Wave Energy Conversion using Machine Learning Forecasts and Model Predictive Control

By Paul D. Sclavounos and Yu Ma
Department of Mechanical Engineering, Massachusetts Institute of Technology
Email: pauls@mit.edu; yuma@mit.edu

Summary

A wave energy conversion (WEC) model is developed for a single-degree of freedom device oscillating in a stochastic sea state. A state-space model is derived for the causal impulse response function of the radiation problem and its non-causal counterpart in the diffraction problem. The force of the power takeoff mechanism (PTO) is regulated by a feedforward controller that requires the forecast of the wave exciting force which may be estimated online by onboard sensors. The controller objective function aims to maximize the wave energy absorbed subject to constraints specific to the PTO. Accurate exciting force forecasts are generated by a machine learning algorithm which may also be used to learn WEC hydrodynamic nonlinearities. The performance of the model is illustrated for a heaving vertical circular cylinder.

WEC Equation of Motion

Assuming linear potential flow, the equation of motion of a single degree of freedom WEC in heave in the time domain is governed by the Cummins equation:

$$(m+A_\infty)\ddot{\zeta}(t)+\int_{-\infty}^{t}K_r(t-\tau)\dot{\zeta}(\tau)d\tau+C\zeta(t)=f_e(t)+f_m(t) \tag{1}$$

Where, m is the mass of the structure, A_∞ is the added mass at infinite frequency, K_r is the impulse response function of the wave radiation force, C is the restoring coefficient, f_e is the incident wave excitation force and f_m is the PTO machinery force (Falnes, (2002)).

The radiation and diffraction impulse response functions are obtained from the Fourier transform of the frequency domain transfer functions computed by WAMIT™. For the purpose of implementing the control algorithm, the impulse response functions are cast in state-space form. Nonlinear free surface and viscous effects may affect the WEC hydrodynamic loads for large amplitude motions and may be learned online by a machine learning algorithm analogous to that used to forecast the exciting force.

The PTO force $f_m(t)$ is a signal regulated by the feedforward controller in order to maximize the wave energy captured under constraints on the heave displacement, force, active and reactive power of the PTO. The proper settings for these constraints are PTO specific and can be adjusted accordingly. The PTO force is a function of the current values of the system states, which include the WEC kinematics, the states of the radiation impulse response functions and the exciting force.

Because of the non-causality of the diffraction impulse response function, the ambient wave elevation or the exciting force need to be forecasted over a sufficiently large time window into the future. These forecasts require knowledge of either the ambient free-surface elevation which is often hard to measure or of the exciting force which may be estimated by sensors on the WEC. The latter approach is adopted in this note. Accurate forecasts of the exciting force are obtained by using an Artificial Intelligence Support Vector Machine algorithm as summarized below (Sclavounos and Ma, (2018)).

State Space Model of Impulse Response Functions

The governing equation (1) includes a convolution integral $\int_{-\infty}^{t} K_r(t-\tau)\dot{\zeta}(\tau)d\tau$, which represents the wave radiation force. Denoting the convolution term as F_r it can be approximated by a state-space model (Perez and Fossen, (2009)):

$$\begin{aligned} \dot{x}_r(t) &= A_r x_r(t) + B_r\dot{\zeta}(t) \\ F_r(t) &= C_r x_r(t) + D_r\dot{\zeta}(t) \end{aligned} \tag{2}$$

Figure 1 shows the very good agreement of the original kernel function and its state-space approximation.

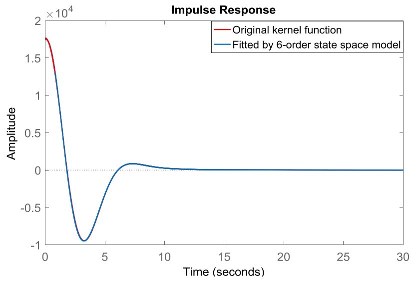

Figure 1. Fitted radiation kernel function

The state-space model of the dynamical system (1) is cast in the standard form:

$$\begin{aligned} \dot{x} &= A_s x + B_s(u+w) \\ y &= C_s x \\ z &= C_z x \end{aligned} \tag{3}$$

Where, $\mathbf{x} = [\zeta, \dot{\zeta}, \mathbf{x_r}]^T$, $u = f_m$, $w = f_e$, $y = \dot{\zeta}$, $z = \zeta$

$$A_s = \begin{bmatrix} 0 & 1 & 0 \\ -C/(m+A_\infty) & -D_r/(m+A_\infty) & -C_r/(m+A_\infty) \\ 0 & B_r & A_r \end{bmatrix} \tag{4}$$

$$B_s = [0, 1/(m+A_\infty), \mathbf{0}]^T, C_s = [0,1,\mathbf{0}], C_z = [1,0,\mathbf{0}]$$

LS–SVM Forecasts of the Exciting Force

The SVM regression uses a mapping into a high-dimensional feature space and its associated inner-product positive definite Kernel to represent the exciting force signal, which is trained using algorithms from optimization theory. LS-SVM is the least-squares version of the original SVM. It solves a set of linear equations instead of a convex quadratic programming (QP) problem of the classical SVM.

Figure 2 shows the performance of the LS-SVM regression method in predicting the heave excitation force which is simulated by convolving the impulse response function with the wave elevations measured in a tank test. The forecast horizon is 5 seconds and the RMS (Root-Mean-Square) error of the forecasted signal is 9.6% of $(4\sigma_{Fex})$. σ_{Fex} is the standard deviation of the exciting force. Using $4\sigma_{F_{ex}}$ as the non-dimensionalization factor is analogous to using the significant wave height for the wave elevations.

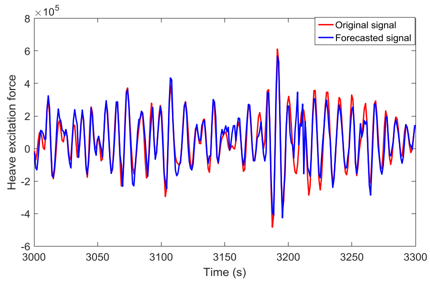

Figure 2. Comparison of the original and forecasted wave exciting force

Model Predictive Control

The objective is to maximize the energy E extracted by the PTO system over a predicted time horizon T_h: $E=\int_0^{T_h} P(t)dt=\int_0^{T_h} -f_m(t)\dot{\zeta}(t)dt$. Therefore, the optimization problem will be formulated as: $\max E=\min(-E)=\min\int_0^{T_h} u(t)y(t)dt$ with constraints on both the heave motion and PTO machinery force: $|z|<\zeta_{\max}, |u|<f_{m,\max}$. The minimization problem subject to an equality constraint (the system dynamics (3)) and inequality constraints (the heave motion and machinery force constraints) forms a non-convex QP problem. Discretizing the objective function with a time step Δt , and modifying the discretized objective function from $J_0=\Delta t\sum_{k=0}^{N-1}(u_k y_k)$ to $J=\Delta t\sum_{k=0}^{N-1}(u_k y_k + r|\Delta u_k|^2)$, $\Delta u_k = u_k - u_{k-1}$ leads to a constrained convex QP problem (Ma et. al., (2018)).

Wave Energy Conversion Results

The performance of the MPC is tested for a heaving cylinder which is neutrally buoyant with radius 5m and draft 8m. The performance of the WEC is simulated under two different sea states (Hs=1.7m, Tp=8.7s; Hs=4.5m, Tp=11.8s) with varying regularization factors r (1e-5, 1e-4, 1e-3) to illustrate its effect on the generated power and corresponding control force and heave motion. The optimization horizon for the MPC is 5 seconds and the wave force is forecasted by the LS-SVM regression. Figure 3 shows the RAO of the heave motion and the two seastate spectra. The constraints $\zeta_{\max}, f_{m,\max}$ are specified by the PTO machinery. The statistical results are shown in Table 1. Figure 4 shows the time records of the cumulative power for different r under the two seastates. Figure 5 shows time records of the heave displacement, heave velocity, wave force, control force and instantaneous power under different values for r. When r is small, the heave amplitude and PTO machinery force are bounded by the constraints. The heave constraint is set to $\zeta_{\max}=H_s$ and the force constraint $f_{m,\max}$ is set to a large value.

Table 1. Statistical results under different regularization factors r

Cases	Sea state 1, r=1e-5	Sea state 1, r=1e-4	Sea state 1, r=1e-3	Sea state 2, r=1e-5	Sea state 2, r=1e-4	Sea state 2, r=1e-3
$\bar{P}$ (KW)	89.2	61.7	41.8	720	590	280
σ_P (KW)	265.6	212.7	86.4	2030	1780	615
σ_{f_m} (N)	4.94e5	3.5e5	1.6e5	1.94e6	1.26e6	5.1e5
σ_ζ (m)	1.16	0.96	0.58	3.76	3.02	1.52

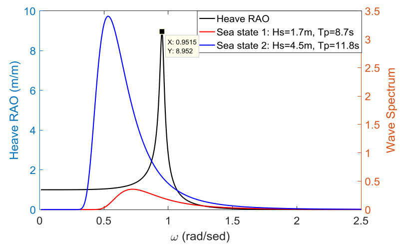

Figure 3. Heave RAO and wave spectra

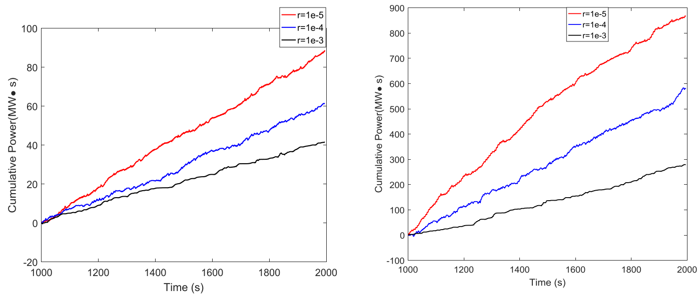

Figure 4. Cumulative power: left (Hs=1.7m, Tp=8.7s), right (Hs=4.5m, Tp=11.8s)

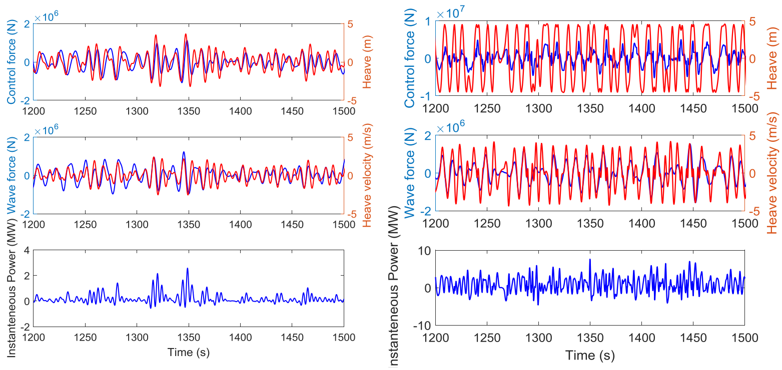

Figure 5. Time records of the WEC performance: left (Sea state2, r=1e-3); right (Sea state2, r=1e-5)

Acknowledgements

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