Function Approximations for Reinforcement Learning Controller for Wave Energy Converters

NeurIPs 2022 : Tackling Climate Change with Machine Learning Workshop

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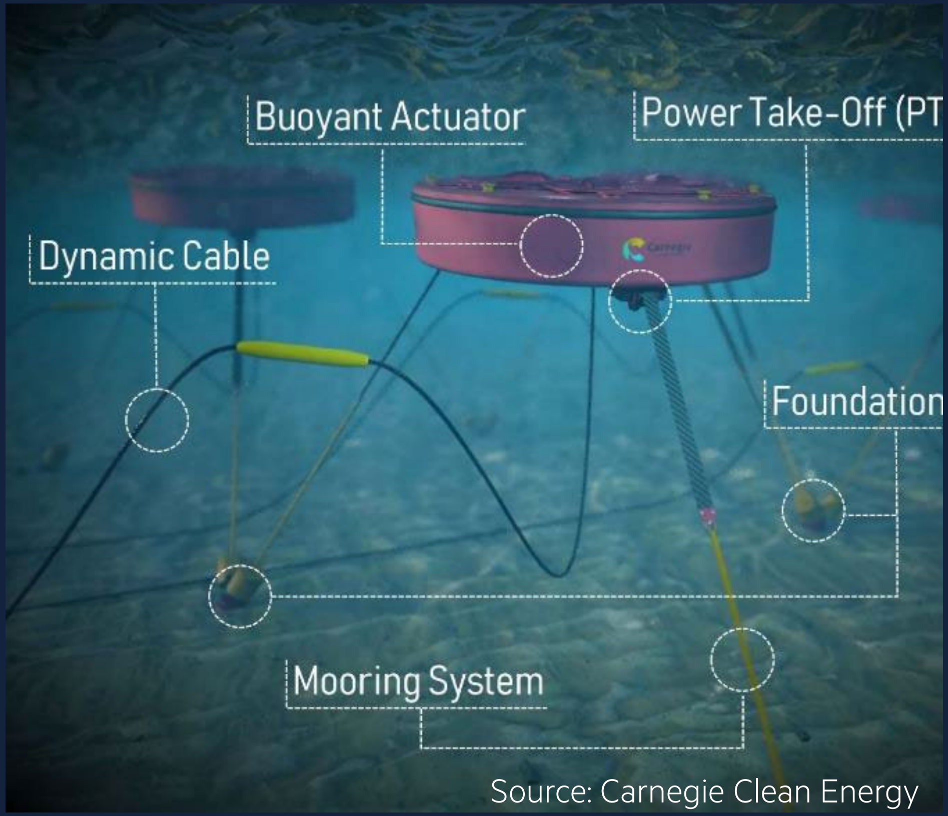
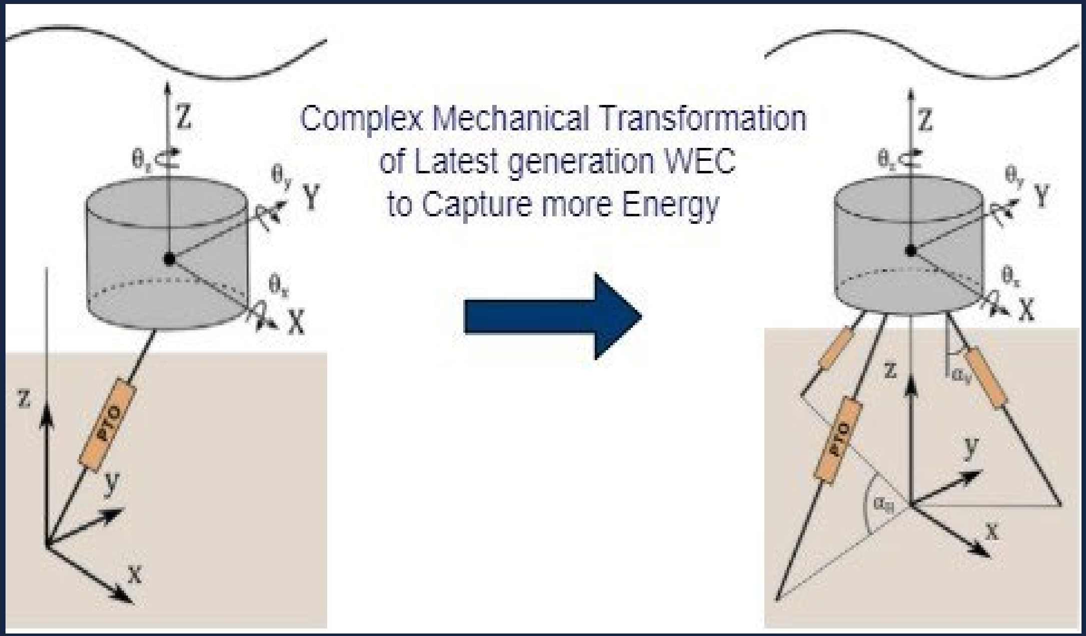


Source: Carnegie Clean Energy

Motivation : Lowering the Levelized Cost of Energy (LCOE) for Wave Energy

- Increase in energy efficiency ↑Revenue
- Reduce structural stress ↓ Maintenance
- Protect from acute weather events

Complex Multi-generator structure ► Complex Optimal Control

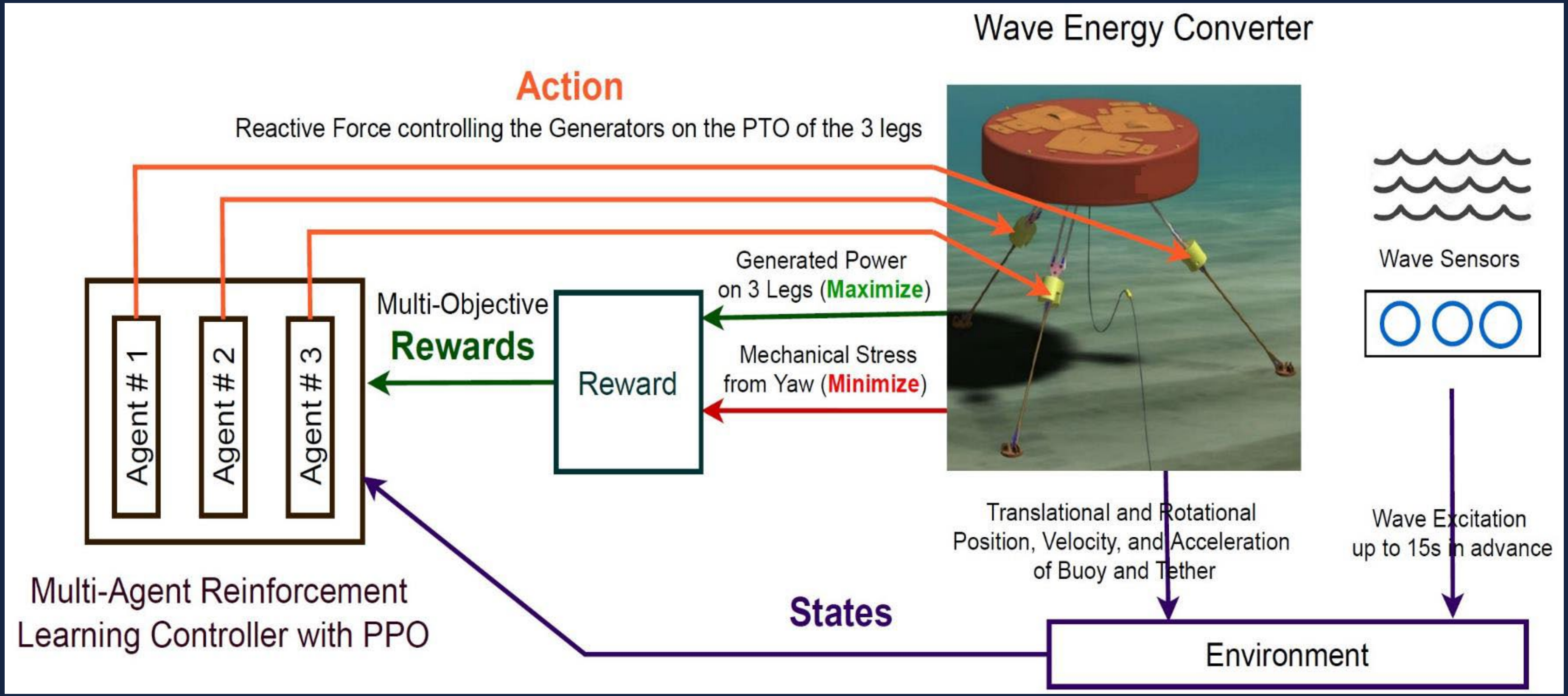


Simple Earlier Generation Wave Energy Converter

Complex CETO 6 Multi-Generator Wave Energy Converter

- To maximize energy capture the simple earlier generation one generator WEC with one tether(leg) design is transformed to having 3 generators on 3 interdependent legs (tethers) to leverage translational and rotational motions
- Complexity of control has gone up significantly with the state-of-the-art Wave Energy Converters (WEC)
- Variability of the waves, angles of wave fronts and asymmetry of the WEC further complicates the control
- Existing controllers like Spring Damper are unable to leverage the full potential of this complex mechanical structure
- Reinforcement Learning is able to better control the reactive forces of the generators on multiple tethers (legs) of WEC

Reinforcement Learning System Architecture



Why Multi-Agent RL is needed ?

- 3 legs and the generators on each of the legs act differently
- Heterogeneity requires Multi-Agent Reinforcement Learning

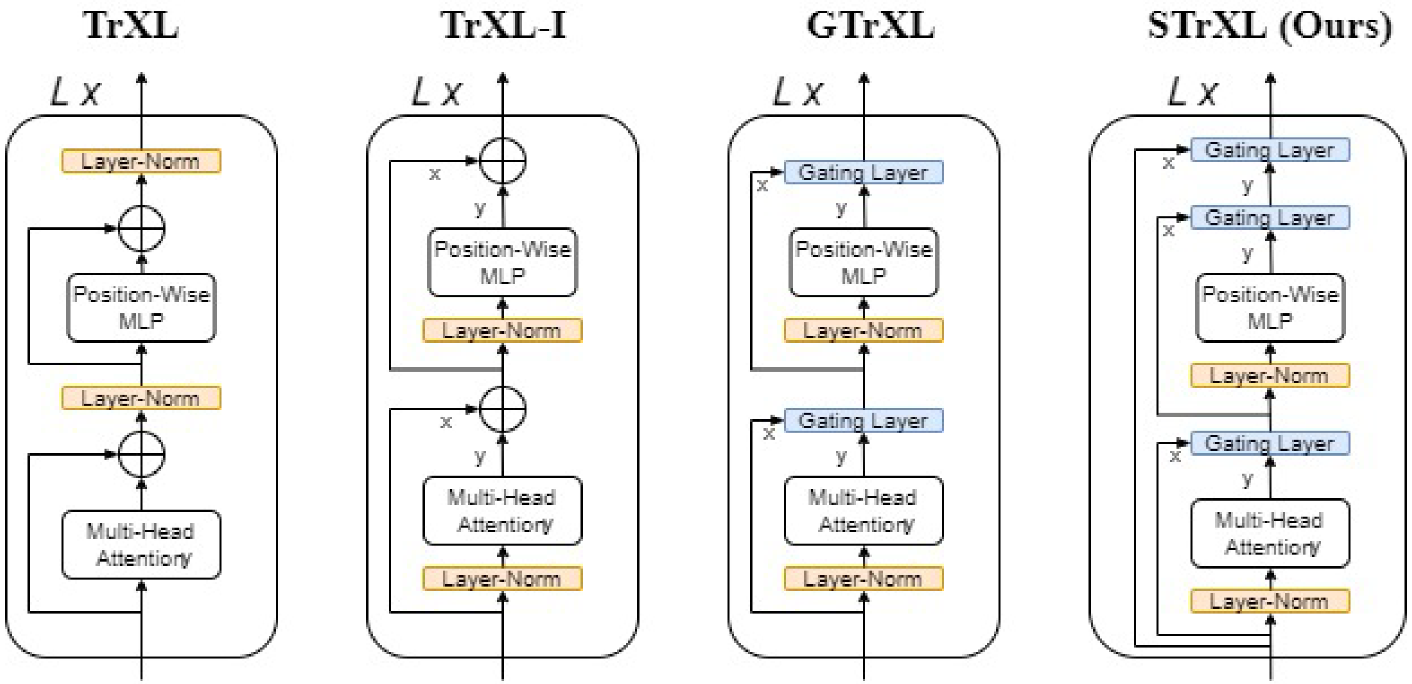
RL environment for Wave Energy Converters

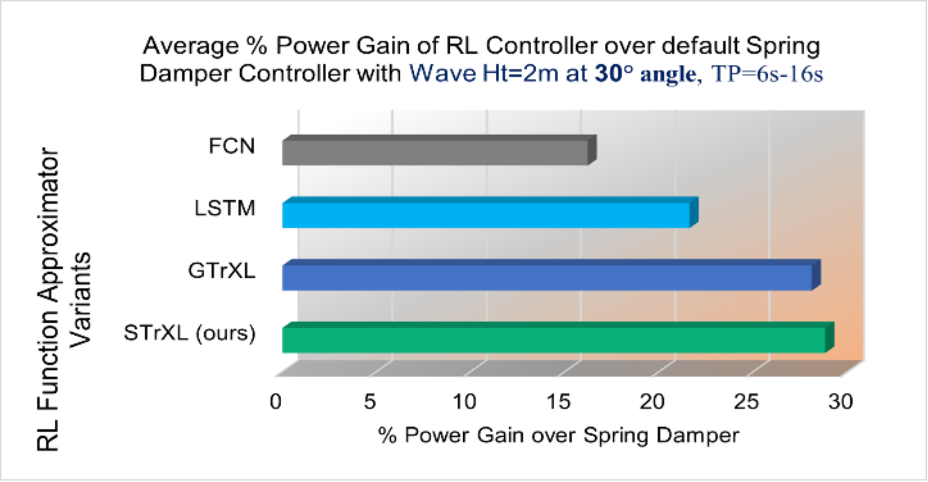
Environment States	
buoy	Translational and rotational position, velocity, acceleration
tether	Extension and velocity
wave	Elevation, and rate of change for present and 10s ahead
yaw	Stressing Rotational motion

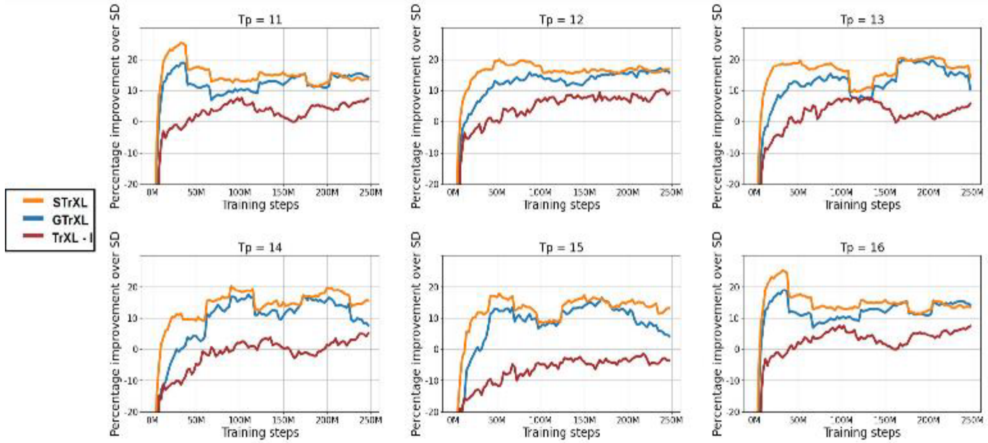
Action
Reactive forces on 3 generators resisting tether extension and buoy movement

Reward	
Power	Own power and parameterized total power
Yaw	Penalty for stress

Our Novel STrXL Transformer architecture for Reinforcement Learning beats SOTA



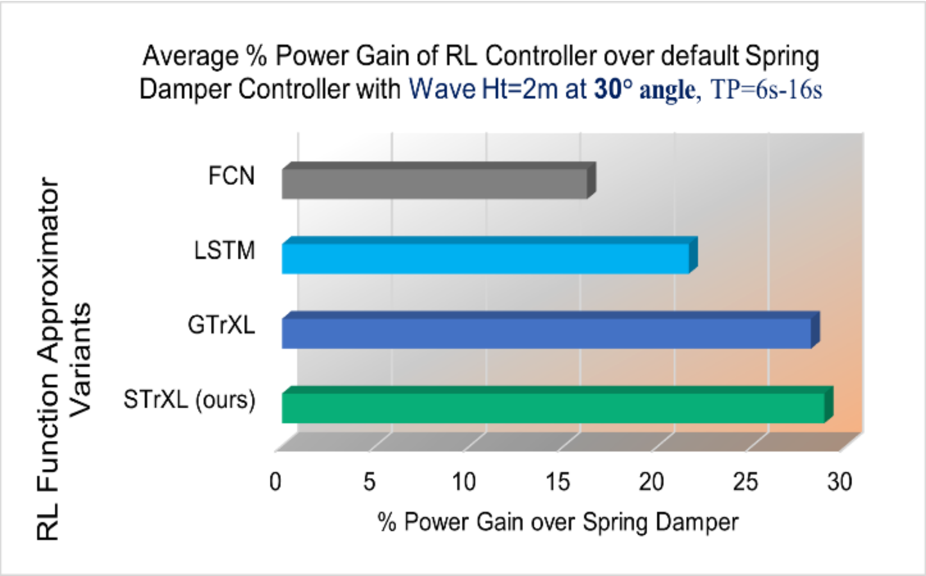


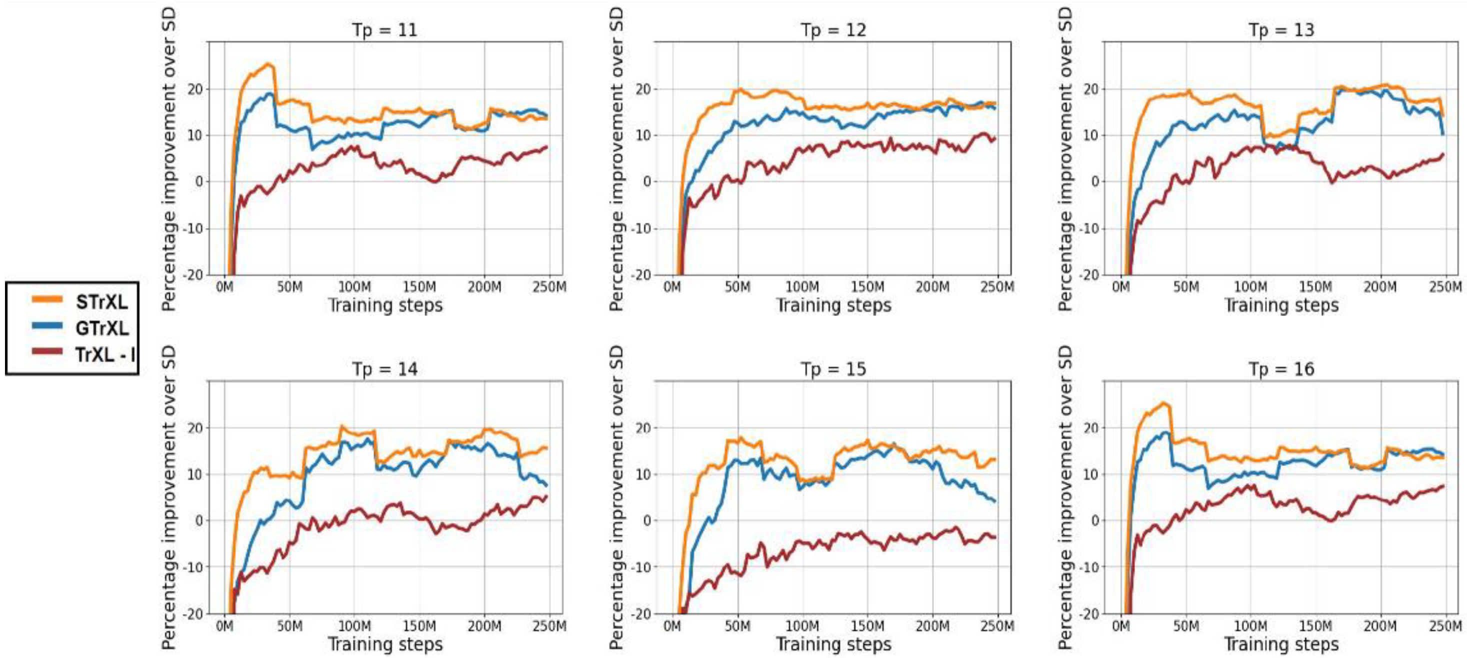


- Our Novel STrXL **beats State-of-the-art** GTrXL transformer on training speed and performance for multi-agent RL for CETO 6 WEC

- Transformers are hard to train for multi-agent RL

Our Novel STrXL beats SOTA GTrXL on Performance and Training Speed

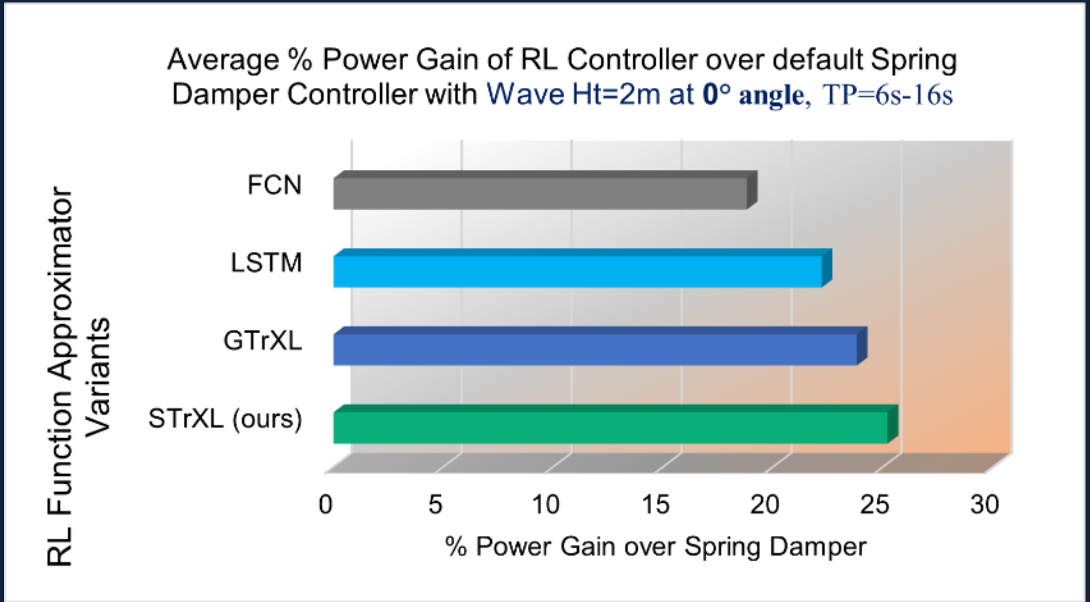


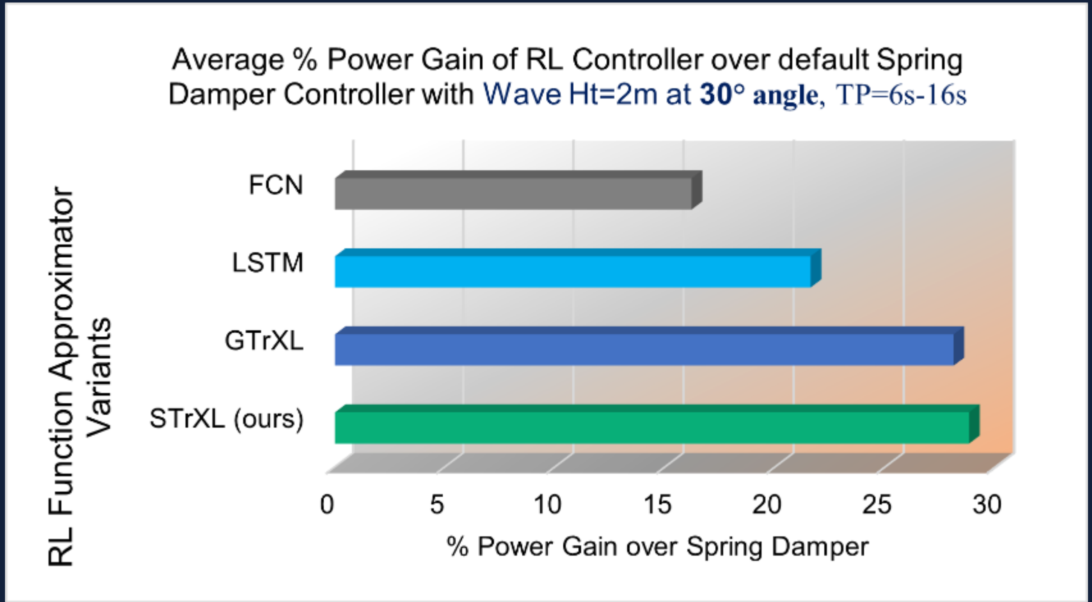


Performance : our Novel STrXL beats State-of-the-art GTrXL transformer for multi-agent RL for CETO 6 WEC

Training Speed : our Novel STrXL beats State-of-the-art GTrXL transformer for multi-agent RL for CETO 6 WEC

RL Controller Power gain (%) over default spring damper (SD) controller for different Function Approximations





RL controller reduces stress : Yaw minimization with RL controller

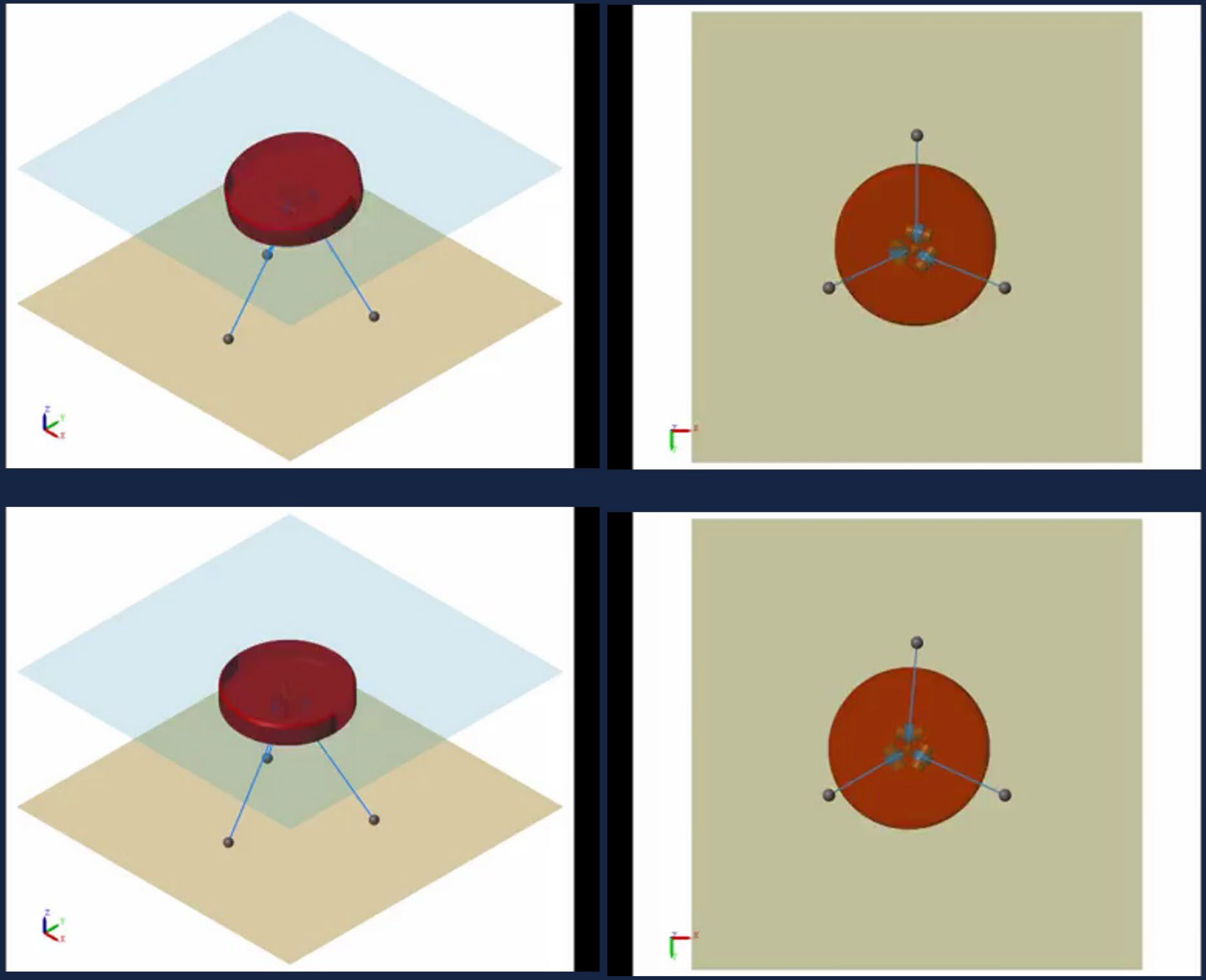
Isometric view

Bottom view

Yaw v/s time

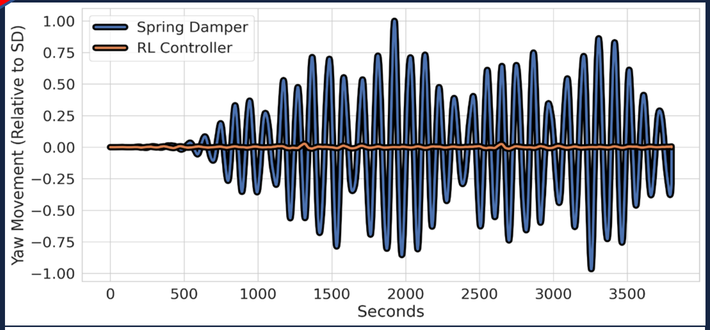
Spring-damper controller

RL controller



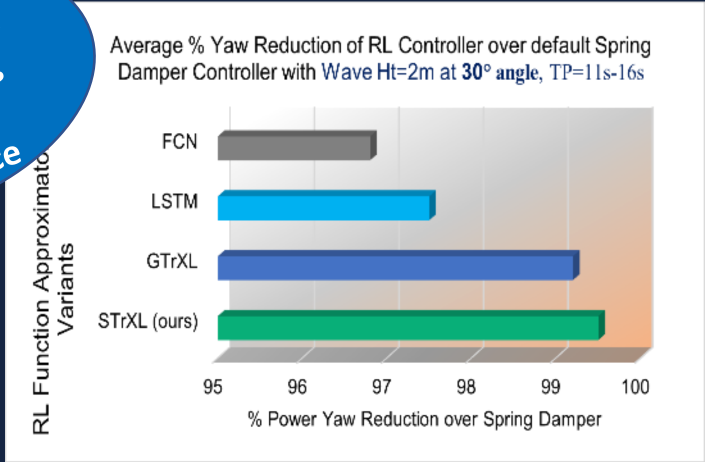
8x Speed

Twisting Yaw higher for Spring Damper

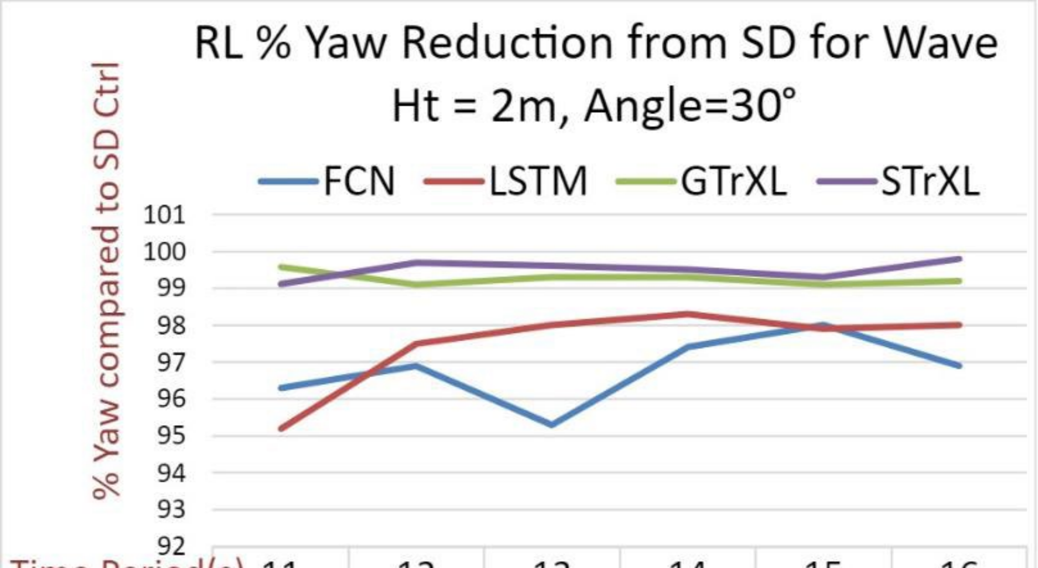


Comparison of Yaw movement between RL and the spring damper (SD) controllers for an episode with wave height of 2m and principal wave period of 12s. Values are relative to maximum SD yaw.

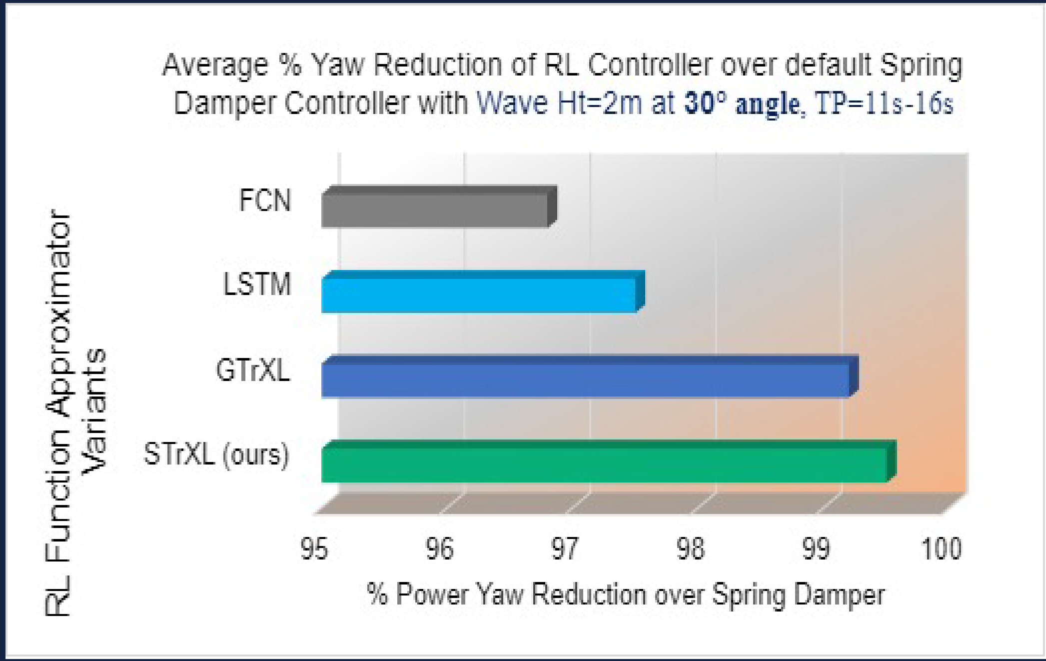
Twisting Yaw minimized with RL minimizing stress and maintenance



RL Controller % Yaw Reduction over default spring damper controller

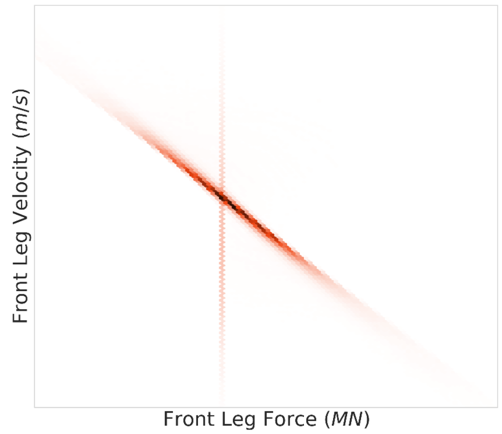


Time Period(s)	11	12	13	14	15	16
FCN	96.3	96.9	95.3	97.4	98	96.9
LSTM	95.2	97.5	98	98.3	97.9	98
GTrXL	99.58	99.1	99.3	99.3	99.1	99.2
STrXL	99.12	99.7	99.6	99.5	99.3	99.8

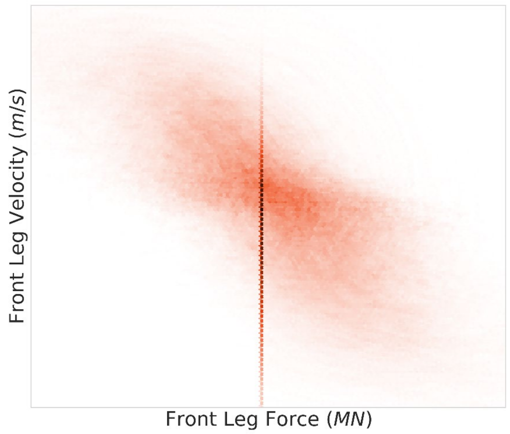


Intuition behind Reinforcement Learning controller performance

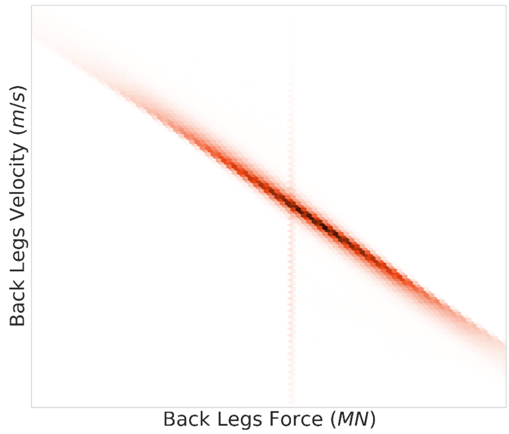
- Spring Damper is more greedy and reactive forces for the generators on the legs are almost proportional to the instantaneous velocity of the tether as energy is captured working against this motion.
- RL controller is fuzzy about the proportionality of reactive force and tether (leg) velocity, as it compromises short-term objectives for greater gains on energy capture at the more opportune segments of the wave cycles with discounted returns.



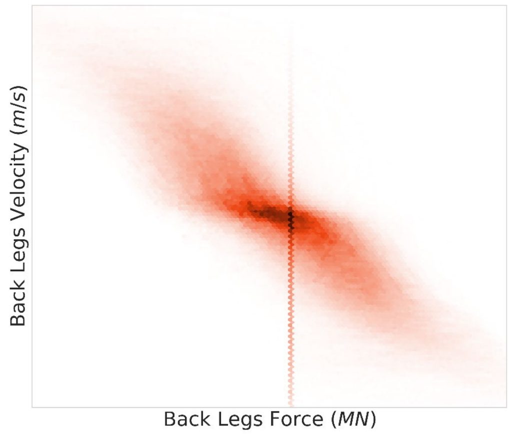
Spring Damper
Front Leg



Reinforcement Learning
Front Leg



Spring Damper
Back Leg



Reinforcement Learning
Back Leg

- Better co-ordination between the multiple generators and legs with varying waves and 6 degrees of motion which the existing state of the art controllers fail to do

Impact of this work on Wave Energy Converters and beyond

- Over 25% power gains boosting revenue opportunities
- Reduced mechanical stress, which impacts maintenance and operating costs
- Actively mitigated survival conditions, helping to preserve capital investment
- This MARL architecture is applicable to other clean energy problems like wind energy, both for individual wind power generators and wind farms
- STrXL can help faster training of Transformers for RL with better performance

Thank You

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