Neural-network based optimisation of compliant mooring systems

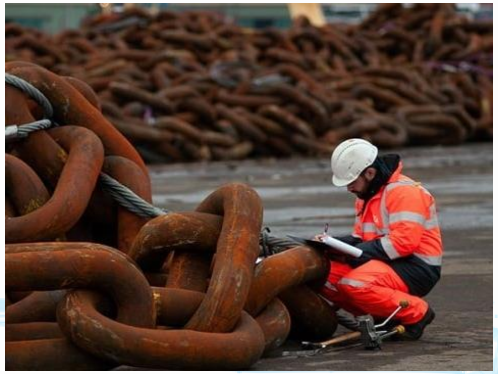
Oscar Festa, PhD student from the University of Southampton

Professor Susan Gourvenec , RAEng Chair in Emerging Technologies for Intelligent & Resilient Ocean Engineering (IROE), University of Southampton

Professor Adam Sobey, Data-centric Engineering lead, The Alan Turing Institute

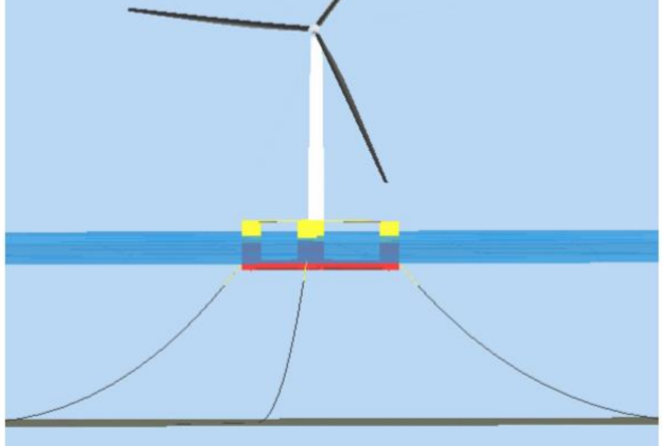
Intro (1/3) – Background

- FOWT mooring systems hold **high cost reduction potential**
- Mooring system design involves striking a balance between **stiffness** and **compliance**
- Cheaper, safer designs could be achieved by **optimising mooring system compliance**

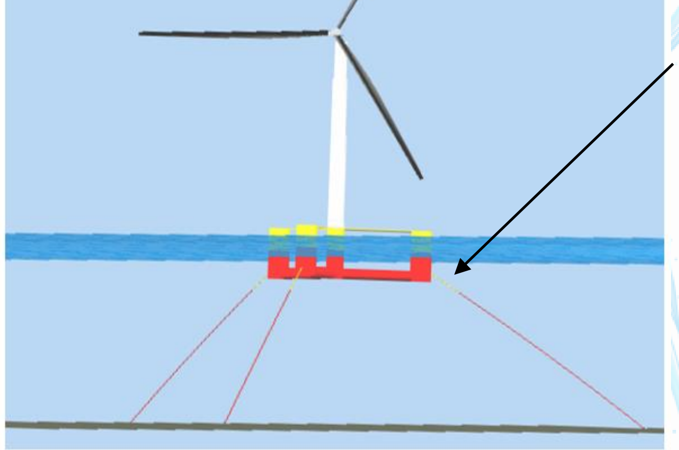


161 mm mooring chain (Maritime executive)

Hywind Tampen anchors (SEMAR)



Catenary mooring: geometric compliance



Taut-inclined mooring: elastic compliance

Load reduction devices (LRDs) can provide additional compliance

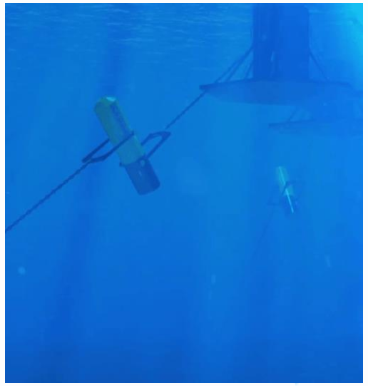
Can we use machine learning to optimise a taut mooring with LRDs?

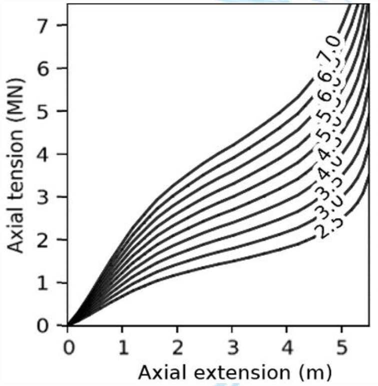
Intro (2/3) – Load Reduction Devices (LRDs)

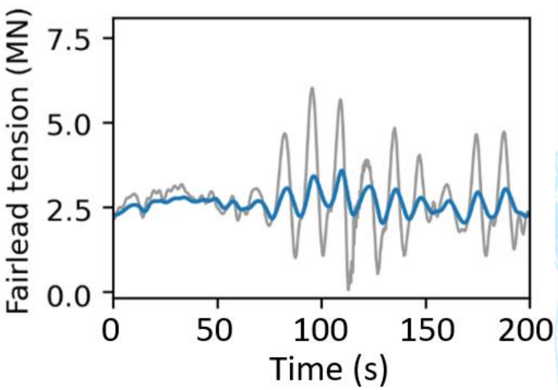
LRDs provide **targeted compliance**, offering high levels of extension without compromising breaking strength.

LRD technology | *Mechanism* | *Typical non-linear stiffness curves* | *Load reduction vs. conventional mooring*

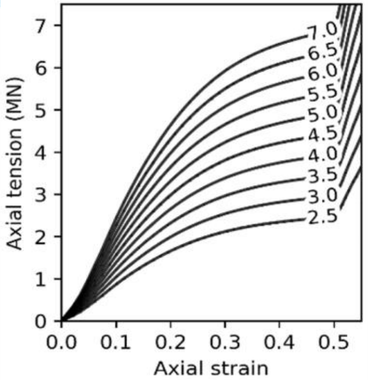
Dublin Offshore LRD
www.dublinoffshore.ie/technology

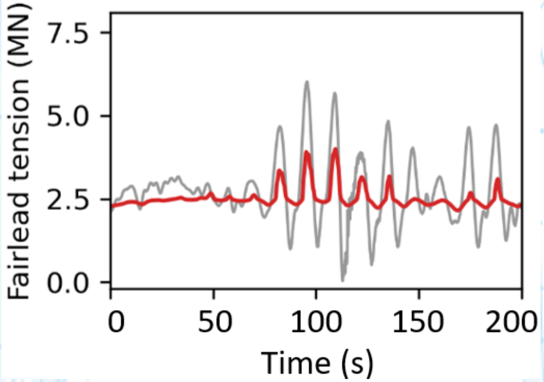






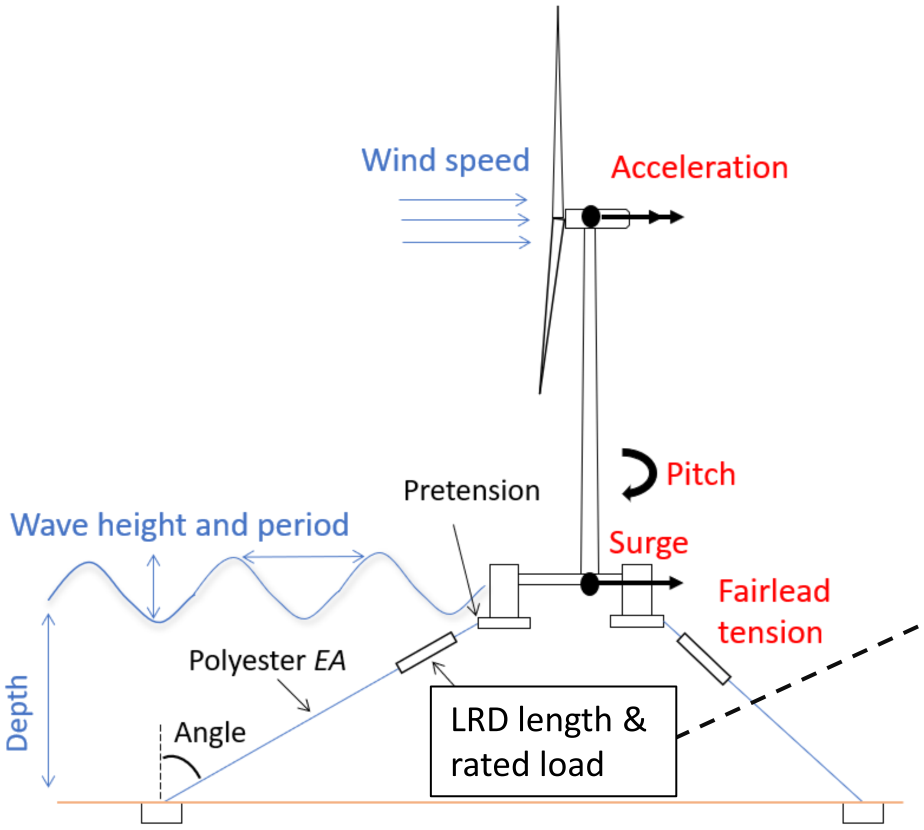
TFI Seaspring
www.tfimarine.com

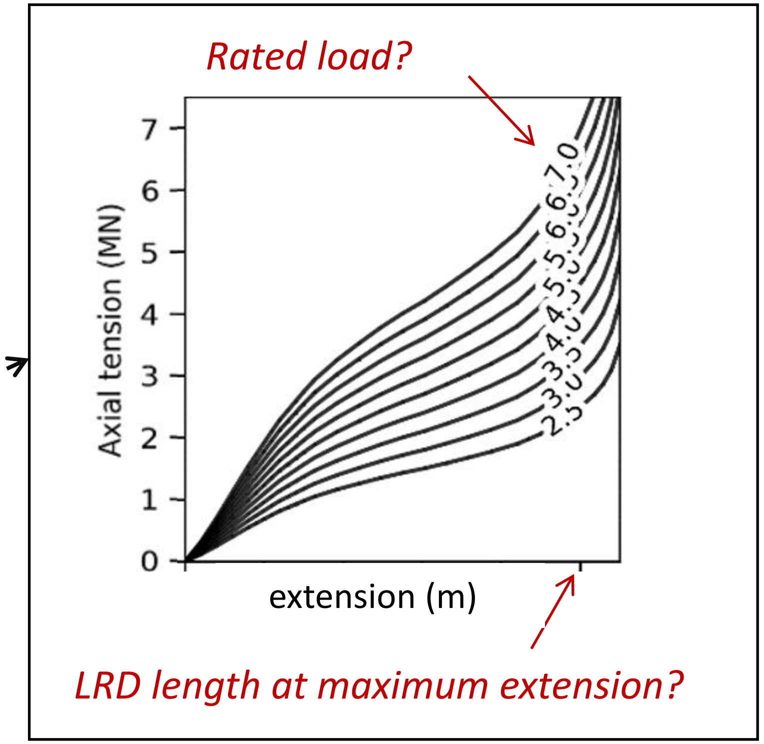




Intro (3/3) – Aim of research

Aim: **Holistic** and **generalisable** optimisation of taut compliant mooring systems including LRDs



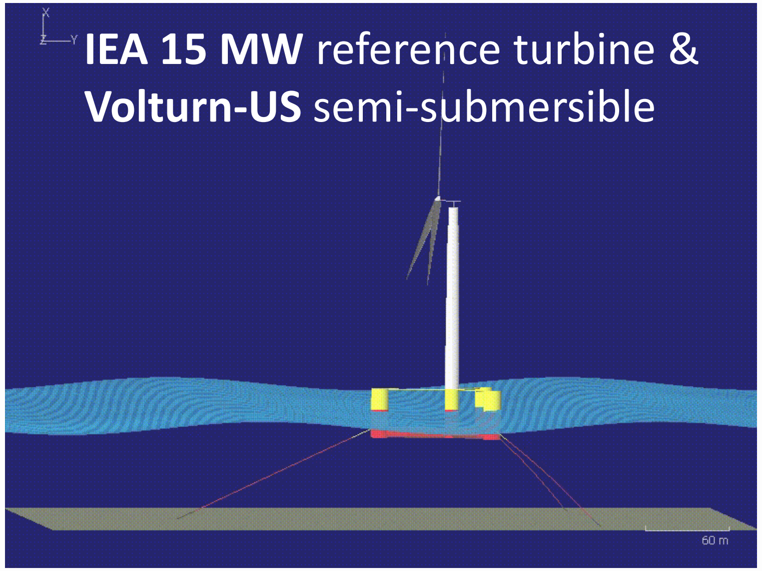


Location-specific parameters, mooring system & LRD parameters, outputs

Method (1/2) – Description of numerical model

Model set-up:

- Fully-coupled aero-hydro-servo dynamic modelling, with commercial software **Flexcom**
- LRDs modelled as non-linear spring elements, with stiffness curves representative of TFI or Dublin Offshore devices



Model parameter ranges:

Mooring & LRD parameters	Design space	
Mooring arrangement	Polyester taut	
Pre-tension (kN)	500 - 2500	
Polyester stiffness *EA* (MN)	30 – 120	
Line angle to vertical (deg)	55 – 80	
LRD rated load (MN)	2 – 7	
LRD spring element length (m)	10 - 30	
LRD curve types	Dublin Offshore, TFI	
Water depth (m)	60-150	
Load case parameters	**Parked**	**Operating**
Hub wind speed (m/s)	25 - 50	10.59 (rated)
Wave height (m)	10 – 25	2 – 15
Wave period (s)	8 – 18	6 – 16
Wind & wave direction (deg)	0	0
Current (m/s)	$0.015\ U_{hub}$	$0.015\ U_{hub}$

Method (2/2) – Neural network

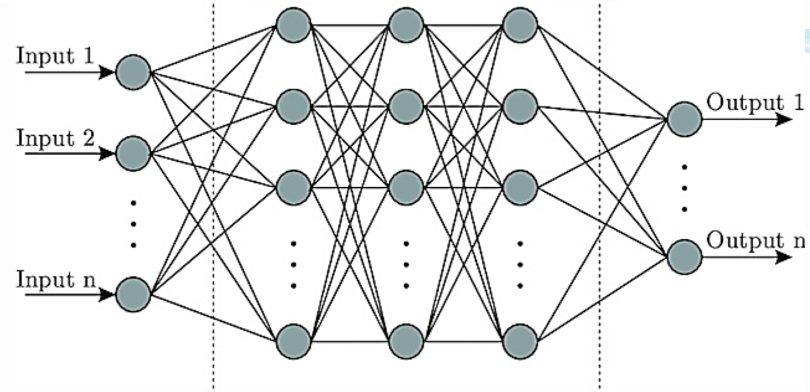
Surrogate neural network trained from 50k dynamic analyses provides an **instantaneous input – output relationship**

Input layers *Hidden layers* *Output layers*

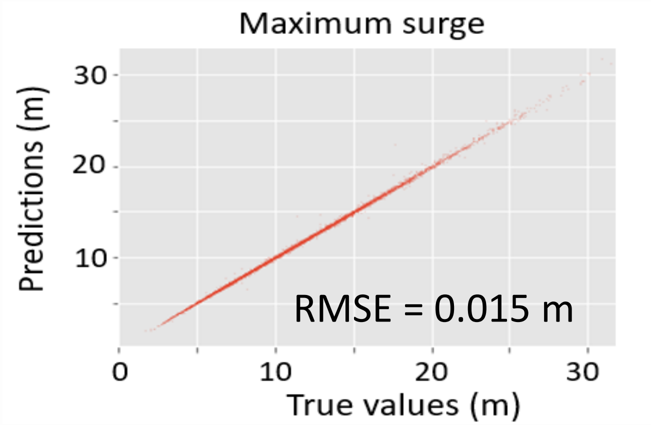
Mooring & LRD parameters

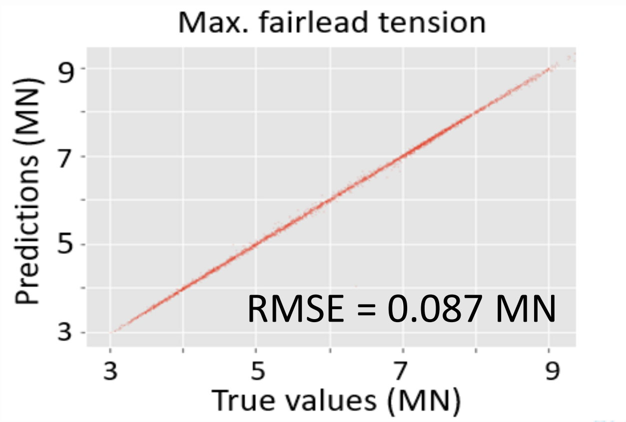
+

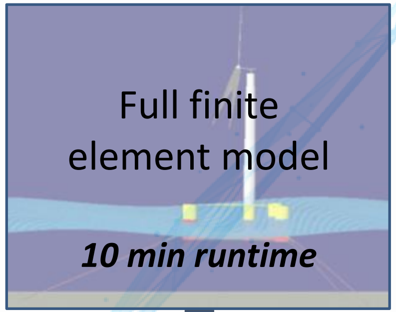
Load case parameters



Fairlead Tension
Surge
Pitch
Nacelle acc.







Data from FE analyses

Train NN

Fixed inputs location-specific parameters: Load case & water depth

NN model 'surrogate' ***0.02 s runtime***

Variable inputs Mooring & LRD parameters

Are outputs satisfactory?

update variables

Outputs

Optimisation

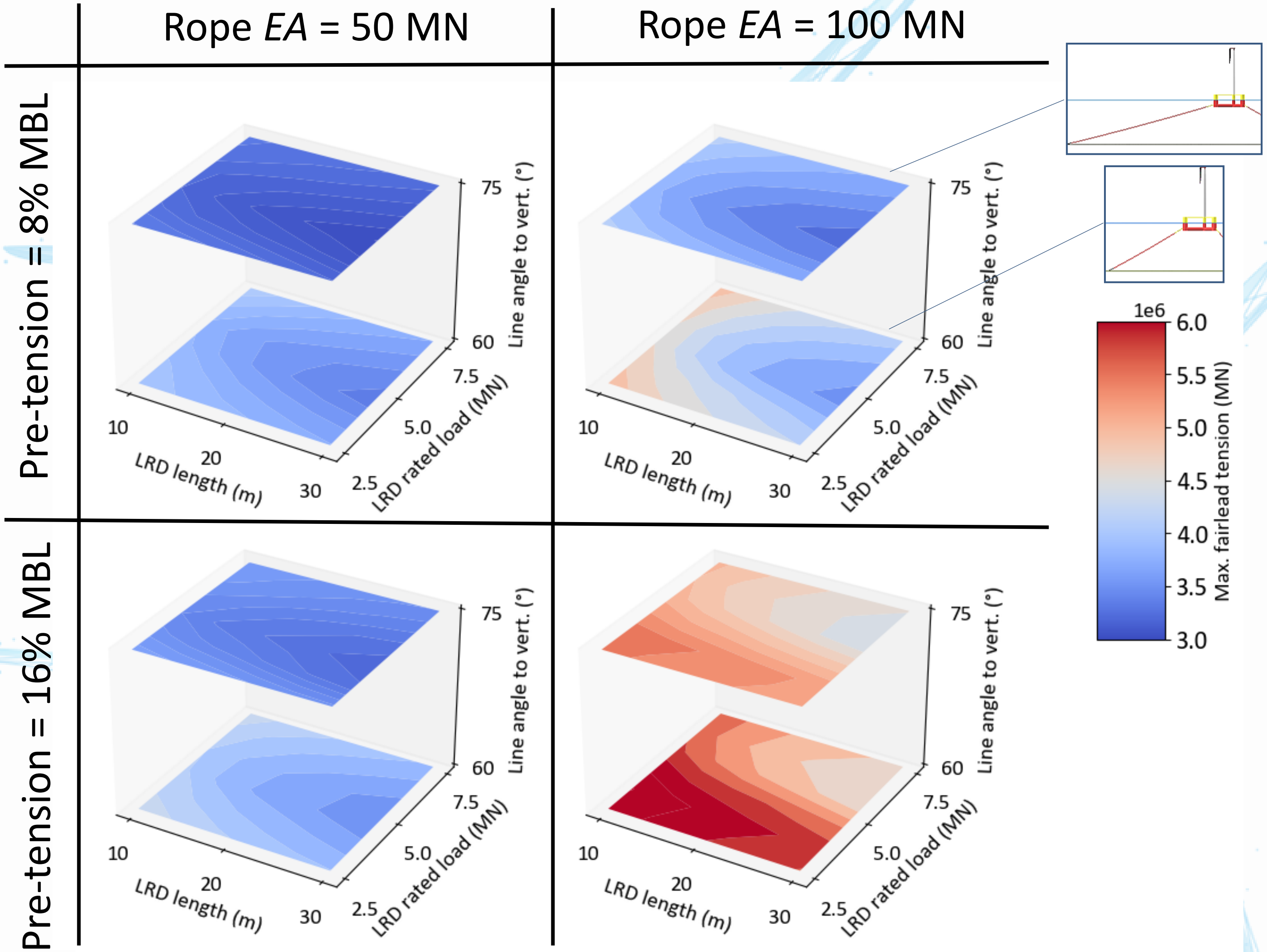
Final result: Optimal mooring & LRD parameters

Results (1/5) – Scenario A: location A, using Dublin Offshore LRD

Location A: Golfe de Fos

Shallow water (70 m), moderate environmental load

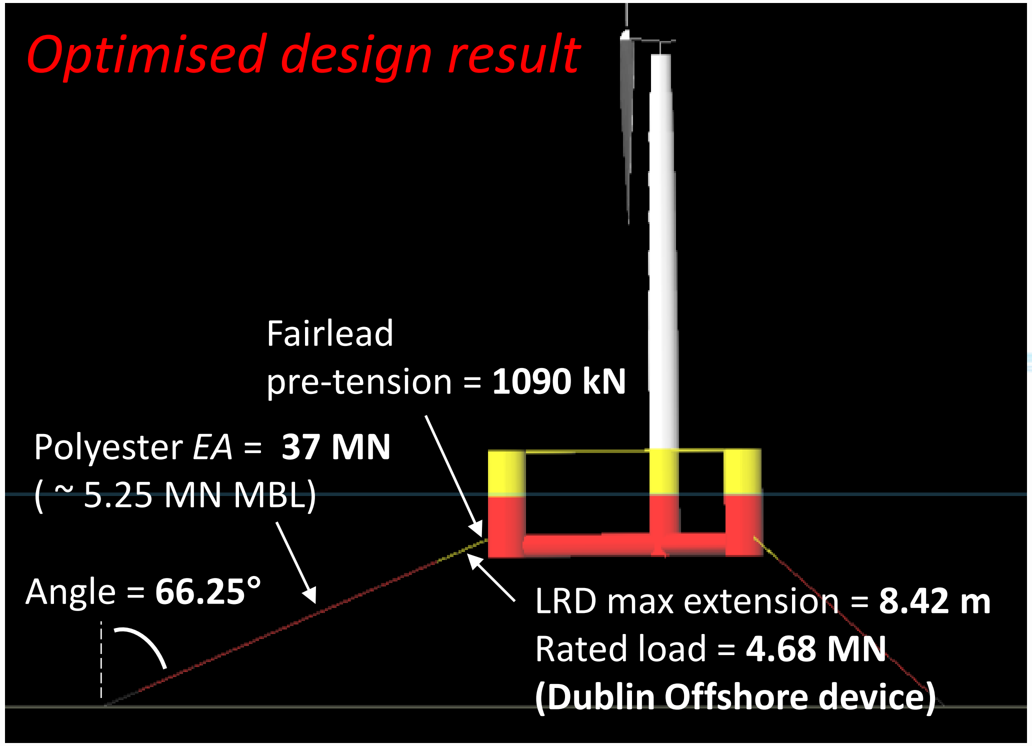
Location A parameters	Parked	Operating
Hub wind speed (m/s)	37	10.59 (rated)
Peak wave height (m)	13.95	7.20
Wave period (s)	11	11
Current (m/s)	0.015 U_{hub}	0.015 U_{hub}



Scenario A design space in parked load case

Results (2/5) – Scenario A single-objective optimisation

- Single-objective: to find the design which **minimises the max. fairlead tension,** within constraints
- Optimisation problem was solved with 2 different methods: 1. simple **gradient-based method,** 2. **genetic algorithm** (both provided similar results)



Performance of optimised design:

	Motion	Output/ Constraint	Constraint utilisation
operating	Surge (m)	7.47/7.5	99.6 %
	Pitch (deg)	4.92/5	98.4 %
	Nacelle Acc. (g)	0.07/0.18	38.9 %
parked	Surge (m)	12.40/15	82.7 %
	Pitch (deg)	1.50/7	21.4 %
	Nacelle Acc. (g)	0.1/0.3	33.3 %

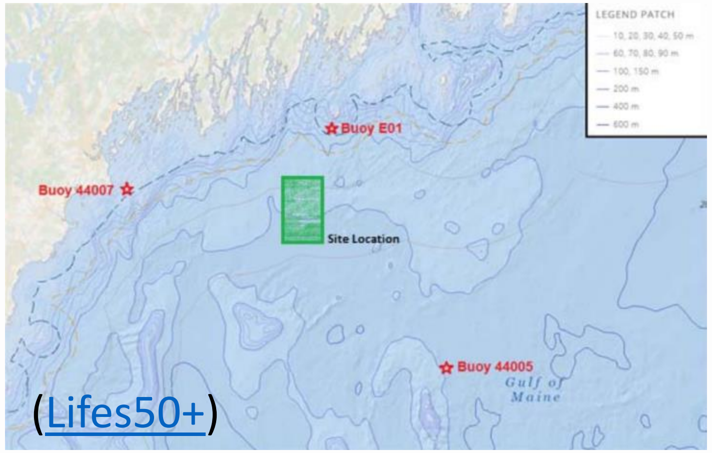
Maximum fairlead tension **= 3.35 MN**

51 % tension reduction and **71 % footprint reduction** vs. 'conventional' catenary mooring

Results (3/5) – Scenario B: location B, using TFI Seaspring

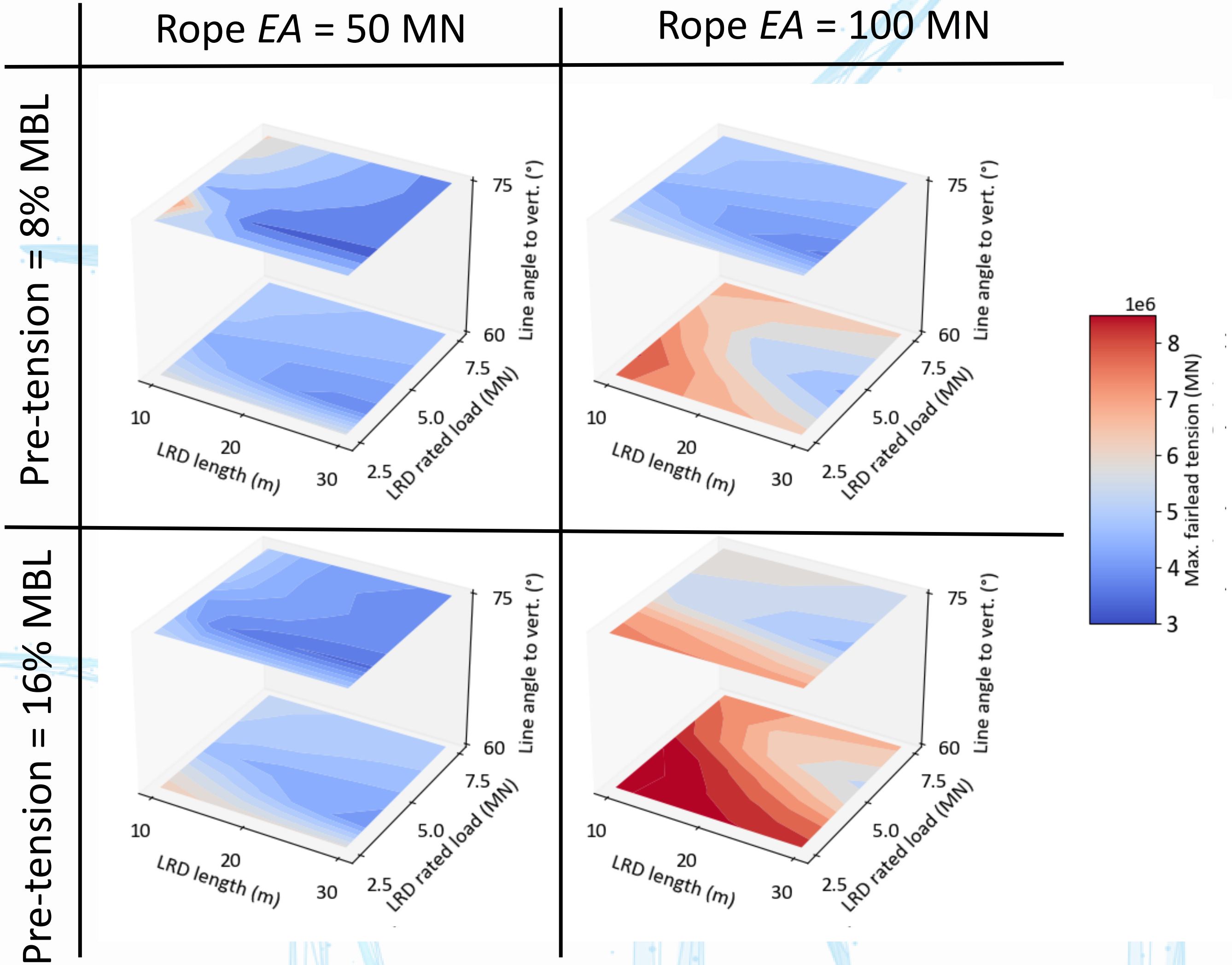
Location B: Gulf of Maine

Intermediate depth (130 m), high environmental load



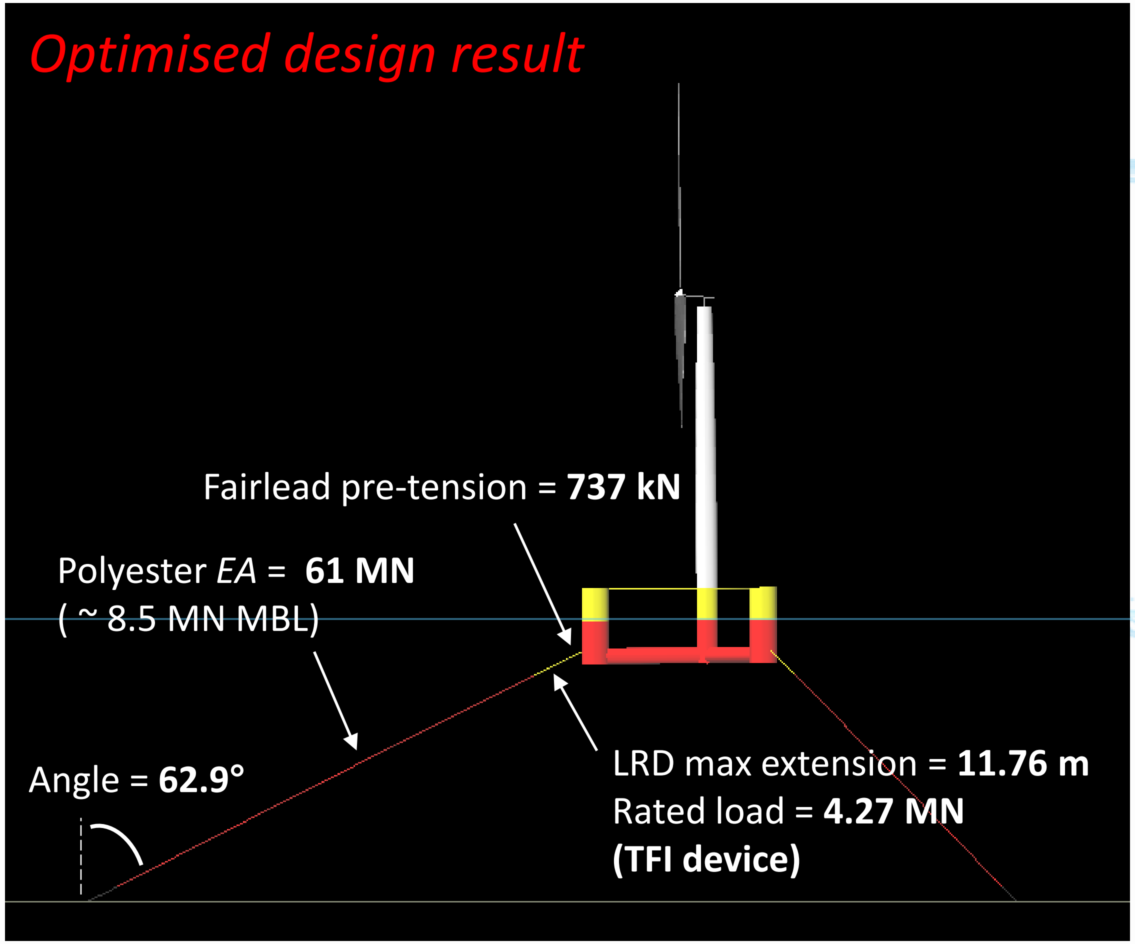
(Lifes50+)

Location B parameters	Parked	Operating
Hub wind speed (m/s)	44	10.59 (rated)
Peak wave height (m)	20	13.8
Wave period (s)	16	13
Current (m/s)	0.015 U_{hub}	0.015 U_{hub}



Scenario B design space for parked load case

Results (4/5) – Scenario B single-objective optimisation



Performance of optimised design:

	Motion	Output/ Constraint	Constraint utilisation
operating	Surge (m)	13.27/15	88.5%
	Pitch (deg)	4.44/5	88.8%
	Nacelle Acc. (g)	0.14/0.18	77.8%
parked	Surge (m)	20.05/30	66.8%
	Pitch (deg)	2.76/7	39.4%
	Nacelle Acc. (g)	0.22/0.3	73.3%

Maximum fairlead tension = **4.02 MN**

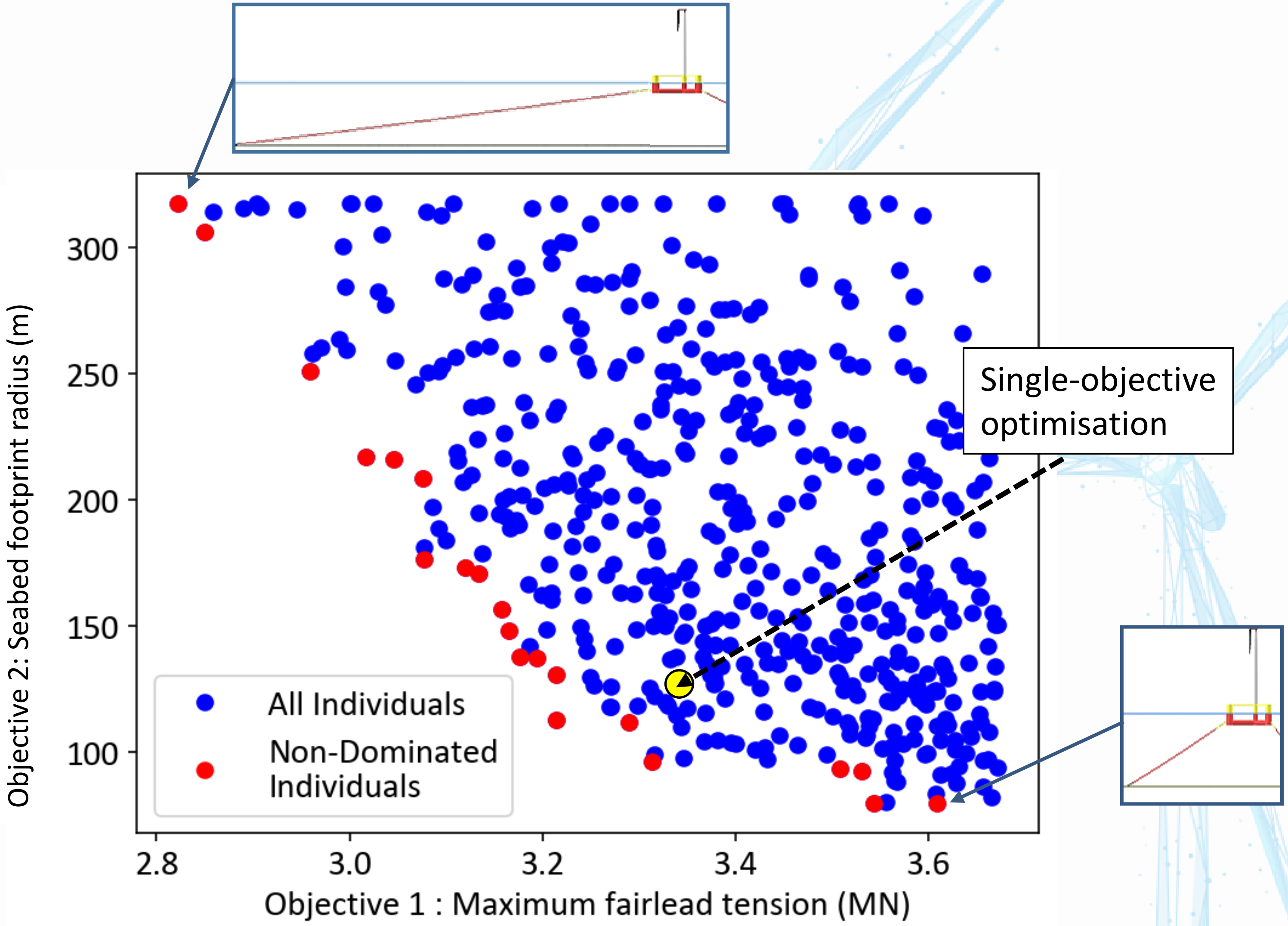
61 % tension reduction and **63 % footprint reduction** vs. 'conventional' catenary mooring

Results (5/5) – Multi-objective optimisation

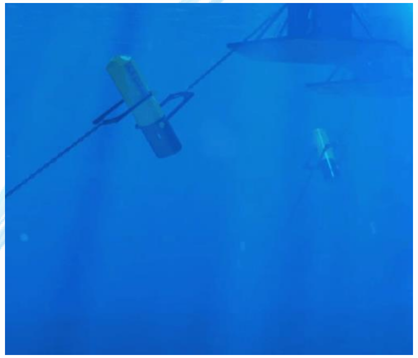
- A **genetic algorithm** can be used to find combinations of design parameters (i.e. 'individuals') which optimise *multiple objectives* simultaneously

- Any of the non-dominated individuals represent an **optimal compliant mooring system**

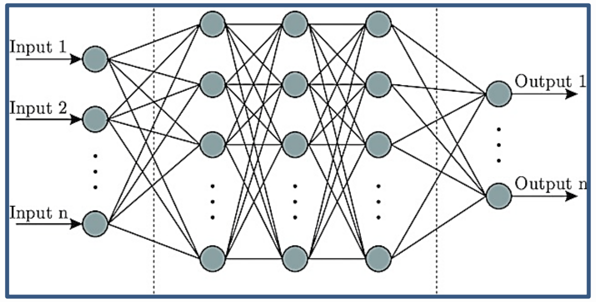
- This can provide **more useful results** than a single-objective optimisation



Conclusions & contact info



Combining **load reduction devices** with taut mooring systems can provide significant **tension reduction** and seabed **footprint reduction**



Using a **neural network-based surrogate model** allows the usage of various optimisation procedures, without running iterative dynamic analyses

This enables us to **reverse the design question**: using typical outputs of dynamic analyses (tension, platform motions etc.) as inputs to the optimisation procedure.

Any questions?
Feel free to get in touch by email: o.g.festa@southampton.ac.uk