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Robust predictive control for heaving wave energy converters

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ABSTRACT

In this paper, a novel robust model predictive controller (R-MPC) for wave energy converters (WECs) is proposed. The controller combines a constrained function-based predictive controller that is responsible for ensuring maximum power extraction and a local model that compensates for system parametric uncertainties and model mismatches. Laguerre polynomials have been deployed to alleviate the computational burden usually associated with the standard MPC techniques. The computer simulation results show that the R-MPC strategy has produced satisfactory and computationally efficient performance with respect to maximizing the captured power, increasing the power conversion efficiency, and enhancing the power take-off (PTO) utilization.

1. Introduction

Wave energy converters (WECs) are devices that capture the energy contained in traveling sea waves and convert them to useful energy (electricity) via a power take-off (PTO) system (Eriksson, 2007). A schematic of a grid-connected point absorber wave energy converter (WEC) is described in Fig. 1, which is made of a heaving body (buoy), a direct-drive permanent magnet linear generator (PMLG), an interconnecting tether, and auxiliary (restoring) springs. The energy capture capability of the WEC is dependent on the site of operation, buoy's geometry, PTO efficiency, and adopted control strategy.

Properly designed control strategy can increase the WEC energy yield, down size the required PTO rating, and prolong the lifetime of the system, thus making the system more feasible economically (Tedeschi & Molinas, 2012). Numerous WEC control techniques have been proposed in the literature, where almost all of them are based on the principle of reactive control proposed in Budal and Falnes (1980). Robust hierarchical control schemes, consisting of a high-level suboptimal buoy velocity reference generator and a low-level servo control loop, are presented in Fusco and Ringwood (2014a, b), Jama, Noura, Wahyudie, and Assi (2015) and Wahyudie, Jama, Saeed, Nandar, and Harib (2015, 2017).

Recently, the effectiveness of model predictive control (MPC) in controlling the WECs has been also discussed in the literature. Predictive controllers offer some exclusive features that have made them such an attractive control solution in the industry. To mention a few, predictive control, as the name implies, optimally generates the control law for each sampling instant based on the predicted future behavior of the system. In addition, it provides a ready platform to incorporate system limitations and constraints, which makes the anticipative nature of the controller further useful (Xi, Li, & Lin, 2013). However, these advantages come at the expense of increased computational complexity, especially for high order systems. In addition, the dependency of controllers on the system mathematical model jeopardizes its practical effectiveness. Therefore, having a fairly accurate mathematical model is of paramount importance (Xi et al., 2013). Classical constrained linear MPC strategies have been proposed to tackle the control problem in the mechanical side of the WEC (Hals, Falnes, & Moan, 2011; Li & Belmont, 2014). These efforts were based on maximizing captured energy of the WECs while limiting the buoy displacement and the PTO force. A modified linear MPC strategy, in which the PMLG copper losses are included, has been also addressed (Jaen, Andrade, & Santana, 2013). Furthermore, a constrained nonlinear MPC has been proposed to control two-body heaving WECs (Richter, Magana, Sawodny, & Brekken, 2013). In Li (2015), MPC method for controlling WECs using a combination of pseudo-spectral and differential flatness techniques is proposed. The method tackles the problems of non-convexity and non-linearity associated with the cost function, constraints, and the system model. A direct transcription optimal control law using Galerkin method along with a truncated Fourier series as basis functions is reported in Bacelli and Ringwood (2015).

In this work, a novel robust model predictive controller is proposed, which maximizes the energy output of the heaving WEC while respecting its physical limitations. The suggested control strategy is a genuine improvement over that proposed in Jama (2015) and Jama, Wahyudie,

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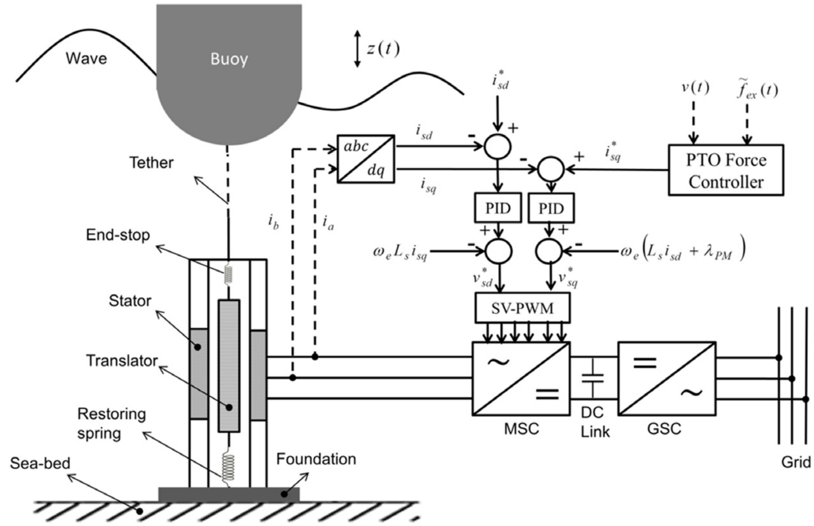

Fig. 1. Point absorber WEC system.

Assi, and Noura (2014). The controller consists of two main parts: (1) a sub-optimal reference-less function-based predictive controller and (2) a local model that compensates for the dynamics that are not captured by the predictive controller due to parametric uncertainties and external disturbances. The computational complexity usually associated with standard MPC is alleviated by parameterizing the PTO force using orthonormal polynomials. In addition, the local model ensures that the energy flow remains positive (i.e., from the sea to the grid) regardless of the sea-state characteristics. The local model contribution is designed so that it does not violate the limitations imposed by the predictive controller. The effectiveness of the proposed controller has been assessed through computer simulations by comparing it to other control strategies.

This paper is organized as follows. The point absorber WEC model is described in Section 2. The formulation of the proposed control strategy is presented in Section 3. The simulation results and the corresponding discussions are found in Section 4. Conclusions are given in Section 5.

2. Point absorber model

2.1. Equation of motion

The device is a single-body heaving wave energy converter oscillating against a fixed reference (i.e., the sea bed), as shown in Fig. 1. The submerged part of the buoy is semispherical. The forces acting on the system can be separated into two groups, the hydrodynamic forces $f_h(t)$ and the mechanical PTO forces $f_m(t)$ (Eriksson, 2007). Therefore, the governing equation of motion can be written as

$$f_h(t) + f_m(t) = ma(t), \tag{1}$$

where m is the total mass of the oscillating body and $a(t)$ is the buoy heave acceleration.

2.2. Hydrodynamic model

The hydrodynamic forces $f_h(t)$ can be decomposed into the following (Falnes, 2002):

$$f_h(t) = f_{ex}(t) + f_r(t) + f_b(t) + f_l(t), \tag{2}$$

where $f_{ex}(t)$ is the wave excitation force, $f_r(t)$ is the radiation force, $f_b(t)$ is the hydrostatic buoyancy force, and $f_l(t)$ is the losses force that could result from known or unknown hydrodynamic forces. Each of the mentioned forces can be modeled as

$$f_{ex}(t) = k_{ex}(t) * \eta(t) = \int_{-\infty}^{t} k_{ex}(\tau)\eta(t-\tau)d\tau, \tag{3a}$$

$$f_r(t) = -m_\infty a(t) - \int_0^t k_r(\tau)v(t-\tau)d\tau, \tag{3b}$$

$$f_b(t) = -S_b z(t), \tag{3c}$$

$$f_l(t) = -R_l v(t) - R_d \, |v(t) - v_w(t)|(v(t) - v_w(t)), \tag{3d}$$

where $k_{ex}(t)$ and $k_r(t)$ are the excitation and radiation convolution kernels, respectively. $\eta(t)$, $z(t)$ and $v(t)$ are the surface elevation of the incoming waves, the buoy heave displacement, and the buoy heave velocity, respectively. The coefficients S_b, R_l and R_d represent the buoyancy stiffness, hydrodynamic generic losses resistance and the viscous drag resistance, respectively. Note that $f_b(t)$ is a function of the buoy heave displacement $z(t)$, where $S_b = \rho g A_w$, that is A_w is the water plane area, ρ is the sea water density and g is the gravitational acceleration. The hydrodynamic losses force $f_l(t)$ is modeled as a summation of a linear and non-linear terms, in which the linear term represents a generic damping (resistive) force, whereas the nonlinear term models the viscous drag force according to Morison's equation (Ballard & Mann, 2013). The viscous drag force is modeled as quadratic function of the wave–buoy relative velocity, where $v_w(t)$ represents the water heave velocity when it is held undisturbed. The viscous drag resistance $R_d = 0.5\rho A_w C_d$, where C_d is the drag coefficient (McCormick, 2010). It is difficult to accurately determine C_d. However, the experimental results for a spherical buoy show that it typically varies between 0.7 and 1.5, depending on the Reynolds number (i.e., from 100 to 1×10^5) (Timmerman & Weelea, 1999). The constant m_∞ is the hydrodynamic added mass at infinite frequency.

Remark. It is important to mention here that due to the spherical geometry of the buoy, the buoy water plane area A_w varies as the buoy heaves, which will introduce non-linear dynamics to the hydrodynamic forces such as the excitation (Froude–Krylov) and hydro-static stiffness forces. However, if the maximum buoy stroke is kept noticeably lower than the buoy radius, the underlying non-linearities can be minimized.

The hydrodynamic software, WAMIT®, was used to solve the excitation and radiation problems (WAMIT, 2006). The frequency domain identification method proposed in Guo, Patton, Jin, and Lan (2018) was utilized to approximate the excitation convolution kernel with a