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Early Career Researcher Posters and Abstracts Booklet

2026 Annual Assembly

Surnames H-L

Engineering and
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Supergen Offshore Renewable Energy

Early Career Researcher Posters 2026

Payvand Habibi, University of Strathclyde Advanced Stress Analysis for Optimised Marine Energy Structures (ASAMES)
Payvand Habibi, University of Strathclyde An Integrated Experimental-Computational Framework for Erosion Analysis of Tidal Turbine Blades
Yadong Han, University of Oxford Unsteady hydrodynamic forces on a forced oscillating rotor
Anna Holcombe, University of Exeter Assessing the contribution of VIV to fatigue damage in dynamic power cables
Sam Hughes, University of Edinburgh Reduced-Order Modelling (ROM) of Tidal Turbine Rotor Blade Structures
Jack Lewis, University of Strathclyde Offshore Wind Farm Layout Optimisation using Simplified Geometric Blockage Metrics
Ye Li, University of Southampton Concrete Composites in Marine Environment, FRP-enabled sustainable concrete for durable floating wind structures
Chenying Liu, University of Oxford Origami-Enhanced Dielectric Fluid Generator for Wave Energy Conversion

Offshore Wind Farm Layout Optimisation using Simplified Geometric Blockage Metrics

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Background

Wind farm layout optimisation (WFLO) often relies on complex wake models or computationally intensive algorithms to improve turbine placement and maximise energy output. This study explores a lightweight alternative, using simple, physics-informed geometric blockage metrics: **Blockage Ratio (BR)** and **Blockage Distance (BD),** as direct reward functions for machine learning-based optimisation.

By integrating these metrics with common optimisation methods, we assess whether such low-cost approximations can produce layouts comparable to those designed using traditional, more computationally demanding methods.

Wake Modelling

Current market FLOW and monopile OFW devices were simulated using a combination of a Gaussian velocity model and the Crespo-Hernandez wake model to account for wake effects and velocity deficits. The simulation was performed using the FLORIS model developed by NREL.

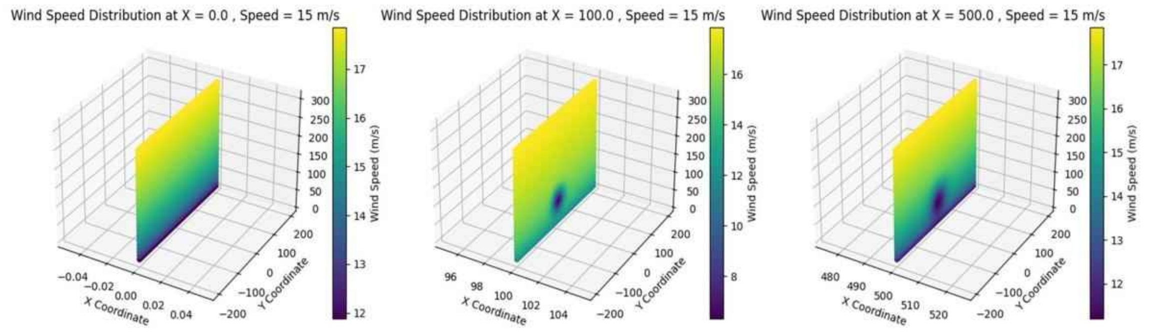
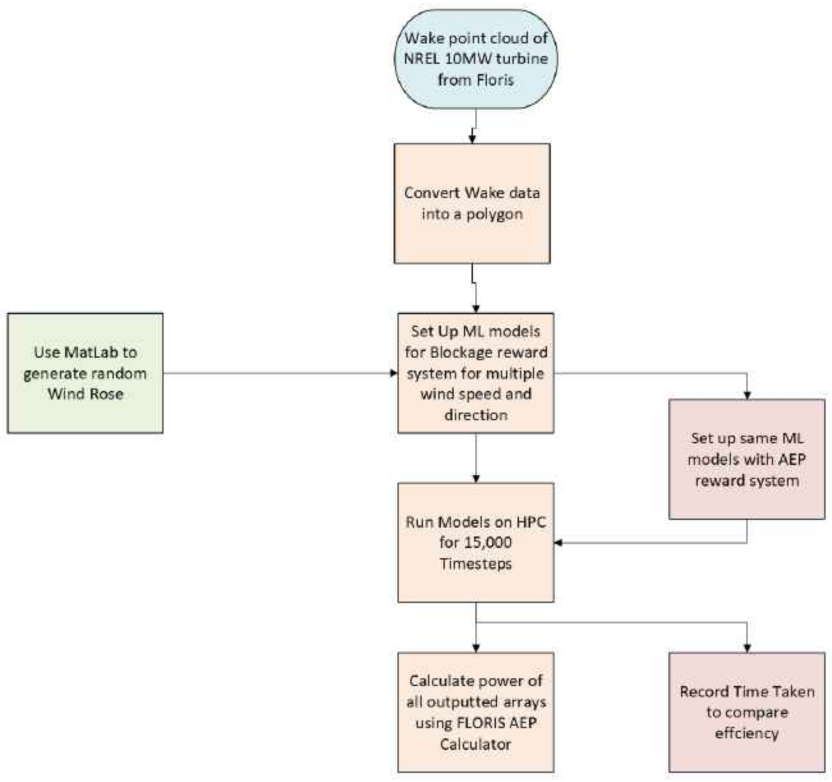


Fig 1: Slices through the FLORIS domain showing the wake expansion of an OWT

Methodology

We use a Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), and a Reinforcement Learning (RL) agent using Soft Actor-Critic (SAC) as our optimisation methods, due to their prevalent use across WFLO literature.



Wake point cloud of NREL 10MW turbine from Floris

Convert Wake data into a polygon

Use MatLab to generate random Wind Rose

Set Up ML models for Blockage reward system for multiple wind speed and direction

Set up same ML models with AEP reward system

Run Models on HPC for 15,000 Timesteps

Calculate power of all outputted arrays using FLORIS AEP Calculator

Record Time Taken to compare effciency

Fig 2: Flowchart showing project pipeline

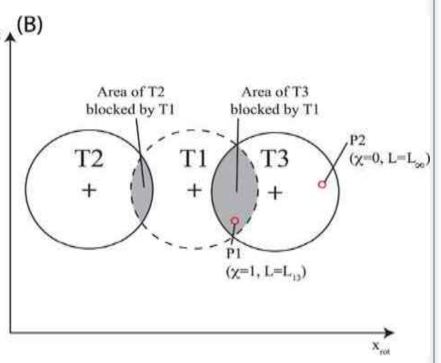


Fig 3: Representation of wind turbines and the related blockage variables

The Blockage reward functions are the optimal Blockage Ratio (BR), as close to zero as possible, and Blockage Distance (BD), as close to one as possible. The relevant equations are presented here:

$$BR = \frac{1}{A}\int_{(x,y)\in A} X dxdy \quad BD = \frac{1}{A}\int_{(x,y)\in A} [L_X + (1-X)L_X]dxdy$$

Results

With a wind Rose as the input wind data, the AEP reward systems slightly outperformed their blockage reward system counterparts. However, the Blockage-based GA and PSO produced more efficient layouts compared to the staggered baseline, as shown in Figure 4.

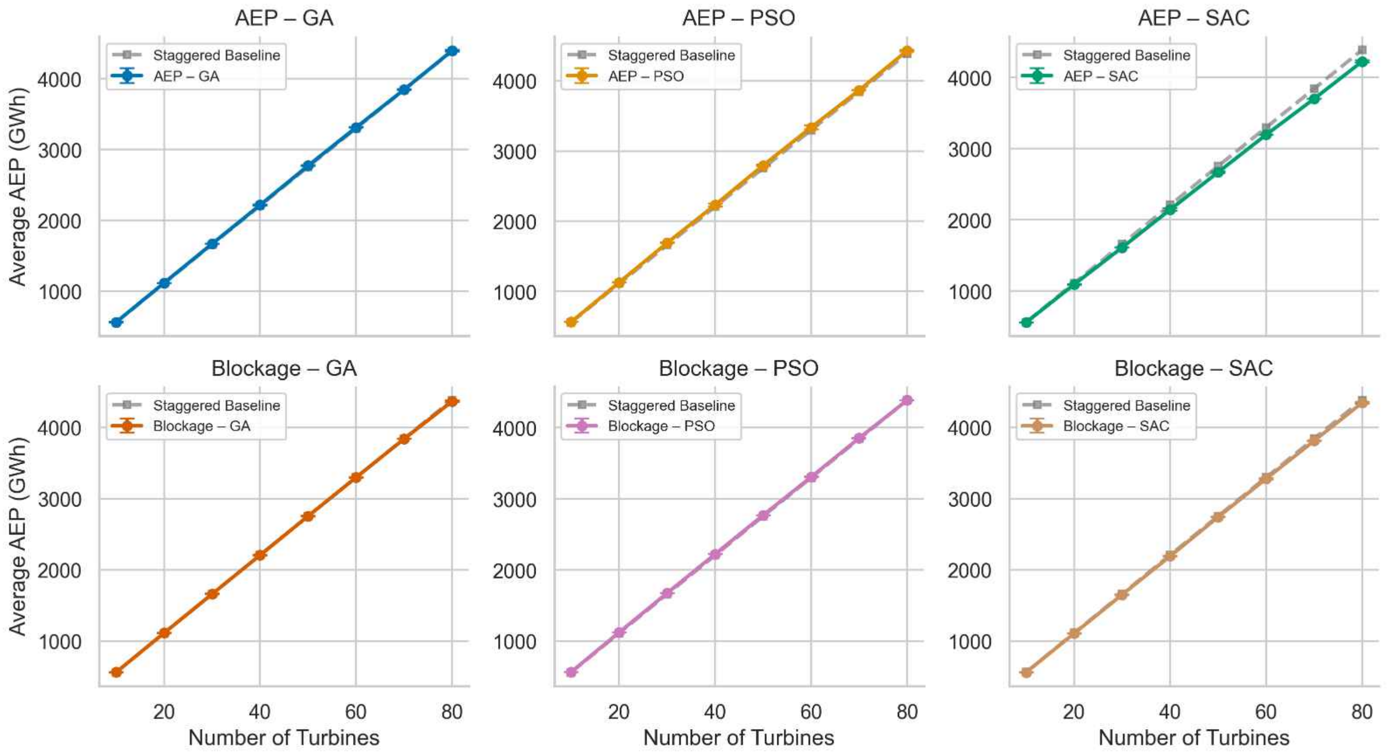


Fig 4: Power Output of all generated turbine configurations

In addition, as shown by Figure 5 below, the Blockage methods were significantly faster than their AEP counterparts, ranging by orders of magnitude of 0.9 – 1.12.

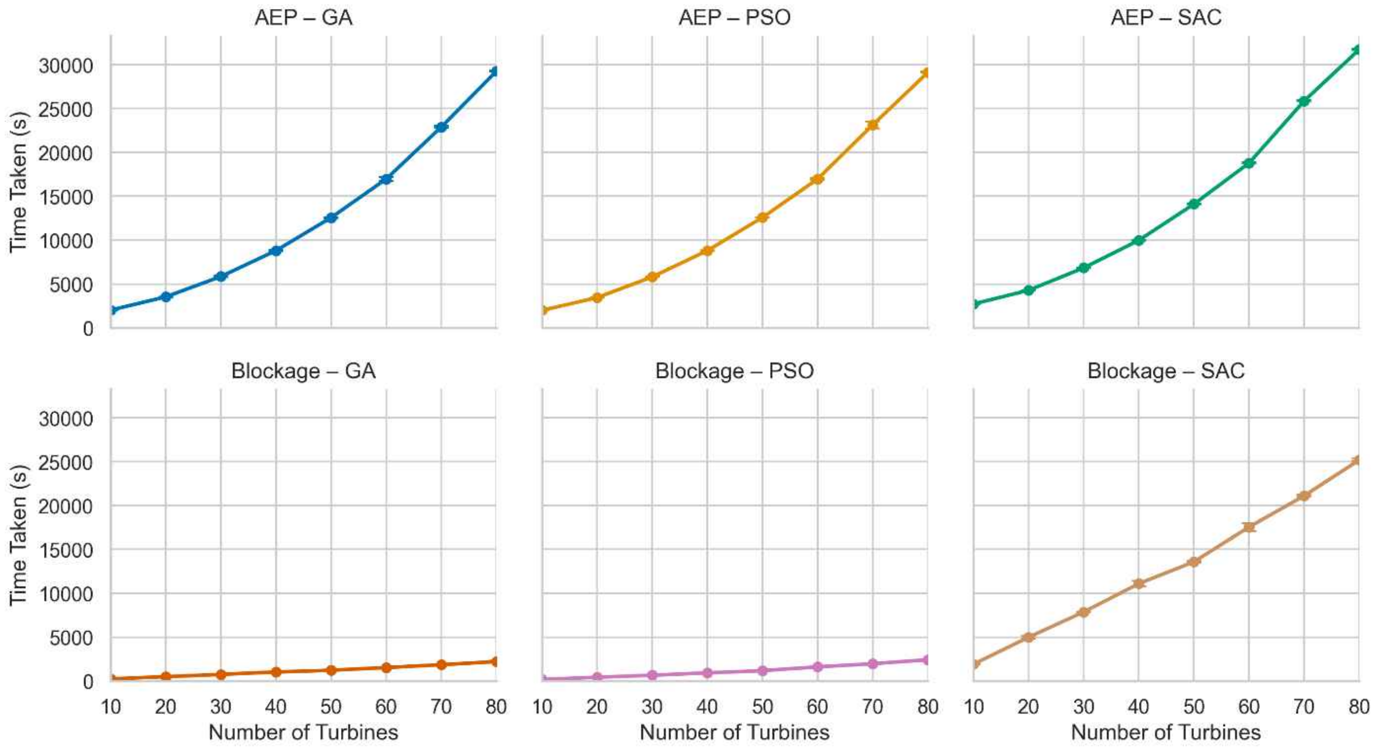


Fig 5: Average time to produce the generated OWF configurations

Discussion and Further Work

Results show that using blockage metrics as a reward function is highly effective and can yield results comparable to standard methods. All machine learning methods achieved significant reductions in optimisation time, which becomes increasingly valuable when scaling to realistic OWF. The simplicity of the blockage framework also supports easy adaptation to varying wind directions and speeds, and it can be extended to floating wind scenarios with only adjustments to wake polygon sizes.

References

- Duvvuri, G.M. et al. (2022) 'Further calibration and validation of FLORIS with wind tunnel data', Journal of Physics: Conference Series, 2265(2), p. 022019.
- Ti, Z., Deng, X.W. and Yang, H. (2020) 'Wake modeling of wind turbines using machine learning', Applied Energy, 257, p. 114025.
- Yan, C., Pan, Y. and Archer, C.L. (2019) 'A general method to estimate wind farm power using artificial neural networks', Wind Energy, 22(11), pp. 1421–1432.

Concrete Composites in Marine Environment

FRP-enabled sustainable concrete for durable floating wind structures

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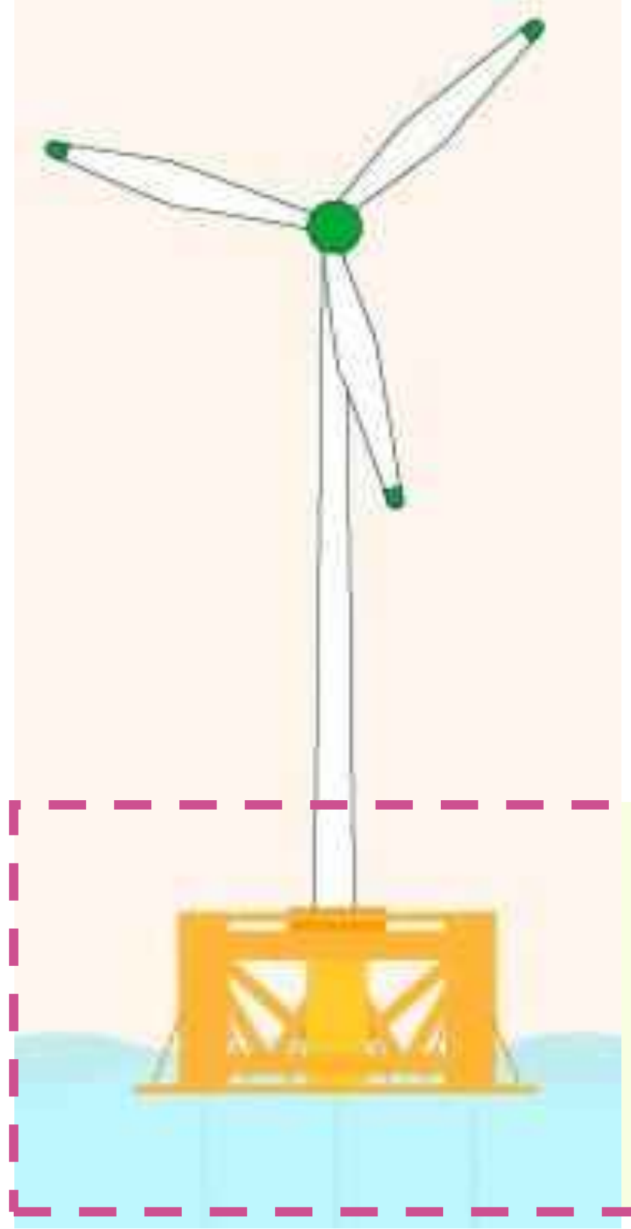
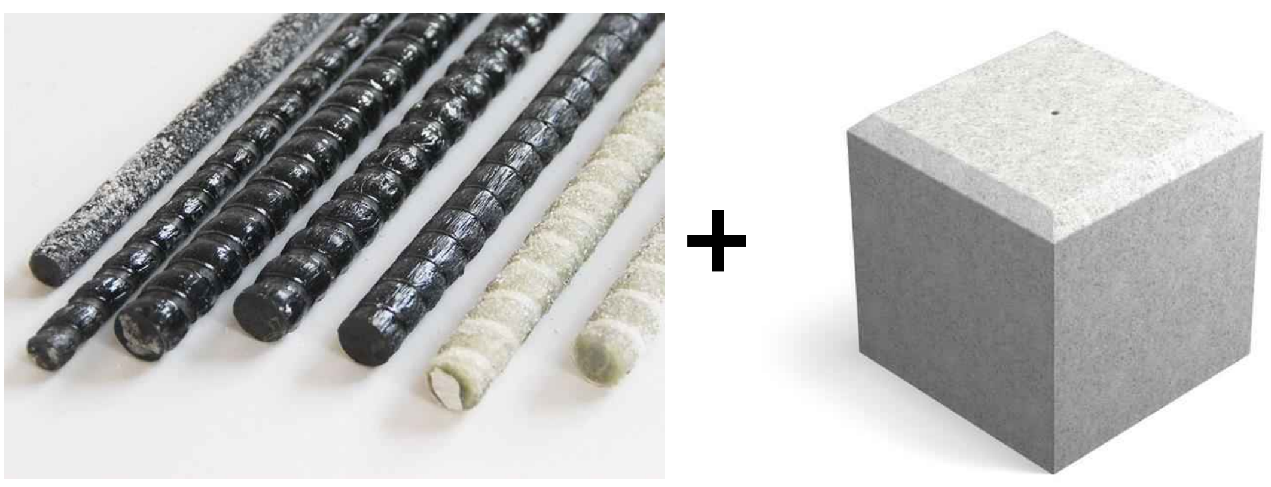
Opportunities for the application of concrete

Requirements for FOW structure

- Harsh Marine Environment (Corrosion)
- Complex Loading Conditions (cyclic fatigue)
- Long-Term Durability Uncertainty (maintenance)
- Cost & Deployment Constraints
- External Supply Chain Uncertainty

Concrete and FRP offer a cost-effective, durable, and locally available solution for next-generation floating wind structures.



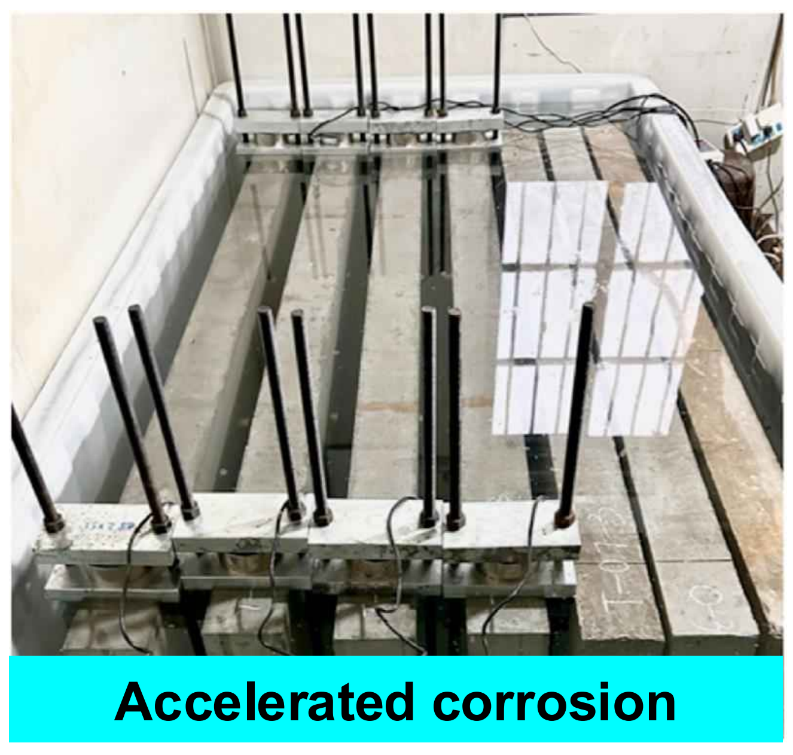


FRP reinforcement offers high strength and removes corrosion constraints, enabling a new design space for sustainable concrete systems, i.e., incorporating low-carbon cements, seawater use, and recycled materials.

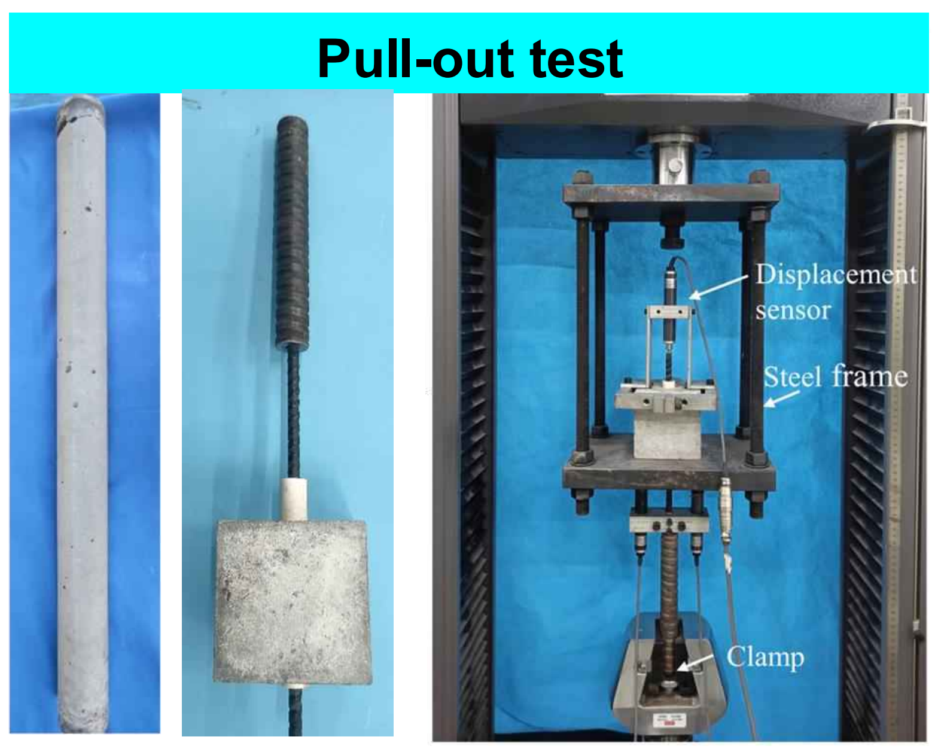
Opportunities for Concrete Replacement

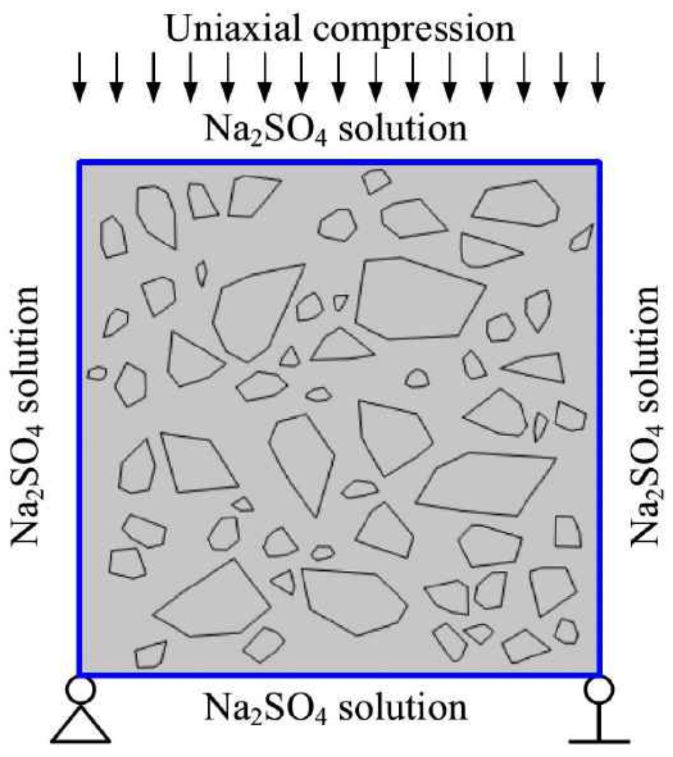
Lower Tower Sections
Columns
Pontoons
Ballast compartments
Working platforms

Concrete Degradation Model and FRP-concrete Structural Durability


Accelerated corrosion

Pull-out test





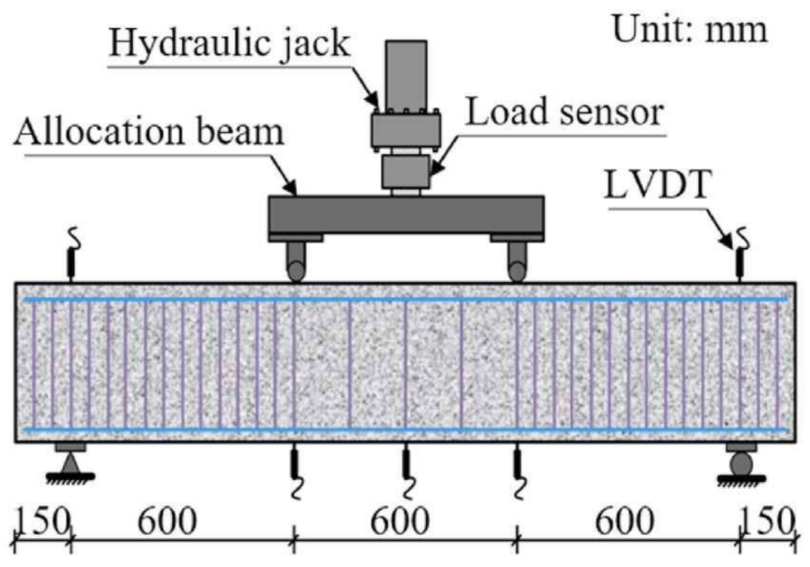
$$\frac{\Delta V}{V} = \left(\frac{\Delta V}{V}\right)_{\mathrm{AFt}} - \left(\frac{\Delta V}{V}\right)_{\mathrm{leach}}$$ Phase change→Volume change

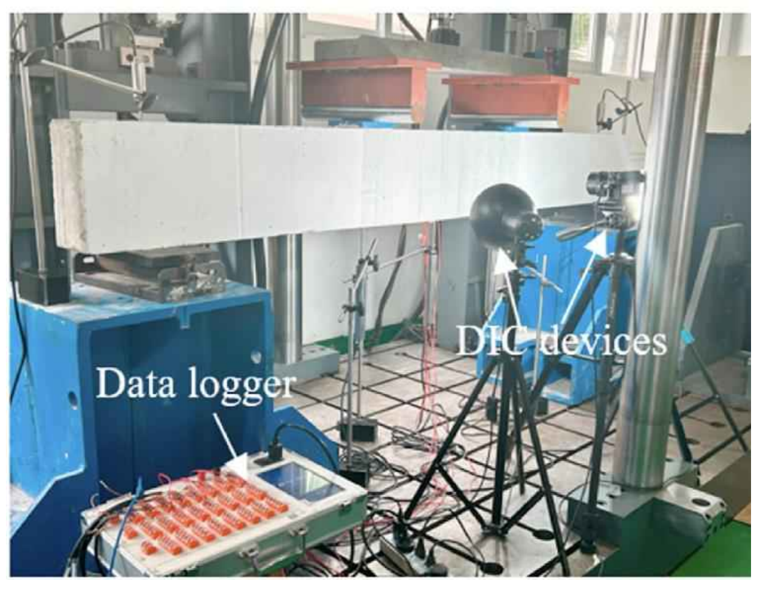
$$\varepsilon_v = \frac{\Delta V}{V} - f \cdot \phi_0$$ Volume→Micro strain

$$\varepsilon^M = \frac{9\phi_m K_p}{3K_p + 4G_s}\varepsilon_R$$ Micro strain→Macro equivalent strain

$$\sigma = (1-d)\,C : (\varepsilon - \varepsilon^M)$$ Strain/stress relation–Damage

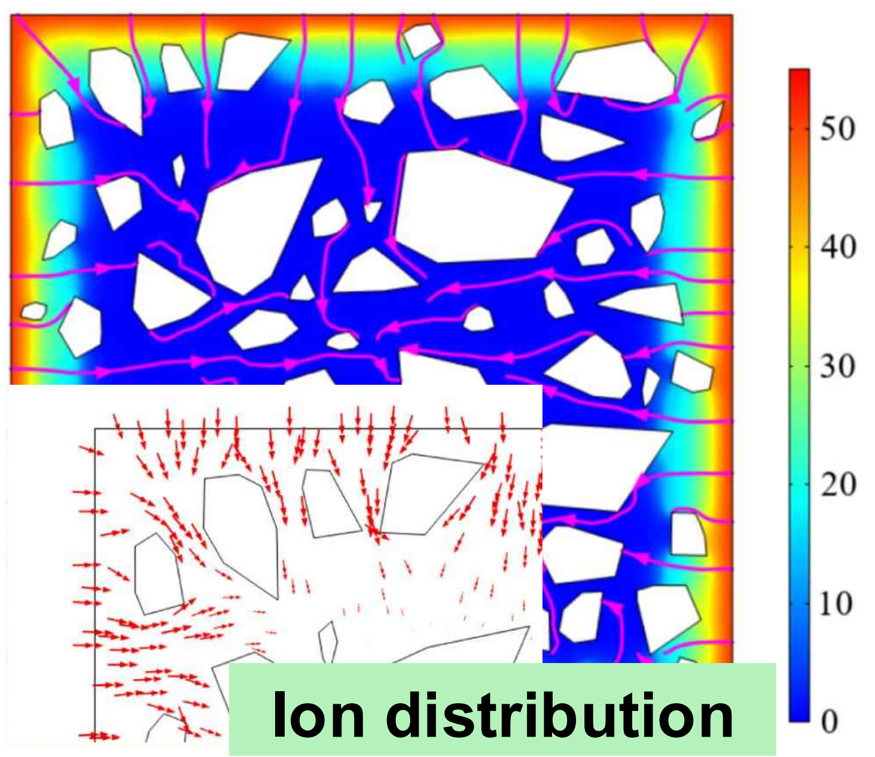
A mesoscale mechanical deterioration model for the chemo-transport-mechanical degradation of concrete.



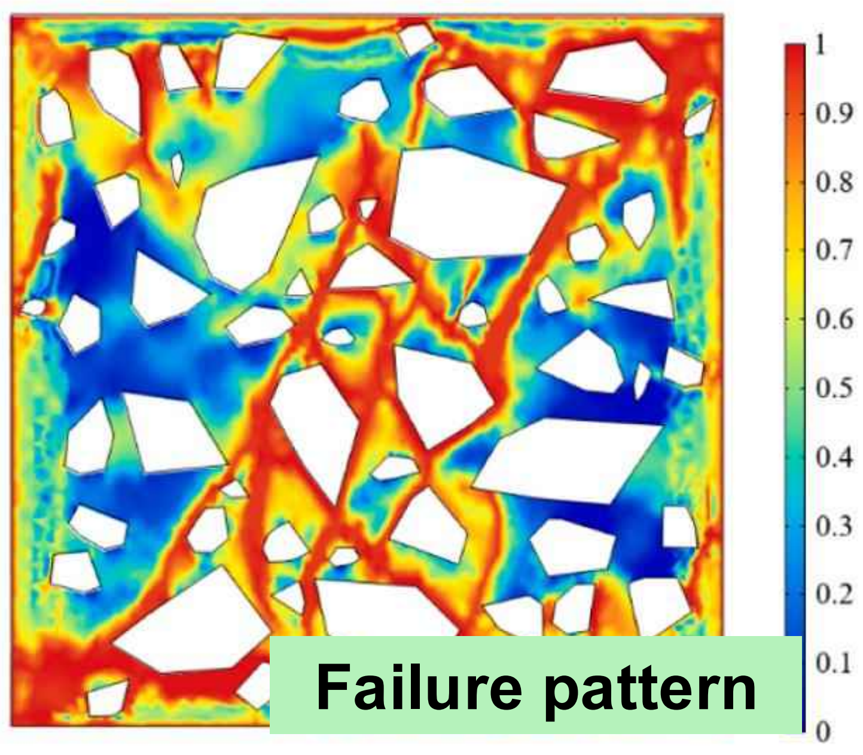


Degradation of FRP, concrete, and composite beams was investigated after exposure to seawater immersion, sustained loading, and high temperature.
Concrete: Normal/Low-carbon concrete using seawater
Rebar: steel-FRP composite bar
Accelerated corrosion: seawater, 0.5 cracking load, 50°C
Test: FRP fracture, Pull-out, Beam bending, Beam fatigue tests (0.4 capacity)

Results and implication

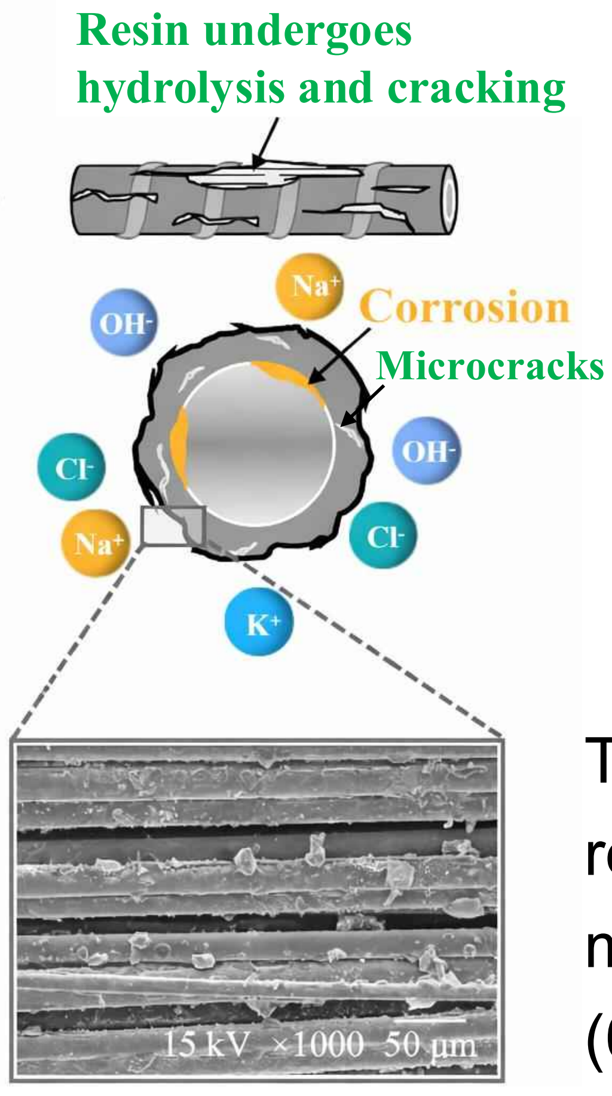


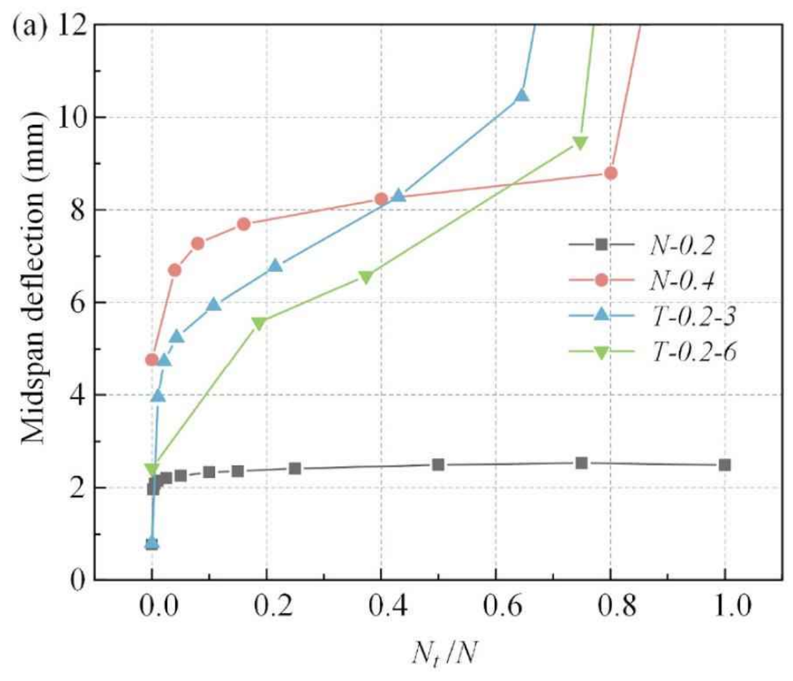
Ion distribution

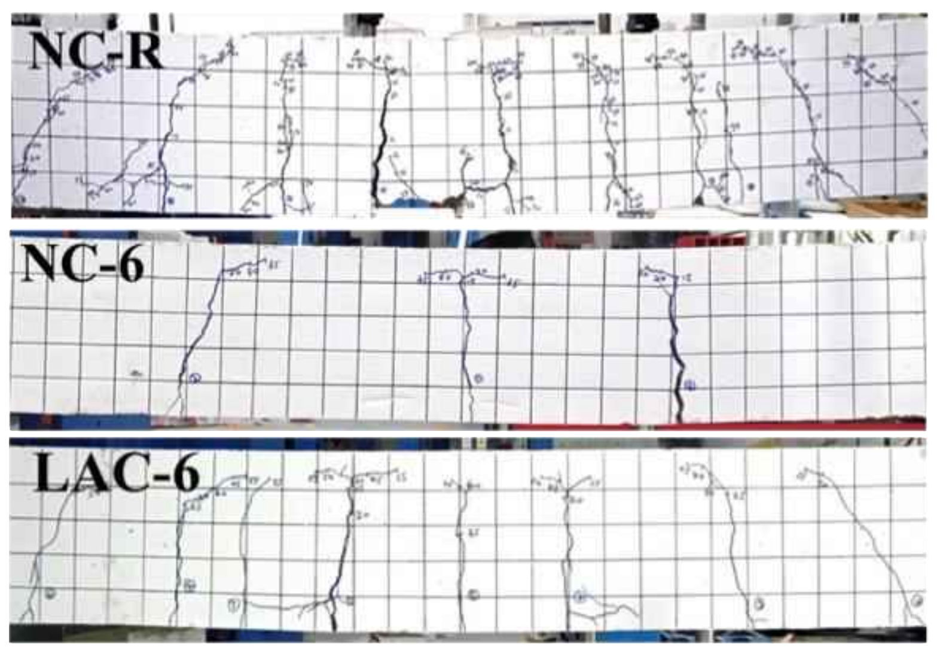


Failure pattern

The model successfully predicts expansion-driven degradation and reproduces observed failure modes, demonstrating that aggregate-induced heterogeneity controls sulfate transport, stress concentration, and crack propagation paths.







The epoxy in FRP in low-carbon concrete showed significantly reduced decomposition depth to only 300 μm. The beams maintained consistent yielding loads and higher ultimate loads (64.0% and 89.8% greater than the normal concrete group).

Higher sustained loading accelerates fatigue degradation, leading to increased deflection and crack propagation. Coupled marine exposure further reduces stiffness and fatigue life by enabling seawater ingress and damage of the SFCB (resin degradation and steel core corrosion).

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Origami-Enhanced Dielectric Fluid Generator for Wave Energy Conversion

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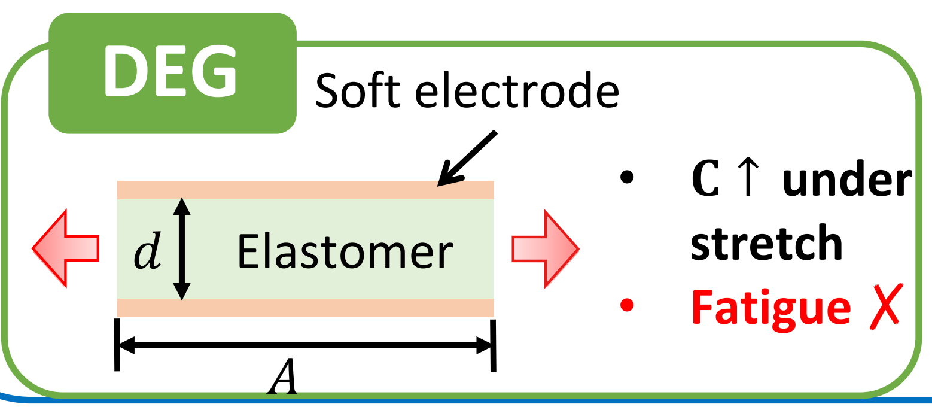
1 Introduction

Ocean waves offer a vast, largely untapped, and sustainable energy resource. In the UK, wave energy has the potential to generate up to 30 TWh/year, about 10% of nation's electricity demand.

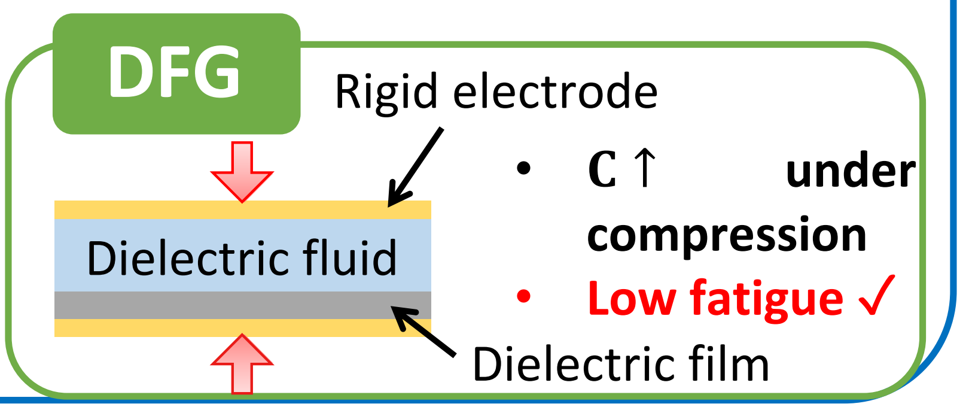
Dielectric elastomer generators (DEG) and dielectric fluid generators (DFG) use **mechanically variable capacitors** to convert wave motions into electricity. A parallel-plate capacitance is

$$C = \frac{\varepsilon_0 \varepsilon_r A}{d}$$

where ε_0 is vacuum permittivity and ε_r is relative permittivity.

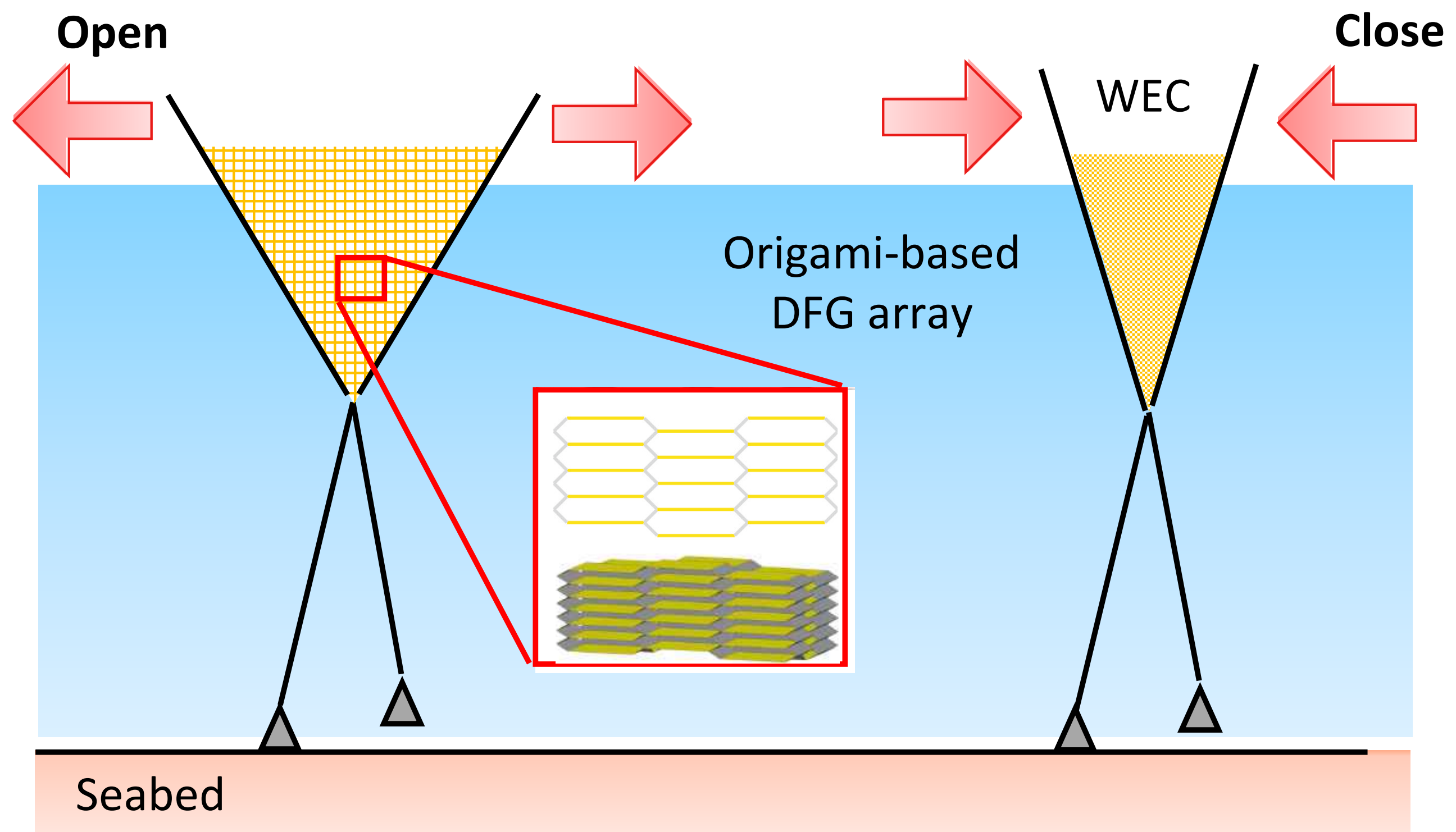


- **C ↑ under stretch**
- **Fatigue ✗**



- **C ↑ under compression**
- **Low fatigue ✓**

2 Why Origami?

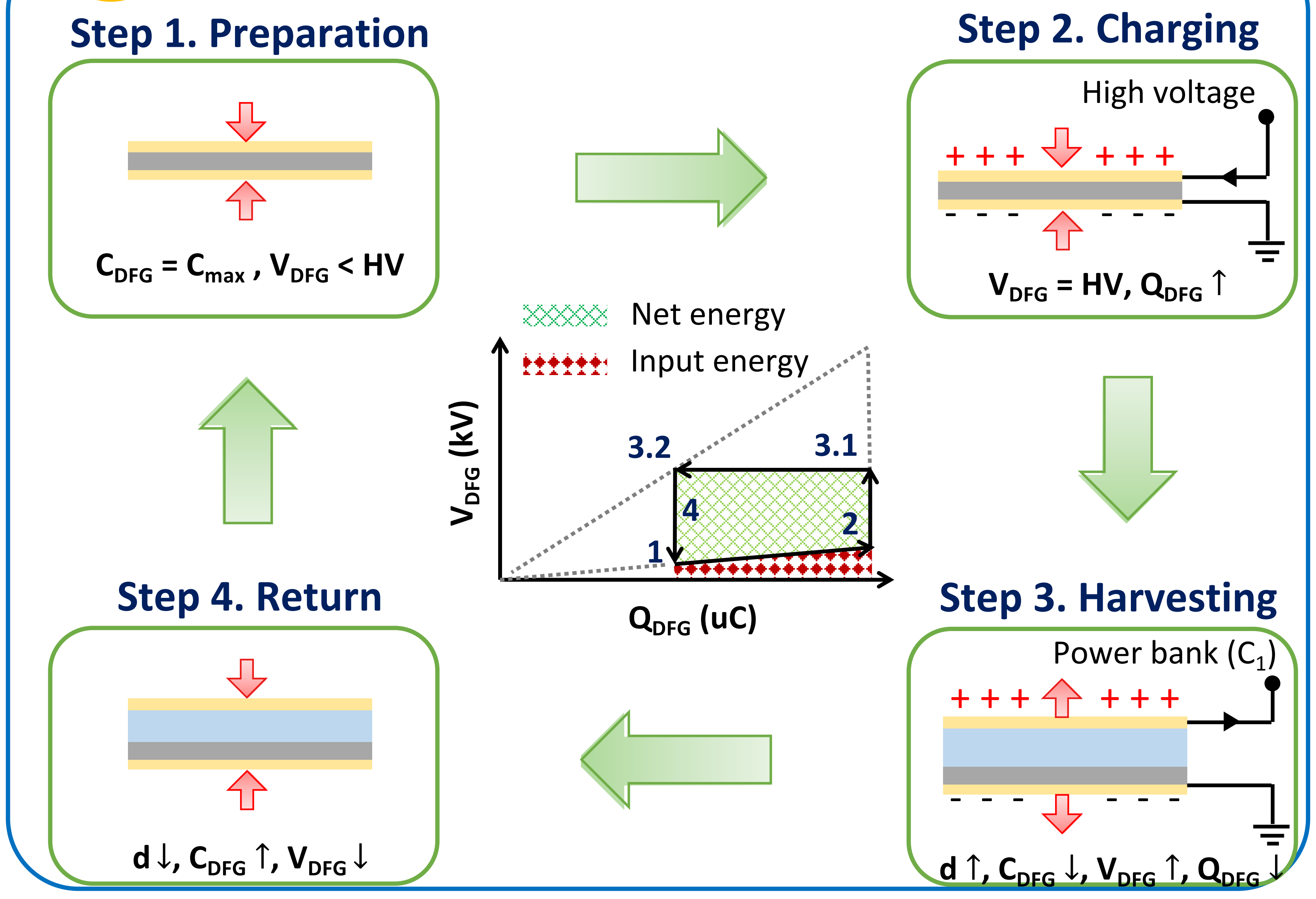


✓ **Easily stackable** for scalable arrays in wave energy converters.

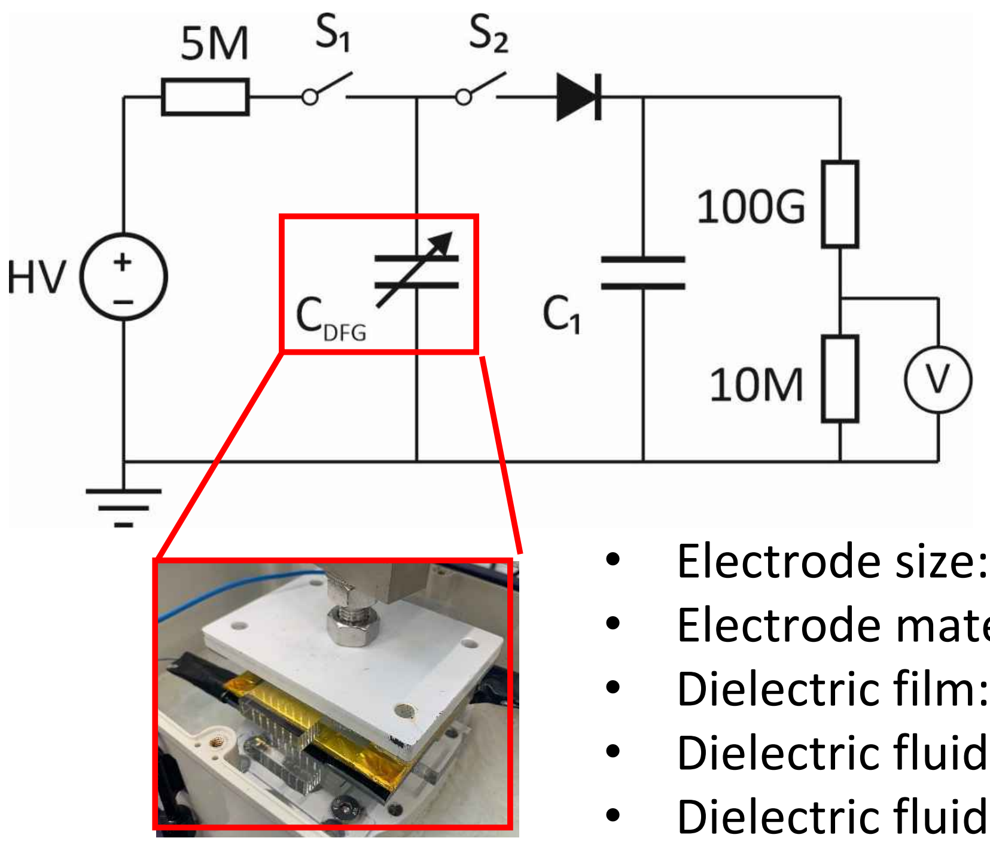
✓ **Stress isolated to flexible joints** further enhances fatigue life.

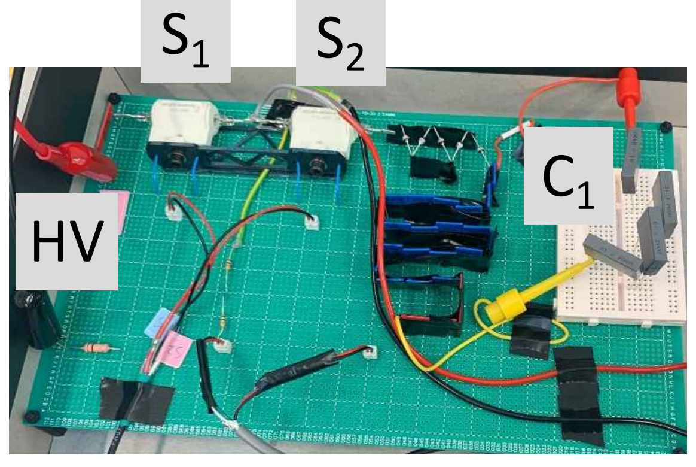
✓ **Precise control** of electrode displacement improves efficiency.

3 DFG Working Cycle



4 Circuit Design and Control

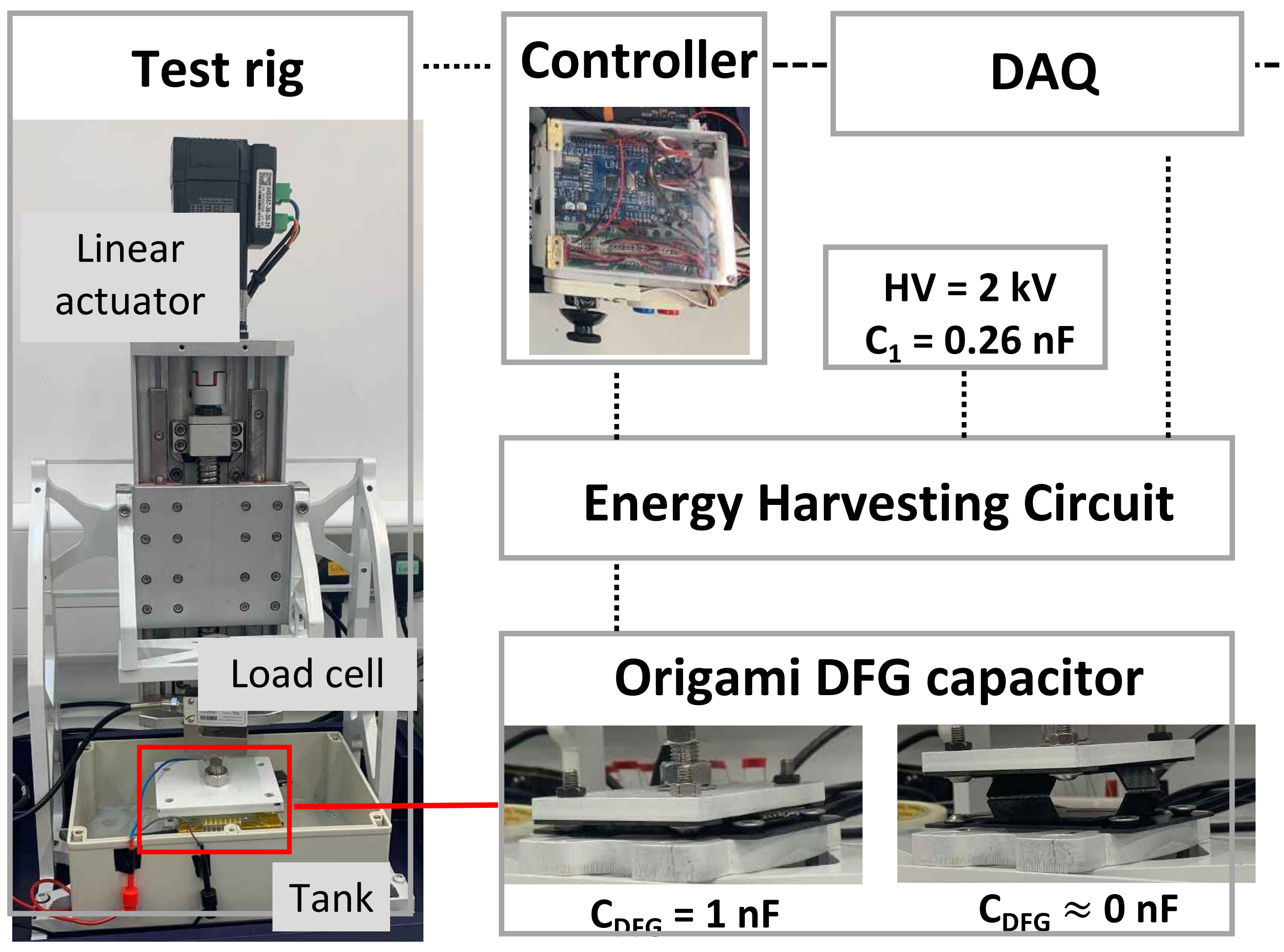




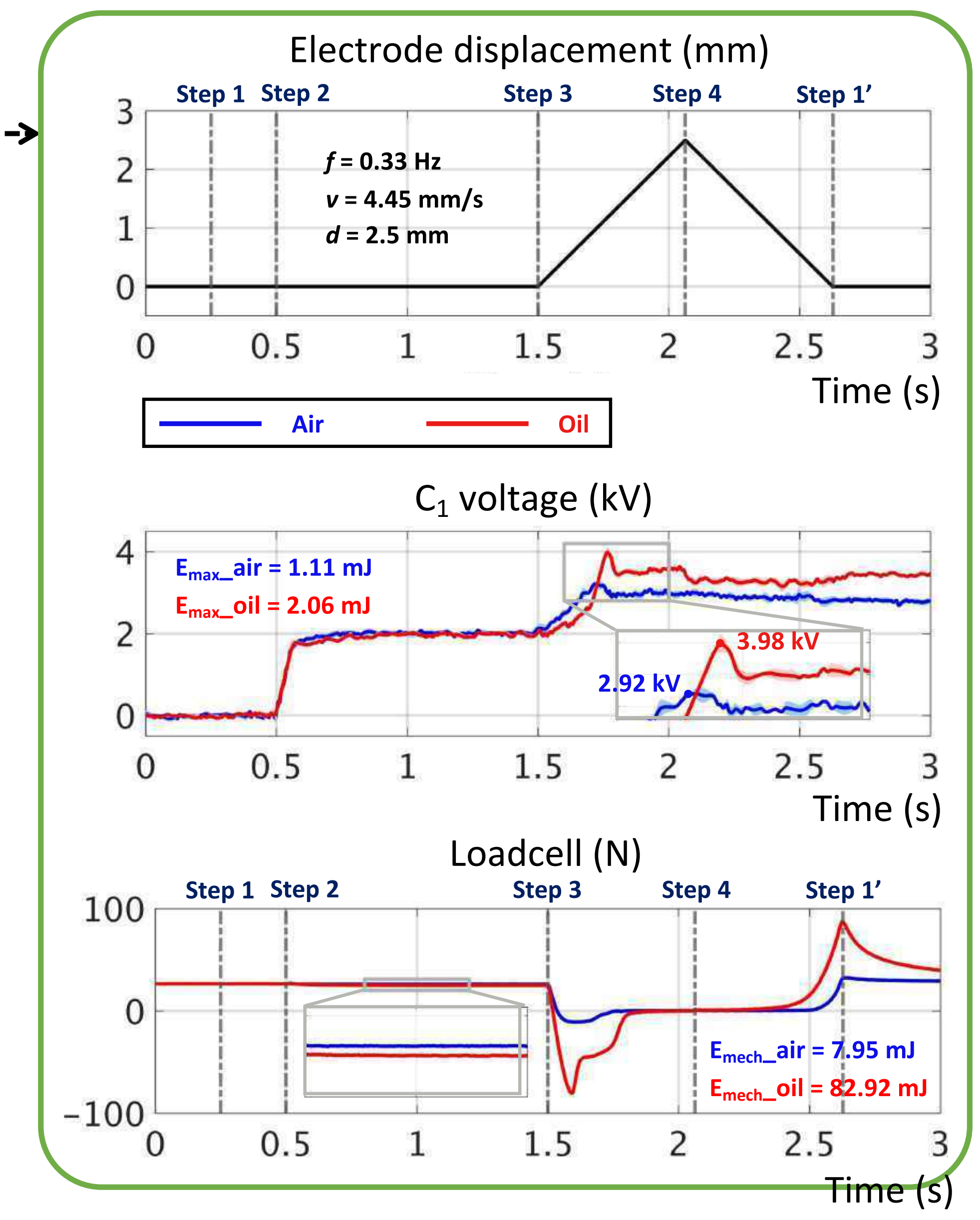
- Electrode size: 60 × 60 mm^2
- Electrode material: copper and conductive silicone
- Dielectric film: polyimide ($\varepsilon_r \approx 3.1, E_{ds} \approx 200$ MV/m)
- Dielectric fluid 1: air ($\varepsilon_r \approx 1, E_{ds} \approx 3$ MV/m)
- Dielectric fluid 2: oil ($\varepsilon_r \approx 3, E_{ds} \approx 45$ MV/m)

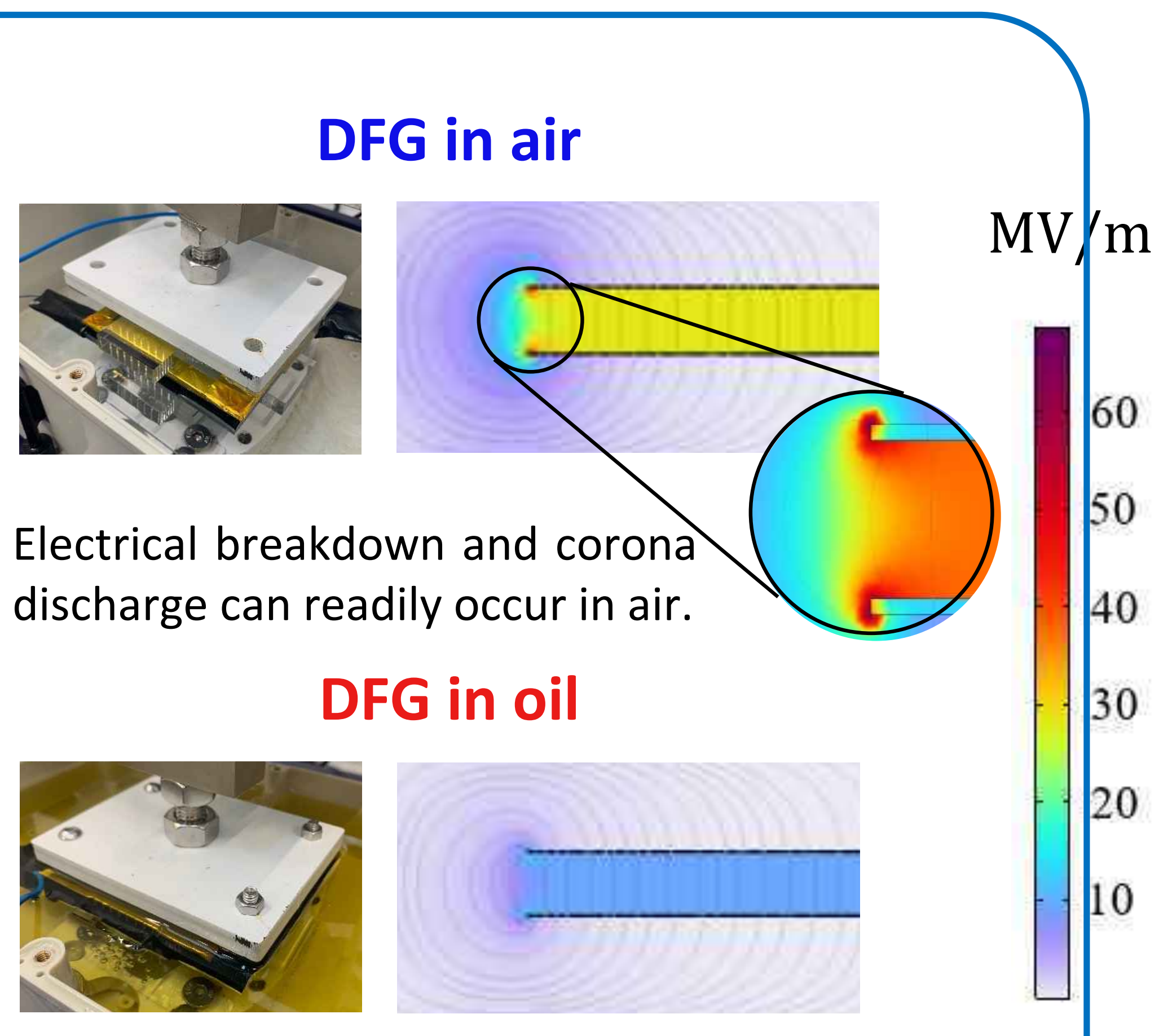
Step 1 ⇒ S1 and S2 open, high voltage (HV) on, DFG idle
Step 2 ⇒ S1 and S2 close, DFG is charged to HV
Step 3 ⇒ S1 opens and S2 closes, DFG upper electrode lifts up
Step 4 ⇒ S1 and S2 open, DFG upper electrode lowers down

5 Single DFG in One Wave Cycle



Actuation frequency (f) and speed (v) are tuneable to match wave dynamics. Electrode displacement (d) is precisely controlled.





Electrical breakdown and corona discharge can readily occur in air.

The higher permittivity and breakdown strength of oil help prevent ionisation and suppress corona discharge, boosting output energy by 85.6%. However, its high viscosity increases mechanical energy demand per cycle, reducing conversion efficiency from 14.0% to 2.5%. Speed control can help improve efficiency.

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