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LEARNING A PREDICTIONLESS RESONATING CONTROLLER FOR WAVE ENERGY CONVERTERS

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ABSTRACT

This article presents a data-efficient learning approach for the complex-conjugate control of a wave energy point absorber. Particularly, the Bayesian Optimization algorithm is adopted for maximizing the extracted energy from sea waves subject to physical constraints. The algorithm learns the optimal coefficients of the causal controller. The simulation model of a Wavestar Wave Energy Converter (WEC) is selected to validate the control strategy for both the regular and irregular waves. The results indicate the efficiency and feasibility of the proposed control system. Less than 20 function evaluations are required to converge towards the optimal performance of each sea state. Additionally, this model-free controller can adapt to variations in the real sea state and be insensitive and robust to the WEC modeling bias.

INTRODUCTION

Although the principles behind wave energy conversion (WEC) have been unveiled, harnessing the wave energy from irregular reciprocating sea motions is a far from trivial problem [1]. Despite the difficulties, extensive efforts have been dedicated to employ advanced control strategies [2] in an attempt to make the Levelized Cost of Energy (LCoE) of WEC comparable to other renewable sources.

The preliminary work on optimization of WEC efficiency using control engineering through reactive control and latching was proposed by Budal and Falnes in the mid-1970s [3]. However, implementing reactive control may exceed the physical constraints of the power take-off (PTO) system, which is impractical due to the associated large motions, forces and power rating of the (PTO). In addition, maximizing the mechanical power of the WEC requires bi-directional power flows, which can give rise to the high peak PTO power tolerance [4] and lead to an increase in the investment. By contrast, latching control eliminates any negative energy flow through a mechanism, such as a friction coupling or a clutch [5]. The resonance condition has been achieved by approximating the optimal time when the floater should be locked. The floater motions are linearly damped during the remaining part of the wave period [6].

The objective of WEC control is to minimize the LCoE while satisfying technological constraints. Hence, researchers naturally try to copy the success of Model Predictive Control (MPC) from the process industries to the wave energy field. MPC solves the on-line optimal control problems under path constraints. Recently, several MPC algorithms have been specifically developed for the WECs [7]. However, in contrast to the traditional reference tracking control problem, the objective function needs to be modified greatly in the wave energy case, which may give rise to a possibly non-convex optimisation problem. In addition, in order to alleviate the heavy computational burden of MPC, the spectral and pseudo-spectral based MPC-like algorithms offer interesting alternatives [8].

However, the overwhelming majority of proposed WEC control algorithms are based on linear model descriptions, which tend to ignore the true nonlinear characteristics of the WEC hydrodynamics, especially when including the control signal.

Many WEC linear models are validated using tank testing with no PTO force given. Under controlled conditions, the relative device/fluid velocity and the wetted surface increases, resulting in an increase of viscous forces and Foude-Krylov forces, which are ignored by linear hydrodynamic theories [9]. Meanwhile, the WEC control objective is to maximise the absorbed power from the sea by exaggerating the motion. This contradicts the popular WEC small oscillation assumption of linear hydrodynamic theory [10]. Furthermore, the device hydrodynamics can change over time due to slow marine biofouling or non-critical failures. Modelling errors arising from un-modelled dynamics, nonlinearities, can result in poor control performance. However, a small number of robust controllers have been proposed for the WEC control studies [11]. Better description of the WEC dynamics are adopted in the work [12], in which a nonlinear MPC algorithm is implemented on a WEC device. A linear time-varying model has been successfully tested experimentally under large motions [13].

Data-driven and learning-based control methods provide interesting alternatives due to their nonlinear function approximation and optimization abilities. Artificial Neural Networks (ANNs) have been adopted to provide real-time system identification for WEC hydrodynamics [14]. Furthermore, ANNs have been successfully implemented on the control of an Archimedes Swing (AWS) WEC device [15]. Recently, a robust adaptive optimal control strategy has been developed by using a critic neural network to approximate the time-dependant optimal cost value [16]. Reinforcement learning techniques such as Q-learning are used to develop a model-free reactive control system for WECs in the work [17].

In this work, a more data-efficient algorithm is innovatively adopted to develop the adaptive complex-conjugate control strategy for WEC devices. The Bayesian Optimization (BO) approach directly searches optimal coefficients of the controller by evaluating an objective function at the end of each simulation episode. The data efficiency has been achieved by using the uncertainty information provided by probabilistic Gaussian Process (GP) models without exploring all the WEC dynamics. The model-free property of proposed method makes WEC performance more robust and practical than the linear model based control methods. The proposed controller is predictionless (does not need future wave force information), although it is shown that it has a competitive performance to optimal control methods which usually need prediction. Numerical simulations are evaluated in both the regular and irregular sea sates based on a WEC-Sim model of the WaveStar device. More details on the relevant dimensions and mechanical properties of the prototype can be found [18].

1 Complex-conjugate control of target WEC system

1.1 Hydrodynamic modelling

The hydrodynamic model of the considered WEC is the benchmark model provided by Wave Energy Conversion Control COMPetition (WECCCOMP), which is organized by Centre for Ocean Energy Research (COER) at Maynooth University, Ireland in cooperation with Sandia National Laboratories, National Renewable energy Laboratory (NREL), Centre for Marine and Renewable Energy (MaREI), and Aalborg University, Denmark. The system to be used in the competition is available on the WEC-Sim (Wave Energy Converter SIMulator)[1]. The floater-wave dynamics in WEC-Sim are calculated by solving the Cummins' equation [19]:

$$\begin{aligned}(m+A_\infty)\ddot{X}(t) = &-\int_0^t K_r(t-\tau)\dot{X}(t)(\tau)d\tau \\ &+F_{ext}(t)+F_{vis}(t)+F_{hs}(t)+F_{pto}(t)\end{aligned} \tag{1}$$

where m is the floater mass, A_∞ is added mass at infinite wave frequency, $\ddot{X}(t)$ is the acceleration vector of the floater, K_r is the radiation impulse response function, $F_{ext}(t)$ is the wave-excitation force, $F_{hs}(t)$ is the hydrostatic restoring force, $F_{pto}(t)$ is the force exerted by PTO system, $F_{vis}(t)$ is the viscous force.

In the frequency domain, this formulation can be defined as:

$$[i\omega(m+A_\omega)+B_v+R(\omega)+\frac{S}{i\omega}]i\omega X(\omega) = F_{ext}(\omega)+F_{pto}(\omega) \tag{2}$$

where ω is the angular velocity, the operator $i\omega$ indicates differentiation, B_v and $R(\omega)$ are the viscous damping and radiation damping respectively, S is the hydro-static restoring coefficient.

The intrinsic impedance of the WEC system is defined as:

$$Z_i(\omega) = i\omega(m+A_\omega)+B_v+R(\omega)+\frac{S}{i\omega} \tag{3}$$

1.2 Complex-conjugate control

Principally, if both the phase and amplitude optima of the floater are satisfied, the optimal wave-body energy absorption of the WEC can be achieved [1]. An ideal PTO can serve as an extra inertia or a spring (as required) so to counteract the intrinsic WEC reactance. Then, the WEC is in phase with the wave excitation force. If the PTO damping is further optimized, the theoretical maximum of the extracted wave energy could be obtained. The optimal PTO impedance is the complex-conjugate of the intrinsic impedance:

$$\begin{aligned}Z_{pto}(\omega) &= Z_i^*(\omega) \\ &= -i\omega(m+A_\omega)+B_v+R(\omega)-\frac{S}{i\omega}\end{aligned} \tag{4}$$

[1] https://wec-sim.github.io/WEC-Sim/

In complex-conjugate control, the sum of mass, damping and spring terms yields the PTO force:

$$
\begin{aligned}
F_{pto}(t) &= M_{pto}\ddot{X}(t) + B_{pto}\dot{X}(t) + C_{pto}X(t) \\
&= -(m+A)\ddot{X}(t) + (B_v + R)\dot{X}(t) - SX(t)
\end{aligned} \tag{5}
$$

The PTO spring coefficient C_{pto} is constant for a given geometry, however values of M_{pto} and B_{pto} need to be adjusted with different values of ω, $B_{pto} = B_v + R$ and:

$$
M_{pto}\ddot{X}(t) + C_{pto}X(t) = -(m+A)\ddot{X}(t) - SX(t) \tag{6}
$$

This is an equation with two unknown coefficients, M_{pto} and C_{pto}, any arbitrary value can be given for one of these coefficients, and the other coefficient can then be calculated. When $M_{pto} = 0$, this is known as the damping-spring reactive control:

$$
F_{pto}(t) = B_{pto}\dot{X}(t) + C_{pto}X(t) \tag{7}
$$

For a single frequency, the values of PTO damping and spring coefficients remain constant. When applying complex-conjugate control at every frequency of a polychromatic excitation, the control is non-causal (future velocity information is required) [20]. Although the wave excitation force can be approximated [21], perfect future knowledge is unavailable in real sea states [22]. Alternatively, a causal controller can be developed to approximate the response of the complex-conjugate controller as closely as possible. The simple causal controller only requires the device velocity as its input.

1.3 Causal realization

Although causal control has suboptimal performance due to its memoryless definition, it can provide competitive performance that rivals prediction-based controllers, which often unrealistically assumes perfect prediction on hand. Surprisingly, the suboptimal causal controller using only device velocity as input can achieve more than 90% of the theoretical maximum [23].

The most common causal controller may be the damping-spring controller as shown in (7). This is a first-order representation, that can only match the response of complex-conjugate controller in a narrow band. However, the causal controller can almost perfectly match the complex-conjugate response when using a second order system [23] [24]:

$$
F_{pto}(s) = \frac{M_{pto}s^2 + B_{pto}s + C_{pto}}{s^2 + a_1 s + a_0}\dot{X}(s) \tag{8}
$$

where $F_{pto}(s)$ and $\dot{X}(s)$ are the Laplace transform of the PTO force and the velocity of the floater, respectively.

In the time domain, (8) can be rewritten as the following integro-differential equation:

$$
\dot{F}_{pto}(t) + a_1 F_{pto}(t) + a_0 \int F_{pto}dt = M_{pto}\ddot{X}(t) + B_{pto}\dot{X}(t) + C_{pto}X(t) \tag{9}
$$

The term on the right hand side of (9) are together in exactly the form of mass-damping-spring controller (5), a_0 and a_1 provide extra flexibility to match the response of complex-conjugate controller. However, this approach may suffer from issues related to closed-loop stability. The gain becomes very large quickly with increasing frequency, resulting in poor stability margins.

1.4 Limitation of complex-conjugate control

For some wave conditions, the complex-conjugate control may result in large motions and unrealistic PTO forces of the WEC. Additionally, the complex-conjugate control requires the PTO to release partial energy back to the waves, that is, the PTO acts as a motor during a short time of the wave period. This implies that the PTO system should have high energy conversion efficiency to absorb energy and feed energy back to the waves. Finding the practical optima of these coefficients numerically is non-trivial, especially when accurate non-linear hydrodynamic models are usually not available. The proposed method in this work is one of updating the controller coefficients at the end of each simulation episode by evaluating the criterion used in the WECCCOMP, which rewards absorbed power and penalises large motions and PTO forces:

$$
Score = \frac{avg(P)}{2 + \frac{|F_{pto}|_{98}}{F_{max}} + \frac{|X|_{98}}{X_{max}} - \frac{avg|P|}{|P|_{98}}} \tag{10}
$$

where the fraction term $avg(P)$ is the average extracted power, $|F_{pto}|_{98}$ is the 98^{th} percentile of the absolute force in a simulation episode, F_{max} is the PTO force constraint, $|X|_{98}$ is the 98^{th} percentile of the absolute displacement in a simulation episode, X_{max} is the PTO displacement constraint, $avg|P|$ is the mean absolute electrical power output, $|P|_{98}$ is the 98^{th} percentile of the absolute electrical power in a simulation episode.

The mechanical-to-electrical conversion efficiency of the linear generator η has been set at 0.7, so that the extracted power is:

$$
P(t) = \begin{cases} \eta F_{pto}(t)\dot{X}(t) & if \quad F_{pto}(t)\dot{X}(t) > 0 \\ F_{pto}(t)\dot{X}(t)/\eta & if \quad F_{pto}(t)\dot{X}(t) \leq 0 \end{cases} \tag{11}
$$

By evaluating this criterion, our proposed optimization method can help the controller to converge iteratively to the practical optimal performance.

2 Bayesian learning causal control

The optimization algorithm adopted in this work is BO, which is a data-efficient method for computing the maximum of expensive objective functions. For example, in this study the objective function is the above criterion, our purpose is to determine the optimal controller coefficients to maximize this criterion. A probabilistic model, such as GP model can be used to map the relation between controller coefficients and objective function. The probabilistic model shows the advantageous properties of providing both predictions and estimates of the uncertainty bounds with respect to the objective functions. In the GP model, the uncertainty is small near the observations, and becomes large when further away from the observations. The trade-off between exploration (areas of high uncertainty) and exploitation (areas close to the current best observation) has been made. Hence, the data-efficiency is achieved by searching and fitting within the required regions, rather than exploring all of the objective function spaces. As shown in Fig. 1, a Bayesian optimization based on a probabilistic model is used to update the controller with a high possibility of increasing the rewards (criteria) and then collecting the new data (controller coefficients and objective function evaluations) to enhance the GP model. By repeating this process, the GP model can iteratively approximate the real objective function in regions with potentially optimal performance. Eventually, the controller learns the optimal controller coefficients by interacting directly with the real waves.

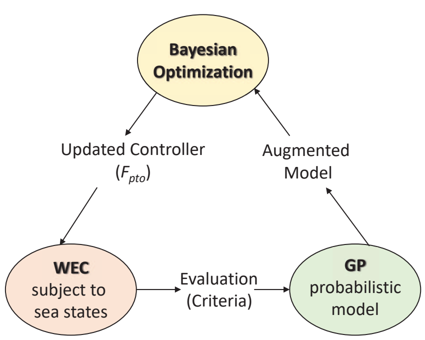

FIGURE 1. Block diagram of the Bayesian learning reactive control

2.1 The Bayesian Optimization approach

BO is a state-of-the-art machine learning framework for optimizing expensive and possibly noisy black-box functions [25]. It is particularly applicable in situations: (i) where the closed-form mathematical representation of the objective function is unknown, although possibly noisy observations of this function can be obtained, and (ii) when the objective functions are expensive to evaluate, such as for robotics and WEC devices, (iii) when the objective function derivatives are unavailable or the problem at hand requires non-convex optimization.

The typical form of Bayesian optimization uses a GP model to approximate the objective function f, where the GP model is usually referred to as a *surrogate function* in BO. Then, the acquisition function is used to determine the next controller coefficients x_{k+1} to be evaluated based on the GP model. The promising regions of the x_{k+1} space are those with high GP mean and high GP uncertainty. Hence, the decision represents an automatic trade-off between exploration and exploitation. This also implies that the BO can find the extrema of the objective functions have multiple local maxima with only a few evaluations.

Formally, the GP is a stochastic process involving an infinite set of variables, any finite subsets of which are jointly Gaussian distributed. GP is widely used in both prediction and control problems [26]. The *priori* statistics of a GP model $f(x)$ can be fully specified by a mean function $m(x)$ and a covariance function $k(x,x')$:

$$\begin{aligned} f(x) &\sim \mathscr{GP}(m(x),k(x,x')) \\ m(x) &= \mathbb{E}[f(x)] \\ k(x,x') &= cov(f(x),f(x')) \end{aligned} \tag{12}$$

where $x \in \mathbb{R}^D$ is the input vector, D is the dimension of inputs, $f(x)$ and $f(x')$ are arbitrary Gaussian scalar variables indexed by x and x'. Generally, $k(x,x')$ is also referred to as a kernel function parametrized by some certain variables θ. The choice of covariance function for Bayesian optimization implementation is the rational quadratic (RQ) kernel with automatic relevance determination (ARD):

$$k(x,x') = h_f^2[1+\frac{1}{2\alpha}r^2(x,x')]^{-\alpha}, \text{ with } r^2(x,x') = \sum_{d=1}^{D}\frac{1}{\lambda_d^2}(x_d - x_d')^2 \tag{13}$$

where h_f governs the output scales and λ_d governs the input scales in each d dimension. The λ serve to the covariance function's smoothness. $\alpha > 0$ is the shape parameter. Also, other commonly used covariance functions can be found in the paper [27], and even can be created for the specifical approximations, for example when the objective function has periodical properties.

The hyperparameter vector values θ can be obtained by optimizing the following log marginal likelihood function:

$$\log p(y|\theta) = -\frac{1}{2}\log|K| - \frac{1}{2}y^T K^{-1} y - \frac{n}{2}\log(2\pi) \tag{14}$$

The optimization of hyperparameters allows the standard gradient-based non-convex optimization methods such as BFGS. After the training, and in order to obtain the target prediction f' for a new given input X' from the *posterior*, the extended joint distribution is illustrated by:

$$\begin{bmatrix} f' \\ y \end{bmatrix} \sim \left(\begin{bmatrix} m(X') \\ m(X) \end{bmatrix}, \begin{bmatrix} k(X',X') & k(X',X) \\ k(X,X') & K+\sigma^2 I \end{bmatrix} \right) \tag{15}$$

with $k(X',X) = k(X,X')^T = [k(X_1,X'), \cdots, k(X_N,X')]$. Based on the theorem of joint Gaussian distributions [27], the forecasting result for the target is represented as:

$$\begin{aligned} \mu(f') &= m(X') + k(X',X)[K+\sigma^2 I]^{-1}(Y - m(X)) \\ var(f') &= k(X',X') - k(X',X)[K+\sigma^2 I]^{-1}k(X,X') \end{aligned} \tag{16}$$

For a given GP model, an acquisition function is used to guide the search for a maximum of the objective function. Here, the Gaussian process upper confidence bound (GP-UCB) algorithm is considered as the acquisition function.

$$\begin{aligned} a_{UCB}(x;\{X,y\},\theta) &= \mu(x) + \sqrt{\eta \beta_K var^2(x)}, \\ \beta_K &= 2ln(DK^2\pi^2/(6\delta)) \end{aligned} \tag{17}$$

where K is the evaluation number, $\delta > 0$ is the probabilistic tolerance, var is variance of GP predictions, $\eta > 0$ is an adjustable conversion efficiency parameter, and β_K is the learning rate to achieve optimal regression [28]. As to which coefficient value of the causal controller should be evaluated next is determined by maximizing the acquisition function:

$$x_{k+1} = argmax_x a_{UCB}(x) \tag{18}$$

2.2 Practical Bayesian learning causal control

In this work, 3 forms of causal controller have been introduced, namely damping-spring (7), mass-damping-spring (5) and second order system controller (9). The damping-spring and mass-damping-spring controller are chosen for regular wave and irregular wave conditions, respectively. Actually, when considering that the WEC normally works over a relatively narrow-band sea state, the controllers using simpler damping-spring and mass-damping-spring controller present similar performance compared with second order system controller, the capture width is very close to optimal complex-conjugate control [23].

The optimal causal controller coefficients are obtained for each sea state by using the hybrid BO algorithm [29]. However, the algorithm may cause damage to the WEC device. In practice, some combination of these coefficients may result in large motion and PTO force, especially in the case of using small damping value subject to big waves. Therefore, the upper and lower bounds of the search range should be given to the BO algorithm. For example, the WEC oscillation amplitude constraints can be guaranteed by choosing larger lower bound for the damping coefficient [30]:

$$B_{pto} \geq LBD = max(\frac{|F_{ext}|}{\omega X_{max}}, 2R) - R \tag{19}$$

where X_{max} is the floater amplitude constraints, LBD is the minimum value of damping coefficient, the value of other coefficients should be considered for large waves in each sea state.

When the optimal coefficient value eventually converges to the upper or lower bounds, the bound can be extended to a new conservative setting according to the displacement observations and real-time recording of the PTO force.

The flowchart of the practical BO algorithm for the reactive control of WEC devices is shown in Fig. 2. In the initialization stage, the objective function f, the initial value x_0 of controller coefficients, upper bound UB and lower bound LB of x_0, PTO force bound F_{max}, and the number of iterations K are initialized. Then x_0 has been evaluated by the simulation model of WEC subject to the sea state. Although the objective function could be evaluated per wave period in a regular wave condition, here the evaluation with a time range of at least 20 periods has been chosen for both regular and irregular waves. However, for irregular waves, even though keeping the value of controller coefficients constant, the criteria score may vary with changing sea state conditions. Fortunately, the criteria scores are linearly proportional to the absolute mean elevation of the waves, then each criteria score can be reformed as an assumed constant value for a given sea state:

$$Sc\hat{o}re = Score - avg(wave)\zeta \tag{20}$$

where the $Sc\hat{o}re$ is the reformed score, $avg(wave)$ is the absolute average elevation of 20 period waves, and the coefficient ζ can be computed using a non-linear least-squares curve-fitting method.

After the first trial, data are collected to build the GP surrogate function, followed by evaluating the new test points calculated by the Bayesian optimization. This procedure has been conducted repeatedly until the iteration number K exceeds the stopping criterion, the algorithm then returns the optimal values of controller coefficients.

3 Simulation Results

The practical BO algorithm is validated under both regular and irregular wave conditions. However, as mentioned earlier, it is particularly hard to calculate the optimal references of complex-conjugate control based on inaccurate numerical model subject to physical constraints. Here, all combinations of controller coefficients are tested for both regular and irregular sea conditions. The global optimal coefficients are then compared with the optimized coefficients of the BO algorithm. Then the performance of proposed learning causal controller corresponding to 6 irregular sea states is presented.

3.1 Learning reactive control in regular waves

The evaluation criteria for all possible configurations of the damping and stiffness coefficients corresponding to regular wave

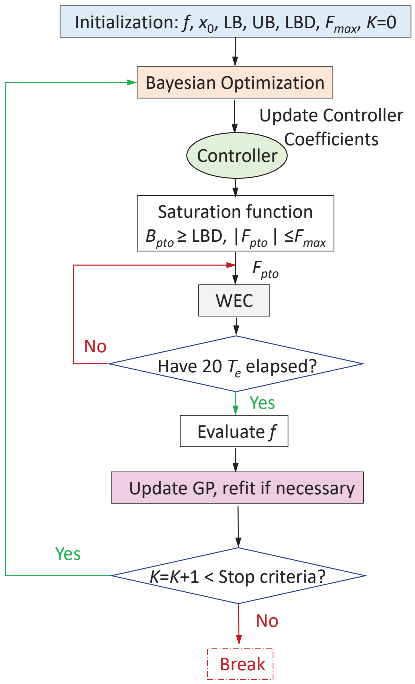

FIGURE 2. Flowchart of the practical BO algorithm for the causal control of WECs

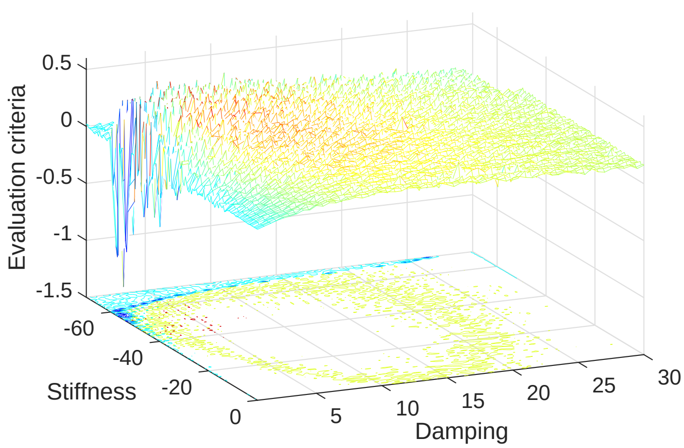

FIGURE 3. Evaluation criteria for all possible configurations of the damping and stiffness coefficients in a regular wave

with wave height $H_e = 0.0625(m)$ and wave period $T_e = 1.412(s)$ is shown in Fig. 3. Every combination is evaluated on the WaveStar WEC-Sim model, and the score is calculated by (2). It is clear that the highest score area is quite small and close to the unstable areas. The WEC unstable state is caused by using a small PTO damping and large negative stiffness coefficients. It is clear that the score landscape appears to be convex, but very rough and noisy, due to non-linear WEC-Sim simulation environment and different initial conditions, such as the floater displacement. In real sea state (irregular sea conditions), the sensors are noisy, which may hinder the use of many gradient based optimization algorithms. By contrast, the complex noisy landscape and expensive function evaluation makes the BO particularly suitable for the WEC complex-conjugate control problem.

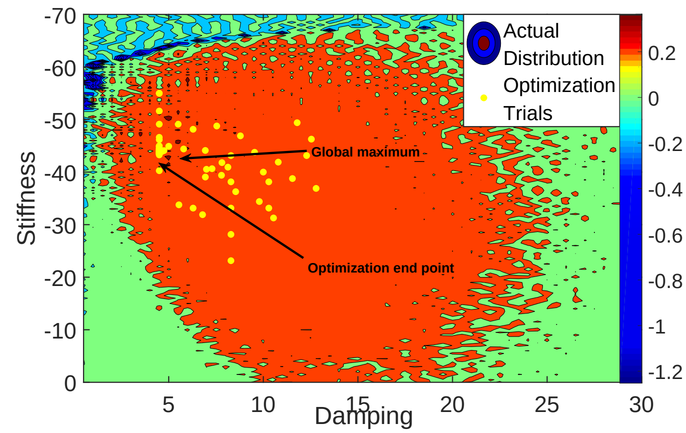

FIGURE 4. 2 Bayesian optimization trials and convergence of the damping and stiffness coefficients in a regular wave

2 BO trials of the damping and stiffness coefficients are depicted on the contour map of actual evaluation distribution. As can be seen in Fig. 4, according to these 2 BO algorithm implementations, the search points eventually converge to the vicinity of the true global optima. It is noticeable that all the trials are located on the right side of the line where damping value $B_{pto} = 4.5$ *units*. This is the lower bound $LB = 4.5$ *units* setting of the search range of the damping coefficient, which is used to handle the amplitude constraint.

Additionally, an extra 3 independent implementations of the BO algorithm with different initial values of B_{pto} and C_{pto} are presented in Fig. 5. Impressively, although starting with different locations, the optimal B_{pto} and C_{pto} eventually converge to the global optima. Less than 20 evaluations are required for the BO algorithm to achieve the convergence. Small variances in the values of B_{pto} and C_{pto} will not affect the criteria of the objective function after 20 evaluations. This indicates that the BO algorithm is capable of finding the optimal of PTO damping and stiffness coefficients reliably and efficiently, when operating under hypothetical regular wave conditions.

3.2 Learning reactive control in irregular waves

A similar efficient performance of the proposed method is demonstrated for the irregular wave case, where a JONSWAP spectrum with wave height $H_e = 0.1042(m)$, wave period $T_e = 1.836(s)$ and $\gamma = 3.3$ is used. As shown in Fig.6, the mass-damping-spring coefficients converge rapidly towards the true global optima within 20 evaluation. This means that under real (irregular) wave conditions, a typical range of wave period is $5-15s$, at most 2 hours, is required to finish the optimization

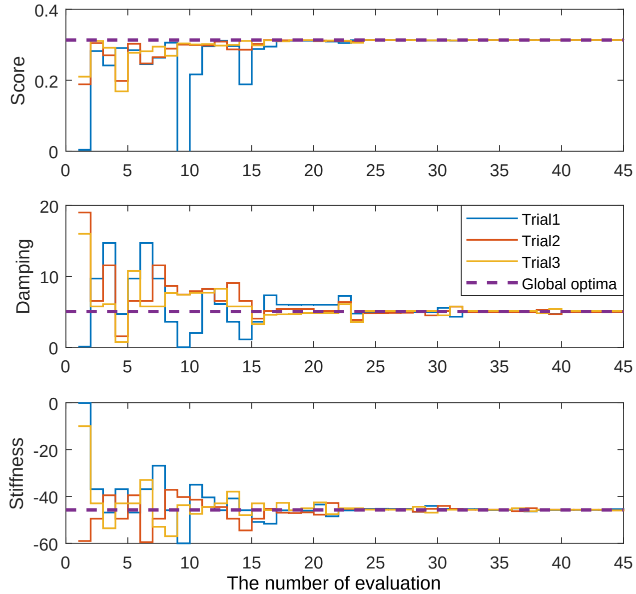

FIGURE 5. 3 regular wave Bayesian optimization trials with different initial parameters

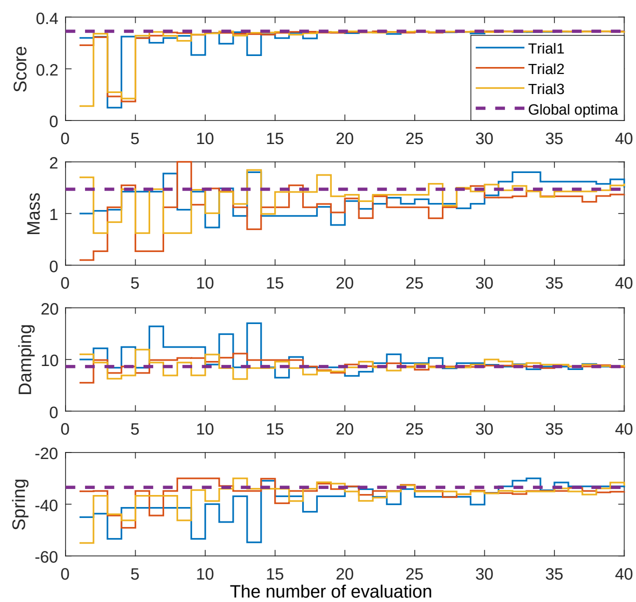

FIGURE 6. 3 irregular wave Bayesian optimization trials with different initial parameters

of WEC control system. This shows great practical potential for real seas implementation.

An extra 5 sea states are used to evaluate the proposed control strategy, the criteria scores are listed in Table 1:

TABLE 1. Criteria scores of 6 wave states

JONSWAP Spectra (He, Te, γ)	Score
S_1(0.0208,0.988,1)	0.0119
S_2(0.0625,1.412,1)	0.1274
S_3(0.1042,1.836,1)	0.3035
S_4(0.0208,0.988,3.3)	0.0150
S_5(0.0625,1.412,3.3)	0.1554
S_6(0.1042,1.836,3.3)	0.3453

4 Conclusions

In this work, a learning causal control method is developed. The causal controller is predictionless and shows competitive performance to optimal control methods, and (i) can adapt to the different sea states, (ii) can avoid modelling errors, (iii) can prevent device from damaging while keeping data-efficient characteristics. The main contribution of this work is making the complex-conjugate control of WEC practicable, reliable, and efficient by using a BO algorithm. Fast convergence and global optimal performance of the BO algorithm is validated in both regular and irregular waves, where only less than 20 function evaluations are required to complete optimization. In practice, the proposed control method can be implemented by using the combination of a host computer and the Simulink Real Time system (such as D-space, Speedgoat). Actually, only the host computer is compulsory to run the BO algorithm, the Simlink Real Time system can be replaced by other commercialized controllers, as long as the controller can communicate with the host computer and implement the varying-PID control algorithm. Interestingly, the mass-damping-spring controller can be regarded as the PID controller, for which parameters are time-varying and set by an external source. The inputs of the control system are position,velocity,wave elevation,and PTO force, while the output is only the PTO force reference, which can be used by the PTO controller (such as motor controller).

REFERENCES

[1] Falnes, J., et al., 2002. "Optimum control of oscillation of wave-energy converters". *International Journal of Offshore and Polar Engineering,* ***12***(02).

[2] Ringwood, J. V., Bacelli, G., and Fusco, F., 2014. "Energy-maximizing control of wave-energy converters: The development of control system technology to optimize their operation". *IEEE Control Systems,* ***34***(5), pp. 30–55.

[3] Budar, K., and Falnes, J., 1975. "A resonant point absorber of ocean-wave power". *Nature,* ***256***(5517), p. 478.

[4] Shek, J. K.-H., Macpherson, D. E., Mueller, M. A., and Xiang, J., 2007. "Reaction force control of a linear electrical generator for direct drive wave energy conversion". *IET renewable power generation,* ***1***(1), pp. 17–24.

[5] Budal, K., 1981. "Model experiment with a phase-

controlled point absorber". In 2nd International Symposium on Wave and Tidal Energy, Cambridge, UK, 23-25 September 1981, pp. 191–206.
[6] Babarit, A., and Clément, A. H., 2006. "Optimal latching control of a wave energy device in regular and irregular waves". *Applied Ocean Research,* ***28***(2), pp. 77–91.
[7] Faedo, N., Olaya, S., and Ringwood, J. V., 2017. "Optimal control, mpc and mpc-like algorithms for wave energy systems: An overview". *IFAC Journal of Systems and Control,* ***1***, pp. 37–56.
[8] Bacelli, G., and Ringwood, J. V., 2015. "Numerical optimal control of wave energy converters". *IEEE Trans. Sustain. Energy,* ***6***(2), pp. 294–302.
[9] Guo, B., Patton, R., Jin, S., Gilbert, J., and Parsons, D., 2018. "Nonlinear modeling and verification of a heaving point absorber for wave energy conversion". *IEEE Transactions on Sustainable Energy,* ***9***(1), pp. 453–461.
[10] Giorgi, G., and Ringwood, J. V., 2017. "Nonlinear froude-krylov and viscous drag representations for wave energy converters in the computation/fidelity continuum". *Ocean Engineering,* ***141***, pp. 164–175.
[11] Fusco, F., and Ringwood, J. V., 2014. "Hierarchical robust control of oscillating wave energy converters with uncertain dynamics". *IEEE Trans. Sustain. Energy,* ***5***(3), pp. 958–966.
[12] Richter, M., Magana, M. E., Sawodny, O., and Brekken, T. K., 2013. "Nonlinear model predictive control of a point absorber wave energy converter". *IEEE Transactions on Sustainable Energy,* ***4***(1), pp. 118–126.
[13] Bacelli, G., Coe, R., Patterson, D., and Wilson, D., 2017. "System identification of a heaving point absorber: Design of experiment and device modeling". *Energies,* ***10***(4), p. 472.
[14] Giorgi, S., Davidson, J., and Ringwood, J. V., 2016. "Identification of wave energy device models from numerical wave tank datapart 2: Data-based model determination". *IEEE Transactions on Sustainable Energy,* ***7***(3), pp. 1020–1027.
[15] Valério, D., Mendes, M. J., Beirão, P., and da Costa, J. S., 2008. "Identification and control of the aws using neural network models". *Applied Ocean Research,* ***30***(3), pp. 178–188.
[16] Na, J., Li, G., Wang, B., Herrmann, G., and Zhan, S., 2018. "Robust optimal control of wave energy converters based on adaptive dynamic programming". *IEEE Transactions on Sustainable Energy*.
[17] Anderlini, E., Forehand, D., Bannon, E., Xiao, Q., and Abusara, M., 2018. "Reactive control of a two-body point absorber using reinforcement learning". *Ocean Engineering,* ***148***, pp. 650–658.
[18] Ringwood, J., Ferri, F., Ruehl, K. M., Yu, Y.-H., Coe, R., Bacelli, G., Weber, J., and Kramer, M., 2017. "A competition for wec control systems". In Proceedings of the 12th European Wave and Tidal Conference, EWTEC.
[19] Cummins, W., 1962. The impulse response function and ship motions. Tech. rep., David Taylor Model Basin Washington DC.
[20] Price, A. A., 2009. "New perspectives on wave energy converter control".
[21] Guo, B., Patton, R. J., Jin, S., and Lan, J., 2018. "Numerical and experimental studies of excitation force approximation for wave energy conversion". *Renewable Energy,* ***125***, pp. 877–889.
[22] Shi, S., Patton, R. J., and Liu, Y., 2018. "Short-term wave forecasting using gaussian process for optimal control of wave energy converters". *IFAC-PapersOnLine,* ***51***(29), pp. 44–49.
[23] Coe, R. G., Bacelli, G., Cho, H., and Nevarez, V., 2018. A comparative study on wave prediction for wecs. Tech. rep., Sandia National Lab.(SNL-NM), Albuquerque, NM (United States).
[24] Nevarez, V., Bacelli, G., Coe, R. G., and Wilson, D., 2018. "Feedback resonating control for a wave energy converter". In 2018 International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM), IEEE, pp. 1286–1290.
[25] Brochu, E., Cora, V. M., and De Freitas, N., 2010. "A tutorial on bayesian optimization of expensive cost functions, with application to active user modeling and hierarchical reinforcement learning". *arXiv preprint arXiv:1012.2599*.
[26] Liu, Y., Patton, R. J., and Shi, S., 2018. "Wind turbine load mitigation using MPC with Gaussian wind speed prediction". In 2018 UKACC 12th International Conference on Control (CONTROL), IEEE, pp. 32–37.
[27] Rasmussen, C. E., and Williams, C. K., 2006. "Gaussian processes for machine learning. 2006". *The MIT Press, Cambridge, MA, USA,* ***38***, pp. 715–719.
[28] Srinivas, N., Krause, A., Kakade, S. M., and Seeger, M., 2009. "Gaussian process optimization in the bandit setting: No regret and experimental design". *arXiv preprint arXiv:0912.3995*.
[29] Acerbi, L., and Ji, W., 2017. "Practical bayesian optimization for model fitting with bayesian adaptive direct search". In Advances in Neural Information Processing Systems, pp. 1836–1846.
[30] Orazov, B., OReilly, O., and Sava, ., 2010. "On the dynamics of a novel ocean wave energy converter". *Journal of Sound and Vibration,* ***329***(24), pp. 5058 – 5069.