WHITE PAPER

WEC CONTROLS – Approaches and Lessons Learned

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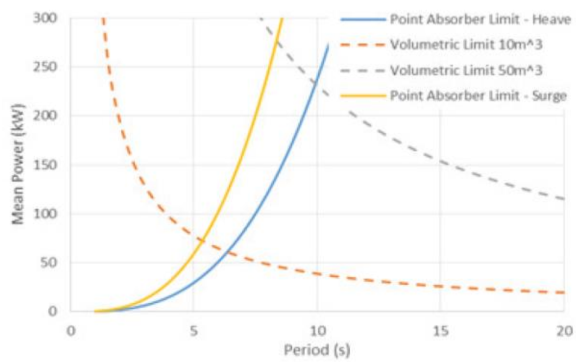

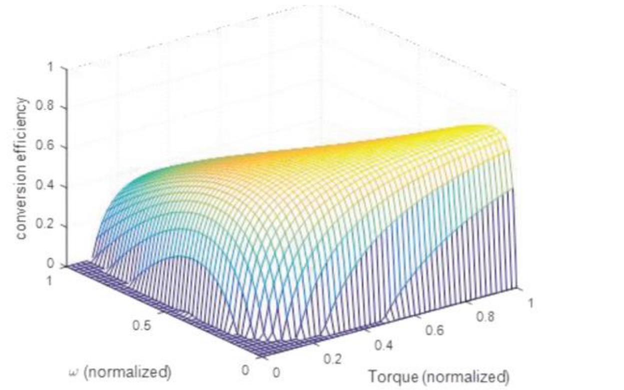

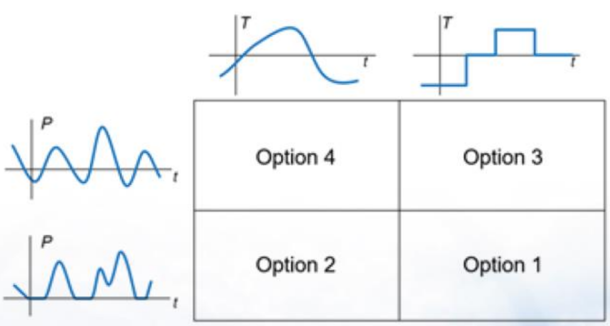

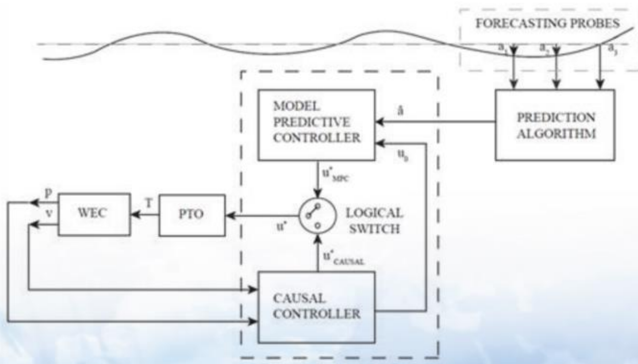

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Introduction

Over the past decade, the controls design thinking within the Wave Energy Conversion (WEC) community has evolved from discrete techniques that have been shown to improve performance for specific device topologies, to generic controls approaches where losses and constraints in the system can be handled efficiently when maximizing power. This constrained optimization is an important feature for optimizing realistic and cost-effective WEC device topologies.

Over the past 5-years, Re Vision Consulting has developed optimal control systems for six different WEC topologies in collaboration with device developers. In the process we have developed a set of capabilities to enable optimal constrained control in any WEC device. This text summarizes some of the key lessons learned.

Most texts on controls are highly technical and require a deep background in controls theory and/or mathematics. The motivation for this white paper is to explain the key concepts in plain English, so that they can be understood by a wide audience. Optimal control needs to be at the center of any WEC device development process, and it is important for the entire design team to have a solid understanding of the challenges and opportunities. For the readers wanting to dive deeper into the controls approaches, references 1-7 listed provide some good background and application examples on the numerical algorithms referred to in this text.

The control system affects power capture, structural loads, and power take off (PTO) design. To achieve true economic optimality in a WEC system, optimal control needs to be considered as part of the design trade-off space. Simply adding controls to an existing WEC device topology will often not yield significant performance improvements, because the PTO may not be able to provide the capabilities needed to improve performance or the device envelope is not optimized to take advantage of advanced controls. Device and PTO attributes can only be optimized if their cost-drivers and their performance impacts are quantified. Constrained optimal control is a key tool in this optimization process.

There are two main controls approaches used within the WEC development community: (1) Causal controllers, which only leverage on-board measurements as feedback to the control law, and (2) Non-causal controllers that leverage a wave-excitation force forecast – typically implemented using Model Predictive Control (MPC). MPC with an accurate wave prediction remains the Tesla of controls approaches, because it has the most extensive set of capabilities that make it useful across the entire range of WEC and PTO topologies.

While causal control with acceptable performance has been demonstrated on a limited set of device topologies, it remains to be explored to what extent causal control laws can approximate the performance of MPC with a wave-forecast. It is important that controls performance does not only relate to energy capture, but also the capabilities of the algorithm to accommodate realistic device-specific constraints such as PTO force, velocity, acceleration, and powerflow.

In general, our view is that during the device development process it is important to understand the fundamental upper limits of a particular configuration and use sensitivity studies to understand the trade-offs involved in arriving at an economically optimal configuration. MPC can serve as an important tool to explore this trade-off space, because it allows us to establish upper limits of constrained systems, which is not easily done using analytical methods. Once these trade-offs are fully understood, the designer can turn to the evaluation of simpler control strategies to further reduce complexity in the system. That could include the elimination of the wave-prediction required.

It should be pointed out that the cost of predicting ocean waves (a requirement for effective MPC implementation) is very small compared to the cost of the device itself at commercial scales. A simple 1% improvement in power capture would pay for the cost of the wave prediction system many times over in a wave farm. Causal controls approaches may be useful at smaller scales required for applications within the blue economy such as recharging unmanned vehicles at sea, where the economic calculus is driven by reliability and operational simplicity and not just performance.

This review aims to provide a synthesized overview of the critical challenges and opportunities in the design of control systems for WEC Devices and provide relevant examples. It is based on the experience of optimizing six different WEC topologies over the past five years at Re Vision Consulting. Theory is kept to a minimum to facilitate understanding by a broad audience.

1 - Defining Optimality

Control of WEC devices plays a critical role in improving power capture, decreasing structural loads, and reducing PTO requirements in WEC systems. Because optimal control affects all of these WEC performance-related measures, it is important to define optimality in an economic context and not just use it as a proxy for power capture. In many cases, a WEC device can become structurally very efficient by leveraging control to widen the resonance response – effectively forcing resonance using the PTO. While this may improve power capture, it will very likely also increase cost. In very simple terms, LCoE is cost divided by energy capture. So it is important to address the numerator and denominator in this equation to find an optimal configuration.

As a result, the controls objective for any WEC device can be defined as maximizing average electrical power output — subject to constraints such as motion amplitudes, forces, and powerflow— while considering all wave-to-wire losses in the system.

Using optimal controls approaches that allow for constraints to be placed on the variables that affect the economics (Levelized Cost of Electricity) of the device, we can perform sensitivity studies around key parameters and assign techno-economic weighting functions to find a global optimal configuration of the WEC topology in question. These weighting functions are driven by the design trade-off space of the WEC design itself and are specific to the device topology but ultimately allow us to minimize the LCoE at the power plant level. As such, optimal control becomes just another step in the design spiral process for WEC devices. This type of process can also be termed controls co-design.

2 – Theoretical Limits and the Value of Forecasting Waves

Before engaging in the controls design of a WEC device, it is useful to benchmark the performance using theoretical upper limits. This can serve as a benchmark against which different controls approaches can be evaluated. Such theoretical limits have been established for point absorber devices and can be visualized using the Boudal diagram.

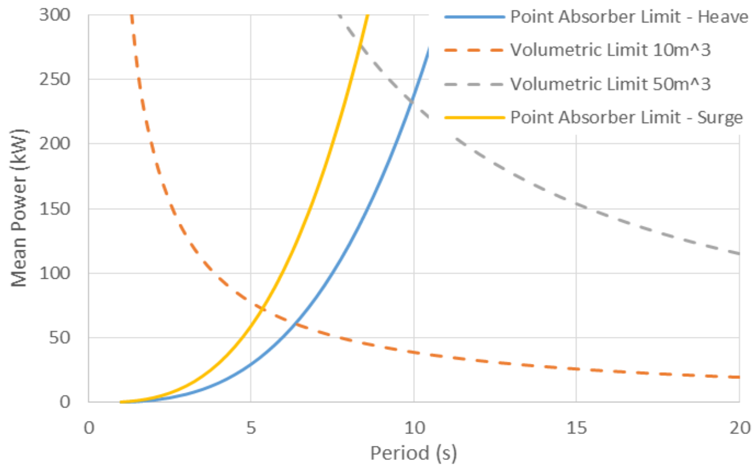


Figure 1 - Theoretical Upper Limits of Point Absorbers (Wave Height = 1m)

Point absorbers have two theoretical limits, the point absorber limit (solid lines in figure 1) is independent of the device dimensions and simply represents how much power can be extracted from a device as a function of wave period. For a heaving point absorber, this maximum capture width is L/2Pi (blue solid line), whereby L is the wave length, while a surging point absorber has a limit of L/Pi (yellow solid line). The dotted lines represent the volumetric limits, relating an absorbers active volume to its upper limits of power capture. The active volume refers to the volume of the absorber buoy that is being dynamically displaced during the absorbers oscillatory motion. For illustrative purposes volumetric limits for two different device sizes are shown.

As one can see, in short-period waves, performance is limited by the classical point absorber limit, while in longer period waves the performance becomes limited by the active absorber volume. A larger device will shift the intersection between these two limits to longer period waves, while a smaller device will shift that limit to shorter period waves. The relevance of this shift becomes only apparent once considering the relevant ranges of wave-periods encountered at a deployment site. In general, we are interested in a period-range of 5s-15s.

Causality is an important consideration when deciding on the choice of a controller applied to a WEC device. In control theory, a causal system is a system where the output depends only on past measurements. A causal controller in WEC devices therefore relies exclusively on device states that are measurable on the system itself. From a WEC controls perspective, the question is to what extent and under what circumstances causal control can yield maximum power capture and what situations may benefit from having a forecast of excitation forces.

There are a number of different factors that need to be considered when looking at the issue of causality in WEC controls problems – and by extension the ability of a purely causal controller to insure that the optimality condition is met. The following paragraphs outline some of the likely causes of non-causality, which drives the need for a wave forecast.

Non-Causality of Wave excitation Forces - The impulse response function of a WEC device has a non-causal part on the order of only a few seconds. This causality mainly arises because the response function is relating wave height to wave excitation force. This issue can be partially addressed by using pressure as a feedback variable in the controller. The transfer function between pressure and excitation force is of lower order, which is helpful in the controls design process.

Operational Regime of the WEC Device - Work by various researchers has shown that for a limited set of WEC device configurations, causal controllers can achieve performance levels that are comparable to the performance levels of a controller that leverages a wave excitation force forecast. The devices for which such results were obtained are heaving point absorbers that operate in a regime where complex conjugate control or impedance matching yields maximum energy capture and it assumes that a 4-quadrant PTO that allows for continuous force control is available and actuator delays are neglected. Such impedance matching control strategies (also called complex conjugate control) are only effective at wave periods where the device performance is limited by the Point Absorber limit. It is unclear to what extent such strategies are effective in longer period waves, where volumetric limits are imposing a constraint. In this region the device motion response is amplitude limited and optimality is more difficult to achieve using causal control laws.

In the time-domain, the motion-response of a WEC absorbing maximum power is sinusoidal when only point absorber limits are present. As volumetric limits are imposed, the optimal response starts to look more like a step response. In literature this is also referred to as bang-bang control. This response arises because wave excitation forces are highest during the peak and trough of the wave so that in order to capture the maximum amount of energy, one would need to time the motion of the device to coincide with the maximum excitation forces. Optimality in that case can only be guaranteed with a wave forecast of 1 wave period.

Active Constraints and PTO Delays - The PTO will have limits in respect to how fast it can be actuated. These limits can be introduced into the controls problem as velocity and acceleration constraints, but effectively they introduce a delay into the controls action, which would suggest that wave prediction can provide a benefit. This causality issue can also be present when an actuator is force or powerflow limited, which is the case in most PTO's.

Recent development in the wind energy community have shown that predicting excitation forces on wind-turbine blades (using Lidar) allows a control system to significantly reduce structural loads while maximizing power capture. This is a useful application example, because assuming no limits on actuator acceleration, force and speed, one could design a system that uses just feedback control laws to do the same. However, because any control action takes time to take effect (i.e. actuate blade pitch on a wind-turbine blade), a forecast can greatly improve the overall system response. In effect the optimal control law becomes non-causal because of the actuator delay. This type of actuator delay is obviously not only important for wind but in a wide range of application spaces including robotics and aviation.

PTO Coupling to Primary Resonance Modes - Many devices feature coupled resonant modes (such as heave, pitch, and surge). To capture power, they transfer energy between these interacting modes and power extraction happens normally in only a single mode. For such systems, the PTO cannot always be used to force the device into resonance because the mode coupling is limiting the PTO's ability to force a system into resonance. These loosely coupled systems can benefit from control action that occur well ahead of the device response, because it takes time for the system to respond. This "weak coupling effect" is similar to dominant PTO constraints within the WEC system.

Extreme Event Protection - Some device and PTO configurations have slow-acting mechanisms to protect a system from overload. This could be a slow-moving actuator valve or other means of protecting turbo-machinery from overload. Without an ability to predict ocean waves, such mechanisms are used on a sea-state by sea-state basis to avoid the worst waves within a wave-train. Forward looking controls informed by wave prediction can significantly improve the ability of the controls system to maximize energy capture during these sea-states while effectively protecting the WEC device.

It remains to be explored to what extent causal control laws can approximate the performance of MPC with a wave-forecast. In general our view is that during the device development process it is important to understand the fundamental upper limits of a particular configuration and use sensitivity studies to understand the trade-offs involved. MPC can serve as an important tool to explore this trade-off space, because it allows us to establish upper limits of constrained systems, which is not easily done using analytical methods. Once these trade-offs are fully understood, the designer can turn to the evaluation of simpler control strategies to further reduce complexity in the controls system design. That could include – among other things - the elimination of the wave-prediction required. It should be pointed out that the cost of predicting ocean waves is likely going to be very small compared to the cost of the device itself at commercial scales.

It should be pointed out that causal and non-causal controls frameworks are complimentary in nature. Causal control laws can be used to augment and improve non-causal controllers. The integration of causal and non-causal controllers can also yield benefits in respect to improved robustness and resilience against faults in the wave prediction sensing system. Finally, emerging applications within the blue economy will be focused on smaller WEC systems that can benefit from the reduced complexity in causal controllers.

Finally, the device models generally increase in complexity as the design matures from a concept to a fully built system that incorporates mechanical end-stops and non-linearities not fully understood at the concept design stage. Building on a controls-algorithm framework that provides sufficient flexibility to accommodate these different constraints while insuring optimality is an important aspect of a controls design process.

3 - The Controls Frameworks Considered

While many different controls approaches have been applied to WEC devices, there is a fundamental distinction between feed-forward and feed-back controllers. Feed-back control laws are typically optimized off-line in the computational domain using iterative or analytical approaches. Once optimized the control law can be efficiently implemented in the time-domain and tends to be computationally inexpensive. In general, they require access only to present device state information that can be obtained and/or estimated using on-board sensors. Using dynamic control laws, these states can account for a relevant time-history of the WECs states (i.e. velocity and acceleration terms).

Feed-forward controllers leverage estimates of the future wave excitation forces to maximize controls objectives. Because excitation forces are partially non-causal[1], true optimality requires feed-forward control. However that optimality comes at a cost – the need to predict the future wave excitation forces acting on a WEC device.

The controls algorithm frameworks used herein consists of a causal controls optimization framework developed by Professor Scruggs at the University of Michigan and a non-causal feed-forward control algorithm framework based on Model Predictive Control (MPC) developed at Re Vision Consulting. Both control algorithms have been successfully applied to a number of different WEC topologies and provide a natural complimentary fit for each other. The following illustration shows the main elements we pursued in our controls development work.

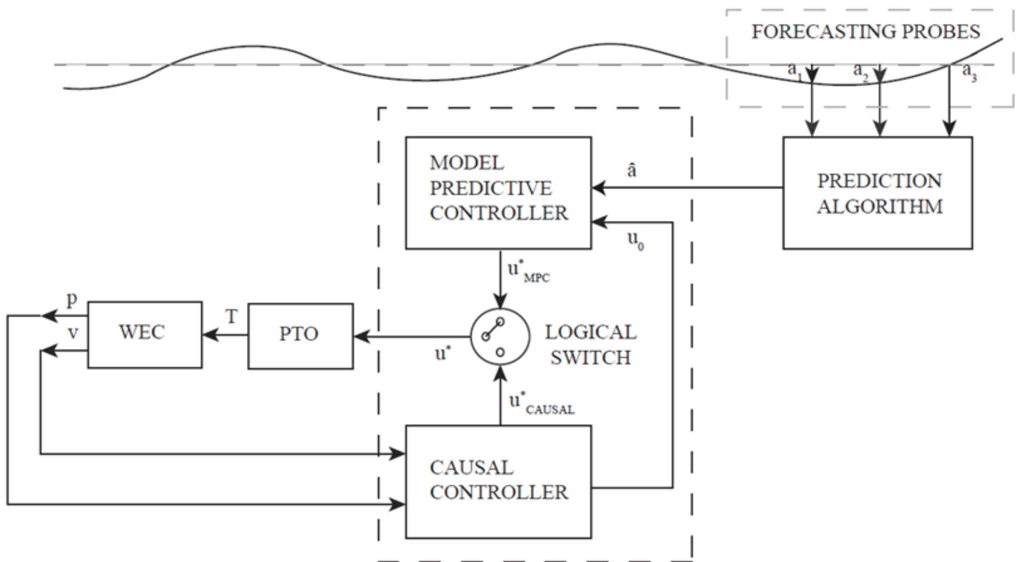


Figure 2 - Control algorithm framework

While MPC tends to yield better performance, it relies on a wave forecast that may fail due to sensor malfunctions and/or sea states that are difficult to predict. The causal controller will provide a useful fallback option. Causal controllers may also be useful if the WEC to be controlled needs to be more robust (i.e., remote market applications) and does not warrant the additional cost of the wave prediction required to operate the MPC controller.

The main elements of the controls algorithm framework can be broken down into the following sub-systems:

Model Predictive Controller – This controller is using predicted wave information to optimize the PTO forces over a future receding time horizon. Different types of MPC algorithms are used depending on the device and optimization objectives for a particular device type.

[1] Accurately determining the excitation force on a WEC device requires some future knowledge of the wave surface elevation. The non-causal part of the excitation force kernel refers to the portion of the transfer function (wave to force) that is not known from past measurements.

Causal Controller – This controller is using a dynamic feedback law that is optimized on a sea state by sea state basis. The feedback controller uses only the position and velocity of the WEC device as feedback variables to provide an optimal PTO force command. While viscous linear damping or coulomb damping can be considered causal controllers, we are leveraging a dynamic control law, outlined in subsequent sections, which provides an optimal dynamic PTO response. In general, we use linear viscous or coulomb damping as baselines for our performance comparisons.

Wave Prediction Algorithm – The wave prediction algorithm leverages up-wave measurement information to provide a wave excitation force forecast. As part of our work, we have deployed an array of eight measurement probes to evaluate the practical limitations of a realistic wave prediction system deployed at sea.

In addition, we cover the following topics:

Systems Identification - For controls development purposes, we use various systems identification[2] and model reduction techniques to come up with a controls model that is "good enough" for controls purposes. The systems identification process becomes more difficult as more realistic topologies are introduced. This may include the added complexity of identifying suitable models for complex electrohydraulic systems that are typical for WEC devices.

PTO Loss Model - This is an important consideration, which has only been superficially considered in the literature. As part of our work, we incorporated the losses from a detailed hydraulic-electric PTO system.

Controls Validation - As part of our controls optimization process, we have validated the feed-back and feed-forward control laws using wave tank testing. To do so, we had to ensure that the PTO at model scale accurately emulated the forces of the full-scale PTO. At this stage, reducing risk involves identifying any deviation in the fluid-structure interaction effects from theoretical models used to optimize the control laws.

4 - The Controls Design Process

The controls design and optimization process can be divided into a few distinct phases. It is important to recognize that this process is iterative, meaning that as the device developer moves through the Technology Readiness Levels (TRL) and the device characteristics are refined and become better understood, the control system needs to be re-optimized to handle the additional information.

Plant Model - Any controls design process starts out with the development of a computational model of the device itself. Typically, this initial model is a time-domain model that reflects the device's physics. In this paper, we call this the plant, because it's primary aim is to accurately model the wave-to-wire dynamics and energy losses as accurately as possible, without much concern to its computational efficiency and/or stability. To be useful for controls purposes, it needs to model all aspects of the power conversion process from wave to wire and capture all relevant dynamics. Over time, this model is validated using various testing and validation methods, improving the confidence in it.

[2] The field of system identification uses statistical methods to build mathematical models of dynamic systems from measured or simulated data.

Reduced-Order Plant Model – This model approximates the physics of the plant model, but it needs to be fast and stable, while providing sufficient accuracy. The model needs to be "good enough" for controls purposes and model reductions need to be checked consistently against the truth model to ensure that they do not significantly alter controls outcomes. Systems identification techniques are commonly leveraged during this process, or more elegant analytical approaches are used to develop reduced-order models. State-space modelling is a standard technique in the numerical modelling of physical systems. This approach allows us to conveniently model physical signals such as buoy position and velocity as states of the model. Frequency-dependent terms, such as radiation damping,[3] can be embedded in such a model by including additional states in the overall system. Nonlinearities such as viscous drag[4] can also be accommodated within this framework to effectively model losses due to dissipation.

Controls Optimization – During this phase, a controls method such as MPC is used and optimized to maximize electrical power while respecting various constraints on the system. The reduced-order plant model is used during this phase to optimize the controller itself. Extensive verification and validation (V&V) is carried out to ensure controls performance. The end-product is a control system that can be used on the device itself.

Controls Validation – As in the development of any hardware, a control system must be validated before it is ready for deployment in the real system. The most effective way of systematically eliminating errors and issues is Incremental validation, which can include the following:

1. V**alidation using high-fidelity plant model** — If adequately validated, a high-fidelity plant model can be used to validate the controller in the computational domain by driving the truth model with the controller and observing if the outputs remain accurate.
2. **Wave tank testing** can be used to validate that the fluid-structure effects are adequately modeled. Because controllers tend to try to maximize a device's motion amplitudes, it may push the device into a response range that have previously not been validated, revealing non-linearities and other phenomena that are not well understood. Because the PTO is difficult to scale physically, it is better to emulate its forces/torques than to down-scale it. This can be accomplished effectively using off-the-shelf motion control software and hardware.
3. **Hardware-In-The-Loop (HIL) testing** — Various versions of HIL testing can be used for incremental validation of the controller. For example, the PTO could be tested on a rig that emulates the forces exerted by wave action.
4. **At-sea validation** — This is the final step of testing the integrated control/PTO/device system.

It is important to understand that the process itself is iterative and the validation process will trigger changes to the plant and controls model, leading to a need to re-optimize the controller before testing

[3] Radiation damping is the damping force that results from the motion of the WEC device, causing radiated waves that act as an energy dissipation mechanism.

[4] Viscous drag is the force that is induced on a body motion relative to the fluid because of turbulent energy dissipation in the fluid. This viscous drag typically increases quadratically with relative velocity (between body and fluid).

can continue. Overall, this iterative nature of the process should become a part of the design-spiral process for a WEC device.

5 – Device Topology Related Issues

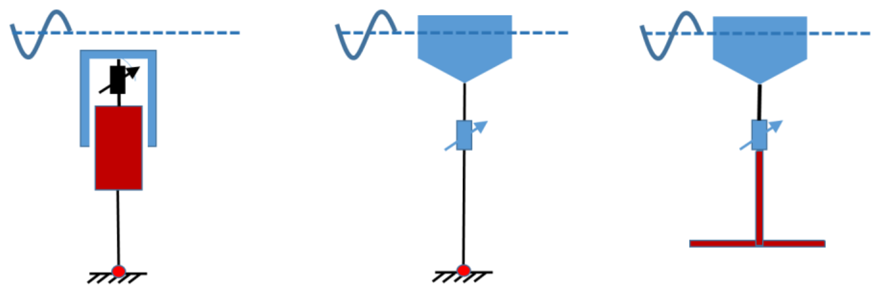
To gain a comprehensive understanding of how the WEC device topology affects the controls design process, we worked in collaboration with several device manufacturers on different device topologies that capture a wide range of challenges encountered in the controls design. Controls-related device characterizations are summarized in Figure 3 and 4. Characteristics given are not meant to serve as absolute references but rather as generic guideposts for these types of representative device topologies. Diverse topologies introduce a number of challenges into the controls optimization process. Three main concerns need to be addressed during control design:

1. **Computational Efficiency of the Controls Model**: The controls model is used to optimize the response of the device over time and needs to be computationally fast enough to allow the controller to run faster than real-time without losing fidelity. Impacting the complexity of that simulation are among others: (1) the number of bodies, (2) the number of degrees of freedom (DoF) that are important for power-capture, and (3) the loss model to capture wave-to-wire losses.

2. **Non-linearities in the System Response**: WEC system non-linearities can come from a wide range of sources, including: (1) Non-linear Froude-Krylov force[5] due to a variable free surface area, (2) Non-linear wave-resource, and (3) viscous dissipation terms. Of the three, viscous dissipation is the most common non-linear term for WEC devices. While these terms are almost always non-linear to some degree, they can in many cases be linearized with satisfactory results. The degree of non-linearity in the system will drive the control algorithm choice.

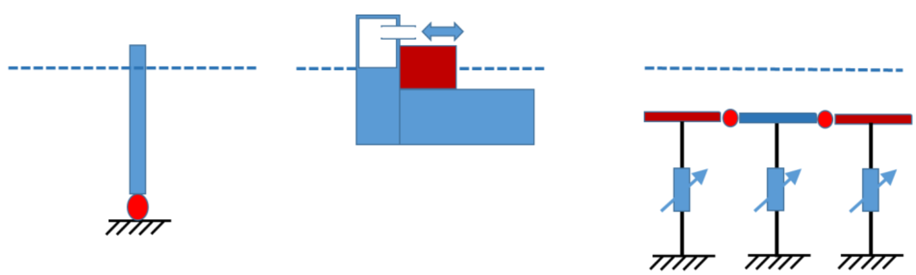
3. **Constraints Required**: Motion and PTO constraints, as well as required asymmetric responses, can affect the execution efficiency of controls algorithms. They also affect the controls approach, because asymmetric constraints will require the use of different MPC algorithm classes than symmetric constraints.

[5] The Froude-Krylov force is the total force of the fluid acting on the body.



Topology	Subsea Pressure Differential	Heaving Point Absorber	Heaving Point Absorber
Reaction Point	Seabed	Seabed	Subsea Reaction Plate
Relevant DoF	1-DoF	1-DoF	3-DoF
# Bodies	1	1	>1
# PTO's	1	1	>1
Range of CD	<0.5	<0.5	0 – 4
Uni-Direct. Force Constraint	No	Yes	No
PTO End-Stop Constraint	Yes	No	Yes
Hydro Motion Constraint	Yes	Yes	Yes
Linear Wave Theory OK?	Yes	Yes	Yes
Non-Linear Froude Krylov	No	No	No

Figure 3 – Controls-relevant characteristics of topologies 1-3



Topology	Shallow Water Surge	Backward Bent Duct	Subsea Pressure Differential
Reaction Point	Seabed	Self-Reacting	Seabed
Relevant DoF	1-DoF	4-DoF	1-DoF
# Bodies	1	1	>1
# PTO's	1	1	>1
Range of CD	1 - 5	<0.5	2 – 4
Uni-Direct. Force Constraint	No	No	No
PTO End-Stop Constraint	No	No	Yes
Hydro Motion Constraint	No	Yes (internal free surface)	No
Linear Wave Theory OK?	No	Yes	Yes
Non-Linear Froude Krylov	Yes	No	No

Figure 4 – Controls-relevant characteristics of topologies 4-6

Because some of the terms used in the above figures may be unfamiliar to the reader, a brief explanation of terms is provided herein:

Relevant DoF - While rigid bodies are typically defined as six degree of freedom (DoF) systems, only a few of them are relevant from a power production and controls point of view. Reducing DoFs when establishing a controls model for a WEC device is critical to improve the computational efficiency of a model.

Range of Coefficient of Drag (CD) – This represents the range of quadratic CD values, which relate the viscous damping force to the WEC device velocity. In general, larger CD values on relevant DoFs of the absorber body will suppress resonant motion amplitudes, leading to limitations in how much performance of a particular topology can be improved. The CD values are also important for controller design. Large CD values often require a non-linear controller implementation, which tends to come at a much higher computational cost than linear controllers.

Unidirectional Force Constraint – This constraint was only required for the tethered heaving buoy and guarantees that the tether always stays under tension. Unidirectional constraints affect the choice of MPC.

PTO End-Stop Constraint – This is important for device topologies that have linear PTOs and where end-stop constraints are needed to protect the PTO.

Hydro Motion Constraint – In many cases, the device needs to be prevented from fully submerging or completely emerging out of the water. This is the case for all the heaving buoy configurations.

Linear Wave Theory – For most power-producing sea states, linear wave theory is sufficient to characterize the fluid-structure effects. In our work, only the shallow-water-surge WEC design required a different treament of the excitation force kernels to account for the shallow-water effects.

Non-Linear Froude-Krylov (FK) Force – For devices where the water-plane area varies throughout the oscillation cycle, the FK-forces need to be modified. This was the case for the shallow-water-surge WEC device, where the surface-piercing part of the flap can submerge in larger waves.

The following paragraphs describe some of the key observed behaviors To illustrate how these factors affect controls.

Viscous drag: a key factor in the optimization of any WEC device is the viscous drag acting on the device absorber body. Optimizing power absorption requires for motion amplitudes to be maximized. This is typically achieved by forcing a device into resonance and/or by forcing a proper amplitude and phase response of the absorber body to the incident wave. As motion amplitudes and velocities become larger during resonance conditions, the viscous drag starts to dominate the losses in the system, limiting the performance upside of any control strategy. The following illustration compares the performance of a slowly tuned device against the performance of the same device using optimal MPC control. It shows that, as the coefficient of drag increases, the relative improvement potential using optimal control starts to diminish. Effectively, the larger CD values suppress any resonant motion required for improved power capture, limiting the improvement attainable with control.

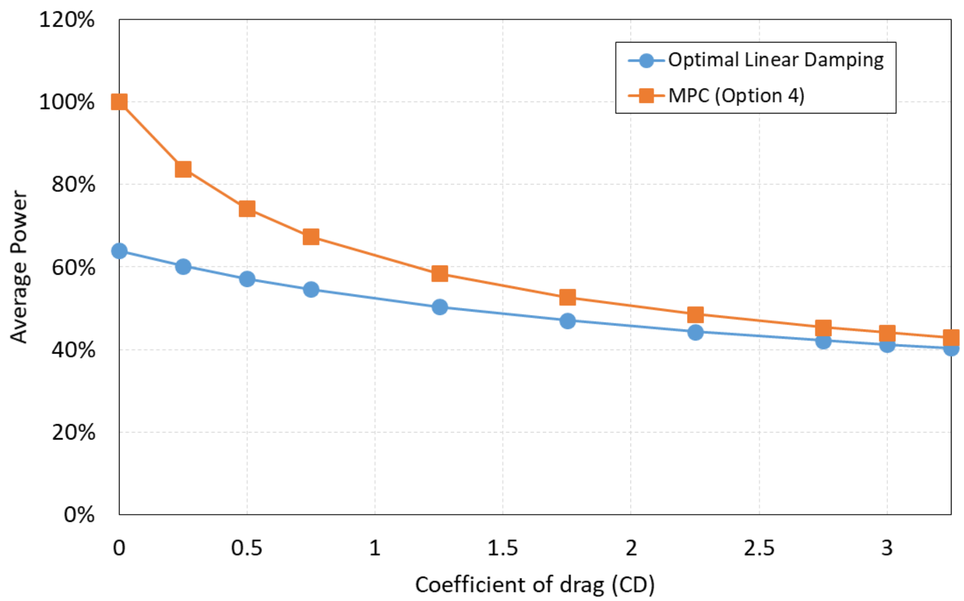


Figure 5 – Normalized performance comparison between MPC and optimal linear viscous damping as a function of the quadratic drag coefficient for shallow-water-surge WEC. H = 2m, T = 10s.

Weak PTO coupling to primary absorption mode: The largest relative performance improvements from optimal control were observed on the heaving point-absorber topology. In that case, the PTO was directly in the load path between the primary absorption mode of the buoy (heave) and a fixed reference (the seabed). This allowed the PTO to force the buoy into resonance at all frequencies. Other topologies, such as the BBDB or the two-body point absorber, show smaller relative improvements, because the PTO is only weakly coupled to the primary power absorption modes and can therefore not force the motion phase relationship as well over the full range of relevant wave periods. While the annual average power capture for the heaving point absorber at the Department of Energy's reference resource site increased by more than 200%, the BBDB improved by only about 20%. Benchmarking such performance limits before engaging in full controls optimization can help to narrow the scope for the controls work.

6 – The PTO Model and its Effects on Controls Design

One of the core constraints in the overall system is the PTO. Because the PTO is a key cost driver, imposing reasonable constraints on its capabilities will help contain cost. Constraints that can affect PTO cost include position, velocity, acceleration, force/torque, and power flow amplitude and direction. For example, a hydraulic PTO may use a hydraulic piston pump as the primary actuator, which has a stroke limit that must never be exceeded. This can be introduced as a position constraint in the optimization problem to avoid end-stop violations that would otherwise affect the mechanical integrity of the PTO and device structure. In a similar way, velocity and acceleration constraints can be used to keep the PTO within an envelope of acceptable limits, satisfying reliability concerns. Power flow constraints can be imposed to limit instantaneous power flow, which directly affects the cost of the PTO as well as power flow direction. A positive power flow constraint, for example, precludes the transport of reactive energy for maximizing power capture, which would require a more costly PTO to implement. Finally, PTOs may be able to produce only discrete force levels – typical in hydraulic systems, where a fixed displacement pump pressures fluid in an accumulator at fixed pressure.

To better understand the trade-offs with different types of PTO capabilities, we have categorized all the PTOs into four different categories. This categorization allows us to establish fundamental trade-offs and subsequently refine them based on the specifics of the physical system. These four options are illustrated below.

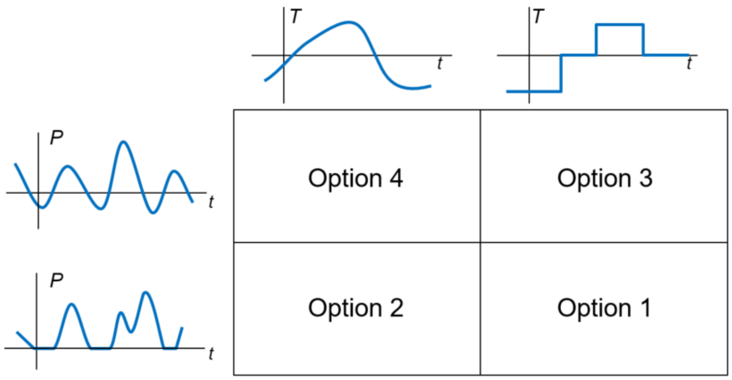


Figure 6 - PTO Options 1-4

Option 1 – Uni-directional power flow (damping only) with discrete force/torque values. This topology would be representative of a very simple hydraulic PTO, where the PTO force is given by a fixed system pressure. We still allow for that force to be switched between high and low and optimize the timing of these switching events.

Option 2 – Uni-directional power flow (damping only) with continuous force values. In this case, the force can be continuously varied, but only positive power flow is allowed. This uni-directional power flow constraint allows us to model PTOs that cannot act as an actuator (i.e., return power to the sea to maximize performance).

Option 3 – Same as Option 1, but allowing for bi-directional power flow.

Option 4 – Same as Option 2, but allowing for bi-directional power flow.

PTO capability and cost increase as PTO topology becomes progressively more complex from Option 1 to 4. This increased complexity can also be associated with higher failure rates. If properly weighted in a techno-economic model, these attributes can be translated into LCoE, allowing for an identification of the optimal topology for a given WEC design. While the complexity of the physical PTO increases with increasing capability, it is actually much easier to implement an optimal control algorithm for such an unconstrained system than for a heavily constrained one or one involving only discrete force levels. The following illustrations show the time domain behavior of the control forces for Options 1-4 using optimal control. Responses were computed using Model Predictive Control and are meant to illustrate these different response types for a flap type WEC.

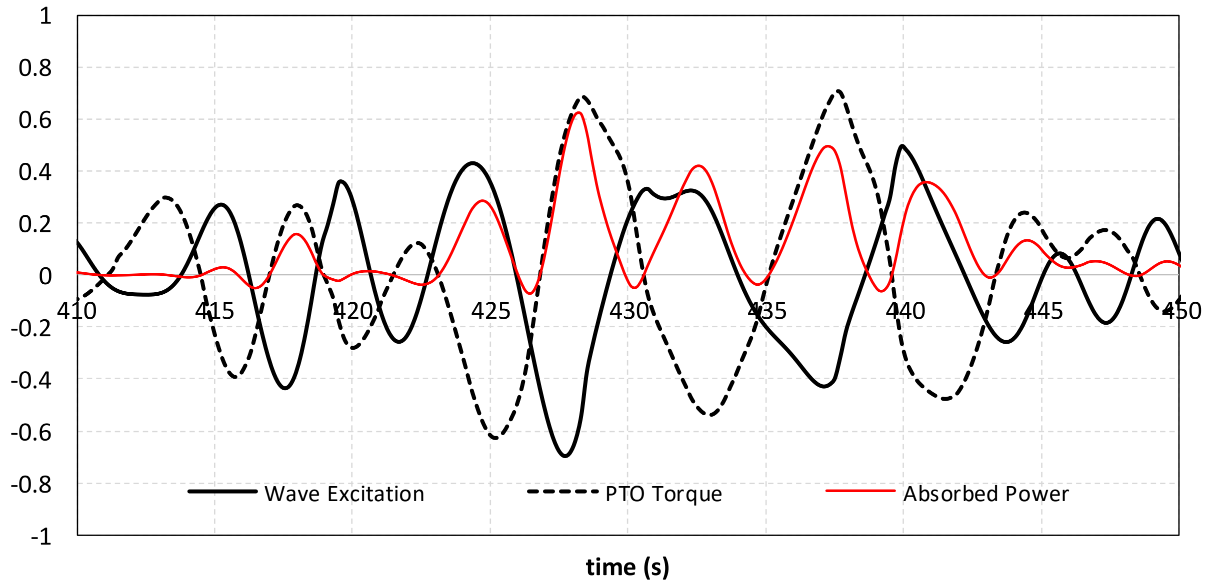


Figure 7 - Normalized response of surge WEC under control option 4 (Note: negative power flow)

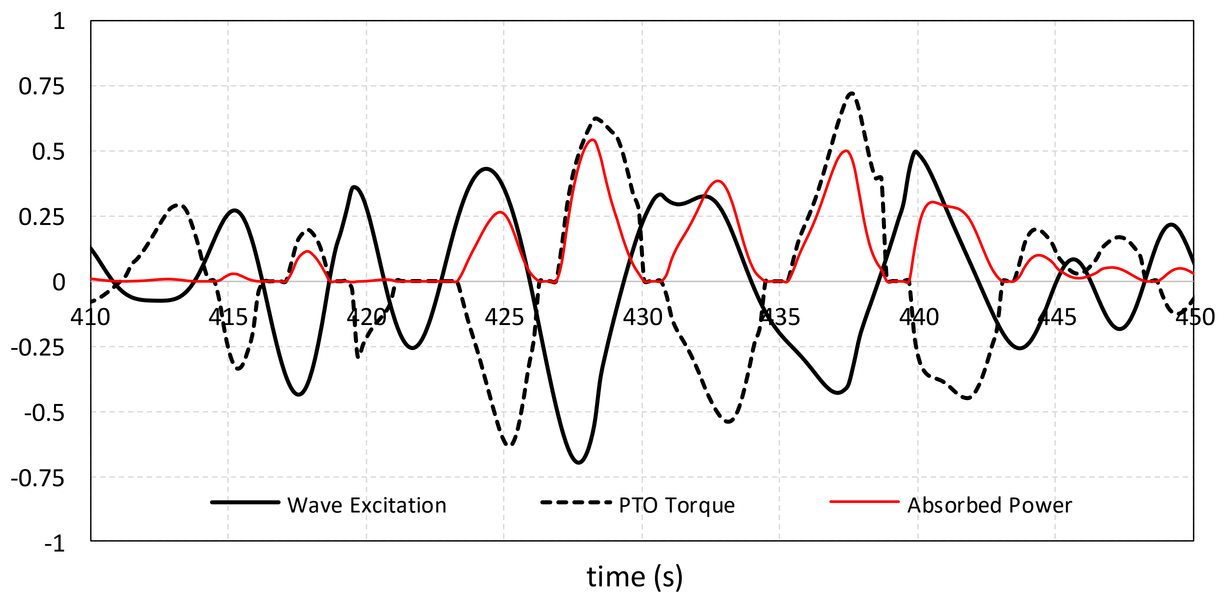


Figure 8 - Normalized Response of Surge WEC under Control Option 2 (Note: no negative power flow)

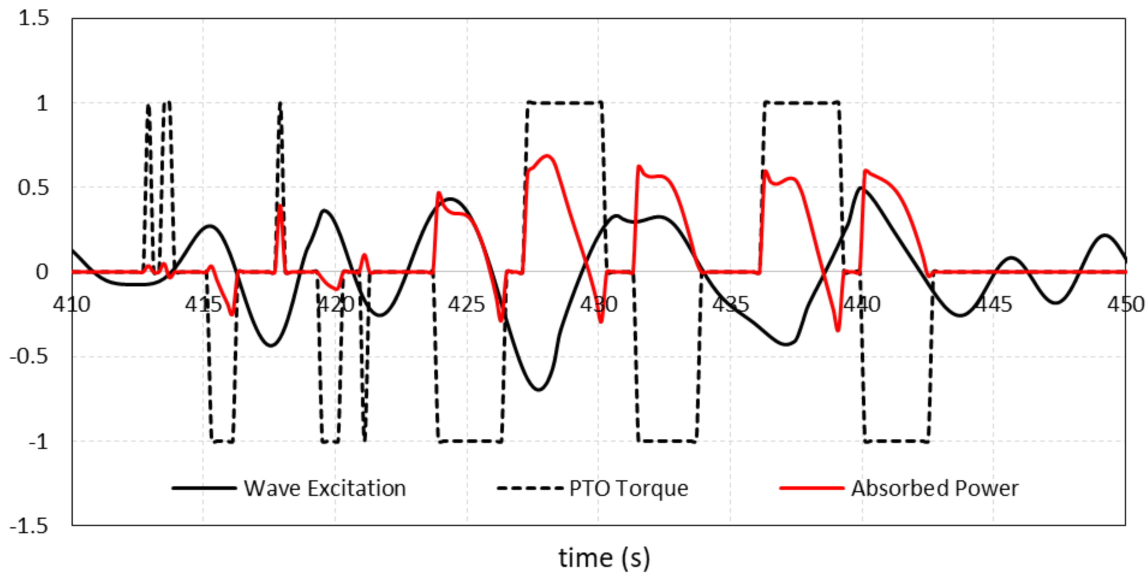


Figure 9 - Normalized Response of Surge WEC under Control Option 3 (Note: negative power flow allowed)

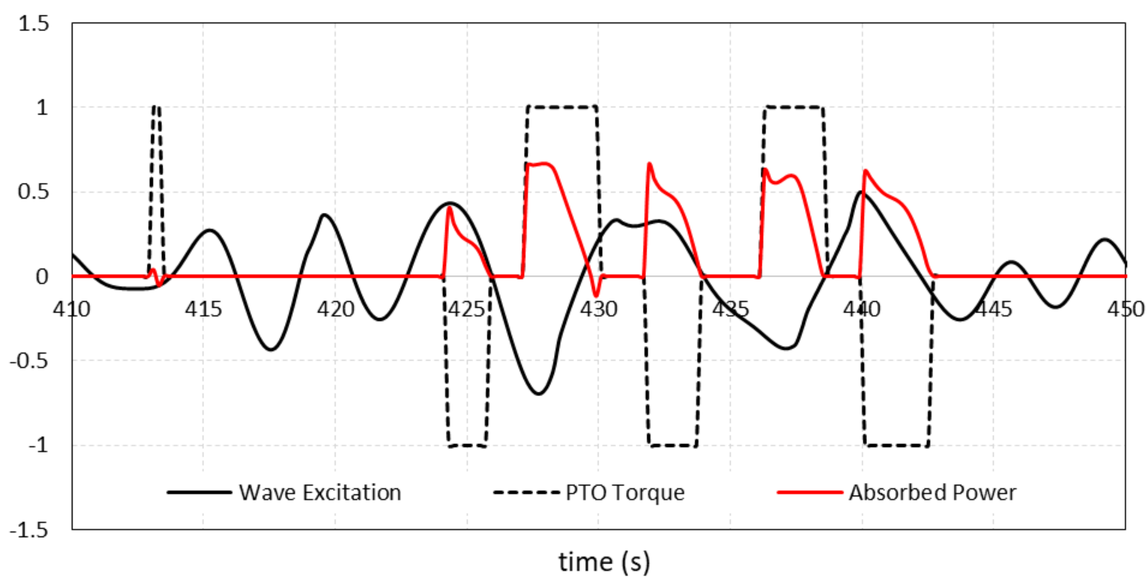


Figure 10 - Normalized Response of Surge WEC under Control Option 1 (Note: no negative power flow allowed)

In general, we found that, if the WEC device under consideration has sufficient inertia (added mass inertia + device mass inertia), performance levels for Options 1 and 3 will be very close to those for Options 2 and 4.

Once these basic PTO options have been evaluated, they can be refined, with appropriate constraints on PTO force levels, power flow magnitudes, and switching frequency introduced to match the capabilities of a realistic power conversion system. This top-down approach also lines up well with a techno-economic optimization process that will need to be brought along to identify the cost for each of these configurations.

7 - Loss Models

Modeling the dissipation in the power train is essential when designing optimal control systems for WEC devices, because the objective is to maximize the *generated* power, not the *absorbed* power. However, it is often much more straightforward to control the absorbed power directly. Consequently, control decisions involving the absorbed power must anticipate the dissipation between absorbed and generated power. Such loss models can be as simple as a single efficiency number during conceptual design stages of a WEC device. However, as a WEC designer moves to a more realistic power train, the loss model must reflect this added complexity accurately.

In the course of this project, we developed an extremely detailed model of the hydraulic dynamics in the power train for the Surge WEC device for Resolute Marine Energy. This model is highly complex, involving nonlinear differential equations, high-frequency switching valves, and numerous saturation limits. Such a model, although essential for accurate simulation, is not conducive to control design, because its complexity makes it very difficult to analyze. As such, this highly accurate model was distilled to create a less accurate but still useful “control-oriented” PTO model.

This simplified model estimates the transmission dissipation in the power train as a nonlinear algebraic function of the flap torque, T, and angular velocity, ω. This model is physically meaningful, in the sense that it first approximates the high-pressure line flow Q_h and pump flow Q_p as

$$\begin{aligned} Q_h &= G_0 + G_1 T + G_2 \omega T \\ Q_p &= H_0 + H_1 \omega \end{aligned}$$

and then approximates the dissipation from these as

$$\Phi = \Phi_{00} + \Phi_{01} Q_h + \Phi_{02} Q_h^2 + \Phi_{20} Q_p^2 + \Phi_{21} Q_p^2 Q_h + \Phi_{30} Q_p^3 + \left(1 - \eta_p\right) T \omega$$

where η_p is the static efficiency of the pump, and the parameters Φ_{ij}, G_i, and H_i are all algebraic functions of the physical parameters of the power train. (There are 24 distinct physical parameters, including pipe diameters, pre-charge pressures, and switching frequencies.)

This model, it should be remembered, is only an approximation of the true behavior. However, care was taken to be very explicit about what approximations were being made. These include the assumption that certain dynamics in the power train are “fast” in relation to the dynamics of the flap and waves and may be viewed (for the purpose of control decisions) as responding instantaneously. This eliminated the differential equations from the more accurate model. Additional simplifications were made by assuming that the pressure drops in the power train due to fluid flow were small in comparison to the accumulator pressures.

For a given PTO configuration, PTO conversion efficiency becomes a simple function of velocity and torque. This type of model can be fitted easily and used effectively in the controls development process.

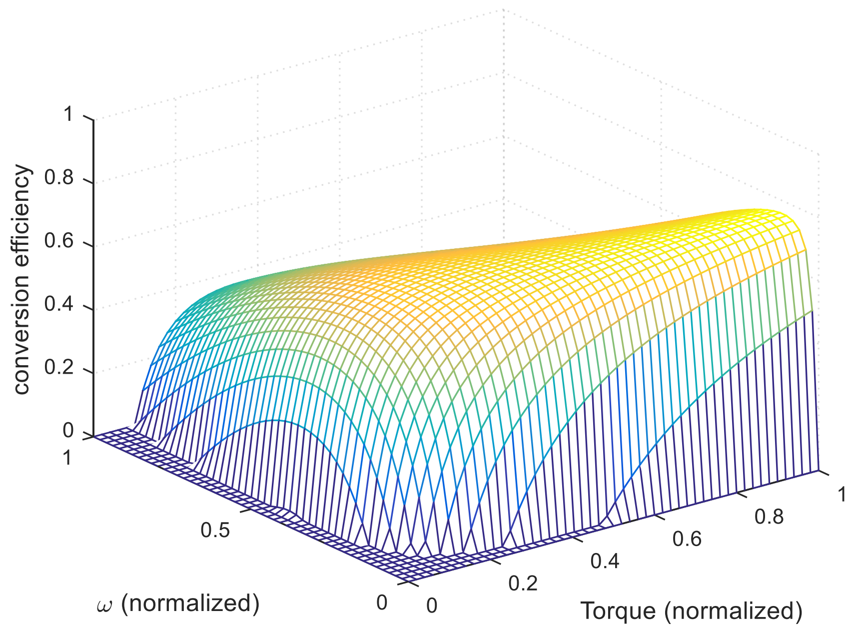


Figure 11 – Sample loss model used for controls-design purposes.

Because the approximate loss model is algebraically related to the parameters of the physical system, systematic parametric sensitivity studies can be conducted to determine how the performance of optimal control varies with these parameters. This provides an extremely useful and essential tool that can be leveraged in both the PTO and the controls optimization process. The final velocity/torque efficiency can be expressed easily as a polynomial function and used in the reduced-order plant model of the WEC device for controls purposes.

8 - Systems Identification Methods

System dynamics model for WEC devices are typically developed from frequency domain data that are obtained from Boundary Element Method (BEM) codes, such as WAMIT, Nemoh, or analytical models. Frequency domain data is then augmented in the time domain with non-linear terms for viscous damping and other non-linearities. These models are typically not directly suited for controls development purposes, and a reduced-order model is required to make it fast-enough in the optimization process. This proved particularly challenging for the oscillating water column (BBDB), which has four heavily coupled oscillatory modes that must be described in the dynamic system.

In order to design controllers (both causal and MPC) for the oscillating water column, it was first necessary to develop an accurate linear finite-dimensional state-space model. By "linear finite-dimensional," we mean that, at any given time *t*, the dynamics of the system can be described by a system of ordinary differential equations of the form:

$$\dot{x}(t) = Ax(t) + Bu(t)$$
$$y(t) = Cx(t) + Du(t)$$

where $x(t)$ is a continuous, finite-dimensional vector of coordinates, $u(t)$ is a four-dimensional vector of incident wave forces on the BBDB system, defined as

$$u = \begin{bmatrix} \text{incident heave force} \\ \text{incident surge force} \\ \text{incident pitch force} \\ \text{incident chamber pressure} \end{bmatrix}$$

and $y(t)$ is a four-dimensional vector of response velocities co-located with these forces. This is a challenge because the true physical system is the consequence of partial differential equations, which may be thought of loosely as an infinite-dimensional state-space. Consequently, any finite-dimensional model, as described above, constitutes an approximation, and the goal is to find the best approximation for a given dimensionality of x. The dimension of x should be as small as possible to enhance the efficiency and practicality of the control designs based on this model. However, because the accuracy of the model decreases with dimensionality, there is a trade-off between accuracy and practicality.

One of the things that make MPC challenging for the BBDB is that the finite-dimensional model has four inputs and four outputs. There are consequently 16 input/output channels, all of which must be estimated accurately by the finite-dimensional model. A reasonable approximation without any model reduction techniques yielded a total of about 190 states, which proved detrimental to the computational efficiency of the MPC algorithm.

To address this issue, we refined a subspace-based system identification technique to generate the finite-dimensional model. Subspace techniques are analytically sophisticated but very widely used methods for generating such models. They have the distinct advantage of being scalable to systems with many inputs and outputs, as well as systems requiring higher-dimensional state vectors to achieve desired modeling accuracy. The drawback to these techniques is that the physical meaning of the internal states becomes lost. Figure 12 illustrates how accuracy improves as the number of states is increased. A reasonably accurate model is identified with about 50 states, representing a four-fold reduction in states compared with the original model.

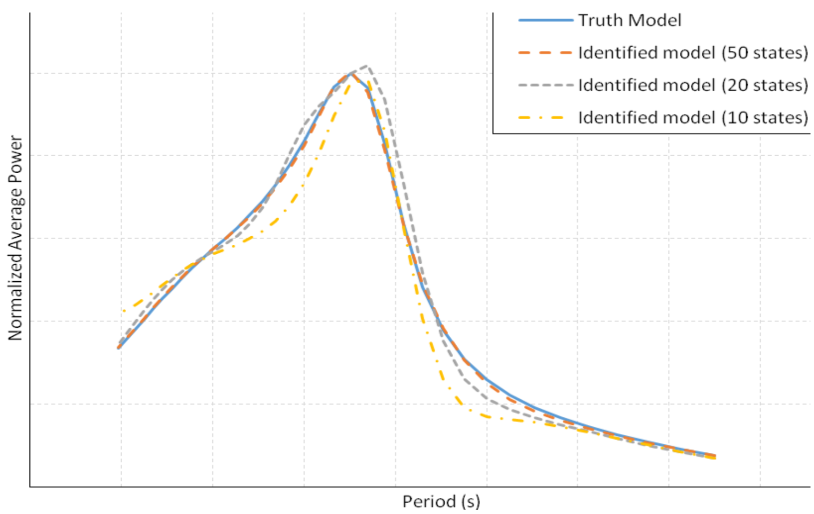


Figure 12 – The truth model Vs. identified models

9 - Model Predictive Control

Receding-Horizon MPC involves successive gradient-based optimizations, performed significantly faster than real time, in which both the constraints and the cost function to be optimized are specified. The cost function considered in the present work includes the wave energy captured and the PTO energy consumed over the finite horizon of time in the near future being considered; this time horizon is gradually receded as the actual time advances. Iterative optimization of the cost function is performed while adjusting the free parameters in the system (that is, the "control variables"), in a manner which minimizes the cost function, over the gradually-receding horizon, while respecting the various control and state constraints specified on the problem.

Model Predictive Control (MPC) represents a well-suited framework for maximizing the performance of WEC devices. Given an accurate wave prediction, MPC outperforms all the other control strategies for any device (Hals et al 2011). From a development perspective, this class of algorithms is very flexible as it can be adapted easily to work with different WEC types, PTO topologies, and their respective constraints. Several types of MPC have been used by the broader WEC development community. Faedo et al (2017) provide a comprehensive review of MPC and MPC-like approaches.

A key issue with MPC is achieving an execution speed or computational efficiency that makes it real-time capable. Because the optimization problem is serial in nature and only limited parallelization is possible, this is a serious consideration in the selection of an appropriate MPC algorithm framework. In general, there is a trade-off between computational efficiency and the capabilities of any given approach. Because MPC is an iterative time-domain approach, MPC performance is highly sensitive to the efficiency of the controls model and the method by which constraints are introduced. This is why systems identification and model-reduction techniques are so important in the controls design process. We have worked with a number of different MPC variants to meet control needs in an optimal manner and have in that process developed our own variants to meet specific requirements. In general, linear MPC can be made faster than real time for most applications, while non-linear MPC is more problematic in this respect, and real-time capability is largely a function of the complexity of the controls model, non-linearity, and the types of constraints imposed. Table 1 maps optimization requirements against the two classes of MPC algorithms used. It should be noted that the non-Linear MPC framework has been expanded by Re Vision Consulting.

Table 1 - Capability Comparison of Linear and Non-Linear MPC Frameworks

Algorithm	Continuous control	Discrete control	Asymmetric constraints	Non-linear dynamics	Motion constraints	Force constraints
Linear MPC	✓				✓	✓
Non-Linear MPC	✓	✓	✓	✓	✓	✓

A secondary issue when optimizing a controller with MPC is that the algorithm may get stuck in a local optimal solution and not reach a global optimal one. Benchmarking the performance against analytical results (such as point absorber theory) can support the debugging process to ensure that the algorithm is converging on optimality. Figure 13 compares performance outputs by the control laws applied. Please note how MPC approaches the point absorber and volumetric limits.[6]

[6] Point absorber and volumetric limits are the upper bounds of performance for a heaving point absorber.

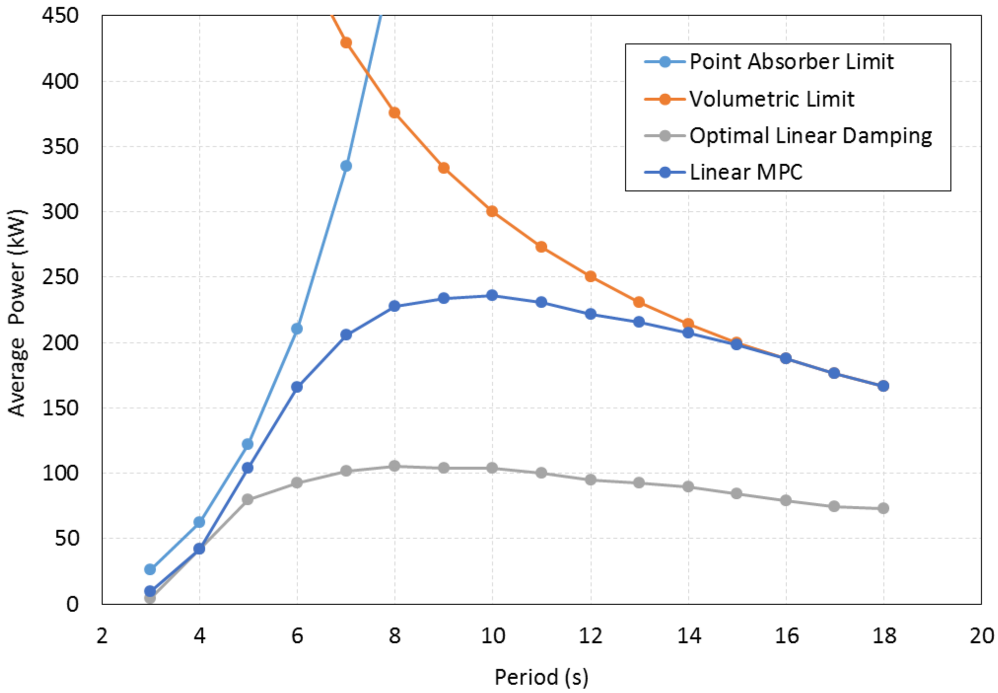


Figure 13 - Benchmarking of different controls laws against theoretical limits

10 - Wave Prediction in Real Seas

MPC relies on a prediction of the wave-excitation forces over a sufficiently long prediction horizon. Wave-prediction methods can be generally categorized as either auto-regressive or deterministic. Auto-regressive models extrapolate future wave excitation forces from a given measured history by fitting a model to it. This type of model tends to do well for a few seconds into the future, but these predictions are generally insufficient in length to meet the requirements of optimal feed-forward control for most WEC device topologies. For wave predictions to be "good enough" for controls, they need to be accurate enough and predict sufficiently far into the future to provide optimal results.

The required prediction horizon for MPC algorithms is a strong function of the device topology and configuration. In general, devices with a high inertia and weak coupling between the primary absorption mode and PTO require a longer prediction than devices with a low inertia and strong coupling between the primary absorption mode and PTO. Herein, we refer to this as a strongly coupled closed-loop response. The explanation for this observed phenomenon can be broken down into two distinct problems: (1) the non-causality of wave-excitation forces (Falnes 2002) and (2) the coupling between control action and motion response.

The more dominant prediction horizon driver appears to be how closely coupled the closed-loop response of the dynamic system is to the control input. This becomes apparent when evaluating the optimal prediction horizon for other topologies in this paper. Figure 14 shows the average normalized absorbed power as a function of the prediction horizon for two different topologies. It illustrates that the optimal prediction horizon for the RME Surge WEC device is longer than for the heaving point absorber. In some cases, that prediction horizon requirement is reduced to only about half a wave period, which opens up interesting alternatives to replace a deterministic wave forecast with an auto-regressive model and/or use causal controllers.

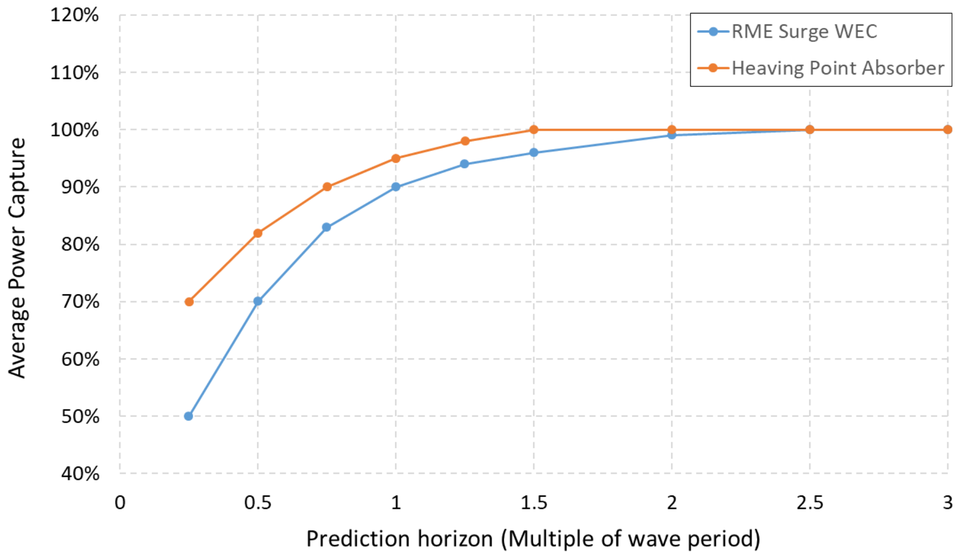


Figure 14 - Normalized performance as a function of the prediction horizon for a heaving point absorber and a surge WEC device.

A second issue to consider is the accuracy of the forecast. To better understand this issue, we carried out a sensitivity study to phase and amplitude errors of the forecast for a simple heaving point absorber. The study's results, summarized in Figure 15, demonstrate that MPC is more robust against wave-amplitude prediction errors than phase prediction errors. It shows that a change in the phase error causes a bigger reduction in power than a change in the amplitude error.

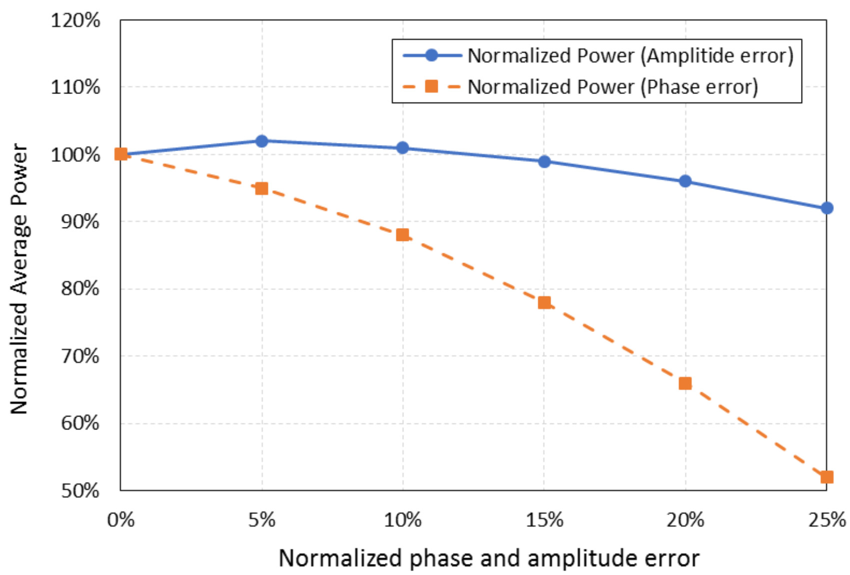


Figure 15 - MPC sensitivity to amplitude and phase error in the wave prediction

To understand how well waves can be forecasted in the open ocean, we carried out a field campaign in Santa Cruz, assimilated data from six custom-built wave-measurement buoys, and predicted the wave field to a down-wave location, where a seventh wave measurement buoy was located. The down-wave measurement buoy was then used to validate the wave prediction from the up-wave buoys. Various methods of identification, propagation and correction were applied and tested to minimize wave prediction errors. The final result showed that a mean absolute amplitude error of less than 15% is attainable for a forecasting time horizon that is about twice as long as the dominant wave period. Figure 17 provides a snapshot of the actual and predicted wave surface elevation with a 20s forecasting horizon (roughly twice the wave period in this case).

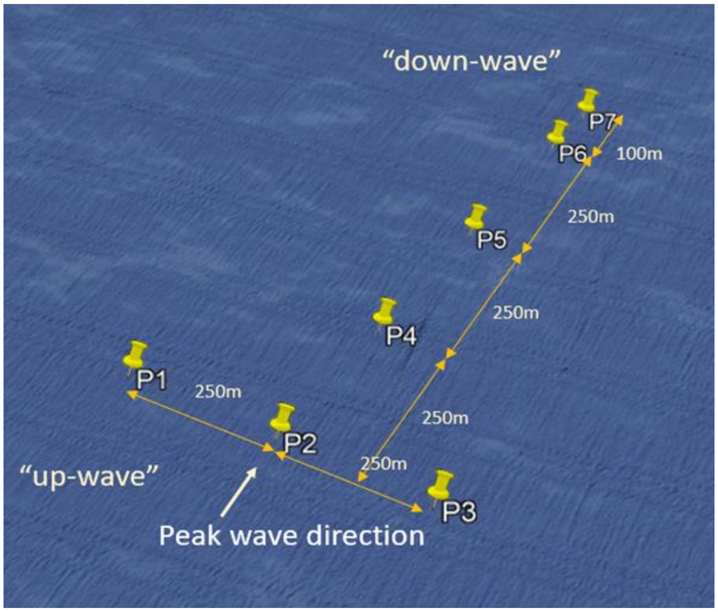


Figure 16 - Wave Probe Layout

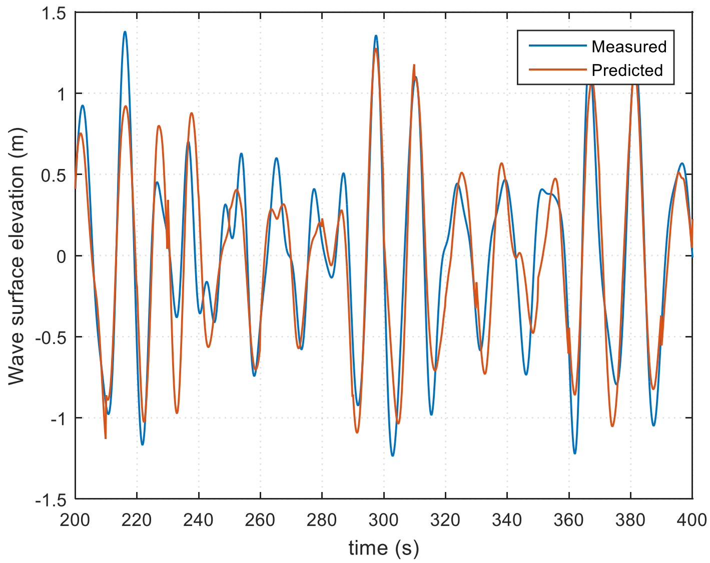


Figure 17 - Wave prediction from field campaign showing measured vs. predicted (propagated) wave surface elevation.

To understand the impact of this error on MPC, we used the predicted surface elevation values to compute a controls command with MPC and the actual values of the wave-surface elevation to drive the system dynamics model. This approach allowed us to understand the performance degradation due to the introduction of realistic prediction errors. The results for a simple heaving point absorber for a given sea state are shown in Table 2.

Table 2 - Performance Effects of Wave-Prediction Error

Controls Method	Absorbed Power	Normalized
Optimal Linear Damping	16.3 kW	100%
Optimal Causal Control	25.8 kW	153%
Linear MPC (No Prediction Error)	47.9 kW	293%
Linear MPC (Realistic Prediction Error)	39.6 kW	242%

Performance degradation is a function of the device topology and its sensitivity to the error as well as the control algorithm itself. However, a net improvement over the feed-back control system can be clearly demonstrated. Since this benchmark has been performed, we have been able to significantly improve the wave prediction accuracy from our systems using better instrumentation and improved algorithms and expect MPC performance to be very close to the idealized MPC version. We should also point out that the causal controller only used the PTO velocity as a feedback variable. The causal controller could be improved by assuming that either the wave surface elevation at the device or the wave pressure forces are known. Both of these assumptions would require additional instrumentation on the device.

An alternative way of measuring the wave resource is using X-band radar. Radar is a remote sensing technique and can image a large free surface area continuously. This allows for the identification of the fully directional nature of the wave field. The disadvantage of this type of measurement is that it requires an elevated platform to mount the radar (typically > 8m), and accurate measurements require Bragg waves to be present on the ocean surface. Bragg waves are the tiny ripples on the ocean surface that form when wind blows on it and provide a steep side from which the radar reflects better. Measurements in general were observed to be adequate when wind-speeds exceeded 2m/s.

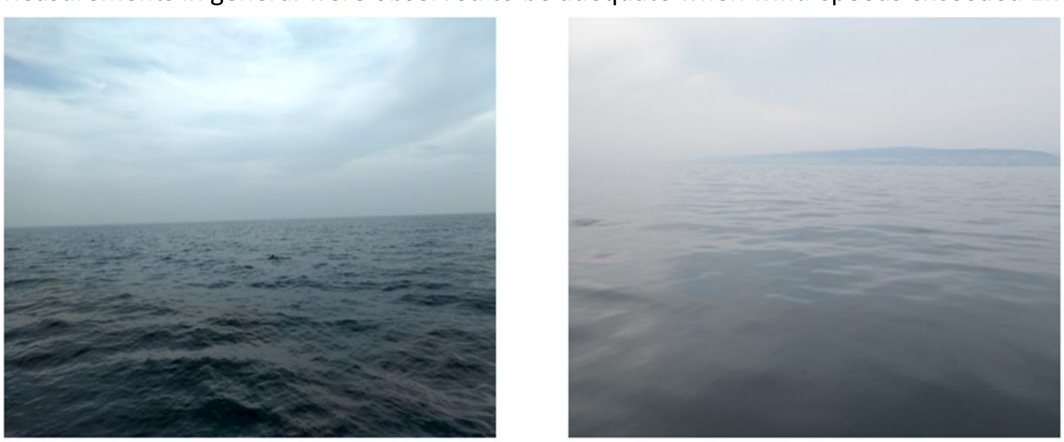


Figure 18 - Ocean Surface with wind-speed > 2m/s (left) and 0.5m/s (right)

As part of our efforts, we developed an algorithm base and tested it at sea using a radar system that measures the radial velocity of the wave field using Doppler measurements form an X-band radar

(9.8GHz) that was modified to fit this application. The radar scans the wave field over a radius of about 1.5km at a rotational speed of 2s. The following illustration shows the radar operation principle.

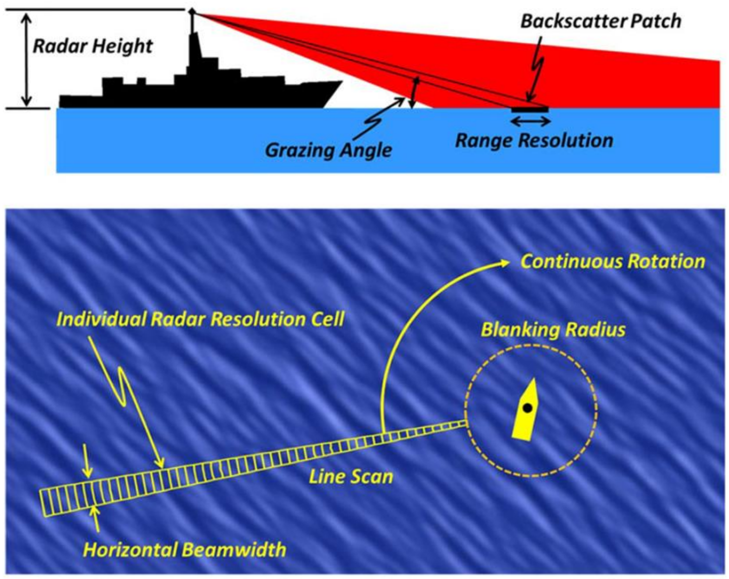


Figure 19 - Wave Radar Working Principle

In the wave prediction process, the radar image is used to identify the wave-field present, which is then propagated forward in space and time to provide a prediction of directional wave components at a target location. These wave components are subsequently used to compute the wave excitation forces from the WEC device using the excitation force kernel, which is WEC device specific.

Multiple buoys were located within the radar measurement area to allow us to compare wave predictions obtained from the radar-based wave-prediction system with the actual surface elevations. The results showed that reasonable wave prediction accuracies can be obtained and that they are comparable to the ones obtained using wave measurement buoys. The following figure shows an example time-domain record of predicted wave surface elevation values compared to buoy measurements.

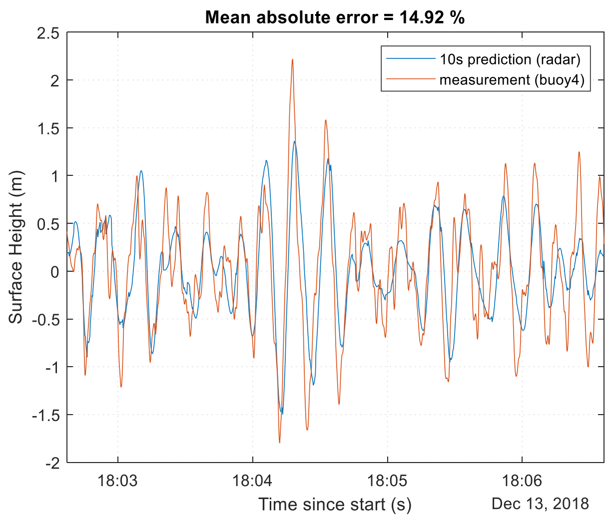


Figure 20 - Example Time-domain record of wave prediction accuracy

Overall, the outcomes from our work shows that relatively accurate wave predictions can be obtained at sea, enabling Model Predictive Control (MPC) on at-sea WEC devices.

11 - Causal Control Approaches

In situations where it is undesirable or impossible to furnish a control algorithm with accurate information about future wave loading, power generation decisions must be made solely on the basis of present and past measurement data. Such a situation requires that these measurement data be used as feedback to a decision algorithm that determines, in real time, desired control actions for maximal power generation. This general concept is known as *causal* control, because there is no explicit incorporation of a prediction algorithm into the decision process.

In Scruggs et al (2013), a general technique for causal control of linear WEC systems is presented. In this technique, the wave-excitation force is modeled as a stochastic process with a known spectrum, and control decisions are made using only localized feedback information. In other words, deployed wave-forecasting sensors are not used, and feedback information is limited to dynamic phenomena in the immediate proximity of the WEC, as well as the WEC response itself. Subject to these assumptions, the optimal causal control algorithm maps these localized measurements into power generation commands. To be more explicit, suppose that the $y(t)$ represents the vector of localized feedback outputs used in the causal control design. This vector would almost certainly comprise the PTO position and velocity, as well as other localized variables. Similarly, let $u(t)$ represent the vector of controllable quantities for each PTO in the WEC system, such as flap torques and generator currents. The causal control design constitutes the design of an algorithm that formulates $u(t)$ from the values of $y(\tau)$, for $\tau \leq t$.

It is shown in Scruggs et al (2013) that, when the dynamic model of the WEC is linear and the PTO loss model is quadratic, the optimal causal controller developed in this framework can be represented as a linear transfer function and can be solved exactly as the solution to a LQG (Linear Quadratic Gaussian) problem. Such controllers can be broken into an observer subsystem (Kalman-Bucy filter), which estimates the full dynamic state of the WEC system, and a state feedback controller, which makes decisions on the basis of these estimates to maximize power in the absence of wave-prediction information.

Although it is presumed that the stochastic spectrum of the wave loading is known, this constitutes considerably less information than the precise knowledge of the wave loading itself. Estimation of this stochastic wave loading spectrum can be readily accomplished by recursive time series analysis techniques and, in fact, can be accomplished without direct measurement of either the wave force or elevation in the proximity of the WEC. This is illustrated in the study by Scruggs and Nie (2015), in which the stochastic spectrum of the wave loading is recursively identified, while only the position and velocity of the PTO must be measured. However, in causal control schemes it is generally the case that the best-possible performance can be improved through the use of additional sensing, including local wave elevations, incident wave forces, and so forth.

One of the challenges faced in the design of causal controllers for WECs is that the conditions that bring about the LQG paradigm (i.e., linear dynamics and quadratic loss models) are rarely accurate enough to adequately capture the device behavior. In such situations, it is possible to extend these techniques, in an approximate sense, via the use of Gaussian closure. Nie et al (2016) illustrate this on the flap-type WEC, although the technique can in principle be applied in many other situations. The fundamental idea behind Gaussian closure techniques is that, under the assumptions of linear dynamics and quadratic loss, the stationary probability distribution of the state of the WEC and the surrounding fluid can be characterized exactly as a Gaussian distribution. The presence of nonlinear dynamics and non-quadratic loss results in the departure of this distribution from a true Gaussian function. Gaussian closure techniques proceed by finding an approximate Gaussian solution to the problem, which minimizes an associated solution error residual. This procedure allows for the stationary stochastic performance to be approximated in a computationally efficient manner, through the solution of a small set of non-linear algebraic equations. When this approximate technique is used to evaluate performance, causal feedback laws can be optimized efficiently.

The design of causal controllers requires certain precautions that do not arise as readily in the MPC framework. These stem from the fact that, because causal control algorithms are not given access to future wave-loading information, they compensate for future uncertainty through the use of feedback. The presence of a feedback loop into the WEC control architecture raises the possibility that the control loop could destabilize. This can occur due to a mismatch between the dynamic model of the WEC used for optimization and the true dynamic behavior. As such, it is an essential part of causal WEC control design to ensure that the controller is robust to model uncertainty. Nie et al (2016) show that this robustness may be ensured through the use of the classical Loop Transfer Recover (LTR) technique. Although conservative, this technique has the advantage of being very straightforward to apply.

Another challenge faced in causal control design is the accommodation of constraints. By contrast, in the MPC framework it is straightforward to place explicit limits on PTO displacement and force, as well as other quantities that must be ensured to stay within bounds. In causal control design, techniques to accommodate constraints must be applied in such a manner that they do not introduce instabilities into the feedback system. Scruggs (2017) proposes a general and robust technique for the design of causal WEC controllers that can guarantee a finite PTO displacement.

Alternate Prediction-Less Controls Approaches

There are a number of interesting hybrid controls approaches that we reviewed. Our main MPC approach, including wave prediction can be thought of as the “Tesla” of control systems, because it has the most comprehensive capabilities in respect to accommodating non-linearities, and constraints in a WEC system. On the other end of the complexity spectrum we considered a set of robust techniques for causal optimal control developed by Prof. Jeff Scruggs that does only use PTO velocity as a feedback variable to optimize the controls response, requiring no additional instrumentation. Between these two approaches there are a number of options that could be considered interesting variants of the above two approaches. Todate, we have not benchmarked these variants, so it remains unclear what the benefits/limitations of these methods are. Benefits are likely going to be device specific and cannot be generalized easily.

Pseudo-Spectral Methods – Receding horizon pseudo spectral control (RHPC) is documented in references 12-14, and uses periodic basis functions. Despite the non-periodicity of the input wave signal, a simple Fourier PS method is successfully used as a Feedforward control algorithm, by applying suitable windowing functions to the input signal when necessary. The method has been applied to a hinged barge and a heaving sphere. A key advantage of this method is an improvement in computational performance over full MPC.

Causal Control using Fluid Pressure as Feedback – The use of fluid-pressure as an input to estimate the system state is useful in that it addresses some of the causality issues in the WEC controller design. References 15 & 16 document the implementation of a causal controller called Feedback Resonator

(FBR) that uses a complex conjugate controls law to maximize performance. Several implementation variants of this complex conjugate control law are presented with a simple PI controller appearing to approximate the response adequately. A second variant of this controller was developed to tune an MPC controller to enforce constraints on the unconstrained FBR controls law. Validation data is presented on a 1:17 scale heaving point absorber in irregular seas. It should be pointed out that as a result of the device-scale, the radiation potential of the device is limiting device performance for all sea-states evaluated. This is a response-region where complex conjugate control is known to work well and wave forecasting is not as important. It is unclear what the performance trade-offs would be for a device with more realistic constraints and non-linearities.

MPC using an Autoregressive Excitation Force Forecast – Auto-regressive models are useful to forecast the wave resource a few seconds into the future. Auto-regressive models are usually fitted to historical measurements of wave surface elevation, fluid-pressure or PTO forces to estimate future values. These predictions can be used to provide a short term forecast to run the MPC algorithm. However, the forecasting horizon may be insufficient to accommodate actuator delays or discrete force control in an optimal manner.

12 - Wave Tank Validation

Validating a controls strategy in the wave tank is a useful step to reduce modeling errors. However, the scope of that validation needs to be clear from the beginning to maximize the investment into such a program. A key consideration is that costs for constructing and testing WEC devices increase exponentially with increasing scale. As a result, the core question is how small of a model can be built while still obtaining useful validation data from the model-testing campaign.

The fluid-structure interaction effects can be scaled well from relatively small-scale models. The core issue is often how the PTO can be modeled at a small scale to represent the behavior of the full-scale system. Building small-scale models of the PTO is usually unrealistic, because friction becomes dominant at smaller scales. As an example, consider a very large model that is tested at 1:10 scale. The Froude-scale for power is ^3.5, so that we are producing 10^3.5 = 3,162 times less power in the model scale experiment than at full-scale. It is virtually impossible to retain Froude similarity for any electro-mechanical system over this scaling range.

Fortunately, off-the-shelf electronic actuators and controls can be effectively leveraged to mimic the behavior of a full-scale PTO. In our case, we leveraged servo-drives to provide the motion response and implemented closed-loop feedback controllers to track the Froude-scaled force/torque behavior of the full-scale system. Specifically, we leveraged an off-the-shelf LinMot actuator/drive that was programmed to track a reference force value. A load cell and PID loop were used to separate any dynamic behavior of the actuator from the device dynamic. Figure 21 and 22 shows that setup for a heaving point absorber. Using a fast-tracking PI control loop was essential in allowing the system to track any demand torque provided by the real-time controller. In our case, we leveraged a SpeedGoat system that allowed us rapidly to design and implement control loops in a convenient Simulink environment.

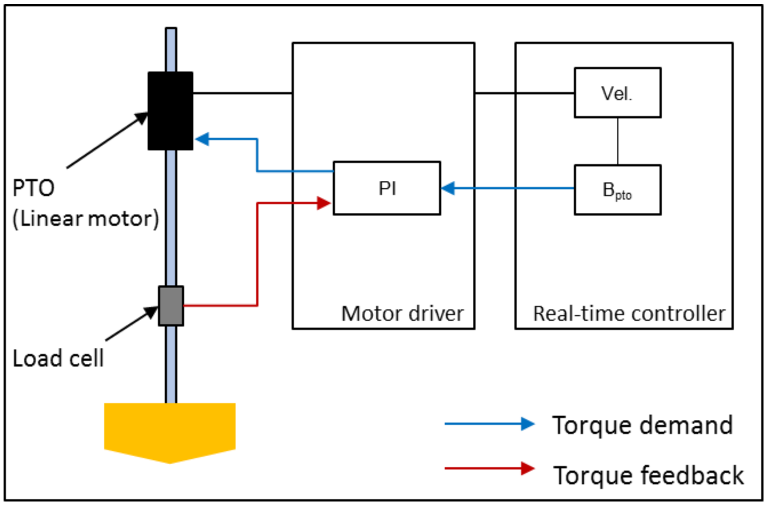


Figure 21 - Controls and force-tracking setup for testing a heaving buoy

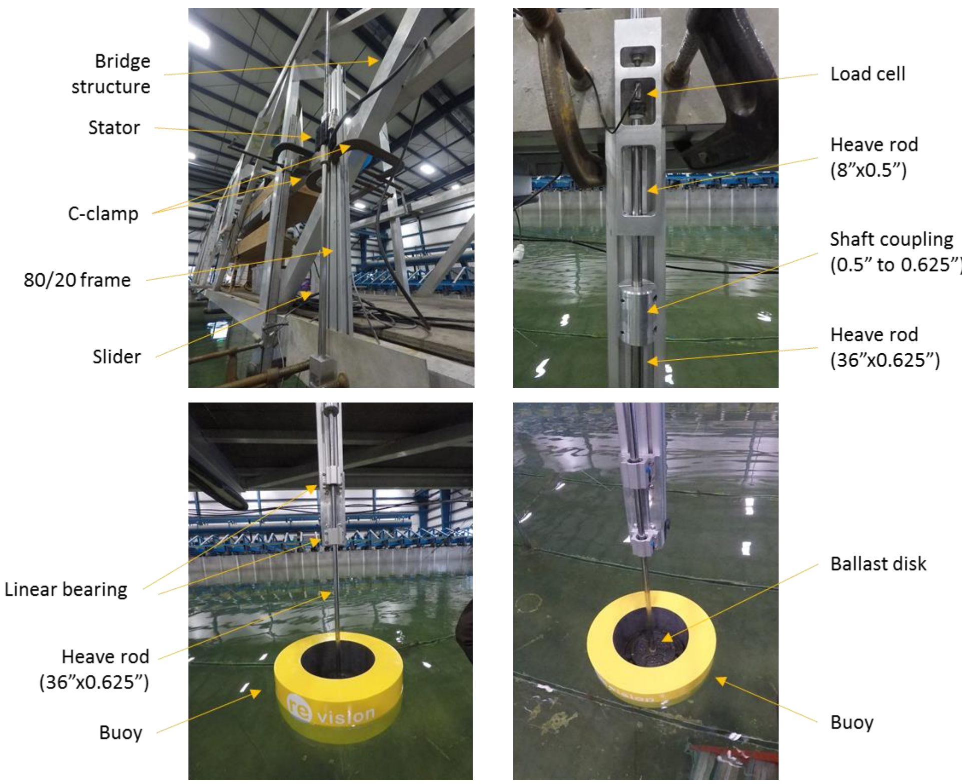


Figure 22 - Physical setup of test in wave tank at the Oregon State University

Issues encountered and resolved during our test campaign involved the PTO emulator and included (1) force-tracking Issues requiring fine-tuning of the PID loop, (2) measurement noise on the load cell, (3) bearing issues, and (4) an outdated driver on the SpeedGoat system that introduced delays into the control loop. While these issues were all resolvable, they illustrate the added complexity encountered with this type of setup compared with the more traditional, passive mechanical means of providing a viscous damping force.

The causal controller was implemented directly on the SpeedGoat system because it is computationally very efficient. However, we were unable to test the MPC controller in real-time, because the algorithm is not real-time capable at model scale. Instead, with the knowledge of exactly which waves were pre-scribed, we pre-computed optimal PTO command values offline and synchronized the pre-computed PTO command values with the wave-maker start signal. This allowed us to achieve our appropriate controls validation objective at this model scale.

13 – Robust In-Ocean Setup and Validation

In order to enable robust application of controls at sea, suitable HW and SW needs to be integrated. To do so, we built a small demonstrator WEC device and designed a controls architecture that allowed us to fully re-use controls algorithm codes developed and tested during earlier phases and therefore enable rapid prototyping and controls testing. While we initially tried to use a Speedgoat system, we found that the Simulink-based architecture was too constrained and did not allow us to execute many of computationally efficient codes written in Matlab and C. We also found that the Speedgoat HW system was not very robust encountering several driver related issues.

The overall controls topology is shown in the following figure and consists of: (1) a set of wave measurement buoys that transmit wave information in real-time to a wave-prediction algorithm, (2) a computer that runs the wave-prediction algorithms and provides a wave excitation force forecast, (3) a controls computer that uses the wave prediction and sensor feedback from the WEC device to compute an optimal response, and (4) a National Instruments cRio front end that provides robust industrial-grade I/O capabilities and incorporates low-level control to protect the hardware from overload and provides error handling capabilities. These systems communicate with each other over a low-latency ethernet-based communication link, called the Pacemaker that insures real-time communication.

The separation of these systems allowed for systems to be developed and tested concurrently so that the development of the different components would not interfere with each other. The same system was also used for hardware in the loop testing by running a WEC device emulator on the cRio device. Overall, this setup enabled a seamless development process, resulting in efficient project execution.

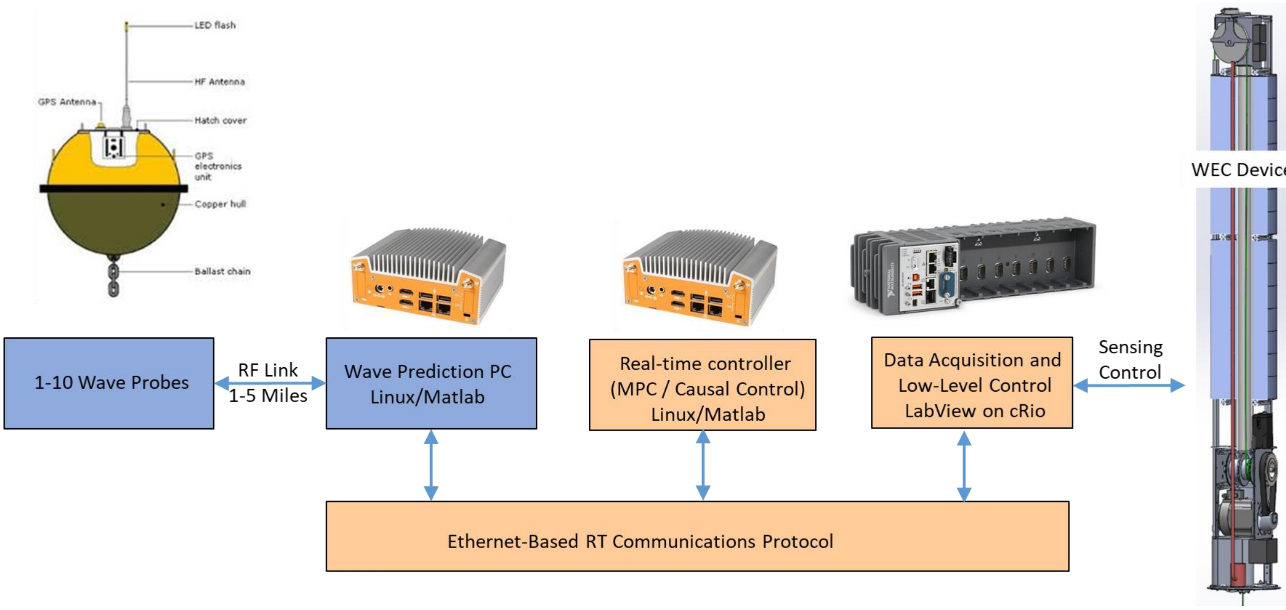


Figure 23 - Controls Topology for In-Ocean Deployments

The WEC device is a slender cylindrical buoy with a diameter of 0.5m and a height of 4m, and is connected to the seabed over a tensioned wire. The wire tension is controlled using a rotary winch that is driven by a commercial servo motor/drive system. Peak power output from the drive system is 8kW. To ease permitting requirements, the buoy was only deployed temporarily in about 20m of water depth in the Pacific Ocean off Santa Cruz, California, while being connected to a vessel for power.

Figure 24 - LabView Controls Interface

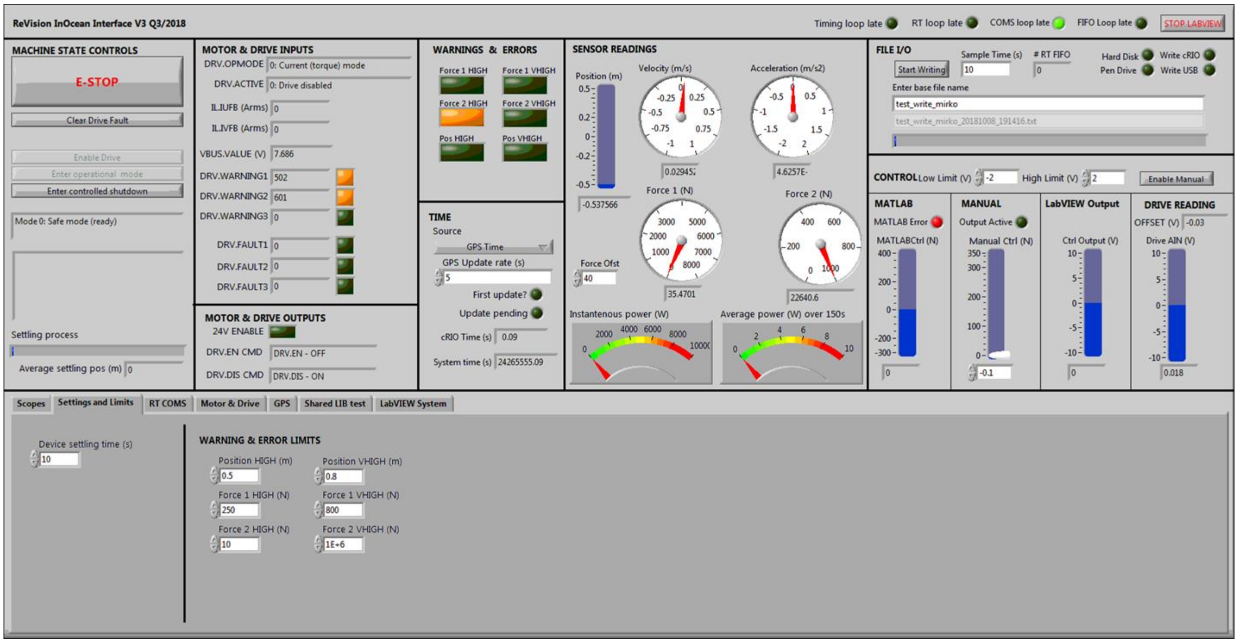


Figure 25 - Demonstrator WEC Device: Scale (left), Build images (right)

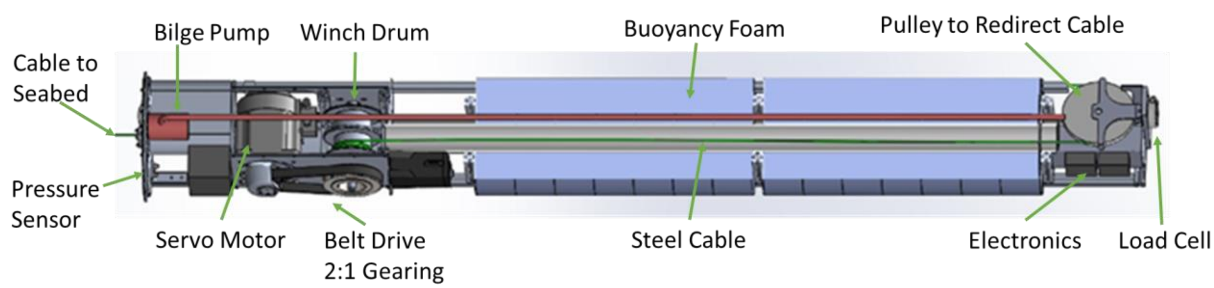


Figure 26 - Identification of Major Buoy Sub-Systems – Device in horizontal position

The deployment was carried out using a 52foot long research vessel with appropriate lift capabilities. The following images shows the deployment of the system and subsequent installed position off the coast in Santa Cruz in about 20m water depth.

Figure 27 - Buoy deployed at sea (left) and on deck before installation (right)

At-sea testing included initial validation using a velocity-dependent damping term and subsequent application of Model Predictive Control showed that the numerical simulations agree well with the at-sea time-domain execution showing that MPC control can be executed on devices at sea. Further testing will be required to fully validate a number of different controls strategies.

Final Thoughts

In this paper, we reviewed causal and non-causal controls approaches and their application to WEC devices. Both controls frameworks are universal in nature and can be adapted and applied to most WEC topologies found within the literature. The key controls objective can be summarized as maximizing electrical power output while considering all losses in the system and respecting constraints. This type of constrained optimization is required to address successfully realistic WEC controls optimization problems.

The Need for Wave Prediction – While causal control with acceptable performance has been demonstrated on a limited set of device topologies, it remains to be explored to what extent causal control laws can approximate the performance of MPC with a wave-forecast. It is important that controls performance does not only relate to energy capture, but also the capabilities of the algorithm to accommodate realistic device-specific constraints such as PTO force, velocity, acceleration, and powerflow. It should be pointed out that the cost of predicting ocean waves (a requirement for effective MPC implementation) is very small compared to the cost of the device itself at commercial scales. A simple 1% improvement in power capture would pay for the cost of the wave prediction system many times over. Causal controls approaches however may be useful at smaller scales required for applications within the blue economy such as recharging unmanned vehicles at sea, where the economic calculus is driven by reliability and operational simplicity and not performance.

Controls Co-Design - Working with a number of different topologies at different TRL levels, we found that the performance improvements attainable for any given WEC are in general less than initially projected from theory and/or simplified models. This is because various constraints and losses in any realistic WEC system tend to reduce motion amplitudes that are required to improve power capture. In many cases, the PTO system's ability to modulate PTO forces/torques efficiently and cost effectively in real-time limits the performance upside potential of any WEC approach. It is therefore important that controls design be integrated into any WEC development effort, beginning with the conceptual design. Techno-economic models can become effective tools for evaluating trade-offs between performance and the incremental cost of additional PTO capabilities, leading to an optimized WEC design.

During the device development process it is important to understand the fundamental upper limits of a particular configuration and use sensitivity studies to understand the trade-offs and design-drivers involved in arriving at an economically optimal configuration. MPC can serve as an important tool to explore this trade-off space, because it allows us to establish upper limits of constrained systems, which is not easily done using analytical methods, or linearized frequency-domain methods. Once these trade-offs are fully understood, the designer can turn to the evaluation of simpler control strategies to further reduce complexity in the system.

Real-time Capabilities – The computational cost of control systems in WEC devices span about 2 orders of magnitude - anywhere from 10X slower than real time to 10X faster than real-time. This means that some of the more complex, non-linear MPC approaches cannot yet be used in realistic applications. However, we have to remember that computational capabilities are rapidly advancing and according to Moores law, which predicts a doubling a computational power every 18 months, a 10X improvement will require less than 6 years to materialize.

Robustness – While we demonstrated that causal and non-causal controllers can be implemented on at-sea WEC devices, our work also shows that these controls and wave prediction building blocks need to be incredibly robust and fault tolerant to be useful on at-sea devices. Further work will be required to turn these controls capabilities into building blocks to enable at-sea optimal control.

As optimal controls in WEC devices continues to evolve, it is shaping what type of systems will become cost-competitive in the future, and is impacting how we fundamentally think about wave energy extraction.

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