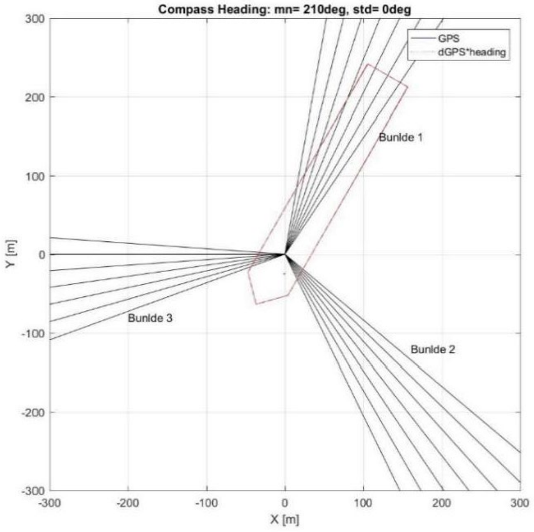
Existing Digital twin models (joint industry project)

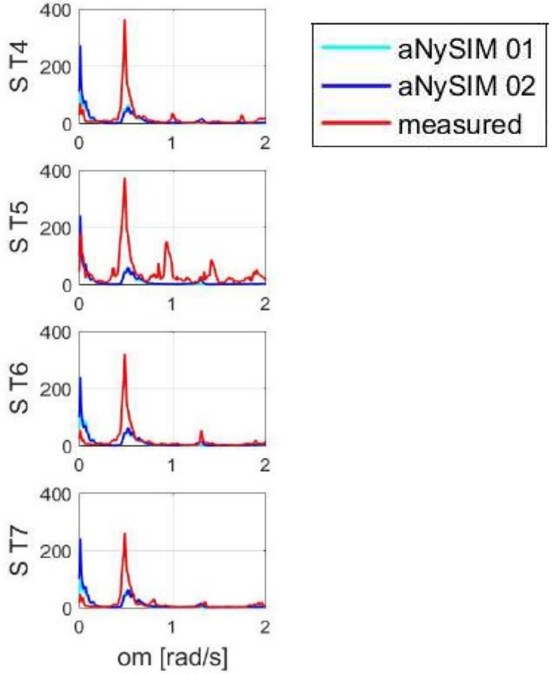
MooringSense (European Union’s Horizon 2020)



Maritime Research Institute Netherlands (MARIN)

INPEX Ichthys LNG





(Pauw et al.,2021)

What is next?

True Digital Twin?

Discover the unknown!

Results

Results

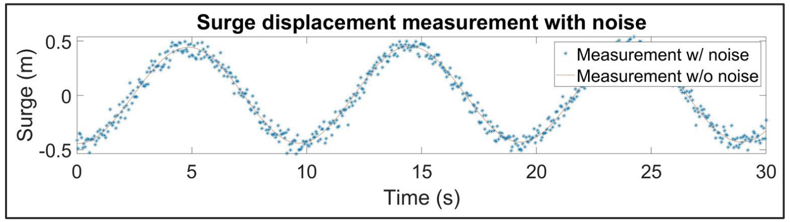
Physics-based Mooring force prediction with Kalman Filter, based on 3DOF platform motions

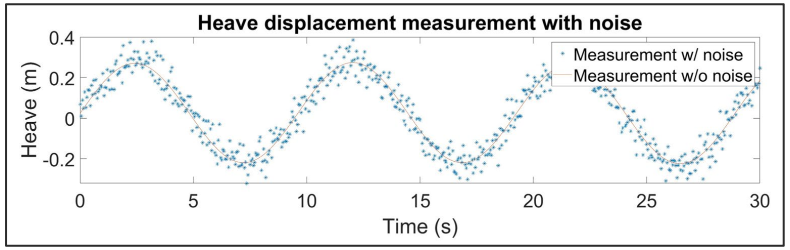
Sea state definition and the simulated “unknown” sea state time history

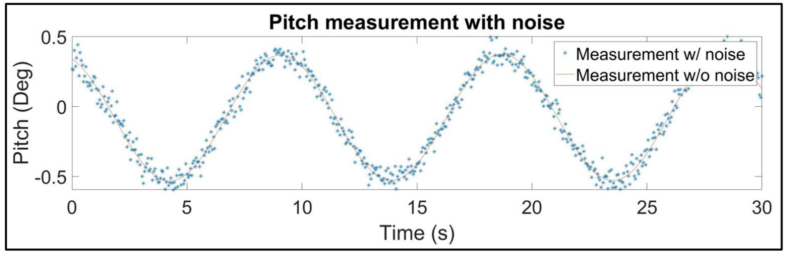
Sea State (SS) no.	Wave Height Hs (m)	Wave Period Ts (s)	Remark
1	2	8.93	bank model
2	2.5	9.63	validation
3	3	10.20	bank model
4	3.5	10.68	validation
5	4	11.10	bank model
6	4.5	11.47	validation
7	5	11.80	bank model

Met-ocean properties of West of Barra, Scotland from LIFES50+

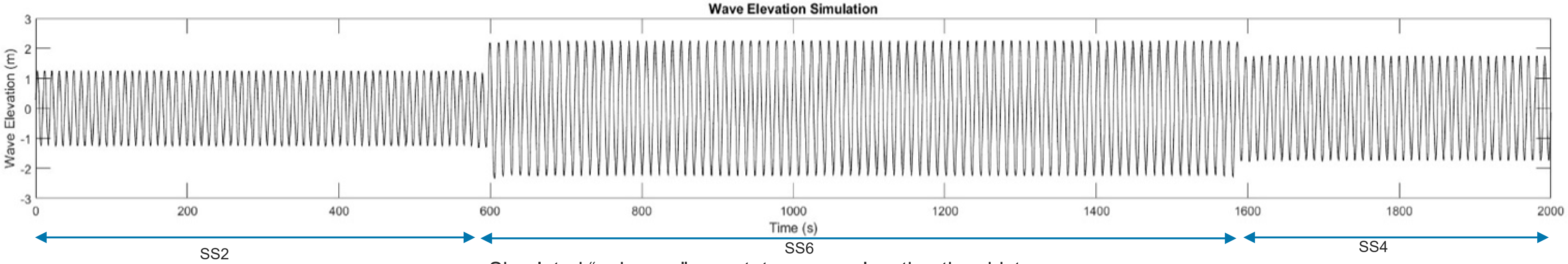
A Gaussian noise signal of zero mean and standard deviation of 0.05m heave, 0.05m surge and 0.05 degrees pitch with reference to the accuracy of a typical motion sensor MRU







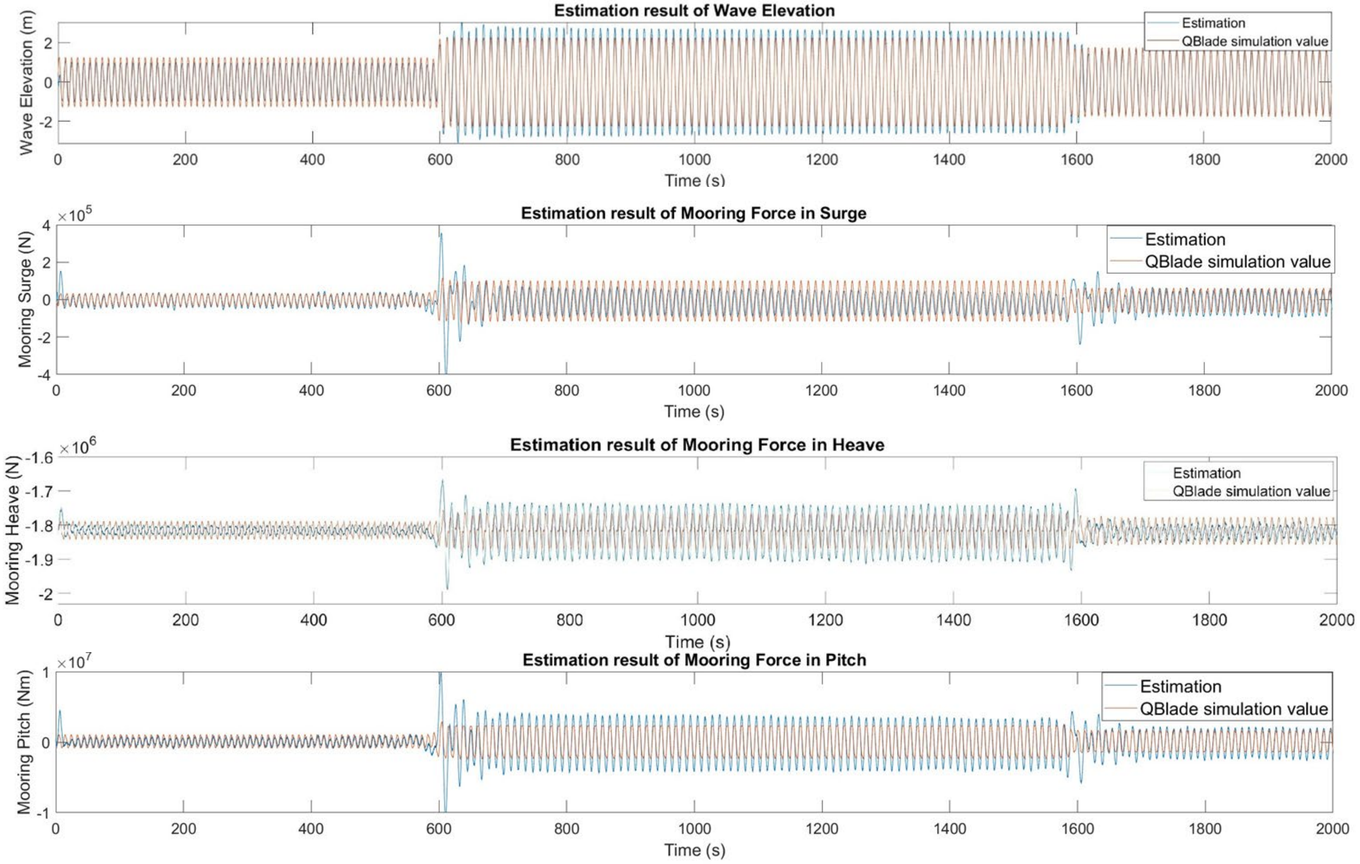
(Yung, Xiao, Incecik & Thompson, 2023)
ASME IOWTC2023-119374 *“Mooring force estimation for floating offshore wind turbines with augmented Kalman Filter: a step towards digital twin”*



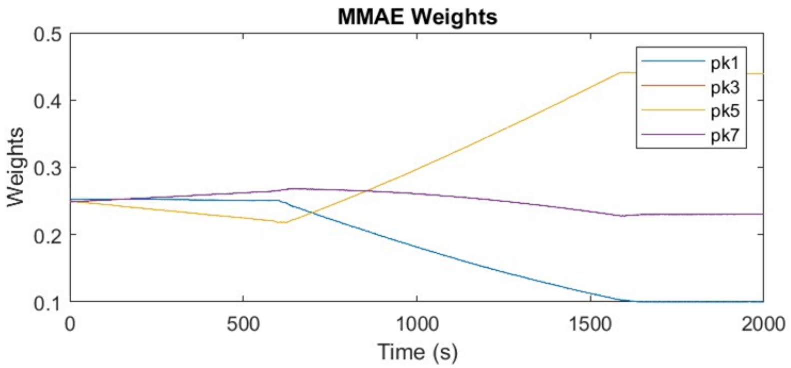
Simulated “unknown” sea states wave elevation time history

Results

Unmeasurable states estimation



Estimated vs. simulated “unmeasurable” states, wave elevation and mooring forces



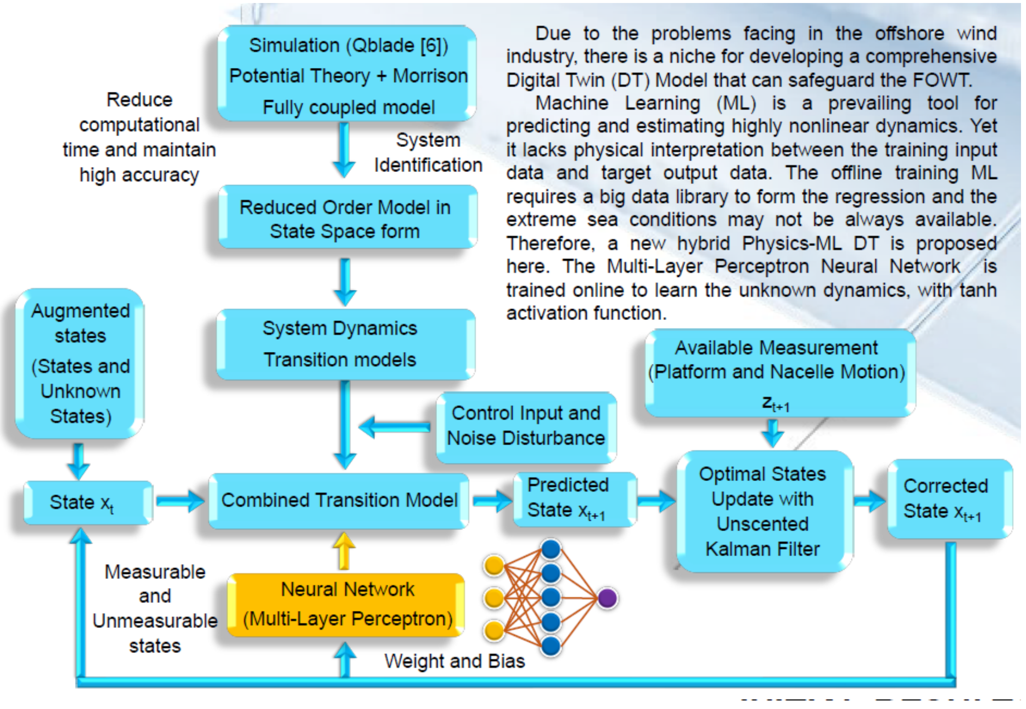
Adapting different sea states

(Yung, Xiao, Incecik & Thompson, 2023)
ASME IOWTC2023-119374 *“Mooring force estimation for floating offshore wind turbines with augmented Kalman Filter: a step towards digital twin”*

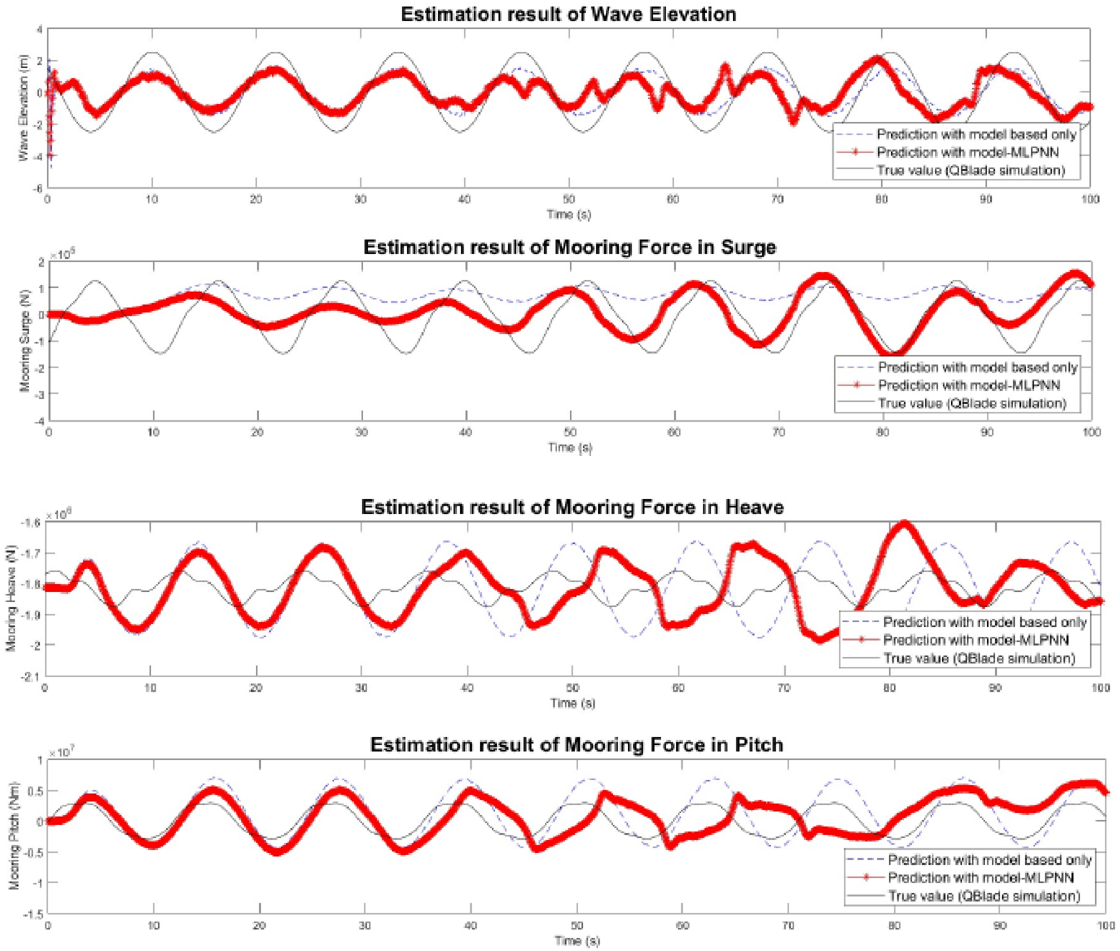
Results

Training Neural Network with Kalman Filter

Predict unknow sea state scenario



Yung, Xiao, Incecik & Thompson,
CENSIS Tech Summit 2023



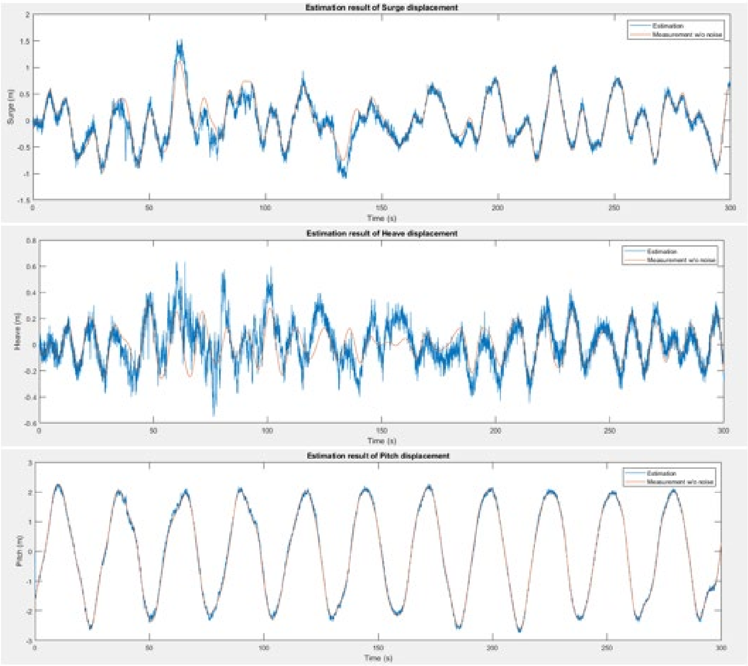
Neural network learning online and converge

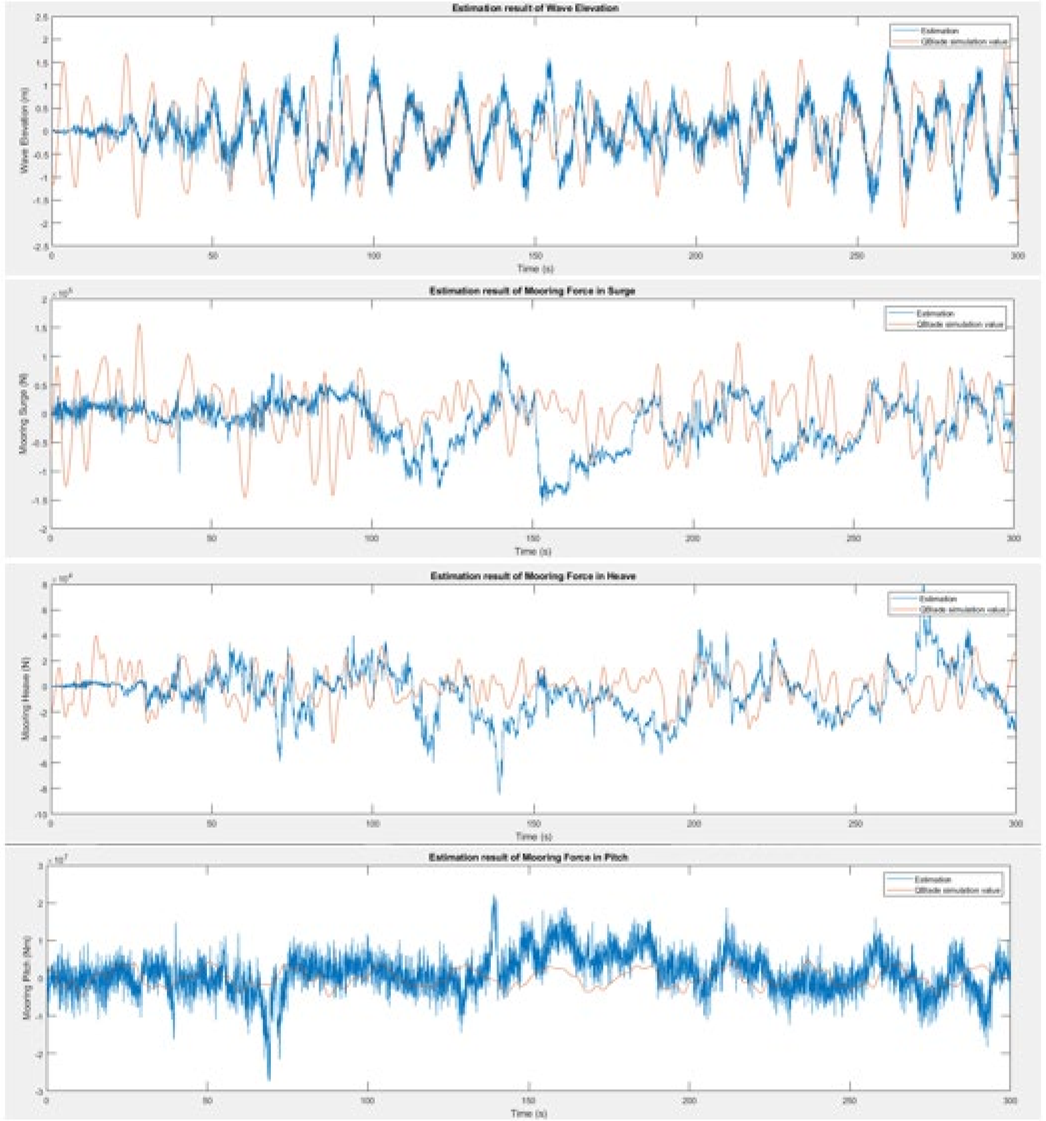
Results

Data Assimilation online and converge

Irregular wave (realistic sea state) with aerodynamics coupling
Pierson–Moskowitz (P-M) spectrum
Hs=3m, Tp=10.2s (Scotland, LIFES50+ project)
Wind speed 13m/s

Noisy measurement filtering





Predict internal forces and wave reconstruction based on noisy measurement of floater responses, initiated from arbitrary condition
→ Able to capture the amplitude and trend

(Only force variations are shown)

Conclusion

- Valid results in estimating the unmeasurable states e.g. internal forces
- Provide an alternative solution for structural health monitoring of the moorings and can be extended to other part of the FOWT
- Avoid the underwater sensor fragility problem under severe sea wave conditions and directly utilize the measured platform data with the high confidence and accuracy
- Potentially reduce extremely high costs in operating and maintenance
- Wave reconstruction help improve the control strategy of the FOWT for maximising power harvesting and reducing load

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Thank you
Q&A

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